COMPARATIVE STUDY OF SUPPORT VECTOR MACHINE AND HAMMING DISTANCE USED FOR IRIS RECOGNITION

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ABSTRACT

This paper presents a comparative study of two well-known classification techniques of iris patterns, along with detailed description of some preprocessing steps. In preprocessing stage, Circular Hough Transform and Canny Edge Detector are employed for iris segmentation, while for iris normalization and feature extraction, the Rubber Sheet Model and one-dimensional (1-D) Log-Gabor Filter are used respectively. Finally for classification/matching of iris patterns, Hamming Distance and Support Vector Machine (SVM) are applied. The evaluation results on CASIA V.1 dataset show that Hamming distance algorithm is more suitable for the classification (with average accuracy of 93.85 %) of iris patterns.

KEYWORDS: *Iris Recognition, Biometric, Circular Hough Transform, Hamming Distance, Support Vector Machine*

INTRODUCTION

Biometric identification is the task of validating the identity of an individual through biometric information. Biometric characteristics are *behavioral* (e.g. voice, gait, and handwriting) and *physiological* (e.g. fingerprint, face, iris, DNA)[1]. The ophthalmologists A. Bertillon and F. Bruch were the first who proposed that iris patterns could be used for the recognition of an individual, while John Daugman developed the first iris based identification system[2]. Iris recognition has several advantages over other biometric recognitions methods due to its solidity, universality, quirky, and calm nature.

Iris is a narrow diaphragm and it is a type of physiological biometric feature, as shown in Figure 1[3]. It consists of distinctive features and it is so complex to crack and therefore can be utilized for biometric identification. Its enormous variability among different persons and stability throughout person's life make it a better choice for identification purposes[2,4].

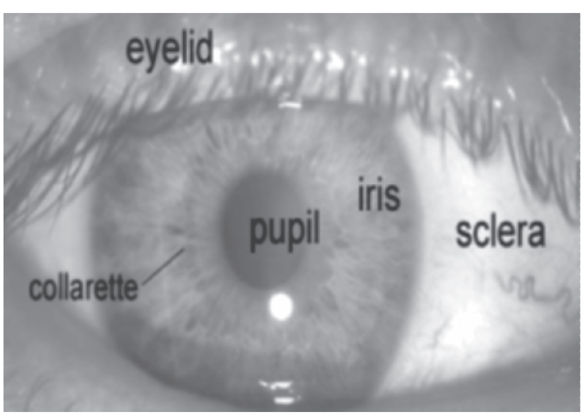

Figure 1 Iris Image

In the identification process of an individual based on iris, firstly an eye's image is acquired. Then, this image is preprocessed, in which noise removal, illumination scaling, segmentation (iris localization), and normalization take place. Thirdly, features are extricated, and in last the classification/matching is carried out. So, image acquiring, preprocessing, feature extrication, and classification/matching are the four main steps of iris recognition system. This paper discusses different steps involved in iris classification and also a compares the classification performance of two well-known iris classification techniques (Hamming Distance and SVM). Hamming distance has the capability of one-to-many iris templates comparison. While SVM is a machine learning method based on minimizing the classification error.

BACKGROUND STUDY

Bertillon and Bruch were the first by whom it was proposed, that Iris features could be utilized for an individual's identification, and John Daugman was the first, who developed iris recognition system[2]. In this system, iris is localized by Integro- differential and hamming distance is utilized for the iris's feature matching.

Boles and Boashash[1] proposed Wavelet Transform (WT) algorithm for extrication of iris features from

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the image of a person's eye. This system can work in the case of noisy images, possible illumination, and variations of distance between face and camera. Gray levels profiles are consider here for the representation. From the iris portion of the eye's image one-dimensional (1-D) signals are extracted and then zero-crossing of these signals are obtained. Ma et al.[5], suggest another method, in which a bank of symmetric filters is used to extricate iris attributes from the iris's image, and for matching purpose, they suggested *nearest features lines* (NFL). While Wildes[6], proposed a scale, traslation and rotation invariant approach for the extraction and analysis of iris features with multi-channel filtering and wavelet transform.

TISSE et al.[7] incorporated Integro-differential operator/gradient decomposed Hough transform (for the iris localization), and two-dimensional (2-D) Hilbert Transform (to get the apposite information from the iris texture). As iris localization is one of the pivotal steps in the iris recognition systems, here in this paper the main focus is on iris localization. In Aly Desoky et al.[8] method, iris images are fused to get iris template using accurate feature data. Feature accuracy weight matrix is calculated from the selected images according to the used/known level of noise, which speed up the classification process and reduce the memory required for storage.

Yoon et al.[9] employed a number of classifiers including the SVM for iris identification. Roy et al.[10], used SVM for the classification purposes in iris recognition process, and figure out that SVM out performs Artificial Neural Network (ANN). In Hashmi and Momoh J.E Salami[11], method SVM is utilized for the classification of person based on iris template. The feature size transformed to 1-D vector, so the resized vector curtails (having dimensions of 1 x 480) through averaging which resulted in speeded up of classification process.

In this work a new approach for the iris recognition is proposed where Circular Hough transform is used for the iris detection in the eye's image, Rubber Sheet Model[2] is used for the normalization and 1-D Log Gabor filter is employed for the feature extraction. The performance of the novel feature in evaluated on SVM and Hamming Distance.

IRIS RECOGNITION SYSTEM

The process of identification one's identity through iris, consists the following steps, which are explained in detail here below.

Image Acquisition

Image acquiring is one of the salient and tough job in the iris based biometric recognition. In this work experiments are performed on a well-known iris' images database provided by CASIA (Chinese Academy of Science Institute of Automation)[12], composed of 108 different classes each representing an individual. Each class has 7 images. So, total 756 images are used for evaluation. These images are taken in two sessions, 3 images of each individual are taken in first session, and the next 4 images of each one, are taken in the second session.

Preprocessing

Mostly the images taken through CCD (Charge-Coupled Device) camera contains irrelevant information (e.g. eyelashes, eyelids, and pupil). In pre-processing step these unnecessary information are removed. Iris localization and iris normalization are the two main steps, in this stage of iris recognition system.

Iris Localization

As earlier mentioned, that in the iris images there may be some unwanted parts. Therefore, a mechanism is required to detach these antiquities as will as to locate the annular iris region. If eyelids are obstructing some region of the iris, then only that portion below the upward eyelid and above the downward eyelid should be considered (obstructing parts of iris should not be entertained)[4]. During iris localization process on the captured images both boundaries (i.e. border between pupil and iris, and border between iris and sclera) are found. Figure 2 point up the segmentation process. Iris segmentation consists of edge detection using Canny edge detector and Circular Hough Transform (for iris detection). The Iris borders are mentioned in three terms; center coordinates of the circle x, y, and radius r[8].

Circular Hough Transform

Through Circular Hough Transform (CHT) algorithm

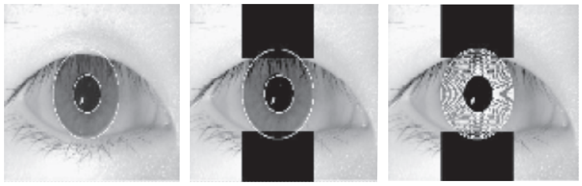

Figure 2. Iris segmentation

an edge plot is find out by reckoning the first derivative of the intensity values of an eye's image and then thresholding them. Circle parameters are chosen, through vote casting in Hough space, at each edge point. These parameters are the center coordinates and radius, which are sufficient to define a circle. This procedure used by a Wilds[6], Tiss et al.[7], and Ma et al.[5] in their works.

$$X^2_C \text{ x } Y^2_C = r^2 \quad (1)$$

As it is said earlier that iris and pupil boundaries are calculated through Circular Hough Transform. First Canny edge detector is employed to give an edge map of the capture. For the outer boundary between sclera and iris the first derivative is biased vertically, for inner edge between iris and pupil, horizontal and vertical gradients are equally weighted. In CASIA database of iris images the pupil's radius values are in the range 28 to 75 pixels, while for the iris' radius values these are in the range 90 to 150 pixels[7].

Iris Normalization

Iris normalization refers to adapting the segmented iris image for the aspect extrication. After segmentation of iris's portion from the eye's image, the segmented region is converted into fixed defined dimensions. The normalization process will transform doughnut iris into rectangular iris region, which would have the same fixed dimensions, so that two photograph of the same iris under different circumstances will have the characteristics features at same spatial locations. For normalization purpose of iris region Rubber Sheet Model (RSM) is utilized. This RSM firstly proposed by Daugman[2,4].

Rubber Sheet Model

This method maps each point of the iris image to polar coordinates (r,), where [0-1], [0-2] are the ranges of "r" and "" respectively. This procedure is shown in Figure 3. The localized iris area is then mapped from Cartesian coordinate to normalized non-concentric polar representation of a defined size by applying the following Equations 2,3 and 4.

$$I(x(r,\theta),\ y(r,\theta)) \rightarrow I(r,\theta) \quad (2)$$

With

$$x(r;\theta) = (1 - r)\ x_p\ (\theta) + r x_1\ (\theta) \quad (3)$$

$$y(r;\theta) = (1 - r)\ y_p\ (\theta) + r y_1\ (\theta) \quad (4)$$

A fixed defined number of data points are taken along each spiral line. So, that a fixed number are selected irrespective of the fact that how thin or wide the radius is at a appropriate angle. The normalized form created by tracing to find the Cartesian coordinates features points

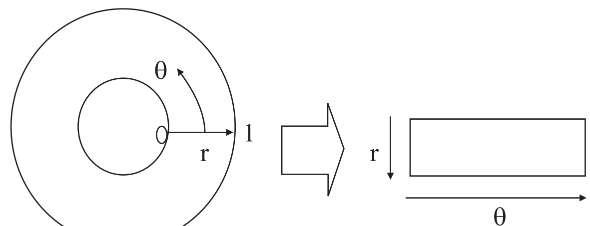

Figure 3. Rubber Sheet Model

from the angular and radial localities in the normalized image of iris. Thus the "doughnut" shape iris region is transformed to the rectangular shape.

Feature Extraction

In this step, salient features are extricated from the rectangular iris's image (which is obtained through Rubber Sheet Modal) for the authentic identification of individuals. The most distinguishable features are required to be encoded and get the iris pattern to compare it with several other iris patterns, for personnel recognition based on iris. Features are of different categories, e.g. Spectral, Geometrical, and Textural. Here textural features are extricated from the iris image. For this purpose 1-D Log Gabor Filter is employed.

Gabor filter

Gabor filters are capable to present perfect combine sketch of a wave/signal in spatial frequency as well as in space. This Gabor filter is built by attuning sine and cosine signal with a Gaussian. As sine signal is perfectly identified in frequency domain, but not in space[13]. The center frequency of the filter is achieved by the repetition of sine/cosine wave, while the bandwidth is found out by the Gaussian width. An alternative to the Gabor Filter is the Log-Gabor filter[9]. The concealing process generates a bitwise pattern (template) consisting the bits of information. Figure 5, shows the template that is produced from the normalized iris, as shown in Figure 4.

1-D Log Gabor Filter

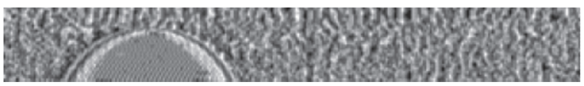

Figure 4. Normalized Iris

01 00 00 10 11 11 01 01 00 10 10 11 11 01 0100 10 10 11 01 01 01 01 01 00
10 10 01 11 00 01 11 10 11 10 10 00 10 01 10 00 11 01 10 11 00 01 01 11 10

Figure 5. Bit pattern presenting template

Field[14] Proposed that the natural captures can be coded in a nice way through filters that have Gaussian transfer functions (GTF) when inspected in logarithmic frequency scale. The frequency response (FT) of Log-Gabor is given by Equation 5.

$$G(f) = \exp\{\_0.5 \text{ x } \log\left(\frac{f}{f_0}\right)^2 / \log(\sigma/f)^2\} \quad (5)$$

Where is the center frequency, and gives the bandwidth of the filter. This filter has two paramount attribute of this filter, firstly Log-Gabor functions have no DC element, and secondly the transfer function of the Log-Gabor filter has an elongated tail at the high frequency end[13].

MATCHING

The final step in the iris identification system is the classification/matching, of an individual iris template with the iris template in database. Various template-matching methods exist, like Weighted Euclidean Distance[7], Normalization Correlation, Hamming Distance[6], and Support Vector Machine[11,15]. Here Hamming Distance and Support Vector Machine are employed, and comparisons of these techniques are carried out.

Hamming Distance

Hamming Distance computes the number of same bits between these bit patterns. Through Hamming distance between these two bits pattern, it can be decided whether the two patterns belong to same iris's images or different image. Each iris's region gives a bit-pattern, which is dissociated to that produced by another iris. On the other hand, those two iris's codes that are generated from the same iris, these will be hugely correlated. The advantage of Hamming Distance is that the matching process is fast as the bit-patterns are in the binary form[5].

The Hamming Distance will be found out by using only the bits pattern, got from the iris' circular area. This is incorporated as Equation 6.

$$HD= [\frac{1}{N - \sum_{k=1}^{N} A_{nk} \ (OR) \ B_{nk}}] \sum_{j=1}^{N} A_j \ (XOR) B_j (AND) A_{nj} \ (AND) B_{nj} \quad (6)$$

Here and are two bit-patterns, and are the two noisy kernel for and , and N is the count of bits in each pattern. Theoretically two iris patterns extricated from same iris will have Hamming Distance 0.00, but practically this is not happened, because normalization cannot be done perfectly and also some unpredictable noise may be there. These changes may be due different circumstances like lighting, camera lens, and temperature etc. So, some dissimilarity will be there when juxtaposing two iris templates belonging to same class[16-18]. Therefore, a threshold value would be used for the decision, weather the two iris's templates are similar or not.

SUPPORT VECTOR MACHINE

SVM as a classifier employed for the recognition of an individual, based on iris code. SVM is binary classifier, which ideally divides the two classes, and also transforms non-linearly detachable classes problem into linearly detachable problem[15]. SVM is based on machine learning procedure of formational risk reduction.

As an input, SVM catches data points, and for every given input data it foretells the two possible classes from which we got the outcome. Firstly this algorithm was proposed as linear classifier[9].

Later on it was also equipped to utilize kernel approach due to which this system became able to map non-linear patterns into the feature space. The concept behind the data classification by SVM is that it takes k-dimensional data as in input and separates that data using k-1 dimensional hyper-plane. So, it aggrandizes the gap of the data points. The gap is the smallest path of a sample to the conclusion plane. The space of the conclusion plane from the neighborhood occurrence of the personal data points' set should be as large as feasible[15,19].

RESULTS AND DISCUSSION

In this comparative study total of 756 images from CASIA V.1 database[19] are used. These images are divided into 108 classes each of 7 images, which are captured in two different terms/sessions, 3 in 1st term and 4 images in 2nd term.

To get best identification rate, in the proposed work employs the parameterization process to adjust the different parameters like radial and angular resolution, "*r"* and "", filters' count*,* filter's wavelength, and filter's bandwidth given as "". The proposed work use 1D Log-Gabor filter with bandwidth 0.5, while the radial 40 and angular resolution values are set 240.

Hamming Distance Results

This proposed system in common draw up four conceivable decisions; it can take two decisions for the approved (authorized) person, whether it is accepted or rejected, and similarly two decisions for the imposter (unauthorized) whether it is accepted or rejected. But the efficiency of the system is computed on the basis of the rate at which the system rejects the approved person and accepts the unauthorized person. So, False Accept Rate (FAR) and False Reject Rate (FRR) are used as evaluation criteria and the exactness of the propound algorithm is computed as:

$$FRR = FR_N/AA_N \ X\ 100\% \quad (7)$$

$$FAR = FR_N/IA_N \ X\ 100\% \quad (8)$$

Where $_N$ is the count of false rejection and $_N$ *is* referred to the count of false acceptance, while AA_N, and IA_N are the count of legitimate and imposter (unauthorized) person's attempts respectively.

Table 1. FRR and FAR for different threshold values in hamming Distances

Threshold	FRR (%)	FAR (%)
0.5	0.00	99.5
0.45	0.00	7.6
0.4	0.24	0.005
0.35	21.39	0.002
0.3	37.88	0.00
0.25	65.62	0.00
0.2	99.05	0.00

A number of experiments are performed; the experimental results are shown in the Figure 6. Both the values of FRR and FAR should be optimized in order to make correct recognition and to obtain highest success rates. The threshold value of 0.4 provides the acceptable values for both FRR and FAR. So we conclude that threshold value of 0.4 gives the best possible recognition results.

After selecting the best threshold value for Hamming Distance, the algorithm is tested on 15 different iris images and the HD values were recorded that are shown in Table 3. These values show the accuracy of the system as there is only one match for all 15 iris images that is given by value '0', and all of the rest values are greater than the set threshold, consequently very less chances of false acceptance.

To evaluate the accuracy of hamming distance, a number of experiments have been performed on CASIA database. For each experiment the FRR, FAR and recognition accuracy were recorded as shown in Table 3. The average accuracy of these random experiments comes to be 93.858 %. Figure 6 also shows the FRR, FAR, and accuracy for the each experiment.

SVM's Results

The SVM is also employed as a matching technique, in order to form the utilizer model based on an individual's iris data. In SVM only hyper-plane that aggrandizes the margin between two sets is used. Margin is the path between the closest data to the hyper-plane. A number of experiments are performed which resulted in an average accuracy of around 89.56%, average FAR 0.01%, and average FRR 10.42%. The results of these experiments are shown in Table 4**.** and in Figure 7.

Table 2. HD values for 15 different individuals

Iris	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0	0.4559	0.4709	0.482	0.4673	0.4529	0.4651	0.4499	0.4706	0.4776	0.4698	0.4775	0.4545	0.4814	0.4767
2	0.4559	0	0.4737	0.4826	0.4708	0.4478	0.4706	0.4644	0.476	0.4564	0.4392	0.4874	0.4804	0.4843	0.465
3	0.4709	0.4737	0	0.4786	0.4707	0.4484	0.4582	0.4799	0.4868	0.449	0.4697	0.4832	0.4884	0.4806	0.4501
4	0.482	0.4826	0.4786	0	0.4658	0.4641	0.477	0.4705	0.467	0.4615	0.4665	0.4476	0.4149	0.4642	0.4594
5	0.4673	0.4708	0.4707	0.4658	0	0.4711	0.4582	0.4777	0.4717	0.4862	0.4764	0.4544	0.4746	0.4825	0.449
6	0.4529	0.4487	0.4484	0.4641	0.4711	0	0.4642	0.4697	0.4771	0.4674	0.4634	0.4936	0.484	0.4691	0.4262
7	0.4651	0.4706	0.4582	0.477	0.4582	0.4642	0	0.4571	0.4772	0.4651	0.4715	0.4656	0.4693	0.4753	0.4331
8	0.4499	0.4644	0.4799	0.4705	0.4777	0.4697	0.4571	0	0.4838	0.4746	0.4591	0.4875	0.4689	0.469	0.4782
9	0.4706	0.476	0.4868	0.467	0.4717	0.4771	0.477	0.4838	0	0.4516	0.4717	0.4774	0.4617	0.4422	0.4736
10	0.4776	0.4564	0.449	0.4615	0.4862	0.4674	0.4651	0.4746	0.4516	0	0.4569	0.4737	0.4657	0.4266	0.4392
11	0.4698	0.4392	0.4697	0.4665	0.4764	0.4634	0.4715	0.4591	0.4717	0.4569	0	0.4801	0.4424	0.4834	0.4534
12	0.4775	0.4875	0.4832	0.4476	0.4544	0.4936	0.4656	0.4875	0.4774	0.4737	0.4801	0	0.4826	0.4746	0.4616
13	0.4545	0.4804	0.4884	0.4149	0.4746	0.484	0.4693	0.4689	0.4617	0.4657	0.4424	0.4826	0	0.4196	0.4503
14	0.4814	0.4843	0.4806	0.4642	0.4825	0.4691	0.4753	0.4692	0.4422	0.4266	0.4834	0.4746	0.4196	0	0.4603
15	0.4767	0.4654	0.4501	0.4594	0.449	0.4262	0.4331	0.4782	0.4736	0.4392	0.4534	0.4616	0.4503	0.4603	0

Table 3. Experiments and Results of HD

	FRR (%)	FAR (%)	Accuracy (%)
1	10.20	0.00	89.80
2	4.10	0.00	95.90
3	6.16	0.00	93.84
4	6.16	0.00	93.84
5	4.09	0.00	95.91

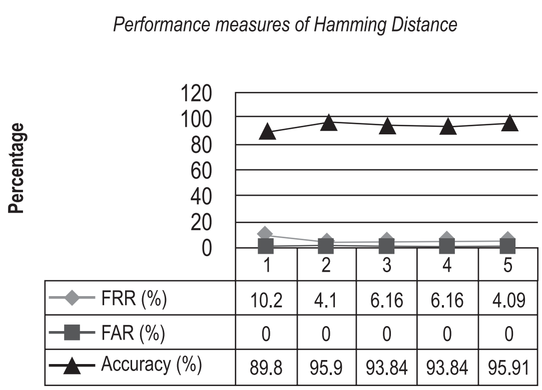

Figure 6. Performance measures of Hamming Distance

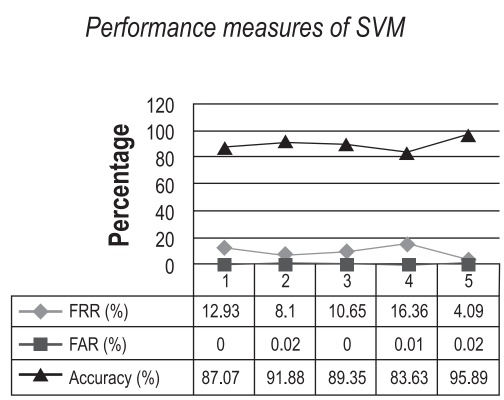

Figure 7. FRR, FAR and Accuracy of SVM

CONCLUSION

In the experimental process two problems have been emphasized: comparisons of two classification algorithms i.e. Hamming distance and SVM, and the parameterization of Hamming Distance algorithm. Based on the experimental results on CASA V1 dataset, it can be concluded that Hamming distance classifier with threshold value of 0.4 is comparatively more suitable for the iris recognition purposes than its competitor Support Vector Machine.

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