Iris Recognition System based on Multi-resolution Analysis and Support Vector Machine

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ABSTRACT

Iris recognition system is becoming more popular day by day and is being used in many sectors for authentication replacing traditional methods like password, ATM etc. Iris recognition system is more accurate due to unique and stable iris patterns. Here, a feature extraction method based on multi-resolution analysis is proposed. Iris image is represented at multiple resolution levels and feature vector is formed by combining detailed information obtained at different resolution levels. Further, support vector machine classifier is used for recognition purpose to handle nonlinearity of features. Experiment is performed using CASIA 3.0 database with an objective to arrive at optimum number of features with high recognition rate.

General Terms

Pattern Recognition, Machine learning.

Keywords

Iris recognition, Multi-resolution analysis, wavelet transform, support vector machine, RBF kernel

1. INTRODUCTION

Now a day, more is the use of technology; more is the security issue for this digital world. Generally authentication is done through password, pin code, pattern lock, ATM, token, however these ways are found to be less secured and useful to literate only. Illiterate masses are uncomfortable with these ways of authentication. Therefore, unique attributes of human body, possibly be one of the solution for authentication where literacy is not mandatory. To overcome these problems, biometric authentication is found to be most promising and hence used in many sectors since this is based on unique physical or behavioral attributes like fingerprints, iris, retina, voice, signature etc. Out of many biometric features, iris patterns are believed to be different for each person and even different for the two eves of the same person and found to remain stable almost at all times. The iris is a thin, circular structure in the eye. Iris controls the diameter and size of the pupils and the amount of light reaching the pupil [1, 2]. Iris is between Pupil and sclera (see Figure 1).

In iris recognition system, first important step is to separate iris separated from eye image after capturing eye image. Once iris is separated, features are extracted and enrolled to database. The last step is recognition. Recognition can be done in two ways: Like providing password, in verification, features are matched only with stored features of the claimant i.e. one to one matching to verify whether claimant is the same person or not. In identification, features were matched with all database entries i.e. one to many matching to recognize a person as authorized or unauthorized. Sachine Gengaje, PhD Professor, Department of Electronics Walchand Institute of Technology, Solapur



Fig 1: Human eye image

2. RELATED WORK

First Iris recognition system was developed by John Daugman in 1990 but the first statement about uniqueness of iris was given by J.H. Doggar [3] in 1449 and followed by F.H. Adler [4] in 1953 where they stated that as human beings are having different fingerprints, they also have different iris patterns. John Daugman introduced first iris recognition system [1] based on 2-D Gabor wavelet for creating features and hamming distance for finding matched identity for a huge database. For iris localization, he proposed integro-differential operator for detecting inner and outer boundaries. He also proposed homogeneous rubber sheet model to convert circular iris ring into rectangular form and extracted phase information using 2-D Gabor wavelet. 2048 phase bits or 256 bytes were calculated as an iris code. Phase information is used instead of amplitude information. Boolean exclusive-or operation is applied on iris codes i.e. hamming distance between two iris codes is calculated. Wildes [5] also proposed stable iris recognition system in which canny edge detection, circular hough transform and Laplaian pyramid algorithm. Other methods like active contour model, bisection method, Black hole search method etc. are used for iris segmentation. Most of the researchers used rubber sheet model [1] for normalization. Various techniques are applied for feature extraction. This includes - Gabor Filter, Wavelet Transforms, Discrete Cosine Transform, Hillbert transform, Laplacian of Gaussian filter etc. A number of multi-resolution filtering techniques [6-13] have been proposed especially, STFT or Gabor transform, wavelet transforms have been found promising for feature extraction. For matching or recognition, many researchers calculated distance between enrolled features and stored features and used threshold to recognise the person. Many researchers used Hamming distance for matching feature vectors of binary values. Some of the researcher used Euclidean distance for feature vectors of nonbinary values. Out of calculated distances, class for which minimum distance is obtained is used as recognized class. Normalised correlation, cosine similarity etc are also used for matching feature vectors. Different machine learning techniques like artificial neural network (ANN), fuzzy logic, genetic algorithms, support vector machines (SVM), self organising Map (SOM), etc. are used for recognition purpose.

Many researchers used wavelet transform and obtained coefficients and converted these coefficients in binary form to obtain feature vector and matching is done using hamming distance. A feature extraction method is proposed where coefficients values as used for forming feature vector. These features are mapped into k dimensions using RBF kernel function and passed to SVM classifier for recognition purpose to get stable and accurate iris recognition system.

3. IRIS RECOGNTION SYSTEM

3.1 Image Segmentation

From captured eye images, iris need to be separated. Outer and inner boundaries are detected to separate iris from eye image. Using canny edge detection and circular hough transform, first iris image is separated. To make all irises of same size or dimensions, normalization is applied to segmented iris circular ring using rubber sheet model proposed by Daugman [1]. Normalized image of size 20X240 is obtained as shown in Fig. 2. These iris images are passed as an input for feature extraction and different feature vectors are enrolled for further training and testing.





3.2 Feature Extraction

Feature extraction is the one of the crucial step in order to achieve accurate recognition. Various techniques are applied for feature extraction. This includes – Gabor Filter, Wavelet Transforms, Discrete Cosine Transform, Hillbert transform, Laplacian of Gaussian filter etc. A number of multi-resolution filtering techniques have been proposed especially, STFT or Gabor transform, wavelet transforms have been found promising for feature extraction.

3.2.1 Wavelet Transform

Wavelet analysis allows researchers to find patterns. With multi-resolution analysis, image can be represented at more than one resolution level. This property of wavelet is used for extracting iris features. Discrete wavelet transform (DWT) is used for analysis. When the input function as well as wavelet parameters is in discrete form then the transformation is called DWT. As per Mallat [18,19], the approximation coefficients and detail coefficients are available first by convolution and then retaining every other sample called decimation by a factor of two and is as given by:

$$c_{m,n}(f) = \sum_{k} g_{2n-k} a_{m-1,k}(f)$$
(1)

$$a_{m,n}(f) = \sum_{k} h_{2n-k} a_{m-1,k}(f)$$
(2)

where g and h are the high pass and low pass filters, $c_{m,n}(f)$ are the wavelet / detail coefficients at resolution 2^m , and $a_{m,n}(f)$ are approximation coefficients at 2^m . If the input signal f(t) is in discrete sampled form, then one can consider these samples as the highest order resolution approximation coefficients $a_{0,n}(f)$ and Eq. (1 & 2) represents the multi-resolution sub-band decomposition algorithm to construct $a_{m,n}(f)$ and $c_{m,n}(f)$ at level m with a low pass filter h and high pass filter g from $a_{m-1,n}(f)$ and $c_{m-1,n}(f)$, generated at level m – 1. These filters are called analysis filters. For image processing 2D DWT is used. DWT decomposes the image into four sub-bands. The sub-bands are namely LL, LH, HL,

and HH where L denotes low frequency and H denotes high frequency. Out of four, LH, HL, & HH represent the finest scale wavelet coefficients of details images and LL represents low frequency level coefficients of approximation image. In next level decomposition, LL sub-band i.e. approximate coefficients are further decomposed and process is repeated. (see Figure 3).



Fig 3: Three Levels Decomposition using DWT

There can be three types of DWT depending upon the way of decomposition of the image at higher levels. These are namely Pyramid structured wavelet transform (PWT), Tree structured wavelet transform (TWT), and Wavelet packet transform (WPT). The PWT recursively decomposes the LL i.e. approximation sub-band only to get 2nd level sub-bands; LLL approximation sub-band is further decomposed to get 3rd level sub-bands, and so on. Highest level of decomposition depends upon the wavelet filter used, need of the application and features required for the application at hand. Coefficients obtained from DWT of approximate & detail sub-bands are the fundamental features. In TWT, any sub-band can be decomposed as per the requirement, to form the tree like structure. If all the sub-bands are decomposed at all the levels, will result in the third type called Wavelet Packet transform (WPT).

There are a number of wavelet families from which a mother wavelet may be chosen including the Haar, Daubechies, Coiflets, Symlets and Meyer wavelet families.

3.2.2 Feature extraction using wavelet transform

Features are extracted using 3 approaches: using normalized image of size 20X240, resized normalized image of size 50X360 and cropped normalized image of size 10X240 with an objective to arrive at optimum number of features with high recognition rate. In first approach, TWT and PWT have been applied up to four levels using Db8 wavelet to normalized iris image of size 20 X 240 (see Figure 2). After fourth level decomposition of PWT, 68 approximate, horizontal, vertical, detail coefficients are obtained. After third and fourth level decomposition using TWT, 90 and 30 approximate, horizontal, vertical, vertical, detail coefficients are obtained respectively.

In second approach, normalised image of size 20 X 240 is resized to size 50 X 360 (see Figure 4). TWT have been applied up to six levels using Db8 wavelet to resized image of size 50 X 360. After decomposition using TWT, 92, 24 and 6 approximate, horizontal, vertical, detail coefficients are obtained at four, five and six level respectively.



Fig 4: Resized normalized iris image

In third approach, to remove noise like any part of pupil or eyelashes, top ten rows are selected from the normalized image and resized to size 10X240 (see Figure 5). After decomposition using TWT, 15, 8 and 4 approximate, horizontal, vertical, detail coefficients are obtained at four, five and six level respectively. Thus, using multi-resolution analysis, image has been represented at more than one resolution level.

Fig 5: Cropped normalized iris image

Number of coefficients obtained after decomposition are listed in Table 1.

Since these features i.e. approximate coefficients are decimal values, Euclidean distance formula is applied to check similarity and dissimilarity. To check effectiveness of features, False Acceptance Rate (FAR) and False Rejection Rate (FRR) are calculated using equations 3 to 5. Matching of class is based on minimum Euclidean distance strategy. While finding the distance, four images are selected for Training purpose and three images for testing purpose.

Euclidean distance
$$(X, Y) = \sqrt{\sum_{i=1}^{N} (X_i - Y_i)^2}$$
 (3)

$$FAR = \frac{No \ of \ Imposter \ Acceptnaces}{Total \ no \ of \ matches} * \ 100 \tag{4}$$

$$FRR = \frac{No of Genuine person Rejections}{Total no of matches} * 100$$
 (5)

It was found that considering only approximate coefficients and Euclidean distance, better accuracy could not be found [20]. So, other coefficients i.e. Horizontal, vertical and detailed coefficients are also selected along with approximate coefficients. Increase in number of features may decrease FAR and FRR using Euclidean distance but computations will increase. Hence, different classifier has been used for recognition purpose.

Table 1. Decomposition at different levels

Wavelet Transform	Size of image	Level	No of Coefficients
Db8 (TWT)	20X240	3	90
Db8 (TWT)	20X240	4	30
Db8 (PWT)	20X240	4	68
Db8 (TWT)	30X360	4	92
Db8 (TWT)	30X360	5	24
Db8 (TWT)	30X360	6	6
Db8 (TWT)	10X240	4	15
Db8 (TWT)	10X240	5	8
Db8 (TWT)	10X240	6	4

Many researchers used wavelet coefficients but in proposed method, coefficients of different levels are combined to get detailed iris information. Eight feature sets with different combinations of coefficients at different levels are formed as shown in Table 2. Significance of features is: 'a' – Approximate coefficients, 'v' – vertical coefficients, 'h'horizontal and d'- diagonal coefficients

Table	2.	Proposed	Feature sets
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Sr. No.	Feature set	Features
1	Wavelet approximate coefficients after 3 rd level decomposition using TWT (W_A_3)	Approximate coefficients $\{a_1, a_2, \dots, a_{90}\}$ 90

2	Wavelet approximate coefficients after 4th level decomposition using PWT (W_A_4)	Approximate coefficients $\{a_1, a_2, \dots, a_{68}\}$ 68
3	Wavelet coefficients (approximate , horizontal and vertical) after 5th level decomposition using TWT of resized image (W_AHV_5_R)	$ \begin{array}{c} \{a_1,a_2,\ldots,a_{24,}\\ h_1,h_2,\ldots,h_{24,}\\ v_1,v_2,\ldots,v_{24\}}\\ \hline 72 \end{array} $
4	Wavelet coefficients (approximate , horizontal, vertical and diagonal) after 5th level decomposition using TWT of resized image (W_AHVD_5_R)	$\{ \begin{array}{c} \{a_1,a_2,\ldots,a_{24,} \\ h_1,h_2,\ldots,h_{24,} \\ v_1,v_2,\ldots,v_{24,}d_1,d_2,\ldots \\ \ldots,d_{24} \} \\ 96 \end{array} \right.$
5	Combined coefficients (approximate, horizontal and vertical) of 5 and 6 level using TWT of resized image (W_AHV_5_6_R)	$ \begin{array}{c} \{a_{1},a_{2},\ldots,a_{24,}\\h_{1},h_{2},\ldots,h_{24,}\\v_{1},v_{2},\ldots,v_{24,}\}\\ and\\ \{a_{1},a_{2},\ldots,a_{6,}\\h_{1},h_{2},\ldots,h_{6,}\\v_{1},v_{2},\ldots,v_{6}\}\\ 90 \end{array} $
6	Combined coefficients (approximate, horizontal, vertical and diagonal) of 5 and 6 level using TWT of resized image (W_AHVD_5_6_R)	$ \begin{array}{c} \{a_1,a_2,\ldots,a_{24,}\\ h_1,h_2,\ldots,h_{24,}\\ v_1,v_2,\ldots,v_{24,}\\ d_1,d_2,\ldots,d_{24}\} \text{ and }\\ \{a_1,a_2,\ldots,a_{6,}\\ h_1,h_2,\ldots,h_{6,}\\ v_1,v_2,\ldots,v_{6,}\\ d_1,d_2,\ldots,d_6\}\\ 120 \end{array} $
7	Wavelet approximate , horizontal and vertical coefficients after 4th level decomposition using TWT of cropped image (W_AHVD_4_C)	$ \begin{array}{c} \{a_{1,}a_{2},\ldots,a_{15,}h_{1},h_{2},\\ \ldots,h_{15,}\\ v_{1,}v_{2,}\ldots,v_{15,}d_{1},d_{2},\ldots\\ \ldots,d_{15\}}\\ 60 \end{array} $
8	Combined coefficients (approximate , horizontal, vertical and diagonal of 4 and approximate and vertical of 5 level) using TWT of cropped image (W_AHVD_4_AV_5_C)	$ \begin{array}{c} \{a_1,a_2,,a_{15,h_1,h_2},\h_{15,} \\ v_1,v_2,,v_{15,d_1,d_2,} \d_{15} \\ and \\ \{a_1,a_2,,a_{8,} \\ v_1,v_2,,v_{8,} \} \\ 76 \end{array} $

3.3 Iris Matching/Recognition

In biometric system, extracted features are either enrolled into database or used for recognition. Its works in two modes: verification or identification. Like providing password, in verification, features are matched only with stored features of the claimant i.e. one to one matching to verify whether claimant is the same person or not. In identification, features are matched with all enrolled entries i.e. one to many matching to recognise a person as authorised or unauthorised. From feature analysis, it has been have found that features are nonlinear and hence, support vector machine (SVM) classifier is proposed for classification. Support Vector Machine (SVM) is supervised learning method used for classification in which set of features and its associated class is known. SVMs are based on statistical learning theory, developed by Vapnik in 1995. It uses Structural Risk Minimization (SRM) Principle which is superior to Empirical Risk Minimisation (ERM) principle used in neural networks [21]. SVM tries to find hyperplanes with maximum margins [22] between two classes which can be extended to multiple classes. In M-class problem, it is considered as a set of M two-class problems (one against all). For each class, the decision is seek on optimal discriminant function, $g_i(x)$, i=1,2,...M, so that $g_i(x) > 0$ for x $x \, \epsilon \omega_i$ and $g_i(x) < 0$ otherwise. Classification is achieved according to following rule:

assign x in
$$\omega_i$$
 if $i = \arg \max\{g_k(x)\}$

One more alternative is one against one. In this case, $M^*(M-1)/2$ binary classifier are trained and each classifier separates a pair of classes. The decision is made on majority vote but disadvantage is relatively large number of binary classifiers has to be trained. It is difficult to find simple hyperplane in case nonlinear problems. For those problems, support machines transforms or maps input feature vector into high dimensional space and find hyperplane that separates classes satisfactorily.

$$\mathbf{x} \in \mathbf{R}^{\mathbf{l}} \to \mathbf{x} \in \mathbf{R}^{\mathbf{k}} \tag{6}$$

After transforming the features into k dimensions, inner products will be of transformed k dimensional vectors. Typical examples of kernels used in pattern recognition applications are as follows:

1. Polynomials:

$$K(x,z) = (x^T z + 1)^q, q > 0$$
(7)

2. Gaussian Radial Basis function:

$$K(x, z) = \exp\left(-\frac{||x-z||^2}{\sigma^2}\right)$$
(8)

3. Hyperbolic Tangent / Multilayer Perceptron:

$$K(x,z) = \tan\beta x^T z + \gamma \tag{9}$$

for certain values of scale β and offset γ

Effectiveness of SVM depends on kernel function and its parameters. According to many researchers, RBF kernel is more stable than other kernel function for handling nonlinear data.

4. EXPERIMENTATION

Images of 100 person classes from CASIA V3.0 database [23] are used. Each class contains 7 images which are captured in two sessions. Out of 7 images, 4 images are used for training purpose and 3 images are used for testing purpose. SVM classifier is trained using 400 images and testing is carried out using 300 images. All feature sets, which have been discussed in section 3, of all the samples are extracted and stored separately for training images and testing images. SVM classifier is trained using Gaussian Radial Basis kernel Function for different feature sets and different number of classes and performance of the classifier is measured using both training and testing images. The success of classifier depends on parameter values. Recognition accuracy is found for both training as well as testing images. Here, one-againstone method is used in this approach for classification. Recognition accuracy for training images as well as testing images as shown in eq.10.

Recognition accuracy for training images =

(10)

correctly classified training images Total number of trained images *Recognition accuracy for testing images =*

$$= \frac{correctly \ classified \ testing \ images}{Total \ number \ of \ testing \ images}$$
(11)

Recognition accuracy for training images for all feature set is found to be 100%. Recognition accuracy for testing images is varying (see Figure 6)

Accuracy for first feature set comprising of only approximate coefficients of third level decomposition using TWT is 87.33% whereas accuracy for second feature set comprising of only approximate coefficients of fourth level decomposition using PWT is 76.33%. Since only approximate coefficients are not describing image significantly, approximation coefficients are further decomposed in next level and more detailed information of the coefficients is obtained. Horizontal and vertical coefficients of fifth level are combined in third set and resulting accuracy is 87.66%. Further, diagonal coefficients are added in the set to form fourth feature set but it has been found that diagonal elements are not helpful for improving much accuracy resulting in 88.66%. Then approximate, horizontal and vertical coefficients of fifth and sixth level are combined and formed fifth feature set and accuracy for this set is 91%. Again in the sixth feature set, all four coefficients of fifth and sixth level i.e. approximate, horizontal, vertical and diagonal are combined and found that accuracy is decreased to 90% due to diagonal coefficients. As discussed in 3, only first ten rows are selected to drop the part of pupil and eyelashes, if any and formed next two feature sets. All coefficients of fourth level and got the accuracy up to 93.66%. Further, image is decomposed at next level and horizontal and diagonal components are obtained. These components were almost zero, so only approximate and vertical components are combined in the last set resulting in accuracy 95.33%. Highest Accuracy is achieved using 76 features. Parameters value for sigma is set to 0.1 for resized image and 0.5 for cropped image whereas value for C is set to 100 by experiments i.e. highest accuracy of testing for 100 classes is achieved for these parameter values. Recognition accuracy is shown in Table 3.

Table 3: Recognition accuracy for testing images for 8 feature sets

Feature set	Training Accuracy %	Testing Accuracy %	
1	100	87.33	
2	100 76.33		
3	100	87.66	
4	100	88.66	
5	100	91.00	
6	100	90.00	
7	100	93.66	
8	100	95.33	



Fig 6: Recognition accuracy for testing images



Fig 7: Comparison of recognition Accuracy for testing images using different feature sets

Comparison of all 8 feature sets for all classes is as shown in Figure 7. Selection of top rows removing noise improved accuracy with 76 features.

Comparison with other researchers using SVM and wavelet transform is as shown in Table 4.

Mathadalagy	No of	Recognition Accuracy %	
Methodology	Features	Training	Testing
K. Saminathan [24]	2400	-	98.50
Himanshu Rai and Anamika Yadav [25]	512	-	91.33
Proposed (feature set 7)	60	100	93.66
Proposed (feature set 8)	76	100	95.33

Table 4: Comparison with other methods

5. CONCLUSION

A novel method of feature extraction using multi-resolution analysis and recognition using SVM is proposed. Feature vector is formed by combining detailed information obtained by analyzing iris image at different resolutions. These extracted features are trained using SVM Classifier with RBF Kernel function for recognition. It has been found that recognition accuracy is improved due to combining iris details obtained by decomposing image at different resolution levels. Also, selection of top rows of original normalized image improved recognition accuracy. Number of features is reduced in comparison with other researchers but recognition accuracy is not comparable to 100%. In future, we will try to arrive at optimum number of features with high recognition rate.

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