An Improved Iris Recognition Algorithm Based on Hybrid Feature and ELM

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Abstract. The iris image is easily polluted by noise and uneven light. This paper proposed an improved extreme learning machine (ELM) based iris recognition algorithm with hybrid feature. 2D-Gabor filters and GLCM is employed to generate a multi-granularity hybrid feature vector. 2D-Gabor filter and GLCM feature work for capturing low-intermediate frequency and high frequency texture information, respectively. Finally, we utilize extreme learning machine for iris recognition. Experimental results reveal our proposed ELM based multi-granularity iris recognition algorithm (ELM-MGIR) has higher accuracy of 99.86%, and lower EER of 0.12% under the premise of real-time performance. The proposed ELM-MGIR algorithm outperforms other mainstream iris recognition algorithms.

1. Introduction

Compared with the fingerprint, face, voice prints and other biometric information, Iris recognition is recognized as the best biometric technology, which has the best stability and is a noninvasive technique. It has been widely used in many fields, such as the e-commerce, access control and attendance, etc. In the past few decades, iris recognition technology has achieved a major breakthrough in theory and applications. In iris feature extraction, Daugman proposed a wavelet algorithm, which used the Gabor filter to extract features from iris image [1]. Boles proposed a wavelet zero-crossing detection and correlation analysis algorithm [2]. Wildes proposed the use of a low-pass filter in the iris feature extraction [3]. These are the mainstream iris feature extraction algorithms and the extracted features by these algorithms have good recognition properties, but there are still some drawbacks. Single Gabor filter is easy to discard valid iris information [4], and the iris recognition system proposed by Boles only used the edge texture information of the iris, which has little information.

In terms of iris recognition algorithms, BP neural network was used in iris recognition and classification by Cao and Liu et al; Zhou et al applied support vector machine (SVM) in iris recognition [5-6]. These methods have increased iris recognition rate to some extent, but there are still some deficiencies. BP neural network takes long time, and SVM is aimed primarily at the binary-class problem. For multi-classification, it needs to be combined with the decision tree, hence it increases both the computational complexity and recognition time.

In iris feature extraction, a hybrid feature extraction method combined 2D-Gabor filters and GLCM was proposed. The proposed method can retain the low and intermediate frequency iris texture

information while retaining the high frequency iris texture information. In iris feature recognition, this paper uses extreme learning machine for training the multi-granularity feature vectors, it improves iris correct recognition rate while reducing the recognition time.

2. Hybrid Feature Extraction

Since the sampled iris image includes interference information, such as the eyelids, eyelashes, sclera, etc. So iris image pretreatment is necessary [7].

In order to preserve the iris texture features of every frequency band, this paper uses both 2D-Gabor filter groups and GLCM[8]. Firstly, extracting the 2D-Gabor and GLCM feature vectors of the same normalized iris image, separately. Then, combining the two vectors obtained above, finally, taking the combination vector as the feature vector of the iris image. The combination vector is called multi-granularity feature vector. The multi-granularity feature extraction method is composed of the following steps:

    1)   Obtain a 4-dimensional feature vector from each normalized iris image by GLCM.

        (a)   Energy,

$$UNI = \sum_i \sum_j \left\{ p(i,j) \right\}^2 \tag{1}$$

        (b)   Entropy,

$$ENT = -\sum_{i=1}^{k} \sum_{j=1}^{k} G(i,j) \log G(i,j) \tag{2}$$

        (c)   Contrast,

$$CON = \sum_h \sum_k \left(m_{hk} \right)^2 \tag{3}$$

        (d)   Correlation,

$$COR = \left[\sum_h \sum_k hk m_{hk} - u_x u_y \right] / \left[\sigma_x \sigma_y \right] \tag{4}$$

    2)   Establish a 2D-Gabor filter bank: choice 20 image part of the 2D-Gabor filters with $\theta = 0^o, 45^o, 90^o, 135^o$, f=0.125、0.0625、0.0417, respectively.

    3)   Divide each normalized iris image as $2*16(32)$ blocks.

    4)   Obtain 20 outputs from each image block by performing convolution between the block with the 20 filters (established in Step.2) in area space.

    5)   Concentrate the outputs of each image (obtained in Step 5) into a 20-dimensional vector by calculating their means.

    6)   Obtain a 640-dimensional feature vector by combining all results of 32 image blocks obtained by Step 6.

    7)   Obtain a 645-dimensional multi-granularity feature vector: first, combining the vector obtained by GLCM with the vector obtained by 20 2D-Gabor filters; then, taking corresponding class label as the first element of each combination vector.

3. Iris recognition Algorithm Based on ELM and Hybrid Feature

3.1. Extreme Learning Machine

Extreme learning machine (ELM) was initially put forward by Huang et al. as a novel-learning algorithm of SLFNs[9]. ELM learns much faster with higher generalization performance comparing with the traditional learning algorithms such as BP neural network and SVM.

Given a training set $\aleph = \left\{ (x_j, t_j) | x_i \in R^n, t_j \in R^m \right\}$, where $j = 1,...,N$, hidden node output function $G(\alpha_i, b_i, x)$, and the number of hidden nodes L, the ELM algorithm is composed of the following steps:

    1)   Assign randomly hidden node parameters $(\alpha_i, b_i), i = 1,...,L$.

    2)   Calculate the hidden layer output matrix H.

    3)   Calculate the output weight β : $\beta = H^\dagger T$. Where $H^\dagger$ is Moore-Penrose generalized inverse of H.

3.2. ELM-MGIR algorithm

All the normalized iris images are divided into two parts, and while one part is used to train the ELM, the other part is used to test the ELM [10]. Then, the CRR can be obtained by comparing actual output o_j with except output t_j. The ELM-MGIR algorithm is composed of the following steps:

1) Choice 7 image of each class iris, 3 for training and 4 for testing.
2) Obtain multi-granularity feature vector from the normalized iris images using multi-granularity feature extraction method.
3) Train and test the multi-granularity feature vector given in Step 2 by ELM.
4) Calculate the correct recognition rate (CRR), the equal error rate (EER) and the recognition time.
5) Repeat Step 3 one thousand times, calculate the mean values of the CRR and time as the final results.

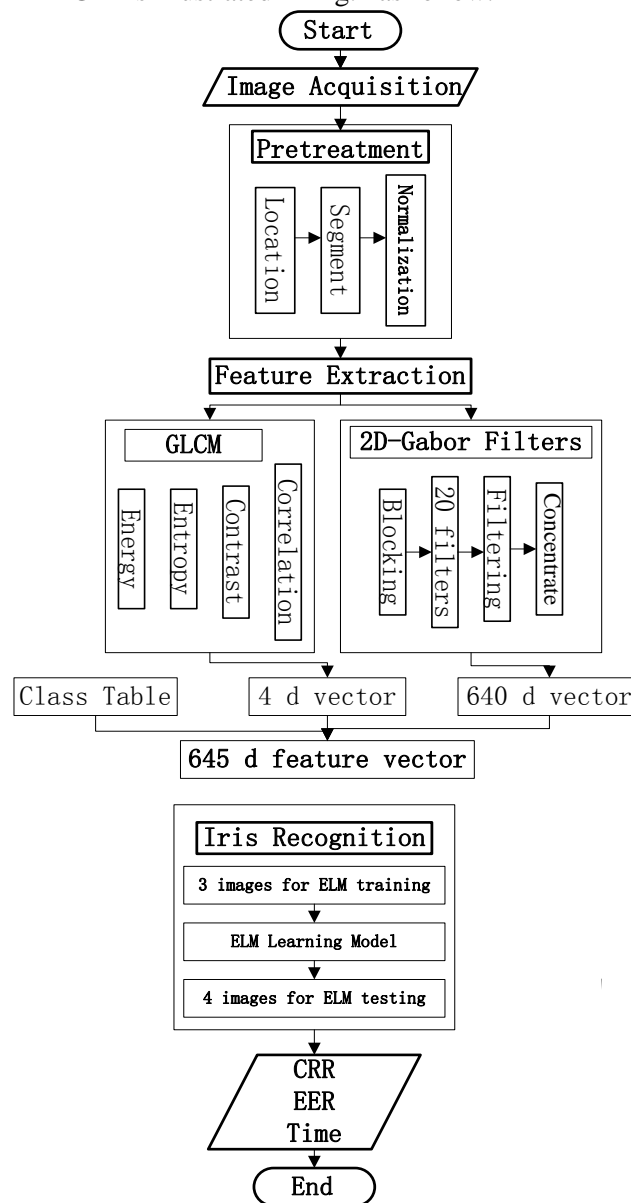The flow diagram of ELM-MGIR is illustrated in Fig.1 as follow.

Fig.1 Flow diagram of ELM-MGIR

4. Experimental Results

CASIA-Iris is widely used in the experiment of iris recognition algorithm. In this paper, CASIA-Iris Ver1.0 and CASIA-Iris Ver4.0-Interval are used in our experiment. In the iris image preprocessing, 7 iris images from each category that over 3 images are classified correctly are selected as the samples and the other 4 images for testing. Finally, 60 kinds of iris images are selected from each iris database that mentioned above. The experiments in this paper are both performed on the PC with Intel i5-3470 CPU 3.20 GHz, 8.00GB memory, and simulated in the programming environment MAtlab2013a.

Experiment 1:

Three feature extraction methods are tested in this experiment to compare our proposed multi-granularity feature with GLCM and 2D-Gabor filters. The classification performance comparison of different feature extraction algorithms is shown in Table 1.

Table 1. Comparison of classification performance

Datasets	Num. of classes	Samples/ Class	Total Samples	Algorithms	Dimension	CRR	Time
CASIA-IrisVer1.0	60	7	420	GLCM	4*1	53.15%	0.0584
				2D-Gabor filters	640*1	97.69%	0.0607
				Multi-granularity	**645*1**	**99.90%**	**0.0689**
CASIA-Iris Ver4.0 (Interval)	60	7	420	GLCM	4*1	34.37%	0.0576
				2D-Gabor filters	640*1	98.86%	0.0602
				Multi-granularity	**645*1**	**99.86%**	**0.0684**

As shown in Table1. Compared to the GLCM and 2D-Gabor filters, the proposed multi-granularity feature extraction algorithm performs better in CRR. The recognition time of the proposed algorithm increases slightly with larger dimension of the feature vector.

Fig.2 illustrates the change of CRR with different number of classes of iris.

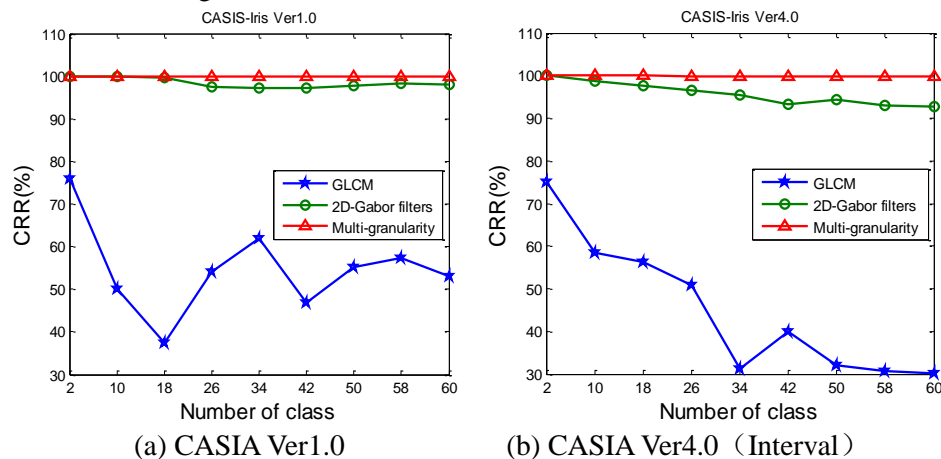(a) CASIA Ver1.0   (b) CASIA Ver4.0（Interval）

Fig.2. CRR of different feature extraction methods

As shown in Fig.2, we can know that GLCM has poor robustness and low CRR, 2D-Gabor filters performs better than GLCM, but with the increasing of the number of iris classes, the CRR decreases. The proposed multi-granularity feature extraction algorithm performs best with the highest CRR and best robustness when compared with GLCM and 2D-Gabor filters.

Experiment 2: For CASIA-Iris Ver4.0-Interval, the comparison of our proposed ELM-MGIR with other iris recognition algorithms is shown in Table 2.

From Table2, we can know that compared with the method used in paper [2] and [3], the proposed ELM-MGIR algorithm increases the CRR by 7% while ERR has a reduction. Compared with the

method used in paper [5] and [6], ELM-MGIR algorithm also has a better performance in CRR and ERR.

Table2. The comparison of ELM-MGIR with other IR algorithms

Algorithm	CRR (%)	EER (%)
Wavelet Zero-crossing[2]	92.64[*]	8.13[*]
Laplacian pyramid[3]	N/A	1.76[*]
Log-Gabor , SVM[5]	99.6[*]	0.3[*]
Gabor feature, SVR[6]	97.39[*]	1.65[*]
ELM-MGIR(propose)	**99.86**	**0.12**

5. Conclusions

In this paper, a multi-granularity extraction algorithm combined 2D-Gabor filters and GLCM is proposed to generate a multi-granularity feature vector. Then, ELM is used to train and test the vectors that obtained by multi-granularity extraction method. Finally, two experiments are performed on the iris datasets: CASIA-Iris Ver1.0 and CASIA-Iris Ver4.0-Interval. Experimental results show ELM-MGIR increases CRR while decreases ERR, and ELM-MGIR algorithm can achieve a recognition speed at 16 fps because ELM can learn faster.

Acknowledgements

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