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Iris Recognition Using Modified Local Line Directional Pattern

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Abstract: In recent years, as one of the emerging biometrics technologies, iris recognition has drawn wide attentions. It has many advantages such as uniqueness, low false recognition rate and so it has broad applications. It mainly uses pattern recognition and image processing methods to describe and match the iris feature of the eyes, and then realizes personal authentication. In image processing field, local image descriptor plays an important role for object detection, image recognition, etc. Till now, a lot of local image descriptors have been proposed. Among all kinds of local image descriptors, it is well-known that LBP is a popular and powerful one, which has been successfully adopted for many different applications such as face recognition, texture classification, object recognition, etc. Currently, a new trend of the research on LBP is to encode the directional information instead of intensity information. LLDP is an LBP-like descriptor that operates in the local line-geometry space. We used modified finite radon transform (MFRAT) to implement the LLDP descriptor for iris recognition and obtained 80.03% accuracy.

Keywords: Iris recognition; LLDP; line response; feature extraction; CBIR

1. INTRODUCTION

The internet has grown rapidly and due to the improvement of internet, the availability of the number of images has also been increased. Hence, the demand for efficient search and retrieval has increased. Although many researches have been done in the field of image search and retrieval, there are still many challenging problems to be solved [5]. The problem of storage and manipulation of images still exist. To overcome these problems, almost all images are represented in compressed formats like JPEG and MPEG [6]. Early techniques of image retrieval were based on manual textual annotation of images. It is difficult to characterize images by interpretation of what we see. Hence, color, shape, and texture based image retrieval started gaining prominence [7].

In the early 1990's, Content Based Image Retrieval (CBIR) [8], [9] was proposed to overcome the limitations of text based image retrieval. Increase in communication bandwidth, information content and the size of the multimedia datasets has given rise to the concept of CBIR [7]. The images can be retrieved by contents of images like color, texture and shape. This system is called CBIR, which is an intensive and difficult area [6]. This technique enables a user to extract an image based on a query from a dataset containing a large amount of images.

A very fundamental issue in designing a CBIR system is to select the image features that best represents the image contents in a dataset [7]. The effective CBIR system needs efficient extraction of low level features like color, texture and shapes for indexing and fast query image matching with indexed images for the retrieval of similar images. Features are extracted from images in pixel and compressed domains [6]. In CBIR, the features of the image are extracted efficiently and then represented in a particular form to be used effectively in the matching of images [6]. Here, floating point data is largely used. Texture analysis, has been widely employed in applications such as remote sensing, medical image analysis, document analysis, face identification, fingerprint identification, iris recognition [2].

Iris recognition is an emerging personal identification method in biometrics. Iris recognition is using the person's iris to identify or verify who the person is. Iris is a thin, circular structure in the eye with a diameter of only about 10 mm. Iris image acquisition is a key issue in iris recognition, as the quality of the captured image greatly affects the performance of the overall system. The captured image should have high resolution and contrast to show the texture in detail.

2. LITERATURE REVIEW

2.1 LBP

The LBP was first introduced by Ojala et al [11]. LBP was introduced for texture classification [3]. LBP is a non-parametric method that captures the local structures of images [4]. The Local Binary Pattern method represents textures as the joint distribution of underlying microstructures, modeled via intensity differences in a pixel neighborhood [12].

A binary pattern was obtained by comparing the neighboring pixels ($N = 8$) in a 3 × 3 window with the pixel in the center of them, as shown in Fig. 1 based on

$$LBP_{P,R} = \sum_{p=0}^{P-1} S(g_p - g_c)2^p \qquad (1)$$

where, $S(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; if \; x < 0 \end{cases}$

g_c is the gray value of the center pixel, g_p is the gray value of its neighbors, P is the number of neighbors, and R is the radius of the neighborhood.

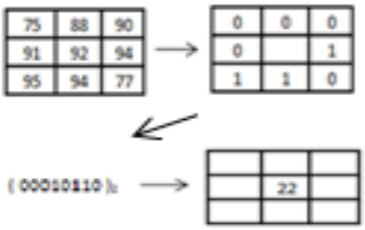

Figure 1. The process of determining the decimal value for a pixel

The LBP feature representation has been used in a wide range of texture classification scenarios and has proven to be highly discriminative. However, a restriction of LBP is its sensitivity to affine transformations [12].

2.2 LTP

As said by Subrahmanyam Murala, R. P. Maheshwari in [3], LBP was extended to a three-valued code called the LTP. Unlike LBP, LTP does not threshold the pixels into 0 and 1, rather it uses a threshold constant to threshold pixels into three values. It uses three-valued function and the binary LBP code is replaced by a ternary LTP code as:

$$f(x, p_c T) = \begin{cases} +1, & x \geq p_c + T \\ 0, & |x - p_c| < T \\ -1, & x \leq p_c - T \end{cases} \quad (2)$$

2.3 dLBP

According to Yılmaz Kaya, Omer Faruk Ertugrul and Ramazan Tekin, [2] in Directional Local Binary Pattern (dLBP), the pixels belonging to the same orientation are compared. The orientation may take 0^0, 45^0, 90^0 and 135^0 through clockwise. After determining the neighbors, the pixel values of them are compared with the value of the center pixel and the other process is carried out as the same as in traditional LBP [2]. The center pixels take the decimal value as its binary value is:

Pc = {S (P0 > P1), S (P1 > P2), S (P2 > P3), S (P3 > P4), S (P4 > P5), S (P5 > P6), S (P6 > P7), S (P7 > P0)} (3)

where, S denotes the comparison.

2.4 LLDP

As mentioned in the paper, Local line directional pattern for palmprint recognition by Yue-Tong Luo, Lan-Ying Zhao, Bob Zhang, Wei Jia, Feng Xue, Jing-Ting Lu, Yi-Hai Zhu, Bing-Qing Xu, the feature extraction in LBP structure descriptor is extended from intensity and gradient spaces to line space. This descriptor is very suitable for palmprint recognition. A new feature space i.e., the line feature space, instead of the gradient space or the intensity feature space, is used to compute robust code. Different coding schemes are exploited to produce LLDP descriptor, which is based on line direction numbers and is much better than all other existing LBP structure descriptors. It achieves better recognition performance than that of bit strings.

3. PROPOSED SYSTEM

3.1 Iris Description

Identification is a one-to-many comparison, which answers the question of "who the person is?" [1]. Iris recognition uses the unique patterns of the human iris to recognize a given individual [13].

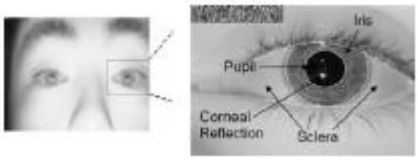

Figure 2. Human Iris

As reported by Jin-Suk Kang, image acquisition is a very important process as iris image with bad quality will affect the entire iris recognition process. For optimal performance, it is essential to acquire high-quality iris images.

3.2 Overview

In [16], Jia et al, proposed a principal line extraction method based on modified finite radon transform (MFRAT). To extract line responses, we use MFRAT. In this paper, to perform iris recognition, we follow three steps namely, indexing stage, searching stage and recognition stage. In the first step, we extract the features of the image such as mean, energy and entropy. These features are then stored in feature vector. Feature extraction is the process of locating an outstanding part, quality and characteristics in a given image [7]. We compare the features between the query image and the dataset images from the corresponding feature vectors in the searching stage. In recognition stage, to find the similarity between the query image and the dataset images, we used the distance measure. To measure the distance for similarity between the images, we use Manhattan Distance. Manhattan distance, which is computed by the sum of absolute differences between two feature vectors of images, is also called the City block distance metric [6].

Step 1: The line responses for four orientations namely 0^0, 45^0,90^0, 135^0 are calculated for every non-overlapping region of the query image as well as the database images. From the line responses, senary code is computed.

Coding strategy: The index numbers of the minimum line response r_4 and the maximum line response r_1 are utilized for coding as:

Senary code = $r_4 * 6^1 + r_1 * 6^0$

Step 2: The next step is to compute the histogram. Histogram is one of the effective summaries of pixel intensity distribution over the image and it also provides a non-parametric statistical summary of information in an image [15].

Step 3: Feature extraction follows histogram generation. Here, features like mean, entropy and energy are extracted. Mean is the average of intensity values and describes the brightness of the image [6]. Energy is measured as a texture feature to calculate the uniformity of intensity level

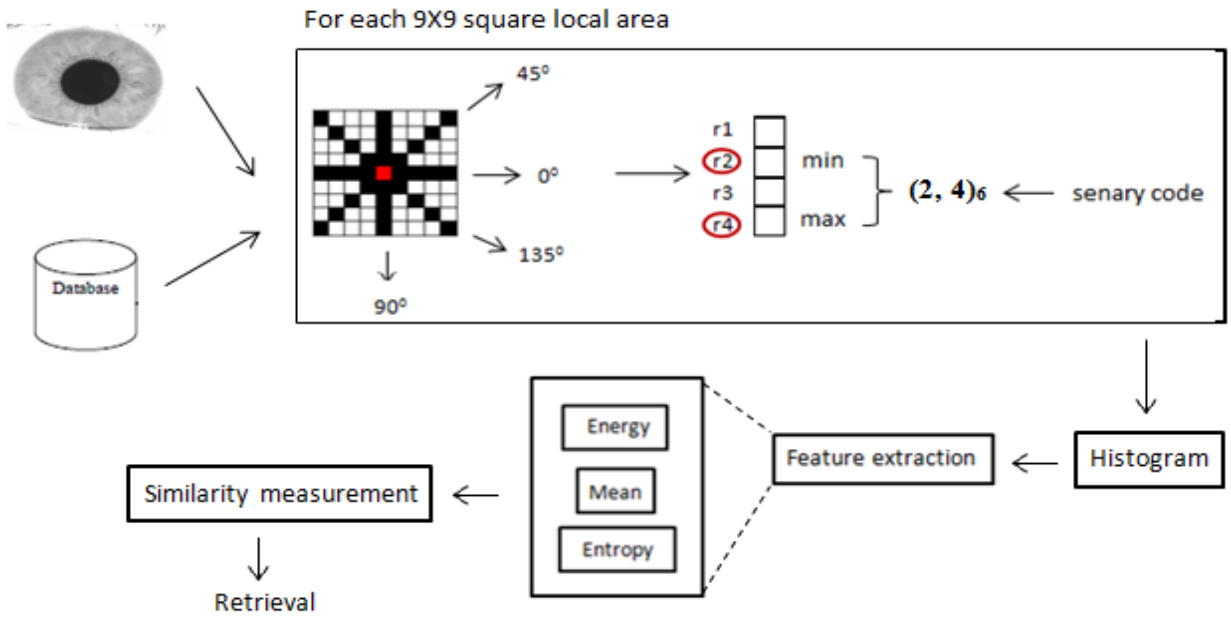

Figure 3. LLDP for Iris recognition

distribution [6]. Entropy measures the randomness of the distribution of intensity levels [6].

Step 4: To find the perfect match for the query image from the images in the dataset, similarity measure is used. Here, we use Manhattan distance as similarity measure. All the extracted features are considered in measuring similarity.

4. RESULTS AND DISCUSSION

As there are many algorithms for palmprint recognition, we tried using the LLDP descriptor with slight modifications for iris recognition. Since the iris lines are not much complicated, we reduced the number of orientations from 12 to 4. By reducing the number of orientations, time complexity gets reduced and hence, less space is enough to store these values. We reduced the size of every non-overlapping square region, thereby utilizing this reduction in time complexity. We converted every pixel values to 16-bit unsigned integer which can store huge values.

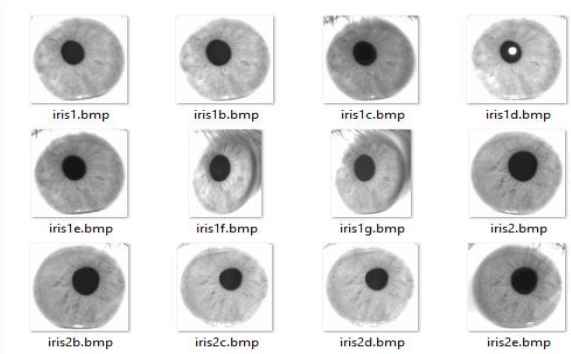

Figure 4. Iris dataset

Out of 254 images in the dataset, we took 12 images for testing purpose. We performed effective match for the query image by extracting some features like mean, energy and entropy out of the image. Fazal Malik and Baharum Baharudin say that the energy with high value shows the distribution of intensity values is for a small number of bins of histograms. If the value of entropy is high then the distribution is among greater intensity levels in the image. This measurement is the inverse of energy. The simple image has low entropy while the complex image has high entropy.

Euclidean distance is most commonly used for similarity measurement in image retrieval [6]. We used Manhattan distance because it is high in terms of precision and robust to outliers [6]. Retrieval effectiveness is the aim of most retrieval experiments. To measure the retrieval effectiveness, we use precision and recall. Precision and recall measures have been widely used for evaluating the performance of the CBIR system [7]. Because of simple calculations and easy interpretation of results, we opted for these measures. Precision is the measurement of the retrieved relevant images to the query of the total retrieved images [6]. Recall is the measurement of the retrieved relevant images to the total dataset images [6]. For example, a CBIR method for a query image retrieves totally 15 images with 9 relevant images out of totally 50 relevant images in dataset. Then the precision is 9/15= 60% and recall is 9/50 =18%. Since, precision and recall has shown different results, we used both the measures together to calculate the retrieval effectiveness but not either alone. However, these two measurements cannot be considered as complete accuracy for the effective image retrieval.

Table 1. Average retrieval rate for various techniques

Average Retrieval Rate	
Technique	**Iris recognition**
LBP	77.80 %
LTP	79.86 %
LLDP	79.97 %
Proposed system	80.03 %

Table 2. Similarity measure using different distance measures for various techniques

Retrieval Accuracy		
Technique	**Euclidean distance**	**Manhattan Distance**
LBP	78.90 %	75.64 %
LTP	81.20 %	82.13 %
LLDP	78.19 %	79.51 %
Proposed system	79.68 %	80.03 %

Table 3. Accuracy rate for different dimensions in iris recognition

Matrix size	Accuracy rate			
	LLDP	**LBP**	**LTP**	**Proposed**
3X3	75.71 %	72.57 %	74.76 %	76.13 %
5X5	77.35 %	74.13 %	76.81 %	78.34 %
7X7	78.84 %	75.87 %	77.96 %	79.1 %
9X9	79.97 %	77.8 %	79.86 %	80.03 %
13X13	80.27 %	78.01 %	80.1 %	80.29 %

It has been observed that the accuracy rate is almost similar when the size of the square local area is fixed to be 9 or 13. Hence, we used 9 as the matrix size.

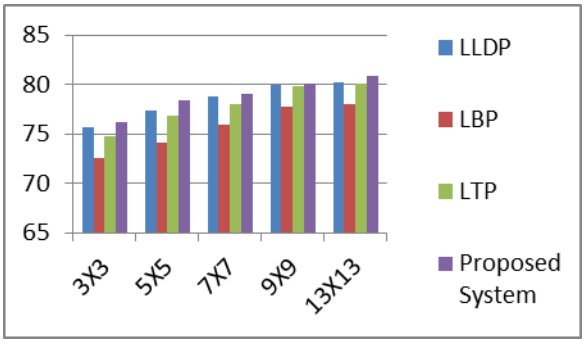

Figure 5. Various dimensions of different techniques with their accuracy rate

5. CONCLUSION

The LLDP descriptor showed better results for palmprint recognition in 13X13 dimension. On applying the same descriptor for recognizing iris, we obtained 80.29% accuracy. By performing slight modifications in the LLDP descriptor, and applying the same for iris recognition, we obtained similar accuracy 80.03% with 9X9 dimension. 12 directions with 15^0 interval were considered in palmprint recognition. We achieved better results even by considering 4 directions with an interval of 45^0 for recognizing iris. This reduction in number of orientations reduces space complexity. Number of computations also gets reduced and hence time complexity gets reduced.

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