

Iris Recognition Under Partial Occlusion Based on Non-negative Sparse Representation Classification

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Abstract—To improve the reliability and accuracy of personal identification based on iris under partial occlusion, this paper proposed a non-negative dictionary sparse representation and classification scheme for iris recognition. The non-negative dictionary includes the Log-Gabor feature dictionary extracted from normalized iris image. The use of Log-Gabor makes the occlusion dictionary compressible, and can reduce the computational cost. Experiments on UBIRIS iris database demonstrated the effectiveness of the proposed Log-Gabor based non-negative sparse representation classification.

Keywords—iris recognition; sparse representation; partial occlusion; non-negative; log-gabor feature

I. INTRODUCTION

With the advancement of information technology and threats on the security, biometric identification is gaining more popularity and more acceptances in public as well as in private sectors. Among all biometric technologies, iris recognition is noted for its uniqueness, high reliability, and non-invasiveness, which make iris recognition a particularly promising solution to automated personal identification[1]. Much work has been done in iris recognition[1-5]. Although some methods can get very high recognition rate in ideal conditions, there are various challenges in the process of iris recognition in un-constrained scenarios, in which partial occlusion will always be a common problem that we cannot avoid. There has been some research work on iris recognition with occlusion. Several researchers have proposed approaches that analyze the iris region in multiple parts and combine the results to reduce the impact of segmentation errors and occlusion in the imaging process. Adam et al. [4] analyze iris texture in eight sub-regions of the iris and fuse the distances from these local windows, with experiments on data from the CASIA dataset. Bastys et al. [5] divide the iris into sectors and calculate a set number of local extrema in each sector at a number of scales.

Motivated by the successful application of sparse representation based classification for face recognition with partial occlusion[6], the recent solution is to apply SRC to represent a test sample with occlusion as a combination of sparse linear combination of training samples and sparse error incurred by occlusion, which has also shown promising results for iris recognition and other biometrics by using Sparse Representation[7][8]. In these methods, the dictionary includes two parts: the feature dictionary and the occlusion dictionary. The feature dictionary is usually constructed with feature vectors extracted from the train samples. The occlusion dictionary is usually constructed using the identity matrix with

the same dimension as the feature dimensions in the feature dictionary. In this scheme, although better recognition rates can be achieved, the huge number of atoms in the dictionary bring a heavy computation cost for the SRC model. So in literature[9], a method using compressed Gabor feature to construct the occlusion was proposed. However, through experiments it was noticed that using such an occlusion dictionary the sparse coding representation of a test sample with partial occlusion was still very dense[8]. On the other hand, in our previous works the Log-Gabor features have been proved to be more suitable to represent the iris features regardless of the background brightness [10]. So in this paper, we introduce Log-Gabor Dictionary and non-negative constraints. An iris recognition method combining the Log-Gabor feature occlusion dictionary and the non-negative occlusion dictionary is proposed to solve the non-negative sparse representation classification model for performance improvement. The motivation of using Log-Gabor Dictionary is to enhance frequency bands that store the discriminative information on which intra-class matching and inter-class rejection are both based. The motivation of using non-negative dictionary is to make the basis atoms in the dictionary more visual and physical meaningful. The proposed method is applied on the UBIRIS database with random occlusion. Experimental results have shown that the proposed method gets better recognition performance comparing to the previous methods.

II. PROPOSED SCHEME

A non-negative dictionary based sparse representation classification algorithm is proposed in this paper. The non-negative dictionary include the Log-Gabor feature dictionary and non-negative occlusion dictionary. Then this non-negative dictionary is applied for solving the non-negative sparse representation classification model.

A. Non-negative Sparse Representation Based Iris Classification(NSRC)

SRC has been successfully applied in some biometrics[7-9]. Based on the assumption that the training iris samples from a single class lie on a linear subspace, SRC searches the representative elements from the training sample dictionary to sparsely represent a test sample. Suppose the i -th iris class has n_i training images, we denote the training samples of the i -th class as $D_i = [d_{i1}, d_{i2}, \dots, d_{ini}] \in R^{m \times n_i}$, and each column of the matrix D_i denotes a sample. For a new test sample $y \in R^m$ from the i -th class, y can be represented via the linear

combination of the samples within D_i , i.e.
 $y = \sum_{j=1}^{n_i} \alpha_{ij} d_{ij} = D_i \alpha_i$, where $\alpha = [\alpha_1; \dots; \alpha_i; \dots; \alpha_k]$ is the representation coefficients.

Suppose that we have k iris classes and gather the training samples of all classes to build the training sample dictionary $D = [D_1, D_2, \dots, D_k] = [d_{11}, d_{12}, \dots, d_{kn_k}]$. Then the linear representation y can be rewritten as $y = D\alpha$, where $\alpha = [\alpha_1; \dots; \alpha_i; \dots; \alpha_k]$. A desirable solution to α will be nearly zero except those associated with the i -th class. The non-zero entries encode the identity information of the test sample. If the number of training samples is large enough, the non-zero coefficients are sparse relative to the length of the coefficient vector. SRC obtains the sparse coefficients by solving the following ℓ_1 -minimization problem when occlusion is not considered:

$$\hat{\alpha} = \arg \min_{\alpha} \{ \|y - D\alpha\|_2^2 + \lambda \|\alpha\|_1 \} \quad (1)$$

Where λ is a positive scalar constant that balances the reconstructed error ($\|\bullet\|_2^2$) and the sparsity of the coding coefficients ($\|\bullet\|_1$).

In case of occlusion for iris recognition, the test sample can be rewritten as:

$$y = y_0 + e_0 = D\alpha + e_0 = [D, I] \begin{bmatrix} \alpha_0 \\ e_0 \end{bmatrix} = Bw_0 \quad (2)$$

where $B = [D, I]$, and the clean iris image y_0 and the corruption error e_0 have sparse representations over the training sample dictionary D and occlusion dictionary I , respectively. The occlusion dictionary I was set as an orthogonal matrix, such as identity matrix, Fourier bases, etc. The sparse coding coefficient w_0 can be solved as Eq(3):

$$\hat{w}_0 = \arg \min_w \{ \|y - Bw\|_2^2 + \lambda \|w\|_1 \} \quad (3)$$

However, in above SRC model the sparse coefficients are both positive and negative, but negative elements are usually insignificant in practical applications. To make the basis atoms in the dictionary more visual and physical meaningful, in this paper we make a non-negative constraint on the dictionary and the sparse coefficient vector in Eq. (3), so that each element in the sparse coefficient vector is non-negative. This formulates a non-negative sparse coding problem, non-negative sparse coding can be given by the minimization of the following cost function[10]:

$$O_F(B, w) = \frac{1}{2} \|y - Bw\|_2^2 + \lambda \sum_i w_i, s.t. B \geq 0, \forall i, w_i \geq 0 \quad (4)$$

The constraint $B \geq 0, \forall i, w_i \geq 0$ guarantees that the basis vector in the dictionary and the sparse coefficient vector are non-negative. Once the dictionary (non-negative feature dictionary and occlusion dictionary) is computed, the estimation of sparse coefficients is an ℓ_1 -regularized linear least-squares problem, which can be efficiently solved by the LARS-Lasso algorithm [11].

B. Log-gabor Feature and Occlusion Dictionary Learning

In the real application, fewer training samples can be collected, and feature selection will become more important. In the current study, Gabor feature have been successfully applied in sparse representation classification[8][9].

In the spatial domain, a 2D Gabor function is a Gaussian multiplied by a complex exponential and can be seen as a Gaussian shifted from the origin in the Fourier domain. Its mathematical properties such as the smooth infinitely differentiable shape, the monomodal modulus and the highly joint localization in space, orientation and frequency make it a good choice for various image processing applications. However, Gabor function also has a few drawbacks:

(i) non-orthogonality which implies non-invertibility which is not really a problem in our feature extraction use.

(ii) its deficiency to cover uniformly the mid-frequencies as it is a bandpass filter.

(iii) its bad coverage of low and high frequencies due to an excessive overlapping.

(iv) the non-zero DC component which increases as the bandwidth is widened resulting from the tails' overlapping of the sum of two Gaussians centered at plus and minus the central frequency.

It is worth noting that natural images are better encoded using filters having transfer functions which are Gaussian viewed on the logarithmic frequency scale [13]. Therefore, a log-Gabor can be a better alternative to the Gabor filtering and can offer attractive power especially in image feature discrimination. Moreover, in our previous work, the Log-Gabor features have been proved to be more suitable to represent the iris features regardless of the background brightness [12]. So in this work, Log-Gabor feature extraction is applied, and the non-negative dictionary includes the Log-Gabor feature dictionary and the non-negative occlusion dictionary, which are applied for solving the non-negative sparse representation classification model.

In proposed scheme, we use a multi-resolution log-Gabor filter to extract the local multi-scale and multi-orientation features to represent the iris image. The log-Gabor filter bank frequency response is given by:

$$H(f, \theta) = \exp \left\{ \frac{-[\ln(f/f_0)]^2}{2[\ln(\sigma_f/f_0)]^2} \right\} \times \exp \left\{ \frac{-(\theta - \theta_0)^2}{2\sigma_\theta^2} \right\} \quad (5)$$

where (f, θ) represents the polar coordinates, f_0 is the center frequency of the filter, θ_0 is the orientation angle of the filter, σ_f determines the scale bandwidth and σ_θ indicates the angular bandwidth. In this work, a bank of 24 log-Gabor filters are applied on each iris image along four scales and six orientations in the range of $[0^\circ, 180^\circ]$ (i.e., $\{0, \pi/6, \pi/3, \pi/2, 2\pi/3, 5\pi/6\}$). As a multi-scale and multi-orientation feature extraction technique, Log-Gabor filter also generates highly redundant features, so in this work down-sample is applied to reduce the feature dimension at the step of Log-Gabor feature extraction.

For the training set A and a test iris sample y with partial occlusion, their Log-Gabor transform results are $X(A)$ and $\chi(y)$. The Log-Gabor feature based sparse representation with an occlusion dictionary introduced could be formulated as:

$$\chi(y) = [X(A), X(A_e)] \begin{bmatrix} \alpha \\ \alpha_e \end{bmatrix} = X(B)\omega \quad (6)$$

Where $X(A_e)$ is the Log-Gabor feature based occlusion dictionary, and α_e is the representation coefficient vector of the input Log-Gabor feature vector $\chi(y)$ over $X(A_e)$. So in the case of occlusion, the sparse coding model for Eq.(6) is

$$\min_{\omega} \left\{ \|\chi(y) - X(B)\omega\|_2^2 + \lambda_i \|\omega\|_1 \right\} \quad (7)$$

In this model, the selection of dictionary $X(A)$ and $X(A_e)$ will have a direct effect on the computation load when solving sparse coding model. The Log-Gabor feature set $X(A)$ can be normalized non-negatively, so we can get the non-negative feature dictionary D in an easy way.

Motivated by the Gabor occlusion dictionary learning proposed in [9] and the non-negative sparse coding proposed in [10], the non-negative occlusion dictionary based on Log-Gabor feature can be learned as follows:

Suppose $X(A_e)$ is denoted as $L(I) = [l_1, l_2, \dots, l_v] \in R^{w \times v}$. The compact occlusion dictionary to learned is denoted as $\Gamma = [d_1, d_2, \dots, d_q] \in R^{w \times q}$, where q can be set as slightly less than v/ρ according to [9] (ρ is the down-sampling factor). Then we can replace $L(I)$ by Γ . The objective function when determining Γ is as follows:

$$J_{\Gamma, \Lambda} = \arg \min_{\Gamma, \Lambda} \left\{ \|L(I) - \Gamma\Lambda\|_2^2 + \lambda_j \|\Lambda\|_1 \right\} \quad (8)$$

Where $\Lambda = [\alpha_1, \alpha_2, \dots, \alpha_n]$ is the representation matrix of $L(I)$ over dictionary Γ , with non-negative constraints: $\forall i, j; \alpha_i \geq 0, d_j \geq 0$, λ_j is a positive scalar that balance the l_1 -

norm term and the l_2 -norm term. Eq(8) is a joint optimization problem of dictionary Γ and the representation coefficient matrix. It can be solved by optimizing Γ and Λ alternatively[9][10].

C. Classification

For iris recognition under partial occlusion, when the non-negative feature dictionary D and the non-negative occlusion dictionary Γ have achieved, the iris image with occlusion can be viewed as the combination of non-occlusion image and occlusion block. The unobstructed portion can be sparsely coded by the non-negative dictionary D learned from the training image, while the occluded portion can be sparsely coded by the non-negative occlusion dictionary Γ . The whole process of the non-negative dictionary based non-negative sparse representation classification is as follows:

When non-negative dictionary $[D \Gamma]$ are learned, the Log-Gabor feature $\chi(y)$ of the test iris sample with partial occlusion is computed for input.

Solve the sparse coding model:

$$\hat{\omega}_\Gamma = \arg \min_{\omega_\Gamma} \left\{ \|\chi(y) - [D \Gamma]_{\omega_\Gamma}\|_2^2 + \lambda_i \|\omega_\Gamma\|_1 \right\}$$

where $\omega_\Gamma = [\alpha; \alpha_\Gamma] \geq 0$ and λ_i is a positive scalar.

Computer the residuals: $r_i(y) = \|\chi(y) - \Gamma \hat{\alpha}_\Gamma - D_i \delta_i(\hat{\alpha})\|_2$.

Output the classification result: $identity(y) = \arg \min r_i(y)$

III. EXPERIMENTAL RESULTS AND DISCUSSION

The aim of the proposed method in this work is to improve the reliability and accuracy under partial occlusion. In order to evaluate the performance of the proposed scheme in noisy conditions especially under occlusion, a noisy iris image database UBIRIS is utilized in our experiments[14].

UBIRIS database is composed of 1877 images collected from 241 persons and it incorporates images with several noise factors (defocus, motion blur and eyelid interference etc.), thus permitting to evaluate the robustness of iris recognition methodologies. In our experiments, some very bad quality iris images which are unsuitable for iris recognition are excluded. At last 900 iris images from 180 subjects (5 images of each subject) with different occlusion ratio are selected to construct a test iris image database, which include some good quality images as well as some noisy images but containing enough information for iris recognition. Sample images of the UBIRIS database are shown in Figure 1.



FIGURE 1. SAMPLE IMAGES OF UBIRIS

The human iris is an annular region between the black pupil and the white sclera. Prior to feature extraction, the iris

image needs to be preprocessed to eliminate uninterested information and enhance interested information. In this work, the main preprocessing steps, as illustrated in Figure 2, consist of localization of the inner and outer iris boundaries, transformation from polar coordinates to a fixed size rectangular image and image enhancement.

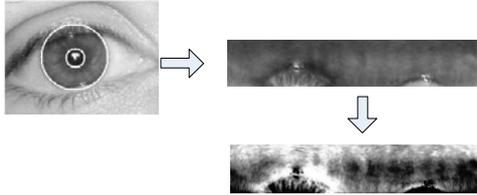


FIGURE II. STEPS INVOLVED IN IRIS PREPROCESSING

Five images of each subject have different occlusion ratio, so in our experiments three images with less occlusion are selected for training samples, and the other two images with more occlusion are testing set, which is used to simulate real authentication to evaluate the performance of the trained system.

In order to evaluate the effectiveness of the proposed scheme, we make a comparison with the traditional recognition algorithms (SRC algorithm based on Gabor feature[9], phase based algorithm[1]). The comparison results are shown in Table I.

TABLE I. RECOGNITION COMPARISON OF DIFFERENT ALGORITHMS

	Recognition Algorithm		
	Phase	SRC	Proposed
Recognition rate(%)	96.7	97.8	98.6

From Table I, we can find that the SRC iris recognition method based on Gabor feature achieved better recognition performance compared with the traditional phase algorithm, which proves the superiority of sparse representation classification in noisy conditions especially under partial occlusions. When a non-negative dictionary based on Log-Gabor features is applied in SRC method can bring obvious performance improvement from table 1, which also proves that the proposed method is an effective solution for iris recognition performance improvement under partial occlusion.

In our proposed method, the non-negative dictionary based on the Log-Gabor feature dictionary is applied. In order to evaluate the effectiveness of Log-Gabor feature dictionary, we also make a comparison with the method based on the non-negative dictionary and Gabor feature. The comparison results are shown in Table II.

TABLE II. RECOGNITION COMPARISON OF DIFFERENT FEATURE

	Recognition Algorithm	
	Gabor based	Proposed
Recognition rate(%)	98.1	98.6

From Table I, we can find that the Log-Gabor based non-negative dictionary method can achieve better recognition

performance compared with the Gabor based algorithm, which proves the superiority of the proposed method.

IV. CONCLUSIONS

In this paper, we proposed a non-negative dictionary based sparse representation classification method, and apply it on iris recognition with partial occlusion. In the proposed scheme, the multi-scale and multi-orientation Log-Gabor feature is applied to learn a non-negative occlusion dictionary instead of using an identity matrix. The learned dictionary not only has lower dimensions, but also enhances the discriminative ability. Experimental results in UBIRIS iris databased show that the proposed method is effective to iris occlusion.

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