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ANGULAR SHIFT MEASURING FEATURE FOR IRIS CLASSIFICATION USING PROBABILISTIC NEURAL NETWORK

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Abstract

The IRIS recognition is becoming popular and gaining the inclusion in the wide applications ranging from the public databases to device authentication. The IRIS represents the unique biometric feature of human, which defines every person differently as there are as many variations as the number of human. The IRIS feature extraction requires the precision, as the circular boundaries are required to be extracted from the given sample, where the chances of error are more and the surrounding parts can be also extracted accidently, which may decrease the overall accuracy of the IRIS recognition systems. The rotational features for IRIS region are controlled by using the rotation detector Zernike moments, which normalize the rotational effect in the rotated samples in order to correctly localize the IRIS feature. The IRIS region of interest recognition is performed using the circular transformation as per defined for the Hough transformation in order to obtain the circular region of the IRIS feature, which further undergoes the low level hessian based feature extraction, where the multi-level difference of hessian feature are extracted from the target image. The speeded up robust features (SURF) has been utilized to extract the hessian features from the image, which are defined as the stronger points after applying the layered blurring with increasing intensity over the given image set. The SURF features are further converted to the binary mask to facilitate the faster execution of the system, which is obtained by using the Fast Retina Keypoint (FREAK) features. The proposed model in combination utilizes the probabilistic neural network (PNN) classification, and has been assessed for the accuracy measures on the basis of various parameters of accuracy. The proposed model has been found efficient and effective for the IRIS based authentication application in our experimental testing of the proposed model.

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I. Introduction

No two irises in the world are exactly identical [14]. Iris is the unique characteristic of every individual by which he/she could be recognized. Iris recognition is fundamentally a method to find other image of iris which has exactly same features as of one image. Iris recognition was started to identity and inhibits the entry of unauthorized persons into offices or other prohibited areas. It also helped to identify criminals [7] [8].

A. Feature Descriptor: The capabilities descriptors describe the data from the pix within the form of the low degree capabilities, colour based functions, matrix first-rate or matrix representation thresholds, texture based function or binary features over the Iris education database. The low-degree characteristic descriptor has been applied in the proposed model in conjunction with the ZMs algorithm for the reason of feature description.

B. Speeded up robust features: The SURF is the method to determine the similarity between the two images by extracting the binary feature after utilizing it as a function of lag to evaluate the one relative to another. The SURF acts as the major feature descriptor for the template matching scheme to measure the visual distance as Squared Euclidean Distance (SED) between the two images objects [2].

C. Zernike moment: ZMs is a characteristic extraction technique from an picture by way of which we will extract worldwide capabilities like amplitude and angle. ZMs have rotational invariance, and can be made scale and translational invariant, making them suitable for lots packages [4].

D. Artificial Neural Network: The Feed Forward Neural Network makes use of activation function. Activation function is used to proportion the output of various layers in Neural Network. Back Propagation is a common method by which we can train the network. Weight Matrix of Neural Network is adjusted with training method to produce needed results. In this system the worth of perceptron is depends upon the inputs and their weight values. In the implementation of perceptron we produce a threshold value and assume if the result will greater than that value the output will be one otherwise zero[2] [9].

II. Literature Review

I. Ismail [2] presents complete iris recognition system in which after enhancing the image using Contrast Limited Adaptive Histogram Equalization (CLAHE), iris features were obtained using Speeded Up Robust Features (SURF). This algorithm provide the advantage of data storage and fast matching and also solve the problems of rotation, scaling, illumination variation and occlusions via using CASIA(V4) database.

S. Sarode [3] presents a review of related work in the iris recognition. Iris recognition offers a highly reliable solution to person authentication. Rather than of using the entire iris code only the bits that are consistent in the iris code considered in the feature matching process, these bits are called best bit. This reduces the computational time and storage requirements of iris code. The iris recognition process is applied to left and right iris separately to enhance the performance and distance score generated for each iris of an individual.

C. Tan [4] define here we need development of effective methods for the accurate iris recognition from far distance face or eye images. For the accurate Iris Recognition at a Distance they use Stabilized Iris Encoding and Zernike Moments Phase Features. A nonlinear approach at the same time account for each native consistency of iris bit and also the general quality of the weight map. For the classification of local iris features they use the Zernike moment based phase encoding of iris features. With three basic databases: 1) UBIRIS.v2; 2) FRGC; and 3) CASIA.v4- distance. Features are extracted using 1D log-Gabor filter and the parameter wavelength of the 3 employed databases.

L. Peihua [6] has been present the Iris recognition algorithm in non-ideal imaging conditions. Here author discuss the issues which arise when images are captured in non-ideal conditions. Noisy factors like the off-axis imaging, pose variation, image blurring, illumination modification, occlusion, reflective highlights and noise so because of these problems iris recognition becomes difficult. We tend to introduce a robust algorithm based on the Random Sample Consensus (RANSAC) for localization of ellipsoid iris boundaries. Random Sample Consensus method can detect the iris boundaries a lot of accurately than the strategies based on the Hough transform. Author describes pictures registration technique which is based on the Lucas C Kanade algorithm. Authors define this technique to account for iris pattern deformation. This system works on filtered iris images. This technique solves the registration problem for every small sub-images and divide the small pictures into another small sub-pictures. Here author use sequential forward selection method and Gabor filters.

III. Experimental Design

The angular shift measurement has been incorporated using the Zernike moments algorithm, which is based upon the radial polynomial based rotation estimation method. The angular rotation is estimated by using the hierarchical evaluation of radial polynomials, which is clearly defined with the following equation.

$$R_{nm(p)} = \sum_{s=0}^{(n-|m|)/2} c(n, m, s) p^{n-2s}.$$

Where the overall variance between the different radial polynomial orders is given by c, and the degree for radial polynomial is given by n, m denotes the azimuth angle. The overall variance (C) for radial polynomial is estimated with following formula:

$$c(n, m, s) = (-1)^s \frac{(n-s)!}{s!((n+|m|)/2-s)!((n-|m|)/2-s)}.$$

Where hierarchical polynomial order for radial polynomials is given by n and step repetition is elaborated with symbol m. The polynomial order must be an non-zero and non-negative value.

A. Fast Retina Keypoints

Fast Retina Keypoints (FREAK) feature algorithm is truly designed for the extraction of the retina features in the binary mask formation. In our model, we have utilized the FREAK over the hessian strongest points extracted with SURF, which eventually returns the binary mask of the SURF features in order to speed up the feature matching process.

B. Proposed Iris Recognition Model

The combined proposed model based upon the amalgamation of FREAK over SURF with angular transformation and Neural Network works in the following workflow:

Flow Chart

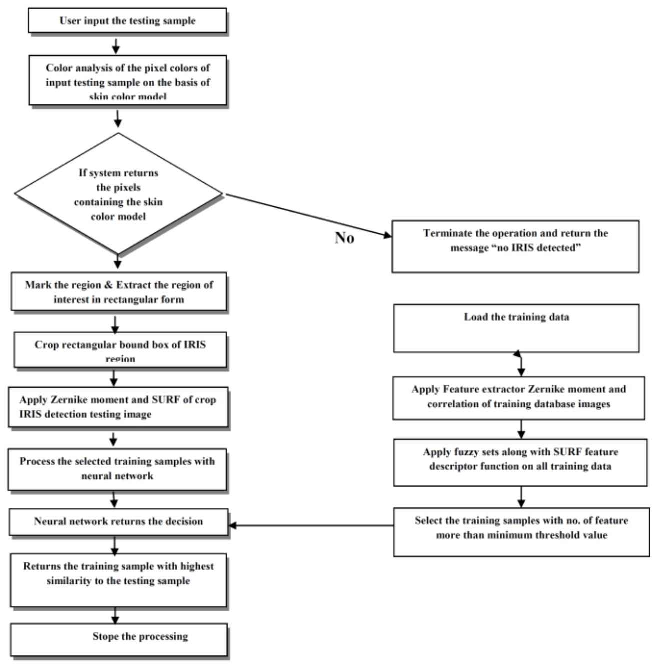

Figure 1. The Flow Chart diagram for the IRIS detection and recognition model.

Algorithm 1: Proposed IRIS Recognition Model.

1. Prompt the user to input the query or target image

2. Perform the image acquisition method to acquire the image matrix from the input image data

3. Apply the angular shift operator to normalize the angular irregularities

4. Apply pixel level assessment over the given image using the overlapping block based method

5. Extract the IRIS region of interest (ROI) based upon the block based assessment of the image matrix.

6. Apply the SURF based hessian feature extraction method over the given image matrix.

7. Apply the FREAK based binary image mask feature extraction method over the given SURF feature descriptor matrix

8. Begin the Probabilistic neural network module.

a. Input the essential parameters

b. Pass the FREAK features to the neural network

c. Load the pre-saved training data from the local disk

d. Prepare the similarity vector based upon the similarity matching and assessment between the query sample and training data objects

e. Return the similarity vector

9. Find the maximum matching sample from the similarity vector

10. Assess the matching feature and return the decision logic.

IV. Result Analysis

Elapsed Time: It defines the overall time taken for the processing of the proposed model for the person recognition or public database lookup using the IRIS features infused with the Neural Network classifier.

Elapsed Time can be obtained by subtracting the start time obtained before the execution from the final time (known as finish time).

Table 1. Elapsed Time.

S.No.	1	2	3	4	5
Elapsed Time	1.15	1.14	1.78	1.32	1.04
Mean Time	1.211	1.211	1.211	1.211	1.211
S.No.	6	7	8	9	10
Elapsed Time	1.04	1.18	0.86	1.45	1.05
Mean Time	1.211	1.211	1.211	1.211	1.211

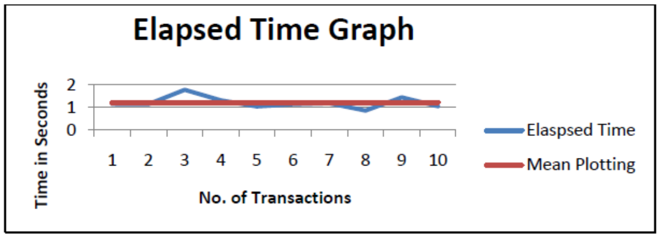

Figure 2. Elapsed time Graph Obtained from proposed model.

The above figure (Figure 1), represents the time based measurement of the proposed model in recognizing the IRIS features for the various subjects and samples from the given database. The proposed model has been analyzed for the time based assessment, where the delay for the sample recognition has been studied and kept under the elapsed time feature. The average recognition time curve defined with the mean plotting shows the consistency of the proposed model in recognizing the IRIS samples in nearly 1-2 seconds in all of the testing rounds.

Table 2. Angular shift based accuracy measurement.

Person / Angles	1	2	3	4	5	6	7
30	8	10	10	10	9	10	10
0	10	10	10	10	9	10	9
-30	10	9	10	10	10	9	10
Overall Accuracy	28	29	30	30	28	29	29

The table 2 clarifies the number of samples per angle obtained from the results of the angular rotation. The proposed model has been found effective when evaluated over the number of samples in the angles defined at 0 degree and 30 degree in each direction.

The table 3 and figure 2 eventually shows the results obtained for the angular shift of the IRIS samples on the different and specific angles. The angular shift based accuracy has been studied for the variation of angles between 60 to -60 degrees, where the accuracy across all of the angular variations have been found adequately efficient for the real time deployment of the IRIS recognition model.

Table 3. Per person accuracy assessment over the 10 samples for each angle for 7 persons.

Person / Angles	1	2	3	4	5	6	7
60	10	10	10	9	9	10	9
45	10	9	9	10	9	10	9
15	10	9	10	10	10	10	10
– 15	10	10	9	10	9	9	10
– 45	9	9	9	9	10	10	9
– 60	9	10	10	10	10	8	9

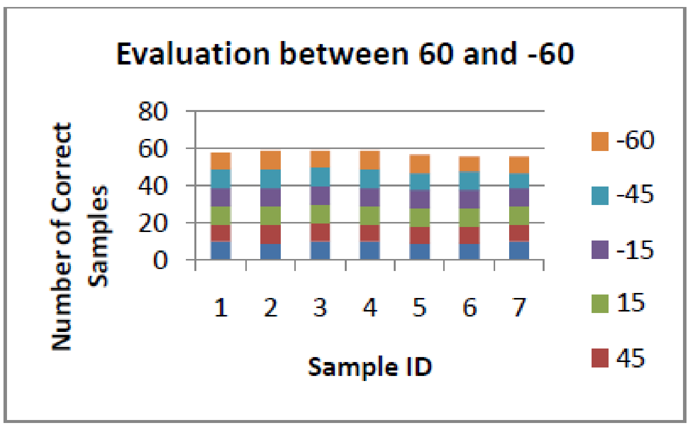

Figure 3. Per person accuracy assessment over the 10 samples for each angle for 7 persons.

Comparison: The results comparison between the proposed model and existing models explains the whole story and clearly shows the improved overall performance of the proposed model, where the proposed model has nearly shown the difference of 8 percent in the overall assessment.

Table 4. Overall accuracy based comparison of proposed model with existing model.

S.No	Algorithm	Database	Overall Accurate IRIS Sample Recognition rate
1	Existing Model	CASIA v4 and UBIRIS v2	88.8%
2	Proposed Model	UBIRIS v2	96.66%

V. Conclusion

The proposed model is based upon the amalgamation of the features of hessian matrix defined with speeded up robust features (SURF) and fast retina keypoints (FREAK) for the feature representation from the input samples, which belongs to the training or testing models. The angular rotation in the given samples has been measured using the Zernike moments based angular shift detection for the rotated samples. The angular shift normalization model enables the model to correctly extract the IRIS features from the given eye samples. The neural network based classification has been incorporated for the matching of the testing and training samples in order to produce the final result according to the defined decision logic. Proposed algorithm is trained and tested on IRIS sample database which contains higher than 1200 image of more than 240 persons for IRIS recognition and with 5 IRIS images of every person. It was found that proposed system of IRIS recognition provides better accuracy (96.66%) as compared to existing IRIS recognition system.

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