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An iris recognition method based on multi-orientation features and Non-symmetrical SVM*

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Abstract: A new iris feature extraction approach using both spatial and frequency domain is presented. Steerable pyramid is adopted to get the orientation information on iris images. The feature sequence is extracted on each sub-image and used to train Support Vector Machine (SVM) as iris classifiers. SVM has drawn great interest recently as one of the best classifiers in machine learning, although there is a problem in the use of traditional SVM for iris recognition. It cannot treat False Accept and False Reject differently with different security requirements. Therefore, a new kind of SVM called Non-symmetrical SVM is presented to classify the iris features. Experimental data shows that Non-symmetrical SVM can satisfy various security requirements in iris recognition applications. Feature sequence combined with spatial and frequency domain represents the variation details of the iris patterns properly. The results in this study demonstrate the potential of our new approach, and show that it performs more satisfactorily when compared to former algorithms.

Key words: Iris recognition, Steerable pyramid, Variation fractal dimension, Non-symmetrical Support Vector Machine (NSVM)
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MOTIVATION

Iris recognition, widely accepted as one of the best biometrics recognition methods in the world because of its stability, uniqueness and noninvasiveness (Adler, 1965; Daugman, 1993; Ma *et al*., 2002; Wildes, 1997), has the potential of applications in very wide areas.

As a kind of pattern recognition to classify the iris correctly by comparing the similarity between irises, two major works are: (1) to find the appropriate features to represent iris properly; and (2) to classify iris patterns based on the features. Wavelet transform is a popular representation in the former iris recognition algorithms (Daugman, 1993; Ma *et al*., 2002). Steerable pyramid is designed to enhance wavelet transform by translation, dilation, and rotation invariance (Simoncelli, 1996). We extract a new kind of feature based on steerable pyramid and fractal geometry to represent the oriented self-similar textures. This feature sequence is translation, dilation, and rotation invariant.

To get a good classifier with high performance, we choose Support Vector Machine (SVM) to do the classification. SVM has recently generated great interest in the community of machine learning due to its excellent generalization performance in a wide variety of learning problems, such as handwritten digit recognition (DeCoste and Scholkopf, 2002), classification of web pages (Joachims, 1998) and face detection (Osuna *et al*., 1997). In traditional SVMs, False Accept and False Reject are treated equally. However, in biometrics recognition, False Accept or False Reject should be emphasized particularly according to different situations. In order to make SVM more feasible in this kind of applications, the concept of Non-symmetrical SVM is proposed and tested in

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this work.

FEATURES EXTRACTION

Fig.1 is 2 common iris images from CASIA iris database. To see it more clearly, we removed the background around annular irises. We can see that the iris consists of many irregular small blocks, such as freckles, coronas, stripes, furrows, crypts, and so on. Furthermore, the distribution of these blocks in the iris is also random. The distinct aspect of the iris comes from randomly distributed features. This leads to its high reliability for personal identification, and at the same time, the difficulty in effectively representing such details in an image. Inspired by fractal geometry, we can regard these irregular texture patterns as a kind of fractal phenomenon. Furthermore, this self-similarity is multi-oriented around the pupil.

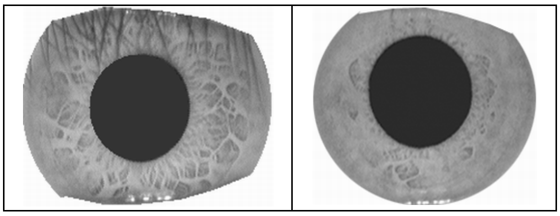

Fig.1 Iris patterns from CASIA database

Variant fractal dimension

Based on the self-similarity we found in iris patterns, we take it as a kind of typical fractal phenomenon. The mathematical way now is to measure fractals by fractal dimension.

Fractal dimension was studied regarding its recognizing and segmenting textures in images (Chaudhuri and Sarkar, 1995). The best known and the most widely used one is box-counting dimension:

$$\mathrm{Dim}_B F = \lim_{\delta \to 0} \frac{\log N_\delta(F)}{-\log \delta} \tag{1}$$

where $N_\delta(F)$ is the smallest number of square (or cubic) boxes with side δ necessary to cover F. Eq.(1) is to count the number of boxes which contain the image. But it is not suitable for reflecting an iris image whose self-similarity is not on the contour but inside the texture instead. Researchers proposed a special fractal dimension for texture images like irises (Gu *et al*., 2004):

$$\mathrm{Dim}_B F = \lim_{\delta \to 0} \frac{\log N_\delta(IsChange(F_\delta))}{-\log \delta} \tag{2}$$

where F_δ is the image covered by square boxes of side δ, $IsChange(F_\delta)$ will be evaluated with two thresholds. Basically it is 1 if the gray scale in F_δ changes, and 0 otherwise. Because a gray image has abundant gray scale variations, it is improper to analyze all the small changes in detail because the dimension value must be close to 2.0 in that case. The solution is setting a threshold. The changes that are bigger than the threshold can be counted as "change". It is Low-Threshold. The reason to set High-Threshold is to reduce the influence of the pupil and the eyelashes in the iris images. Only changes falling between Low-Threshold and High-Threshold will be counted as $IsChange(F_\delta)$.

In order not to leave out any variation details, a moving window (l_a,l_b) is used, which moves by (*Step*). Overlap is allowed when covering the image. The variation fractal dimension of every sub-image can be calculated now. The values of (l_a,l_b) and (*Step*) will affect the size of the feature series directly. For example, for an image of 200×200, when (l_a,l_b) choose (50×50), and (*Step*) is 50, we can get 16 features as the feature series.

$$Feature(I)=(D_1 \dots D_n)$$

where D_i is ith sub-image's corresponding variation fractal dimension. These features are input to the classifier for recognition.

Steerable pyramid

We can see this self-similarity is multi-oriented around the pupil in Fig.1. The variation fractal dimension faces a problem in that the orientation of iris textures is not considered. However, for recognition applications, the orientation information is very important.

To solve this problem, we introduce steerable pyramid into iris feature extraction. Steerable pyramid transform can analyze the anisotropic textures of irises. This transform decomposes the image into several spatial frequency bands, and further divides each frequency band into a set of orientation bands. By studying each orientation band, we can get orientation information of iris textures.

The steerable pyramid (Simoncelli and Freeman, 1995) is a linear multi-scale, multi-orientation image decomposition that provides a useful front-end for many computer vision and image-processing applications. The basis functions are directional derivative operators that come in different sizes and orientations. The steerable pyramid performs a polar-separable decomposition in the frequency domain (Fig.2), thus allowing independent representation of scale and orientation. Since it is a tight frame, it obeys the generalized form of Parseval's Equality: The vector-length (L2-norm) of the coefficients equals that of the original signal. More importantly, the representation is translation invariant and rotation invariant (Simoncelli and Freeman, 1995), which perfectly suits iris recognition.

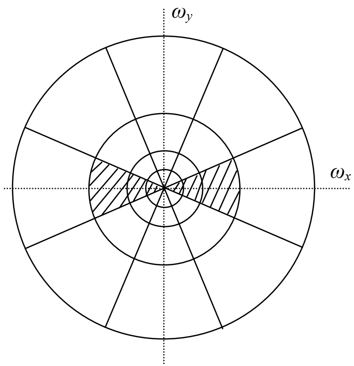

Fig.2 Idealized illustration of the spectral decomposition performed by a steerable pyramid with k=4. Frequency axes range from $-\pi$ to π

A linear image transform represents an image as a weighted sum of basis functions. That is, the image, $I(x,y)$, is represented as a sum over an indexed collection of functions, $g_i(x,y)$

$$I(x,y)=\sum_i y_i g_i(x,y) \tag{3}$$

where y_i are the transform coefficients. In iris recognition applications, an iris image is decomposed into a set of subbands (Fig.3), and the information within each subband is processed more or less independently of that in the other subbands. First, we get a set of orientation bands of an iris image. Then, we calculate the variation fractal dimension upon each of the orientation bands to present the self-similarity of the different orientation bands.

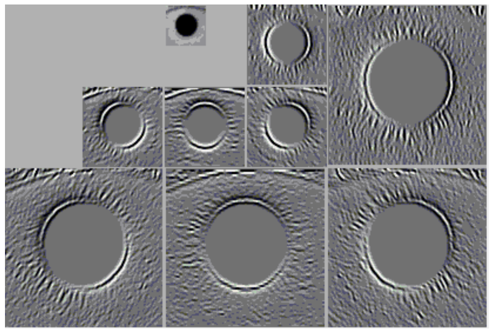

Fig.3 A set of orientation bands of an iris image

NON-SYMMETRICAL SVM

How to build an effective learning system plays a crucial role in the performance of classifiers. Support Vector Machine (SVM) is a promising method for classification because of its solid mathematical foundations which convey several salient properties that other methods hardly provide. However, the traditional SVM has a problem in that it processes False Accept and False Reject without any difference, which limits the feasibility. So we modified traditional SVM as Non-symmetrical SVM to satisfy the various security requirements in iris recognition applications.

Based on the minimization of structural risk of statistical learning theory, SVM works like this (Vapnik, 1998): it maps the input vector $\boldsymbol{x}$ to a higher dimension feature space Z, and constructs a classification hyperplane in this space. The hyperplane H is

$$w\boldsymbol{x}+b=0 \tag{4}$$

Generally, let $S=\{\boldsymbol{x}_i,y_i\}$ $(1\le i\le N)$ be training samples sets of two classes problem, where $\boldsymbol{x}_i$ is the feature vector of each input sample, $y_i=\pm1$ is the class sign. Suppose all samples $\boldsymbol{x}_i$ satisfy:

$$\begin{cases} y_i=1 & \text{if } (w\boldsymbol{x}_i)+b\ge\Delta; \\ y_i=-1 & \text{if } (w\boldsymbol{x}_i)+b\le-\Delta \end{cases}$$

where i=1,…,k. Then we name it as Δ-margin classification hyperplane. The inequalities above can be merged as:

$$y_i(\boldsymbol{x}_i w+b)\geq\Delta \quad i=1,\ldots,k \tag{5}$$

After the dataset is divided into two classes by the hyperplane, the distance of the two datasets is $2/||w||$. The decision-making function is

$$f(\boldsymbol{x})=\mathrm{sgn}\{(w\boldsymbol{x})+b\}$$

Considering there are some samples that cannot be classified correctly by the best linear hyperplane in real world applications, we can add a relax variable ξ_i into Eq.(5), $\xi_i\geq 0$, i=1,…,k:

$$y_i(\boldsymbol{x}_i w+b)\geq\Delta+\xi_i \quad i=1,\ldots,k \tag{6}$$

When there is a mistake in classification, ξ_i is bigger than 0. So we introduce a constant C as the error-punishment. Now the problem of constructing generalized best classification hyperplane is converted to how to minimize the function below under the restricting condition Eq.(6)

$$\psi(w,\xi)=\frac{1}{2}(w,w)+C\sum_{i=1}^{k}\xi_i \tag{7}$$

Now, the decision-making function becomes:

$$f(\boldsymbol{x})=\mathrm{sgn}\left(\sum_{i=1}^{k}\alpha_i y_i K(\boldsymbol{x},\boldsymbol{x}_i)+b\right) \tag{8}$$

By now, SVM takes False Accept and False Reject into the same consideration without any difference. Actually, especially in biometrics recognition, the costs of False Accept and False Reject are different. It needs to be treated in different ways during training. Sometimes, False Accept should be punished by a bigger cost than False Reject. So we modified traditional SVM as NSVM to satisfy the changing security demand by a constant m. We call m non-symmetrical parameter. It is used to adjust the position of the classification hyperplane H:

$$w\boldsymbol{x}+b+m=0 \tag{9}$$

In Eq.(9), $b+m$ can be realized by b' since they are similar variables, then Eq.(9) will be $w\boldsymbol{x}+b'=0$. But it is better to separate them because they have different physical meanings. The parameter m should be emphasized as a special non-symmetrical parameter to be evaluated in the following experiments. $m>0$ means the classification hyperplane H is closer to the center of positive samples. By changing the value of m, the False Accept Ratio (FAR) can be reduced. Consequently the two kinds of mistakes are punished differently. Now Eq.(8) is changed to:

$$f(\boldsymbol{x})=\mathrm{sgn}\left(\sum_{i=1}^{k}\alpha_i y_i K(\boldsymbol{x},\boldsymbol{x}_i)+b+m\right) \tag{10}$$

In this way, we can adjust the position of H according to different security requirements, and H can be different distance away from the two kinds of support vectors. We name this kind of SVM Non-symmetrical SVM.

EXPERIMENTS AND RESULTS

To evaluate the performance of the proposed method, we provide evidence of our analysis on SVM-based iris recognition using CASIA Iris Image Database from the National Laboratory of Pattern Recognition (NLPR), Institute of Automation (IA), Chinese Academy of Sciences (CAS). The database includes 756 iris images from 108 different eyes of 80 subjects. The images were acquired during different sessions and the time interval between two collections is one month, which is a real-world application case simulation.

According to the algorithms discussed above, we implement the iris recognition system and do 5250 times testing. Now we list the experimental result as the widely-used form in Table 1.

Table 1 Comparison of accuracy, FAR and FRR

Features used	Accuracy (%)	FAR (%)	FRR (%)
Traditional fractal	87.89	11.75	0.36
Variation fractal	98.21	1.45	0.34
Variation fractal based on steerable pyramid	99.14	0.63	0.23

We can see that the variation fractal based on steerable pyramid yields much higher accuracy than the traditional fractal.

The non-symmetrical parameter m can be adjusted according to different security demand in Table 2.

Table 2 Comparison of testing result with different *m*

Non-symmetrical parameter m	Accuracy (%)	FAR (%)	FRR (%)
0	97.13	2.78	0.09
0.5	98.51	1.50	0.14
0.8	99.14	0.63	0.23
0.9	99.43	0.31	0.26
0.99	99.50	0.18	0.32

CONCLUSION

In this paper, we present a method which regards the texture of the iris as a kind of fractal and uses steerable pyramid to make the features invariant to translation, scale and rotation. SVM is employed as the classifier. To make the SVM more applicable in biometric systems, we make it non-symmetrical. The experiment results show that the method proposed in this paper is promising. The principles of Non-symmetrical SVM and multi-orientation features can be applied in a wide variety of application fields.

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References

Adler, F.H., 1965. Physiology of the Eye. Mosby, St. Louis, MO.

Chaudhuri, B.B., Sarkar, N., 1995. Texture segmentation using fractal dimension. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **17**(1):72-77.

Daugman, J.G., 1993. High confidence visual recognition of persons by a test of statistical independence. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **15**(11):1148-1161.

DeCoste, D., Scholkopf, B., 2002. Training invariant support vector machines. *Machine Learning*, **46**(1-3):161-190.

Gu, H.Y., Pan, H., Wu, F., Zhuang, Y.T., Pan, Y.H., 2004. The research of iris recognition based on self-similarity. *Journal of Computer-Aided Design & Computer Graphics*, **16**(7):973-977 (in Chinese).

Joachims, T., 1998. Text Categorization with Support Vector Machine. Proceedings of European Conference on Machine Learning (ECML), Springer-Verlag.

Ma, L., Wang, Y.H., Tan, T.N., 2002. Iris recognition based on multichannel Gabor filtering. *Proc. 5th Asian Conf. Computer Vision*, (I):279-283.

Osuna, E., Freund, R., Girosi, F., 1997. Training Support Vector Machines: An Application to Face Detection. Proceedings of the 1997 conference on Computer Vision and Pattern Recognition (CVPR'97), Puerto Rico.

Simoncelli, E.P., 1996. A rotation-invariant pattern signature. *IEEE International Conference on Image Processing*, (III):185-188.

Simoncelli, E.P., Freeman, W.T., 1995. The steerable pyramid: A flexible architecture for multi-scale derivative computation. *2nd IEEE International Conference on Image Processing*, (III):444-447.

Vapnik, V.N., 1998. Statistical Learning Theory. J. Wiley, New York.

Wildes, R.P., 1997, Automated iris recognition: An emerging biometric technology. *Proceedings of the IEEE*, **85** (9):1348-1363.