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Abstract. Multi-source heterogeneous iris recognition (MSH-IR) has become one of the most challenging hot issues. Iris recognition is too dependent on the acquisition device, causing have large intra-class variations, capture iris duplicate data more and more larger. The paper proposed the application of locality preserving projection (LPP) algorithm based on manifold learning as a framework for MSH-IR. Looking for similar internal structures of iris texture, MSH-IR is performed by measuring similarity. The new solution innovation aspects that LPP algorithm is used to establish the neighboring structure of the similar feature points of the iris texture, and the similarity between the MSH-IR structures is measured after mapping to the low-dimensional space, and using the SVM algorithm to find and establish the optimal classification hyperplane in low-dimensional space to implement the classification of multi-source heterogeneous iris images. The experiment based on the JLU-MultiDev iris database. The experimental results demonstrates the effectiveness of the LPP dimension reduction algorithm for MSH-IR.

Keywords: iris recognition; multi-source heterogeneous; manifold learning; LPP

1 Introduction

Iris recognition has been widely used for personal identification due to the unique, complex, and stable texture patterns in iris[1]. MSH-IR means different acquisition devices result in different quality of the iris images of the same collector. As show in (Fig. 1). Hence, MSH-IR causes the low inter-operability[2][3] between the captured devices. It is obvious that there are significant differences at iris texture details among these iris images acquired from different devices. MSH-IR has large intra-class variations, which challenge the conventional well-performed iris recognition systems[4]. Recently, in the some fields of researchers have addressed multi-source heterogeneous and proposed some solutions. In fingerprint recognition, Rose and Jain[1] first proposed cross-platform fingerprint feature extraction and matching algorithm is a problem to be solved in the future. Yang et al.[5] proposed a second-order feature evaluation method based on error rate, decision tree and analyzed the device independence problem in fingerprint image segmentation. In vein recognition, Wang et al.[6] proposed a recognition method based on Local Binary Pattern(LBP) and multi-level structure, better solved the problem caused by different parameters of the device for heterogeneous vein image recognition. In medical terms, Li et al.[7] first explained the importance of equipment independence in application problems such as classification and retrieval of medical images. In iris recognition, Ryan et al.[8] analyzed the inter-operability between different devices from a hardware perspective, in order to illustrate the impact of different types of acquisition equipment on iris recognition. Arora et al.[9] proposed the application of selective image enhancement algorithms to minimize the difference between two cross-device iris images. These methods only focus on how to adjust the sensors or directly process the images, and do not analyze the feature structure of the images, and can not extract more effective feature points. Currently, there are few researchers on MSH-IR at home and abroad. However, public paper on multi-source heterogeneous iris recognition based on manifold learning has not yet appeared.

Manifold learning is developed along with the development of nonlinear data dimensionality reduction[10]. The method is the discovery of potential low-dimensional manifold structures from high-dimensional observation data. Hence, the paper proposes the application of manifold learning to MSH-IR. Manifold learning since Tenenbaum et al[11] and Belkin et al[12] proposed Isometric mapping(ISOMAP) and Laplacian Eigenmaps(LE), such as nonlinear dimensionality reduction algorithms. More and more researchers study the dimensionality reduction of manifold learning [13][14][15], Xiaofei He et al. [16] proposed the Locality Preserving Projections (LPP) based on the LE algorithm. Dimension reduction of data based on local feature structure, The above manifold learning is successfully applied in face recognition. And the most important is these methods pays more attention to the local neighbor relationship between image features. Iris feature is composed of a local texture structure. Express these areas with neighbor graphs, and find similar neighbor structures of similar iris images under different devices, comparison of similarities between textures of multi-source heterogeneous iris images, improve MSH-IR accuracy. So, the paper will analyze the effect of LPP on MSH-IR.

2 Overview of the proposed approaches

In this section, a brief description of the proposed manifold learning approach is given, which incorporates two discriminative learning techniques: LPP and SVM classifier. The main aim here is to local iris texture structures and identify their strengths and weaknesses to enable the proposal of an iris recognition system that integrates the strengths of these two techniques. The overall architecture of this paper is shown in (Fig. 2).

Fig. 1. Iris images captured by different parameters devices. Images in the first row are acquired by Lin Boshi S903, images in the second rows are captured by Sun Time 900A. In the two rows, images of the same columns belong to the same subject.

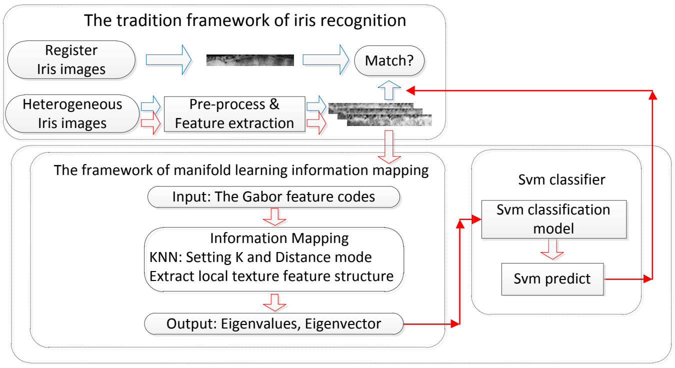

Fig. 2. Overall architecture

2.1 Pre-processing

Since the iris images contains redundant information, such as eyelids, eyelashes, sclera, etc, iris images need to be pre-processing, including quality evaluation, iris localization, enhancement, normalization, ROI interception.

Quality evaluation is a qualified iris images determined by a set of multiple indicators[16]. Iris location is binary image and Hough circle detection of iris images[17] to effectively determine the inner and outer boundaries of the iris. Iris normalization is through the mapping between polar and Cartesian coordinates[18] and iris enhancement is performed by histogram equalization. The approximate circular regions after positioning in the devices I and II are mapped into rectangular regions having a size of 512*64. both devices I and II intercept an ROI (Region Of Interest) having a size of 256*32, since ROI has a lot of effective texture information. As shown in (Fig. 3).

2.2 Gabor Feature Extraction

2D Gabor filter analyzes information in different directions and scales, suitable for extracting local texture features [18][19][20]. The paper selected five scales and eight orientations to get forty filters by Gabor feature extraction. as shown

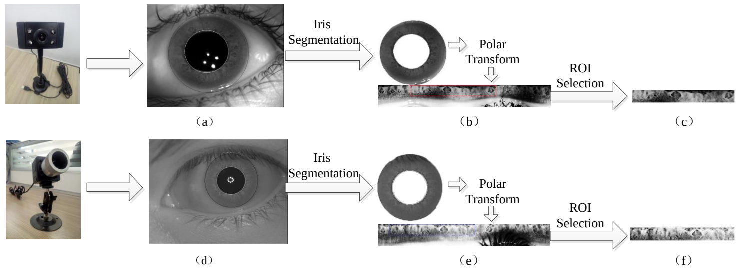

Fig. 3. Fig.3 Iris images pre-processing. (a)-(d) Pre-processing of iris images captured by device I. (e)-(h) Pre-processing of iris images captured by device II. (a)(e) different capture devices; (b)(f) iris location; (c)(g) normalization and enhancement; (d)(h) ROI

in (Fig. 4). direction-based feature coding of iris features, It can be seen that there are large differences in iris texture features under different devices.

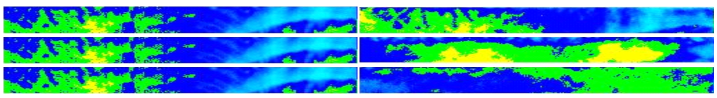

Fig. 4. Iris texture feature. The first row is the same class of iris images texture features captured by the same device; the second row is the different class of iris images texture features captured by the same device; the third row is the same class of iris images texture features captured by different device (multi-source heterogeneous iris images).

2.3 Manifold learning

The framework of manifold learning The manifold structure of the paper is shown in (Fig. 5). Assumed that multiple types of iris samples are input, iris texture manifold is extracted by LPP algorithm, and the local geometry of the sample space is preserved. The optimal domain of each sample and the corresponding projection matrix are obtained by KNN(K-Nearest Neighbor) method, which improves the classification accuracy.

Locality Preserving Projection The basic idea of the LPP algorithm: given a sample data arbitrarily, KNN method is used to construct a neighbor graph of sample points to form an internal structure. When this structure is projected into a low-dimensional space, the local neighbor structure of the original space is preserved in a low-dimensional space. The algorithm formula [15] is as follows: $X = x_1, x_2, ..., x_n \in R^n$ sample points in a high dimensional feature space, $Y = y_1, y_2, ..., y_l \in R^l (l \ll n)$, for projecting to low dimensional feature space

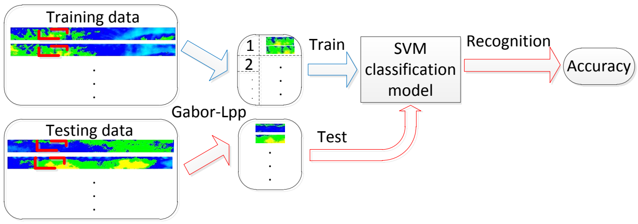

Fig. 5. Multi-source heterogeneous iris recognition manifold learning framework

sample points, transformation matrix V, so the formula is defined as:

$$y_i = V^T x_i, (i = 1, 2, 3, ..., n) \tag{1}$$

y_i and y_j is a pair of sample points of mutual neighborhood, W_{ij} is weight matrix, find the shortest point in the sample to create a local geometry as

$$\min \sum_{i,j} (y_i - y_j)^2 W_{i,j} \tag{2}$$

To prevent zero-direction solutions, add linear constraints $y^T Dy = 1$, equivalent to $V^T xDx^T V = 1$. Laplacian matrix $L = D - W$, D is diagonal array, $D_{ii} = \sum_i W_{ii}$. Purpose function:

$$\min \sum_V V^T xLx^T V \tag{3}$$

$$s.t. V^T xDx^T V = 1 \tag{4}$$

Lagrangian constructor

$$L(V, \lambda) = V^T xLx^T V - \lambda(V^T xDx^T V - 1) \tag{5}$$

$$\frac{\partial L}{\partial V} = 0 \tag{6}$$

$$\frac{\partial V}{\partial \lambda} = 0 \tag{7}$$

$(XDX^T)^{-1}(XLX^T)$ obtained first d minimum eigenvalues $\lambda_1 < \lambda_2 < \lambda_3 < ... < \lambda_d$, then the feature vector corresponding to the eigenvalue is $W = (\omega_1, \omega_2, \omega_3, ..., \omega_d)$.

3 Cross Device Experiment

In order to analyze the influence of the combination of LPP and SVM on MSH-IR, the group of experiments used cross-device experiments. The model is shown in (Fig. 6). i=7 is the optimal number of training samples. Hence, random selected 16 labels of iris images, random selected 7 images as training samples and 8 images as test samples.

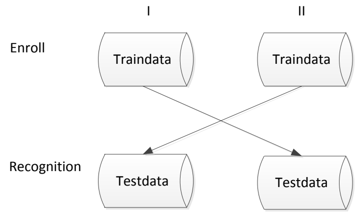

Fig. 6. Cross device model. The iris images captured by device I is used as the training set, the iris images captured by device II is used as the testing set, called I-II; the iris images captured by device II is used as the training set, and the iris image captured by device I is used as the testing set, called II-I.

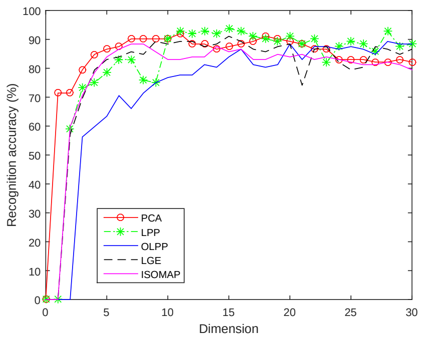

Fig. 7. I-II

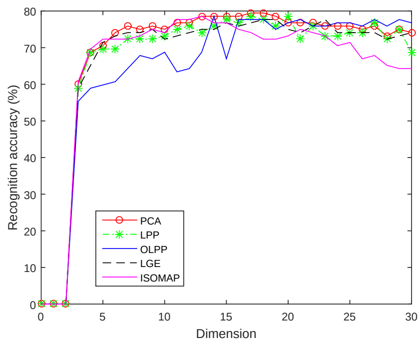

Fig. 8. II-I

As shown in (Fig. 7) and (Fig. 8) that the relationship between the number of projection vectors and the recognition accuracy of five different dimensionality reduction algorithms. Performed on I-II and II-I data sets. recognition accuracy gradually increases as the data dimension decreases until it becomes gentle. It is shows to us that effective to use the dimensionality reduction algorithm to remove redundant information. However, the maximum recognition accuracy of the five kinds of dimensionality reduction algorithms are all in the projection vectors between 8-28. Therefore, when the number of projection vectors selected is 20, it can be seen that the recognition accuracy of the LPP algorithm is the highest.

4 Conclusions

In this paper, we have proposed a manifold learning to solve MSH-IR based on Locality Preserving Projective. Constructing the neighborhood structure of the iris local texture, and comparison of similar structures of multi-source heterogeneous iris in the low-dimensional space, realized the correct identification between multi-source heterogeneous iris images. The core contribution of the paper is based on the framework of manifold learning the relational features to express similarities for multi-source heterogeneous iris feature matrix. LPP reduce the local iris texture features to low-dimensional space and maintain its neighbor structure. Thus the difference between source are take into account for better performance. Experimental results shows that the proposed method achieves promising and competitive performance for MSH-IR. But MSH-IR is worse than the homologous iris recognition. So, we need to further study the new solution based on MSH-IR.

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