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Multi-view Based Gabor Features Fusion for Iris Recognition

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Abstract. Iris is one of the most reliable biometrics because of its uniqueness and stability, hence has played an important role in many biometric applications such as access authentication. While existing Gabor features have demonstrated great success for Iris recognition methods, they are not designed for visually characterize Iris patterns. In this paper, we purposely design 6 Gabor filters after analyzing the texture and spatial information of the iris to extract features. However, the features may have redundant information and some non-effective features, which interfere with the matching process. To fuse the Gabor features obtained through these Gabor filters, we propose a weighted multi-view feature fusion algorithm by minimizing intra-class distance and maximizing inter-class distance. The Particle Swarm Optimization (PSO) algorithm is utilized to solve this nonlinear optimization problem. Experimental results on the popular benchmark dataset CASIA-IrisV4-Thousdand demonstrate that our proposed method utilizing the novel Gabor features and multi-view fusion algorithm outperforms other Gabor feature based methods.

Keywords: feature fusion, Gabor filter, iris recognition, PSO

1 Introduction

Iris recognition is considered to be one of the most accurate and reliable biometric method. After J Daugman proposed the first iris recognition system, many commercial iris recognition systems were produced to process eye images [1-2]. And in most conditions, iris segmentation is a challenging task in the case of noisy images, however it still has made great progress in a limited environment. The traditional algorithms use the binarization method and uses morphological processing to segment the pupil of the image and fit the pupil with the least squares method in order to find the center and radius of the pupil [3-4]. Then segmenting the noise portion as a mask portion. Finally, according to the method segmentation method proposed by J Daugman, the pupil and iris are regarded as non-concentric circles, and the segmented iris is normalized by bilinear interpolation method.

Due to noise, illumination, blurring, and inaccurate segmentation factors, the misidentification rate is very high in a large number of data matching processes. When it comes to matching, most of the methods are image enhancement on iris normalized images, increasing contrast, such as histogram equalization, and then adopting grayscale matching such as SSD, SSDA [5] or SIFT matching. But these methods can't satisfied with most of the actual situation well. Even a little of changes in lighting can have a major impact on this method.

Shaaban A, etc. use the SVM method for the binary classifier method [4]. However, in practical applications, it is faced with multiple classifications, and the binary classifier algorithm will be limited. Tossy Thomas, etc. used the RANSAC method to fit the pupil and iris and get the normalization image and mask image. They extract feature by using cross correlation method and match template by using

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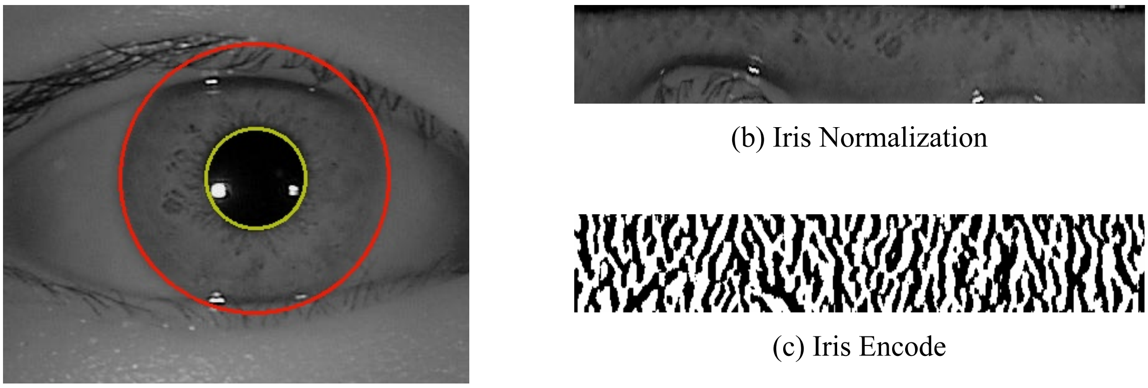
PSR as Similarity Measure. If the match is successful, the cross correlation result matrix will have a distinct peak, otherwise the peak is not obvious or does not exist. According to the peak value we can get the best matching object [6]. Similarly, the method is still susceptible to light intensity. Typical iris recognition method uses a Gabor filter to extract iris texture and matchs [7]. Nadia Othman, etc. [8] used Gabor filter for the normalized iris image to obtain the feature texture image under different views and converted them to a binary images. After that, this method would computed a similarity or different score between the two templates. The experimental results are good and have certain robustness to the effects of light intensity, noise, etc. However, iris features at multi-view have redundant information and some non-effective features. Too many feature attributes may reduce the accuracy of classification results. An improved method is proposed for this problem by Wang F H. They use the amplitude information to fuse Gabor features in different directions of the same scale and encode the merged features. At last they use Hamming distance matching which improves matching speed and saves storage space [9-11]. In this paper, first, we designed 6 Gabor filters to extarct the features of iris according to Thomas p, etc [12]. Second we proposes a weight-based iris feature image fusion recognition algorithm based on Wang F H. According to the different scale feature images, we use PSO algrithm to comput different weights in order to fuse the feature images. Finaly, the ultimate goal is to preserve important features and discard redundant details and improve the accuracy of image classification.

2 Weight-based Feature Fusion (WFF)

Mainstream methods iris recognition including preprocessing, iris localization, normalization, encoding of iris images:

A large number of literatures and methods have been produced since the concept of iris recognition was proposed, and almost all methods are based on the improved algorithm proposed by J Daugman. As you can see, Fig. 1 show the results of the pretreatment and c in Fig. 1 is a typical Gabor preprocessing method. The open source iris recognition software developed by Nodia Othman, etc. have made great progress in iris image preprocessing. However, in many algorithms, it is not considered that the different characteristics of the feature information for different classification or recognition results in the possibility of information redundancy. Therefore, this paper mainly studies the algorithm of iris matching. For the problem of matching and multi-view features, this paper proposes a weight-based feature fusion model.



(a) Iris Localization

(b) Iris Normalization

(c) Iris Encode

Fig. 1. Procedure of iris recognition

According to this thought, we construct a optimization model. For a given set of training samples $F = \{f_1, f_2 \cdots f_N\}$. There are normalized iris sample vectors that fall into categories. The Gabor filter is used to extract features from all training samples to obtain feature vectors $f_{j(h)}^{(k)}$ under six views to form a training sample data set. In this paper we proposes a classification algorithm that optimizes weights, so that the objective function for computing the same type of image is the smallest, and the objective function of different classes is the largest. The core idea is to classify samples belonging to the same class into one class as much as possible. Samples of different classes are separated as much as possible. So we define the objective function is as follows:

$$F(\mu,\omega,f)=\sum_{i=1,j=1}^{N}\sum_{h=1}^{D}\mu_{ij}\delta\Big(\sum_{k=1}^{6}\omega_k f_{i(h)}^{(k)},\sum_{k=1}^{6}\omega_k f_{j(h)}^{(k)}\Big)$$
$$s.t.\quad \sum_{k=1}^{6}\omega_k=1 \qquad 0\le\omega_k\le 1 \tag{1}$$

With this conditions.

$$\mu_{ij}=\begin{cases}1, & i_{label}=j_{label}\\ -1, & i_{label}\neq j_{label}\end{cases}$$
$$\delta(x,z)=\begin{cases}1, & x\neq z\\ 0, & x=z\end{cases} \tag{2}$$

Where $f_{i(h)}^{(k)}$ represents the h-th dimensional belongs to feature of the i-th training sample under the k-th view. $f_{j(h)}^{(k)}$ represents the h-th dimensional belongs to feature vector of the j-th training sample under the k-th view. N represents the total number and D represent the dimensional for training samples. ω_k represents the weights under the k-th view. μ_{ij} is related to the category of the feature vector. When $f_{i(h)}^{(k)}$ and $f_{j(h)}^{(k)}$ are in same classes, ie $i_{label}=j_{label}$, μ_{ij} is 1. Otherwise μ_{ij} is -1.

For a given training sample sets which belong to C categories. If f_i and f_i belong to the same categories and $\mu_{ij}=1$. The corresponding eigenvectors under the action of the $\delta(x,z)$ get the lower the value of the objective function, the bigger the probability that the two images belong to the same class. Contrastly, If f_i and f_i don't belong to the same categories and $\mu_{ij}=-1$. The corresponding eigenvectors can take the maximum value under the action of the $\delta(x,z)$ to distinguish the samples of different classes. The final problem is transformed into finding the minimum value of the objective function

$$W_{opt}=\arg\min_{\omega}(F(\mu,\omega,f)) \tag{3}$$

According to eq.(3), we can know that this is a typical nonlinear optimization problem. Due to the complexity of the training samples and the large sample size, it is difficult to solve the problem by using the conventional linear solution optimization method. The PSO algorithm can effectively solve this problem. It has low requirements on the objective function, and has group sharing only and memory function, which can find the optimal solution faster [13].

3 Solve the Model

The particle swarm optimization algorithm was first proposed by Kennedy and Eberhart [14]. It is an evolutionary computational method, which can quickly find the optimal solution to solve the nonlinear optimization problem effectively [15]. Compared with the genetic algorithm, the PSO algorithm has simple parameters, is easy to implement, high efficiency and can achieve good results. PSO initializes a group of random particles (ω), then find the optimal solution through iteration ω_{best}. In each iteration, the particle updates itself by following two "extreme values", one is the optimal solution the particle itself, called the individual extremum $(pbest)$. The other is the optimal solution found by the entire population currently. This extreme value is called the global extremum $(gbest)$. The degree of "goodness and weakness" of the particles is evaluated by the calculated fitness value. Each particle is continually updated by $(pbest)$ and $(gbest)$, resulting in a new generation of populations.

For example, the j-th particle of N particles is represented as $\omega_j=(\omega_{j,1},\omega_{j,2}\cdots\omega_{j,6})$ in the 6-dimensional sample space. The previous best position of this particle was defined as

$pbest_j = (pbest_{j,1}, pbest_{j,2} \cdots pbest_{j,6})$ and the best global position was $gbest_g = (gbest_{g,1}, gbest_{g,2} \cdots gbest_{g,6})$. And we set the velocity of $j-th$ particle $v_j = (v_{j,1}, v_{j,2} \cdots v_{j,6})$. Then we can update each particle's position according to the following formula

$$v_{j,g}^{(t+1)} = w \cdot v_{j,g}^{(t)} + c_1 \cdot rand() \cdot (pbest_{j,g} - \omega_{j,g}^{(t)}) + c_2 \cdot Rand() \cdot (pbest_g - \omega_{j,g}^{(t)}) \quad \textbf{(4)}$$

$$\omega_{j,g}^{(t+1)} = \omega_{j,g}^{(t)} + v_{j,g}^{(t+1)} \quad \textbf{(5)}$$

Where, t represented the number of iterations, $v_{j,g}^{(t)}$ represented the speed of the $j-th$ particle at the $t-th$ iteration. $V_g^{\min} \le v_{j,g}^{(t)} \le V_g^{\max}$, $\omega_{j,g}^{(t)}$ is the position value of the current iteration number of the particle， $rand()$ and $Rand()$ are random numbers between 0-1.

In the above calculation process， $v^{\max}$ determines the performance of this particle swarm algorithm. The rate of particle movement changes between the current value and the target value. If $v^{\max}$ is too big, particles might move past best solution. If $v^{\max}$ is too small, algorithm convergence will slow down. In many particle swarm optimization experiments, a is generally dynamically set to a number between 0.1-0.2.

4 Experimental Analysis

In this paper, we uses the particle swarm optimization algorithm combined with the preprocessing training sample image calculation to find the optimal weight solution combination and apply the fused texture image to the iris recognition algorithm. The data used in this experiment was published in the Chinese Academy of Sciences in 2012. We randomly selected 300 images of 30 people from this dataset. The main reason for the low recognition rate of this data set is the occlusion of glasses, strong specular reflection, eyelids and blurring. Fig. 2 shows some samples of this dataset. Fig. 3(a) is the the real and imaginary part of 3 sets of Gabor filter templates designed by ourselves and the Gabor filters consist of 6 matrices. Fig. 3(b) is the normalization image processed by proper method which is $64 pixel \times 512 pixel$. Fig. 3(c) is the image encoded Gabor filters.

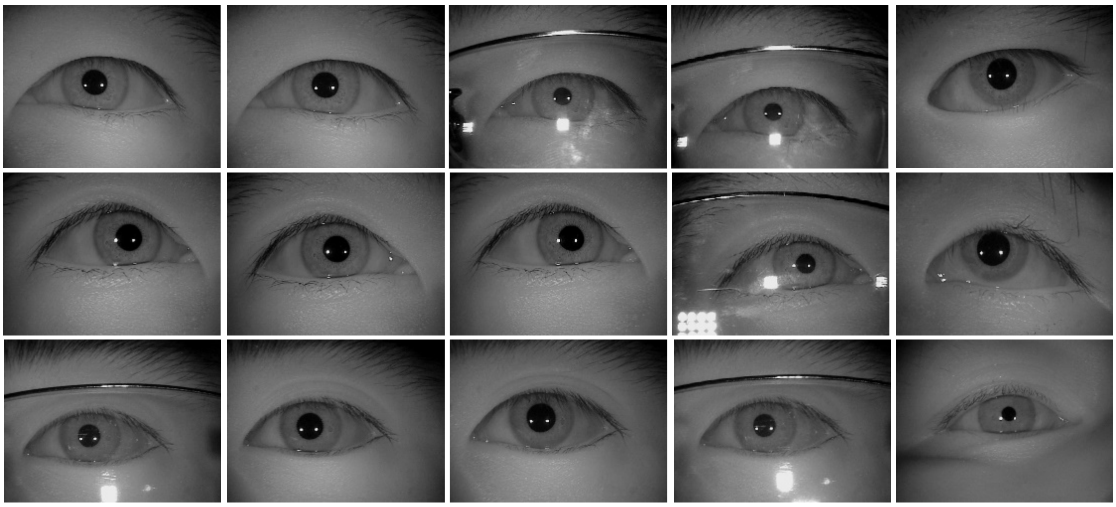
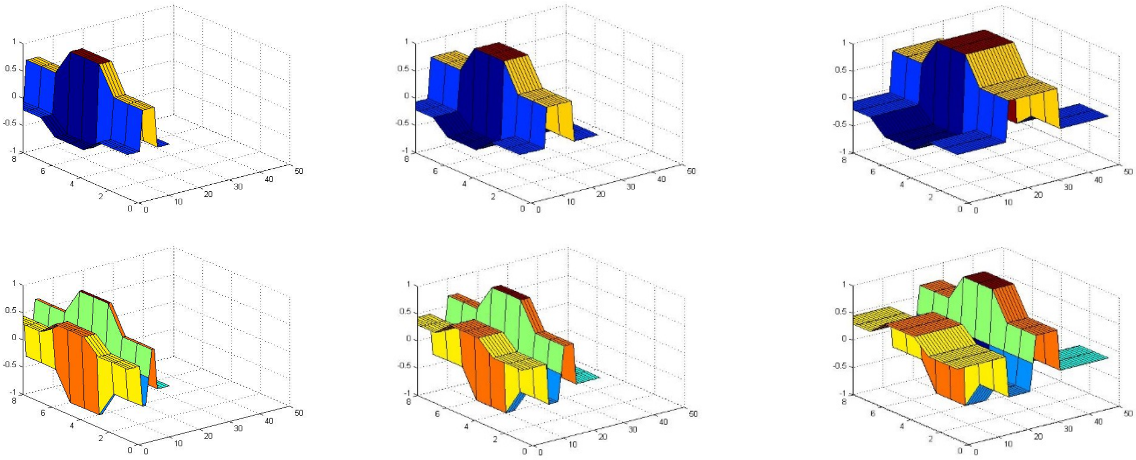


Fig. 2. Examples of images come from CASIA-IrisV4-Thounsand



(a) 6 Gabor filters, each column represents the real and imaginary part of Gabor template

(b) Original Normalization Image (c) Muli-view Gabor filter image

Fig. 3. Original sample and preprocessing sample

In order to obtain the weight combination of feature fusion, bring the preprocessing Gabor texture image into the objective function. Then we construct a adaptive function and find the result by PSO algorithm. The result of the objective function is output during the iterative solution process. Fig. 4 shows the result curve of the objective function in the iterative process.

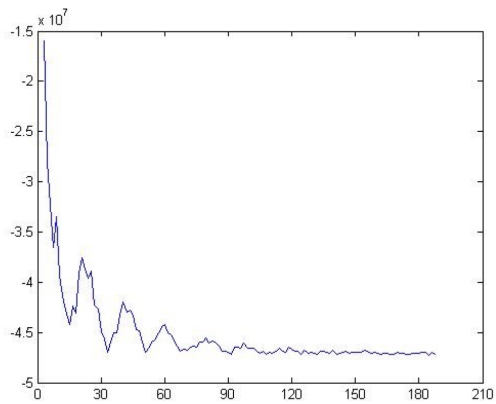


Fig. 4. The result curve of PSO

Similarly, in this experiment, the objective function is used as the fitness function in the PSO solution process. In the calculation process, as the number of PSO iterations increases, the objective function gradually becomes stable and the rate of change gradually decreases to 0. Table 1. reflects the objective function and how it changes with the number of iterations:

Table 1. Gbest value changes with the iterations

iters	obj	gbest
15	-4.413×10^{7}	(0.213, 0.232, 0.121, 0.113, 0.173, 0.148)
30	-4.501×10^{7}	(0.295, 0.305, 0.113, 0.101, 0.104, 0.082)
60	-4.472×10^{7}	(0.368, 0.353, 0.059, 0.095, 0.096, 0.029)
90	-4.715×10^{7}	(0.425, 0.391, 0.047, 0.067, 0.053, 0.017)
120	-4.717×10^{7}	(0.453, 0.428, 0.025, 0.043, 0.042, 0.009)
150	-4.716×10^{7}	(0.471, 0.452, 0.013, 0.037, 0.025, 0.002)
180	-4.716×10^{7}	(0.475, 0.454, 0.011, 0.035, 0.023, 0.002)

As the number of iterations increases, not only will the value of the objective function gradually become stable, but *gbest* will gradually become stable. Finally we get the value $gbest = (0.475, 0.454, 0.011, 0.035, 0.023, 0.002)$ as the weight of feature image. And then we use this value to work on Gabor image and get a rate of recognition.

We randomly selected 200 objects from the first 300 objects in the CASIA-IrisV4-Thousand database for a total of 2000 images. Then we selected 200 images from 200 objects. Every image belongs to different object. The rest 1800 images were used to match the database image. In the matching process, the mask does not participate in the operation. Table 2 shows the matching accuracy and the average time to match 30 times:

Table 2. The result of three algorithms on CASIA-IrisV4-Thousand database

EVALUATING INDICATOR	OSIRIS_V4.1	WFF_XOR	GABOR_NCC	PSP_NCC
Ccuracy(%)	88.61	89.05	72.31	44.70
Time(s)	1.1079	0.2162	3.3853	2.5548

According to Table 2, the matching accuracy of the OSIRIS_V4.1 algorithm and the WFF_XOR algorithm on the CASIA-IrisV4-Thousand are 88.61% and 89.05%. The performance of WFF_XOR based on OSIRIS_V4.1 has improved and time complexity is significantly reduced. As you can see, the time WFF_XOR used is only 1/5 of OSIRIS_V4.1. This means that the algorithm in this paper is more effective on this data set. In addition, WFF eliminates redundant feature texture information and retains the main structural information, so that the refined texture information has more classification features. All of this made WFF more efficient and faster.

Many matching methods worked on grayscale image have limitations, that is, they actually have an effect on grayscale matching, but are greatly affected by illumination changes. For example, PSP_NCC algorithm [5] apply the correlation coefficient matching method on gray image like Fig.3(a), and the reslut is 44.7%. But the GABOR_NCC algorithm [5] worked on gray image to the binary image encoded by Gabor filters. The accuracy is 72.31%. This shows that the algorithm can reduce the influence of illumination on image recognition, and it also shows the superiority of feature fusion.

5 Conclusions

This paper proposes a weight-based feature fusion algorithm WFF_XOR. The algorithm uses particle swarm optimization to solve typical nonlinear optimization problems, and solves a set of optimal solutions. Based on this, a weight-based feature fusion recognition algorithm is constructed. Incorporating the idea of feature fusion into this algorithm makes this algorithm can eliminate redundant information well and retain the main information with classification. According to the encoded images calculated by 6 Gabor filters, the feature fusion algorithm is used to have better effect in iris image recognition. The algorithm can solve the noise and other problems caused by the change of illumination intensity, and has good performance in terms of robustness, recognition rate and recognition speed.

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