Sparsity-based Iris Classification using Iris Fiber Structures

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Abstract: As there is a growing demand for biometrics usage in e-Society, the biometric recognition system faces the scalability issue as the number of people to be enrolled into the system runs into billions. In this paper, we propose an approach for iris classification using three different iris classes based on iris fiber structures, namely, stream, flower, jewel and shaker for faster retrieval of identities in large scale biometric system. A sparsity based on-line dictionary learning (ODL) algorithm is used in the proposed classification approach where dictionaries are developed for each class using log-Gabor wavelet features. Also, a method for iris adjudication process is illustrated using the iris classification to reduce the search space. The efficacy of the proposed classification approach is demonstrated on the standard UPOL iris database.

1 Introduction

Among all the biometrics, fingerprints and iris give more accurate results in uniquely identifying the people based on minutia features. However, the biometric system allows few errors in identification with a threshold at equal error rate. In order to reduce the errors, fingerprint experts look for possible fingerprint matches and enhance the fingerprints to compare the minutia features manually using fingerprint adjudication process. There are scalability issues with the large scale biometric systems where a classification approach is required to reduce the search space. The complex iris texture provides the uniqueness for iris images. Daugman proposed an iris recognition system by using gabor filters and iris codes [Dau93]. Several other researches including Wildes [Wil97], Boles and Boashash [BB98] proposed different iris recognition algorithms by representing the iris texture with Laplacian pyramid construction and 1D wavelet transform, respectively. Few researchers already explored iris classification techniques using hierarchical visual codebook [SZTW13], block-wise texture analysis [RS10] and color information [ZSTW12, PCL13]. So far, there is no classification approach based on the pre-defined iris classes.

Sparse representation has received a lot of attention from researchers in signal and image processing. Sparse coding involves the representation of an image as a linear combination of some atoms in a dictionary [RSS10]. Several algorithms like on-line dictionary learning (ODL) [MBPS09], K-SVD [AEB06] and method of optimal directions (MOD) [EAHH99] have been developed to process training data. Sparse representation is used to match the input query image with the appropriate class. Etemand and Chellappa [EC98] proposed a feature extraction method for classification using wavelet packets. In [SS10], a method presented for the learning of dictionaries simultaneously. Recently, similar algorithms for simultaneous sparse signal representation have also been proposed [RS08], [HA06]. The on-line dictionary learning algorithm alternates between sparse coding and dictionary update steps. Several efficient pursuit algorithms have been proposed in the literature for sparse coding [EAHH99],[MZ93]. The simplest one is the l_1-lasso algorithm [LBRN07]. Main advantage with ODL algorithm is its computational speed as it uses l_1-lasso algorithm for sparse representation.

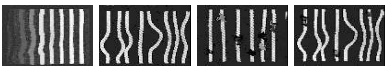
The rest of the paper is organized as follows: In section 2, the proposed iris classification approach and the details of on-line dictionary learning are presented.. Experimental results of the proposed classification and adjudication framework are given in section 3. Conclusions are explained in section 4.

2 Proposed Iris Classification and Adjudication Framework

The proposed iris classification approach uses three different classes of iris images [Fou09] namely, stream, flower, and jewel-shaker as illustrated in Figure 1. The iris structure can be determined by the arrangement of white fibers radiating from the pupil. In stream iris structure, these fibers are arranged in regular and uniform fashion. The arrangement of fibers is irregular in the flower iris structure. In jewel iris structure, the fibers have some dots. The shaker iris structure have both the characteristics of flower and jewel iris structures. The jewel and shaker classes are merged due to rare occurrence and to make the classification proportional among all the pre-defined classes. The arrangement of fibers are illustrated in Figure 5.

(a) (b) (c)

Figure 1: Iris classes: (a) stream, (b) flower and (c) jewel-shaker structures.



(a) (b) (c) (d)

Figure 2: Iris fibers: (a) stream, (b) flower, (c) jewel and (d) shaker fibers.

The following are the steps involved in the proposed iris classification and adjudication framework:

Step 1. *Iris segmentation and normalization* : The pupillary and limbic boundaries [M$^+$03] of an iris image are approximated as circles using three parameters: the radius r, and the coordinates of the center of the circle, x_0 and y_0. The integrodifferential operator [Dau93] used for iris segmentation is:

$$max(r, x_0, y_0) G_\sigma(r) * \frac{\partial}{\partial r} \int_{r, x_0, y_0} \frac{I(x,y)}{2\Pi r} ds, \tag{1}$$

where $G_\sigma(r)$ is a smoothing function and $I(x, y)$ is the image of the eye.

After applying the operator, the resultant segmented iris image is as shown in Figure 3(a). The segmented iris is then converted to a dimensionless polar system based on the Daugman Rubber Sheet model [Dau93] as shown in Figure 3(b).

Step 2. *Feature extraction* [M$^+$03]: The log-Gabor wavelet feature vector of size 240×20 is extracted from the normalized iris image of size 120×20. The resultant feature vector is converted to a single column vector by column major ordering. From each class, some of the iris images are selected to express as a linear weighted sum of the feature vectors in a dictionary belonging to three different classes of iris.

Step 3. *Iris classification using ODL*: An on-line dictionary learning (ODL) algorithm is used to classify the iris data into three different classes to reduce the search space. The weights associated with feature vectors in the dictionary are evaluated using ODL algorithm, which is a solution to l_1 optimization for over-determined system of equations. The feature vectors which belong to a particular iris class carry significant weights which are non-zero maximum values.

The class $C = [C_1, \ldots, C_N]$ consists of training samples collected directly from the image of interest. In the proposed sparsity model, images belonging to the same class are assumed to lie approximately in a low dimensional subspace. Given N training classes, the p^{th} class has K_p training images $\{\mathbf{y}_i^N\}$ i=1,..., K_p. Let b be an image belonging to the p^{th} class, and it is represented as a linear combination of these training samples:

$$b = \mathbf{D}^p \Phi^p, \tag{2}$$

where D^p is a dictionary of size $m \times K^p$, whose columns are the training samples in the p^{th} class and $\varPhi^p$ is a sparse vector.

The following are the steps involved in the proposed classification method:

1. *Dictionary Construction:* Construct the dictionary for each class of training images using on-line dictionary learning algorithm [MBPS09]. Then, the dictionaries $D = [D_1, \ldots, D_N]$ are computed using the equation:

$$(\hat{\mathbf{D}}_\mathbf{i}, \hat{\mathbf{\Phi}}_\mathbf{i}) = \arg \min_{\mathbf{D}_i, \Phi_i} \frac{1}{N} \sum_{i=1}^{N} \frac{1}{2} \|\mathbf{C}_i - \mathbf{D}_i \Phi_i\|_2^2 + \lambda \|\Phi_i\|_1, \tag{3}$$

satisfying $\mathbf{C}_i = \hat{\mathbf{D}}_i\hat{\Phi}_i, \quad i = 1, 2, \ldots, N.$

2. *Classification:* In this classification process, the sparse vector Φ for given test image is found in the test dataset $B = [b_1, \ldots, b_l]$. Using the dictionaries of training samples $D = [D_1, \ldots, D_N]$, the sparse representation Φ satisfying $D\Phi$=B is obtained by solving the following optimization problem:

$$\Phi^j = \arg\min_{\Phi} \frac{1}{2}\|\mathbf{b_j} - \mathbf{D}\Phi_j\|_2^2 \qquad ; \qquad (4)$$

subject to $\|\Phi_j\|_1 \leq T_1,\ and\ \hat{i} = \arg\min_i \|\mathbf{b_j} - \mathbf{D}\delta_i(\Phi^j)\|_2^2, \quad j = 1, \cdots, t.$

where δ_i is a characteristic function that selects the coefficients. Then b_j is assigned to C_i associated with the i^{th} dictionary. It means, finding the sparsest dictionary for a given test data using l_1 -lasso algorithm. Then, test data is assigned to the class associated with this sparsest dictionary.

Step 4. *Iris Adjudication*: The matched iris pairs are compared using the adjudication process to illustrate the match-ability of iris images based on the similarity of iris regions marked with three different colors, namely, green, yellow and red. The green, yellow and red colors indicate good, poor and bad match, respectively. The normalized iris image is divided into different regions and the confidence-level of matching for each region is verified and assigned a color code using the dissimilarity measurement.

(a) (b)

Figure 3: Iris fibers: (a) Iris image segmentation and (b) Normalized Iris Image

3 Experimental Results

The experiments were conducted using the iris images taken from the standard UPOL iris database [DMS+06], [DMTP04], [DM04]. The iris data is collected from 64 subjects, with three samples of left and right eyes from each subject resulting in a total of 384 iris images. Each iris image is of 24 bit RGB color space with a high resolution image size, 768×576. The images were captured using the optical device (TOPCON TRC50IA) which is connected to a Sony DXC-950p 3CCD camera. In the proposed iris classification approach, three classes are manually identified using the iris patterns stream, flower and jewel-shaker as shown in Table 1. These classes are categorized based on the iris fiber structures (texture information), so the images were converted to gray-scale images for further processing. The manual identification of the predefined classes is not required for all the data in large-scale applications, but at least those classes should be identified for the training samples.

Table 1: Iris classes defined based on the iris fibers stream, flower and Jewel-Shaker

Class	# of Images (%)	Subject Ids
Class-1 (Stream)	192 (50%)	001,006,007,008,011, 013,014,016,018,019, 020,021,023,024,026, 027,028,033,041,042, 044,045,050,051,052, 053,058,059,060,061, 062,064
Class-2 (Flower)	102 (26.56%)	002,009,010,015,017, 022,031,036,037,040, 043,047,048,049,054, 056,063
Class-3 (Jewel-Shaker)	90 (23.44%)	003,004,005,012,025, 029,030,032,034,035, 038,039,046,055,057

In order to evaluate the accuracy of proposed classification approach using on-line dictionary learning, the database is split into three sets: training set, testing set and validation set. The distribution of all the three sets are taken in such a way that the 2 samples of each iris image is allotted to the training set and validation set, and the remaining iris sample is given to the test set. The training set consists of 224 images where 112 images are from Class-1 (Stream), 60 images are from Class-2 (Flower) and 52 images are from Class-3 (Jewel-Shaker). The number of test images selected from Class-1, Class-2 and Class-3 are 64, 34 and 30, respectively. A set of 32 iris images is assigned to validation set where 16 images belong to Class-1, 8 images belong to Class-2 and 8 images belong to Class-3.

The experiments were conducted in three different ways of choosing test sets (systematically selecting first, second or third samples of each iris) where the accuracy is almost similar.

In Table 2, the classification accuracy for the validation data set is given. It is observed that 100% classification accuracy is achieved for the dictionary sizes 90 and 120 with residual error value 0.05 as shown in Figure 4. The confusion matrices for both test data and validation data sets are shown in Table 3.

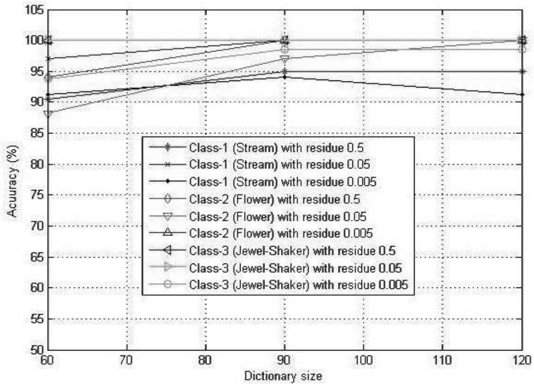


Figure 4: Classification accuracy for three different dictionary sizes 60, 90 and 120

Table 2: Classification accuracy on validation data set

Class	Dictionary Sizes		
	60	**90**	120
Class-1 (Stream)	91.66	**100**	100
Class-2 (Flower)	100	**100**	100
Class-3 (Jewel-Shaker)	100	**100**	100

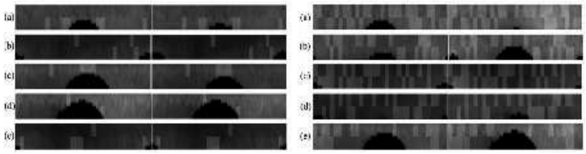
Table 3: Confusion matrix for test and validation data

Class	Testing set			Validation set		
	C1	C2	C3	C1	C2	C3
C1	64	0	0	16	0	0
C2	0	34	0	0	8	0
C3	0	0	30	0	0	8

The adjudication results for genuine iris matches are illustrated in Figure 5(a) and for the impostor iris matches are given in Figure 5(b). The normalized images shown on these figures are taken from CASIA database for better illustration of adjudication process.

4 Conclusions and Future Work

In this paper, a new methodology for iris classification is proposed to classify the iris images into three different classes namely stream, flower and jewel-shaker. The proposed classification approach achieved 100% classification accuracy with dictionary size 90 and residual error 0.05. Finally the adjudication results are illustrated to avoid the identification errors. The proposed method addressed the scalability issue in large scale iris biometric recognition system for faster retrieval of identities. The proposed approach can be applied



(a) (b)

Figure 5: Iris adjudication: LeftSide-(a) genuine iris matches with hamming distances (a) 0.21, (b) 0.19, (c) 0.16, (d) 0.15, (e) 0.19 and RightSide-(b) impostor iris matches with hamming distances (a) 0.48, (b) 0.46, (c) 0.43, (d) 0.51, (e) 0.37

in large scale biometric system in order to reduce the search space and faster retrieval of identities. The manual identification of the predefined classes is not required for all the data in large-scale applications, but at least those classes should be identified for the training samples. The data used for iris classification was collected under visible illumination. Most of the iris recognition systems use the data acquired at near infra-red (NIR) wavelengths. These systems are more accurate among all the existing biometric recognition systems. It is very to hard to label the iris classes in the available standard near infra-red databases. The same experimental setup should be executed for the near infra-red iris database which have more texture information to distinguish the iris labels.

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