Iris Texture Recognition Using Co-occurence Matrix Features with K_means Algorithm

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Abstract

Iris Recognition is a rapidly expanding method of biometric authentication that is well suited to be applied to any access control system requiring high level of security. In this paper k-means algorithm is employed to optimize the database enrollment, this is carried out by choosing the best image (among many) for the same person to be a template in the database. Iris images are mapped into texture features produced from co-occurrence matrix. Experimental results show that the performance of the proposed recognition system gave true identification rate of about 86% when using optimized database and 59% when using selected database.

Keywords : Iris recognition, Co-occurrence matrix, K_means, Feature extraction, Clustering.

1. Introduction

Biometrics refers to the identification and verification of human identity based on certain physiological character of a person. The commonly used biometric features include speech, fingerprint, face, iris, handwriting, gait, hand geometry etc. With the need for security systems going up, Iris recognition is emerging as one of the important methods of biometrics-based identification systems that use pattern-recognition techniques on images of iris to reliably identify a person. It has proven to be a very useful and versatile security measure. The face and speech techniques have been used for over 25 years, while iris method is a newly used technique [1].

The iris is the colored part of the eye behind the cornea, and in front of the eye lens. It is the only internal organ of the body which is normally externally visible. These visible patterns are unique to all persons and it has been found that the probability of finding two persons with identical iris patterns is almost zero. The great pattern variability and the stability over time, makes this a reliable security recognition system[2].

Recognition systems are usually consisting of two phases; training or database enrollment and recognition (identification or verification). The training phase responsible for collecting sample images to be stored as comparable models in the database. Whereas, the recognition phase responsible for identifying the test image depending on comparison with the trained models. A critical step in the iris recognition system is how to design a database of images such that produce competitive results for the recognition test [3].

The interesting point in the field of recognition is the use of one image (or average of multiple images) to construct the training models in the database. Such problem is overcame in the present work, the training phase in the proposed system is developed to stand for database optimizer.

2. Related Works and Contribution

In 1992, John Daugman was the first to develop the iris identification software, it has been tested for a billion images and the failure rate has been found to be very low. His systems are patented by the *Iriscan Inc*. and are also being commercially used in Iridian technologies, UK National Physical Lab, British Telecom etc, while since the early 1990s [4].

Many researches have used the combination of iris recognition and K_means and co-occurance matrix features. Among the published relevant researches are:

i. Wen-Shiung Chen, Ren-Hung Huang and Lili Hsieh presented in [5] a biometric recognition based on the iris of a human eye using gray-level co-occurrence matrix (GLCM). A new approach of GLCM, called 3D-GLCM, which is expanded from the original 2D-GLCM is proposed and

used to extract the iris features. The experimental results show that the proposed approach gains an encouraging performance on the UBIRIS iris database. The recognition rate up to 99.65% can be achieved.

ii. Peihua Li, Xinomin Liv Xiao and Qi Song presented in[6] a roubust and accurate iris segmentation in very noisy images. They proposed a limbic boundary localization algorithm that combines k_means clustering based on the Gray Level Cooccurance Matrix histogram and improved Hough Transform. The proposed approach had proven quite effective according to the independent evaluation of the NICE 1 organizing committee in the UBIRS.v2 a challenging iris database.

iii. Liu Jin Fu Xiao Wang Haopeng presented in [7] a new iris segmentation method based on K-means clustering. They proposed a limbic boundary localization algorithm based on K-Means clustering for pupil detection. they located the centers of the pupil and the iris in the input image. Then two image strips containing the iris boundaries are extracted. The outer boundary of iris is localized based on shrunk image using Hough transform. The proposed method was evaluated in the UBIRIS.v2 testing database by the NICE.I organizing committee and results are well.

The contribution of this work is the use K-means algorithm to build an optimum template database such that K_means will be work as unsupervised learning algorithms to solve the problem of collecting optimum iris templates.

3. Proposed Iris Recognition System

The proposed scheme consists of two subsystems: *iris enrollment* and *iris identification.* The input images are used from the UPOL iris database; the irises were scanned by the TOPCON TRC50IA optical device connected with SONY DXC-950P 3CCD camera. The image quality is high and without occlusions of eyelids and eyelashes. The original images are stored in color with a resolution of 768×576. Fig.(1) shows one sample of the used iris texture. The iris texture in this work is selected from the original image

manually using select tool in Microsoft paint version 5.1; the texture image resolution was 130×130 colored.
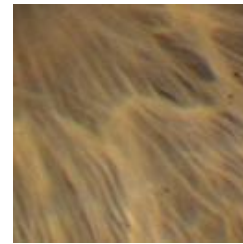

Fig.(1) Iris texture image.

The idea behind database optimization is concentrated in the enrollment phase, so most of effort will be carried out in such phase. Whereas, the recognition phase will be summarized by just finding the similarities between the query iris and templates found in the database. The following subsections explain the task of each phase in details:

3.1 Iris Enrollment

This system is build to enrol the iris in the database for further identification. The steps of such process are summarized in the following:

1. Loading iris image.
2. Decompose the image into Red, Green and Blue (RGB) bands.
3. Convert the RGB color bands to IHS representation. For each band do the following:

i. Perform a uniform color quantization (with quantization level Q_l).

ii. Construct a co-occurrence matrix $P_{dq}(i,j)$ in which the $(i,j)^{th}$ element describes the frequency of occurrence of two pixels (*i* and *j*) that are separated by distance $d=1$ in the direction *q*. Four directions are performed in this work ($\theta=0°,45°,90°$ and $135°$). This produces 4 matrices of $(Q_l \times Q_l)$ integer elements per matrix.

iii. Normalize the 4 co-occurrence matrix $P_{dq}(i,j)$ by dividing each entry by the summation of all entries in the matrix of the same direction. Hence, treating the matrix as a probability density function.

iv. Feature extraction for each normalized co-occurrence matrix:

The human iris is rich in discriminatory properties or features which can be used to distinguish one eye from another. 10 features were chosen from the normalized

co-occurrence matrix, the mathematical definitions of these features are [8,9,10,11,12]:

$$Energy = \sum_{i,j} P(i,j)^2 \quad \text{.......................................} \quad (1)$$

Where
$P(i,j)$ is the $(i,j)^{th}$ entry in a cooccurrence matrix $P_{dq}(i,j)$

$$Entropy = -\sum_{i,j} P(i,j) \log P(i,j) \quad \text{.....................} \quad (2)$$

$$IDM = \sum_{i,j} \frac{1}{1+(i-j)^2} p(i,j) \quad \text{.........................} \quad (3)$$

Where
IDM is the Inverse Difference Moment

$$MaxProbability = Max(P(i,j)) \quad \text{..........................} \quad (4)$$

$$ASMU = \sum_{i} \sum_{j} P(i,j) \quad \text{...................................} \quad (5)$$

Where
ASMU is Angular Second Moment Uniformity

$$Inertia = \sum_{i,j} (i-j)^2 \, p(i,j) \quad \text{...............................} \quad (6)$$

Where

$$CS = \sum_{i,j} \{|i-m_i|+|j-m_j|\}^3 \, p(i,j) \quad \text{.................} \quad (7)$$

Where
CS is theClusterShade

$$CP = \sum_{i,j} \{|i-m_i|+|j-m_j|\}^4 \, p(i,j) \quad \text{.................} \quad (8)$$

Where
CP is theCluster Prominence

$$m_i = \sum_{i} i \sum_{j} p(i,j) \quad \text{......................................} \quad (8.a)$$

$$m_j = \sum_{j} j \sum_{i} p(i,j) \quad \text{....................................} \quad (8.b)$$

$$s_i = \sum_{i} (i-m_i)^2 \sum_{j} p(i,j) \quad \text{...........................} \quad (8.c)$$

$$s_j = \sum_{j} (j-m_j)^2 \sum_{i} p(i,j) \quad \text{..........................} \quad (8.d)$$

$$C = \sum_{n=0}^{N-1} n^2 \sum_{i}^{N} \sum_{j}^{N} P(i,j) \text{ if } |i-j|=n \quad \text{...................} \quad (9)$$

Where
C is the Contrast

$$HC = \frac{\sum_{i,j} (ij)P(i,j) - m_x m_y}{s_x s_y} \quad \text{..........................} \quad (10)$$

Where
HC is Harlick Correlation
m_x, m_y, s_x, s_y are the means and standard deviations of:

$$C_x(i) = \sum_{j} P(i,j) \quad \text{.....................................} \quad (10.a)$$

$$C_y(j) = \sum_{i} P(i,j) \quad \text{.....................................} \quad (10.b)$$

v. Compute the mean of each feature from each direction (θ=0°,45°,90° and 135°), this value of the feature is transformed into a suitable vector form of features.

vi. After extracting features for the three bands I, H and S, then the feature vector, which is called *Iris-Code,* is constructed as a collection of 30 features (10 for each band).

4. Repeat steps (1 to 3) for the training set of iris images for the same iris.

5. Repeat steps (1 to 4) for all irises.

6. Iris-Code normalization: all the features vectors are normalized (i.e., mapped to the range [0,1]) in order to make all features having equal effect on the clustering process, as follows:

for all features in iris-code of all irises, compute f_{norm} as follows:

$$f_{norm} = \begin{cases} 0 & ,if \, f_i < min_i \\ \frac{f_i - min_i}{max_i - min_i} & ,if \, min_i \le f_i \le max_i \\ 1 & ,if \, f_i > max_i \end{cases} \quad \text{.............} \quad (11)$$

Where
f_{norm} is the normalized feature
f_i is the feature value
min_i is the minimum value found for this
        feature among all persons Iris-Codes
max_i is the maximum value found for this
        feature among all persons Iris-Codes

Now, the iris-codes become ready for clustering by K-means.

7. K-means: this procedure is a simple and easy way to classify the 10 Iris-Codes for the same iris through a certain number of clusters (assume k = 2), which can be summarized by the following steps:

1. Select randomly *k* Iris-Codes as centroids, one for each cluster.
2. Take the others Iris-Codes of the same person and associate them to the nearest centroid depending on Euclidean Distance between cluster centroid to each Iris-Code.
3. Re-calculate the *k* new centroids of the clusters resulting from the previous step.
4. Repeat steps (2 and 3) until no more changes are done. In other words centroids do not move any more. Now we have two optimal Iris-codes to this person that are used in a database for the identification process
5. Repeat steps (1 to 4) for all 10 irises.

3.2 Iris Identification

This system performs matching between the query iris image with the stored iris images in the database to decide if it is found in the database or not. The result of this system is the person identity (ID). This process can be summarized by the following steps:

1. Preprocessing: Perform step 1 to step 5 as illustrated in Iris Enrollment section.
2. Iris_Code: the iris code in simply is the normalized values of the estimated features of the iris want to be recognized. The normalized is done by dividing each feature value by the summation of all features values.
3. Iris Matching: this step is based on finding the minimum distance between the input Iris-Code and the preserved Codes in a database, the Minimum Distance Classifier is given by:

$$MDC = \sqrt{\sum_{i=1}^{n}(IrisCode_{DB}(i) - IrisCode_{new}(i))^2} \quad ... (12)$$

where
n is the no. of features

4. Output Stage: this stage is responsible for displaying the person's ID.

4. Test Results

The proposed system was implemented using Visual Basic (Ver.6.0) and the tests were conducted on a Fujitsu PC with Pentium IV (2GHz).

To evaluate the performance of the proposed identification method, several tests were conducted for ten persons (each person has ten images) to construct the iris database. Table (1) shows the percentage of identifying the irises: the first column in Table (1) is the results of using traditional method of database enrollment (average of multiple images), while the second column represent the results of the recognition using k_means to optimize the database.

Table (1)
Comparison between k_means and average based method.

Person ID	Recognition Success Rate	
	Traditional Method	K_means
1	40 %	70 %
2	70 %	100 %
3	30 %	90 %
4	60 %	80 %
5	80 %	90 %
6	70 %	100 %
7	70 %	70 %
8	60 %	90 %
9	40 %	70 %
10	70 %	100 %
Recognition Rate	59 %	86 %

It's obvious from Table (1) that the process of database building using k_means is better than the use of average based database. The results of proposed method gave high recognition rates with distinguished differences in between. In comparison with traditional method, the proposed method is regarded more stable due to less differences appears in the recognition results with different persons.

It is evident that the number of features to successfully perform a given recognition task depends on the discriminatory qualities of the chosen features. The selection of an appropriate set of features is one of the most difficult tasks in the design of iris identification system. Fig.(2) illustrates the performance of each feature alone:
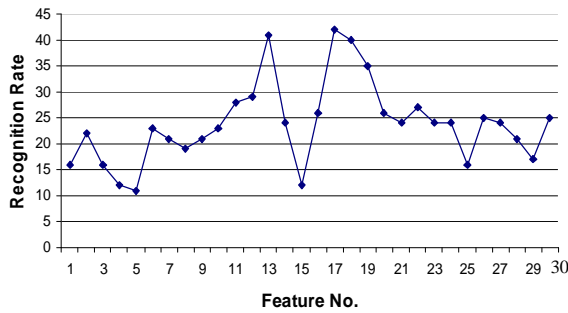
Fig. (2) Discrimination Capability.

X-axis in Fig. (2) represent the number of used features (10 for each band I, H, and S).

Various combinations of two, three, four,…,and ten features have been taken into account to improve the overall success rate of the recognition system, Table (3) presents these combinations starting from 2 features and adding one feature at each time until reaching a combination of ten features. The combination of features is carried out according to their ascending arrangement of the recognition rate in comparison with that of other combination.

Table (2)
Combination of selected features.

No. of Features	Additional Features	Band	Recognition Percentage
2	Harlick Correlation	H	65 %
	Contrast	H	
3	Cluster Prominence	S	72 %
4	Contrast	I	80 %
5	Cluster Shade	I	83 %
6	Contrast	S	86 %
7	Cluster Shade	S	86 %
8	ASMU	S	86 %
9	Inverse Difference Moment	S	86 %
10	Max Probability	I	86 %

Its clear that the combination of 6 features has rate 86% as same as a combination of 10 features , so we choose the combination of 6 features *(Harlick Correlation(H), Contrast(H), Cluster Prominence(S), Contrast(I), Cluster Shade(I) and Contrast(S))* as the optimal one in recognition process instead of computing 30 features (i.e., there are robust features that improve the system performance and there are other features weaken the performance of the

system), so we must reject the weak features this reduces the computational time needed and leads to fast and efficient system.

Before the calculation of co-occurrence matrix the image must be requantized into a limited number of quantized level (e.g., 4,8,16,…) to overcome the high computational complexity resulting from large co-occurrence matrix, Fig.(3) shows the effect of quantization level Q_l on the recognition rate.
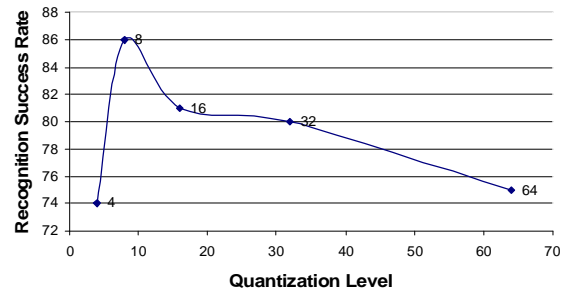

Fig. (3) The effect of quantization level.

It is shown that ($Q_l=8$) is the best quantization level since it gave highest recognition rate.

5. Conclusions

1. Our experimental results show that the idea of using more than one template per class, and the template are found using K_means algorithm, yields superior performance over traditional method, it leads to recognition rate (86%) whereas traditional one leads to (59%).

2. The highest recognition rate is achieved when using a combination of 6 features (Harlick Correlation(H),Contrast(H),Cluster Prominence(S), Contrast(I), Cluster Shade(I) and Contrast(S)).

3. Using Co-occurrence matrix with k_means lead to an improvement in the iris recognition performance.

6. References

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الخلاصة

أصبح التمييز بأستخدام قزحية العين اسلوب واسع الانتشار كونه مناسب تماما للتطبيق على اي نظام مراقبة يتطلب مستوى عالي من الأمنية. في هذا البحث تم استخدام042 خوارزمية الـ k_means لأختيار أفضل صورة (بين العديد) لنفس الشخص لتكون نموذج له في قاعدة البيانات. تم تمثيل صورة قزحية العين بأستخدام خصائص مصفوفة الـ Co-occurrence . لقد أظهرت النتائج ان أداء نظام التعرف على الشخص بأستخدام الـ k_means أعطى نتائج تمييز بنسبة 86% عند استخدام الطريقة المقترحة لتجميع قاعدة البيانات في حين انه اعطى نسبة 59% عند استخدام الطريقة التقليدية في تجميع قاعدة البيانات.

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