Coarse Iris Classification by Learned Visual Dictionary

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Abstract. In state-of-the-art iris recognition systems, the input iris image has to be compared with a large number of templates in database. When the scale of iris database increases, they are much less efficient and accurate. In this paper, we propose a novel iris classification method to attack this problem in iris recognition systems. Firstly, we learned a small finite dictionary of visual words(clusters in the feature space), which are called Iris-Textons, to represent visual primitives of iris images. Then the Iris-Texton histograms are used to represent the global features of iris textures. Finally, K-means algorithm is used for classifying iris images into five categories. Based on the proposed method, the correct classification rate is 95% in a five-category iris database. By combining this method with traditional iris recognition algorithm, our system shows better performance in terms of both speed and accuracy.

1 Introduction

The iris of human eye is the annular part between the black pupil and the white sclera, in which texture is extremely rich. Some examples are shown in Fig. 1. Iris texture is random and unique to each subject[1,2,3], so iris recognition has become one of the most important biometric solutions for personal identification nowadays.

There have been many schemes for iris representation and matching in the recent literature. Daugman[1] extracts iris textures using 2-D Gabor filter. The obtained phase information is encoded to a 2048-bit feature vector. The matching process is done using XOR operation. Wildes[3] suggests using 4-level Laplacian Pyramid to analyze iris textures and using normalized correlation for the matching process. Ma et al.[2] designs a bank of circular symmetric filters to capture the discriminating information along the angular direction of iris image.

All these methods use local features of iris image as the distinctive characteristic, so they can achieve very good recognition results. But all of them require the input iris image to be matched with a large number of irises stored in a database. This matching procedure is very time consuming, especially when the iris database grows large. In order to reduce the search time and computational

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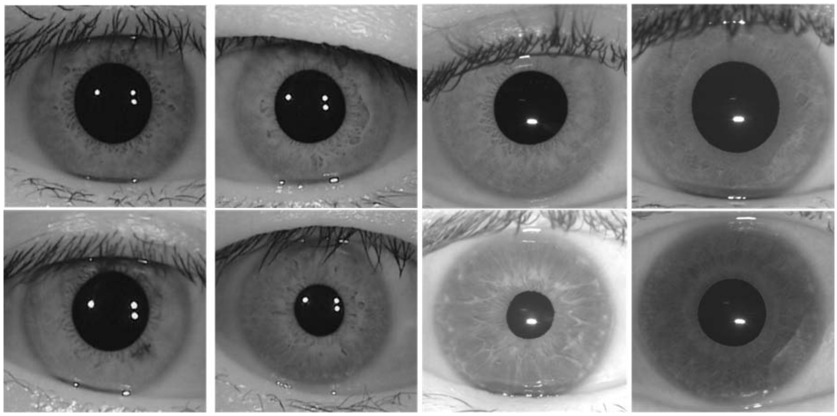


Fig. 1. Examples of iris images from CASIA and UBATH iris databases

complexity, it is desirable to classify irises in an accurate and consistent manner such that the input iris needs to be matched only with a subset of the irises in the database. Yet few attempts have been made to perform automatic iris classification.

In this paper, we propose a novel iris classification approach based on an visual-dictionary-learning algorithm. The main purpose of this paper is to find the global characteristics of iris images to classify irises into several categories, and reduce the number of iris templates that need to be searched when looking for a matching iris. Firstly, compact and yet discriminative visual features, we call them Iris-Textons here, are automatically learned from a set of training images. Then the Iris-Texton histogram was used to represent the global characteristics of iris images. Finally, a K-means classifier classify an input iris into one of five iris categories.

The remainder of this paper is organized as follows. Related work is presented in Section 2. The proposed method is discussed in Section 3. Experimental results are presented and discussed in Section 4 prior to conclusions in Section 5.

2 Related Work and Background

2.1 Iris Classification

Unlike iris classification, much work has been done on fingerprint and palmprint classification. For example, Karu et al.[4] uses the information such as number, type and location of singular points to classify fingerprint images. Wu et al.[5] use directional line detectors to extract the principal lines and then classify palmprints into six categories according to the number of the principal lines and the number of their intersections. Recently, many researchers pay more attention to iris classification. Yu et al.[6] use box-counting method to estimate the fractal dimensions of the iris, then classify iris images into four categories in accordance with the fractal dimensions. Fu et al.[7] use artificial color filter to detect the color information of iris images, and use it to improve iris recognition accuracy and shorten the searching time.

2.2 Texton Theory

Textons are defined as mini-templates that represent certain appearance primitives in images. The definition of texton is governed by a sound model of images in [8]. In fact, a small number of textons can be learned from training images as repeating appearance primitives. Then the texton histogram is used as a kind of global feature of an image. For a single texton, it characterizes the primitive texture pattern which shows the local feature of texture. For a texton histogram generated by a group of textons, it shows the statistical properties of texture, which is a kind of global feature. Therefore, the texton histogram method incorporates both local and global features in texture pattern. In practice, texton theory is widely used for texture recognition and object classification[9], and it shows high classification accuracy. So we extend Texton theory to represent the global feature of the texture-like iris patterns for coarse iris classification in this paper.

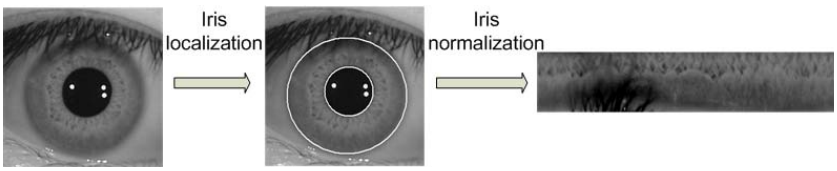


Fig. 2. Preprocessing of iris images

3 Coarse Iris Classification

In this paper, coarse iris classification system includes three basic modules: image preprocessing, feature extraction, and classification. Detailed descriptions of these modules are as follows.

3.1 Image Preprocessing

Image preprocessing plays a very important role in an iris recognition system. Fig. 2 illustrates the main preprocessing steps involving localization, normalization and enhancement. More details can be found in [2]. In our experiment, the size of normalized iris image is 80×512. After preprocessing, translation, scale and illumination variations between different iris images could be complemented.

3.2 Feature Extraction

In this paper, feature extraction process includes two steps. Firstly, we learn a small, finite dictionary of visual words in iris images, which are called Iris-Textons. Secondly, Iris-Texton histograms are used as feature vectors to represent the global characteristics of iris images.

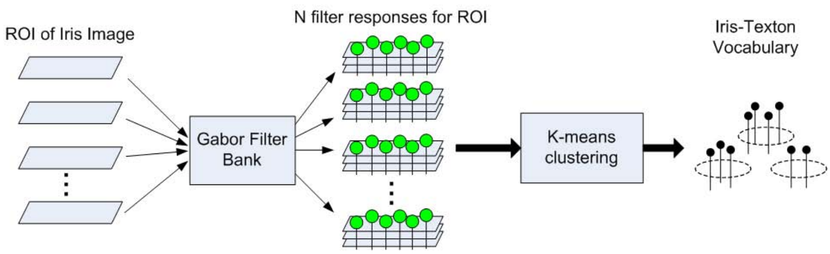


Fig. 3. Learning the vocabulary of Iris-Textons

Learning the Dictionary of Iris-Textons. A schematic diagram illustrating the steps of learning the dictionary of Iris-Textons is shown in Fig. 3. The first step taken to learn a dictionary is filtering. As we know, the Gabor Filters have received considerable attention because the characteristics of certain cells in the visual cortex of some mammals can be approximated by these filters. In addition these filters have been shown to possess optimal localization properties in both spatial and frequency domain and thus are very suited for texture classification problems. Therefore we can characterize a texture by its responses to a set of orientation and spatial-frequency selective Gabor filters that cover the whole frequency space. Typically, an input image (ROI) $I(x, y)$ is convolved with a 2D Gabor filter (here we only use even Gabor filters) to obtain a Gabor filtered image $r(x, y)$.

$$r(x, y) = \iint I(x_1, y_1)h(x - x_1, y - y_1)dx_1dy_1 \tag{1}$$

The computational models of 2D Gabor filters are:

$$h(x, y) = g(x, y) \cdot \cos[2\pi f(x \cos\theta + y \sin\theta)] \tag{2}$$

where $g(x, y)$ is an isotropic Gaussian function given by

$$g(x, y) = \frac{1}{2\pi\sigma^2} \cdot exp[-\frac{x^2 + y^2}{2\sigma^2}]. \tag{3}$$

f and θ are the spatial frequency and orientation respectively. In our experiments, there are a total of 40 even Gabor filters (8 orientations and 5 scales). Each pixel is then transformed to a N= 40 dimensional vector.

The second step is to cluster the filter response vectors into a small set of prototypes, Iris-Textons. These vectors are clustered using a vector quantization algorithm, in particular K-means. K-means method try to find K centers such that after assigning each data vector to the nearest center, the sum of the squared distance from the centers is minimized. It is a greedy algorithm which iteratively performs the following two operations: (1)assign data vectors to the nearest of the K centers; (2)update each of the K centers to the mean of the data vectors assigned to it. These two steps are continued until the algorithm converges and a local minimum of the criterion is achieved. These centers are the Iris-Textons. The associated filter response vectors are called the appearance vectors. In this paper there are totally 64 Iris-Textons which are learned from 400 images, 200 of them are random selected from CASIA[10] and the other 200 are from UBATH[11].

Representing Global Feature of Iris Image using Iris-Texton Histogram. Once a dictionary of Iris-Textons is learned, we can use Iris-Texton histograms to represent the global features of iris images. Each Iris-Texton is represented by the mean of the vectors in this cluster and it is one bin in the texton histogram. For a pixel of iris image, we get a $N = 40$ dimensional vector by Gabor filtering and concatenation, and assigned it to the bin which is the nearest texton. The Iris-Texton histogram is a mapping of 40-dimensional vectors to 64 different Iris-Textons. We can see that the frequent variations of textons denote the richness of micro-textures in iris image. When proper filters are chosen, the Iris-Texton histogram is sufficient in characterizing the global features of iris images. The procedure of computing Iris-Texton Histograms is show in Fig. 4.

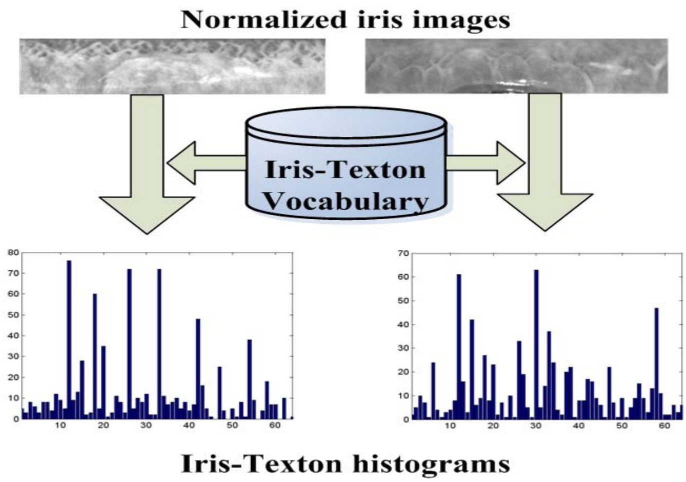


Fig. 4. The procedure of computing Iris-Texton Histograms

3.3 Classification Based on Iris-Texton Histograms

Now the iris textures are presented by Iris-Texton histograms. Our intuition is that iris images can be classified into several categories according to their global features. Here we run k-means algorithm again to achieve proper iris clusters. The k-means algorithm is popular because it is easy to implement and its time complexity is $O(n)$, where n is the number of patterns. In this paper, the Chi-square statistic is used to evaluate the dissimilarity of two texton histograms H1 and H2:

$$\chi^2(H1, H2) = \sum_{i=1}^{59} \frac{(H1_i - H2_i)^2}{H1_i + H2_i} \tag{4}$$

Because it is possible that $H1_i + H2_i = 0$, the summation only includes the non-zero bins.

Compared with parametric classification principles, non-parametric classification strategy is more flexible and avoid the assumption on the distribution of input data. Chi-square is a non-parametric statistic to test the goodness-of-fit of two distributions. The strength of Chi-square statistic suitable for our application is that it is a rough estimation of confidence. This feature makes Chi-square robust against the noises in iris data, such as deformation and occlusions.

If the number of categories is too small, it is impossible to reduce the searching time much, but if the number is too large, it is very difficult to keep high correct classification rate. As a tradeoff, we must choose a proper number in experiments. The choosing of this number will be discussed in next section.

4 Experimental Results and Discussions

4.1 Iris Databases

Extensive experiments were carried out to evaluate the effectiveness and accuracy of the proposed method on a large mixed iris database. It consists of two open iris image databases, CASIA[10] and University of Bath(UBATH)[11] databases. The CASIA iris database includes 8000 images from 400 different eyes of 200 subjects. There are 20 images for each eye. The UBATH iris database has the same size with CASIA, it also has 8000 images from 400 different eyes, 20 images for each eye. So the mixed database is large and includes 16000 images of 800 eyes.

4.2 Results and Discussions

In the first experiment, we randomly select one image from each eye in the mixed database to form the training set, and then the remain images to form the testing set. If the iris images from the same eye are classified into the same category, it means the result is correct. So a statistical test is carried out to measure the accuracy of the proposed algorithm. Correct Classification Rate(CCR), which is simply the percentage of correctly classified irises, is then examined.

Because we use K-means algorithm to find cluster centers, it is very important to choose a proper number of categories, K. If K is too small, it is impossible to reduce the searching time much, but if K is too large, it is very difficult to keep high Correct Classification Rate(CCR) and it may result in that some categories have many iris samples and others have very few. The relation between the number of categories and the CCR was show in Fig. 5. The distributions of irises in each category according to different K are listed in Table 1. As a tradeoff, we choose five as the K in our experiments. In the training process, the training set is clustered into five categories by the K-means algorithm. Then the testing set is used to estimate the performance of this classifier. We only need to calculate the distance between the testing sample and the centers of categories, and choose the shortest one as the testing sample's category label.

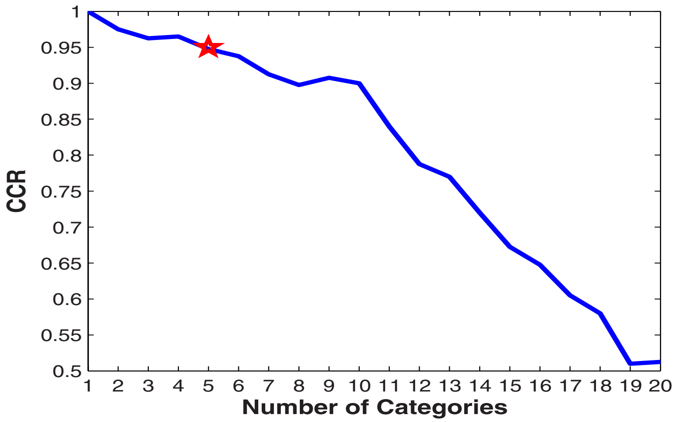


Fig. 5. Relationship between number of categories and CCR

The experimental results are shown in Table 2. The correct classification rate of our method is 95.0% on the large mixed database. And we have neither too much iris templates, nor too few iris templates in any category. It means that the proposed approach has good classification performance. Some examples of each iris category after processing are shown in Fig. 6.

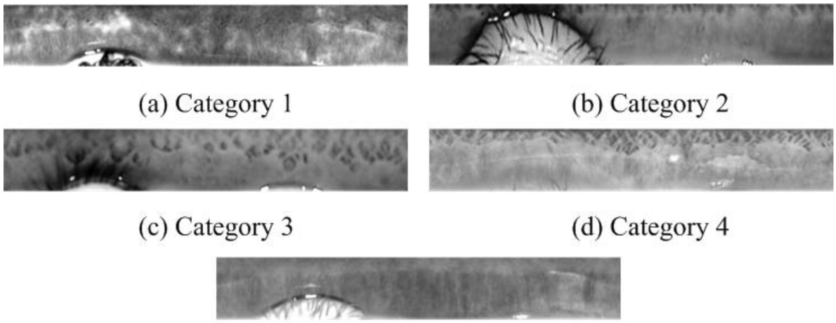
Table 1. Distribution of each category according to different K

K	Distribution of each category (%)						
	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5	Cat. 6	Cat. 7
4	34.8	15.6	20.6	29.0	-	-	-
5	**14.3**	**12.2**	**30.5**	**25.6**	**17.4**	-	-
6	26.2	16.4	22.0	15.7	4.9	14.8	-
7	16.8	14.4	25.8	12.5	20.3	6.6	3.5

Table 2. Distribution of each category and Correct Classification Rate on our database.

Database	Number of Eyes	Distribution of each category (%)					CCR(%)
		Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5	
CASIA & UBATH	800	14.3	12.2	30.5	25.6	17.4	**95.0**

The greatest benefit of using coarse iris classification is to reduce the time in searching. According to the CCR and the distribution of irises in five categories in the first experiment, we can evaluate the size of the database to decide when to use the coarse classification. Suppose N is the database size, T_1 is the time of local feature extraction, T_2 is the time used for coarse iris classification, T_3 is the matching time of two local features and the matching time of global feature can be ignored. In our method, $T_1 = 45ms$, $T_2 = 660ms$ and $T_3 = 1.1ms$ on a



(a) Category 1 (b) Category 2
(c) Category 3 (d) Category 4
(e) Category 5

Fig. 6. Examples of each iris category after processing

PC of Pentium-4 2.8GHz CPU with Matlab. If the computational cost for iris classification is less than the reduced matching time, then coarse iris classification should be adopted.

The objective of iris identification is to find the corresponding templates in central database as soon as possible, so we test how long we need to search until we could reach the genuine template in each identification task. If we query a image without iris classification, the average searching time is:

$$T_{without} = T_1 + 0.5 * N * T_3 \tag{5}$$

By using iris classification, under condition of CCR equals 95.0% and all categories have the same number of templates, the average search time is:

$$T_{with} = T_1 + T_2 + (95.0\% * 0.2 + 5.0\% * 1) * 0.5 * N * T_3 \tag{6}$$

Let $T_{without} = T_{with}$, we can easily obtain that $N = 1579$. It shows that when the database size N is bigger than 1579, the coarse classification can reduce the computational time of the identification system. For an iris database contains 10,000 iris templates, the average searching time can be reduced almost 63% of the original searching time by using coarse iris classification. If the database grows even larger, this method can reduce the computational time dramatically.

The second benefit of using coarse iris classification is to improve the accuracy of an iris recognition algorithm. We complement local features based method with global features, the iris category labels, to strengthen the robustness of iris recognition system. The iris categories can work like a kind of "soft" biometric traits. Although the categories lacks the distinctiveness to identify an iris image uniquely and reliably, they provide some evidence about the iris identity that could be beneficial. In this study, all iris images is classified into five categories by Iris-Texton histograms, and Iris-Texton histograms represent the global features of iris images, so the category information is complement to local features which are used by state-of-the-art iris recognition methods. By the User Weighting fusion method[12], the accuracy and robustness of an iris recognition system can

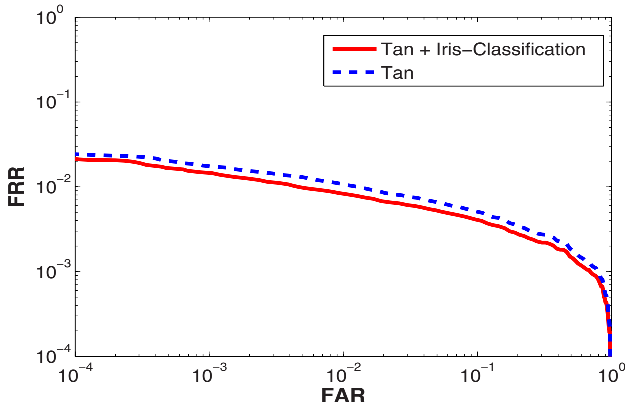


Fig. 7. Comparison of ROC curves of different iris recognition methods

be improved. For the purpose of comparison, the ROCs(receive operating curve) of Tan's[2] and the proposed methods are show in Fig. 7. After introducing coarse iris classification into our iris recognition systems, the equal error rate(EER) is reduced from 1.1% to 0.88%.

5 Conclusion

In this paper, we have presented a novel method for automatic iris coarse classification based on global texture analysis with Iris-Texton histograms. The main contributions of this paper include: (1)A visual dictionary containing typical textons is learned from iris images. Each Iris-Texton characterizes a kind of frequently appeared local patches in iris images. So the global texture feature of an iris image are well presented by the distribution of its Iris-Textons. (2)We show that iris images could be coarsely classified with histograms of Iris-Textons. The experimental results on a large mixed database proves that global features is complementary to local features which are commonly used by iris recognition algorithms. By combining two kinds of features, we get a faster, more accurate and more robust iris recognition system.

In the future, we will also try other approaches to improve the classification accuracy. In addition, we think the global features should play a defining role in the issues on iris coarse classification. So we will try to find out which kind of feature is powerful.

Acknowledgements

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