

An Efficient Dual Stage Approach for IRIS Feature Extraction using Interest Point Pairing

Hunny Mehrotra, Badrinath G. S., Banshidhar Majhi, and Phalguni Gupta

Abstract— This paper proposes a novel feature extraction and matching technique for iris recognition using interest points. The feature set comprises of spatial location of corner points and entropy information of the window around the corner. Corner matching is an elementary problem that is resolved using dual stage approach. At first stage the potential corners are obtained by finding Euclidean distance between spatial coordinates. These potential corners are used to find actual corners based on their affinity around a window, which is measured using Mutual Information (MI). For the purpose of evaluating experimental results three different datasets i.e., BATH, CASIA and IITK are used. The proposed dual stage approach has accuracy more than 98% with FRR of 0.0% and FAR of 2.61%.

I. INTRODUCTION

There exist several approaches for iris identification based on binary and real features [1]. However, these approaches extract the global features from the image that includes some non-texture details as well. Global feature extraction methods also fail under change in illumination, rotation and viewpoint of the two image samples. Thus to overcome these limitations, local feature extraction methods are used.

To obtain local details from an image the location of special points known as interest/corner points are detected that has sharp change in intensity along all directions. These points are detected over the region of interest (texture part of image). As interest point detectors have invariance to rotation, illumination and small viewpoint changes hence it performs better as compared to global techniques.

The interest points between two images are paired using Euclidean distance approach. But distance approach sometimes wrongly pairs the points of two unrelated images because no image statistic is used for finding the proximity between the aligned points. Thus a new approach to measure the texture pattern details using image entropy has been proposed. Entropy is defined as the statistical measure of randomness that is used to characterize the texture of the

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input image. It uses the neighboring image points by taking a window around the corner point for measuring entropy. The location of corner points along with entropy forms the feature vector. Corner point matching is done using a dual stage approach where Euclidean distance is found between the spatial locations of feature points. The distance values satisfying the threshold criteria are used to find Mutual Information (MI) between the entropies. The combined approach works preferably better as compared to the distance and MI based approach independently.

The paper is organized as follows. Next section discusses the related work while preprocessing step of the input iris image has been presented in Section III. The preprocessed iris image is used to detect interest points as discussed in Section IV. The block around detected interest point is used to determine the entropy to measure the randomness of texture information. For pairing of detected interest points a dual stage matching approach consisting of Euclidean distance and MI measures has been proposed in Section V to identify an individual. Experimental results are given in Section VI. Conclusion is given in the last section.

II. RELATED WORK

Various feature extraction techniques have been developed for iris recognition. Daugman [3] uses convolution with 2D Gabor filters to extract phase value from normalized iris strip. Ma et al. [4] use a dyadic wavelet transform on 1D signal to generate iris code. Wildes [6] applies a Laplacian-of-Gaussian filter at multiple scales to produce a template. Iris coding method based on differences of Discrete Cosine Transform (DCT) coefficients of overlapped angular patches is presented in [7]. Tisse et. al [8] uses analytical image concept to extract pertinent information from iris texture. Few authors have worked for real feature values like Boles and Boashash [9] consider circular bands of iris as 1D signals. A wavelet transform is applied on 1D signal and zero crossing representation is used for coding. Gan and Liang [10] use Daubechies-4 wavelet packet decomposition and use weighted Euclidean distance for matching.

III. PREPROCESSING AND ENHANCEMENT

Preprocessing involves detection of inner and outer iris boundary using Circular Hough Transform [2]. The annular region lying between the two boundaries is transformed into a rectangular block [3].

The transformed rectangular region is enhanced to

improve the texture details and make it illumination invariant [4]. The intensity variation along the whole image is computed by finding the mean of 16×16 block to estimate the background illumination. The mean image is further expanded to the size of the original image using bicubic interpolation. Finally the background illumination is subtracted from the original image. The lightening corrected image is further enhanced using adaptive histogram equalization approach.

IV. FEATURE EXTRACTION USING INTEREST POINTS

Iris is rich in texture features comprising of furrows, coronas, rings, crypts etc. Recognizing an individual using these features makes iris a robust system. However due to change in scale and illumination the texture features may exhibit change in characteristics. Thus scale space representation of texture pattern may obtain more useful information from the normalized iris image [15]. To characterize the features in scale space, special points known as interest points are obtained.

An interest point is a location in an image which has a well-defined position and can be robustly detected; i.e., an interest point can be a corner but it can also be an isolated point or local intensity maximum or minimum, line endings, or a point on a curve where the curvature is locally maximal. For an input image if a window $w(u,v)$ around a point (x,y) is considered then all shifts result only in small change if the $w(u,v)$ is a patch, if $w(u,v)$ is edge then shift along edge will result in small change but shift perpendicular to edge will result in large change. However if $w(u,v)$ is an interest point or an isolated point then shift along all directions results in a large change shown in Fig. 1. This property is used to detect interest points from an image.

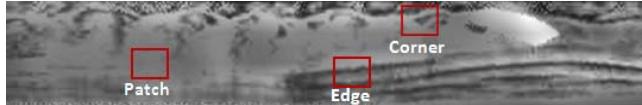


Fig. 1 Image blocks having change in intensity

Harris corner detector [5] is a well known interest point detector used in this paper. For each pixel (x,y) in the enhanced iris image I , autocorrelation matrix M is obtained as given by

$$M = \begin{bmatrix} AC \\ CB \end{bmatrix} \quad (1)$$

In M , A and B is defined as first derivative of image along x and y direction respectively and is computed using

$$A = \left(\frac{\partial I}{\partial x} \right)^2 \otimes G, \quad B = \left(\frac{\partial I}{\partial y} \right)^2 \otimes G \quad (2)$$

C is defined by

$$C = \left(\frac{\partial I \partial I}{\partial x \partial y} \right) \otimes G \quad (3)$$

where G is the Gaussian window used for convolution. Instead of using a Gaussian window a square window can also be used. But a square window results in variable distance for different directions from the center pixel of the window to the edge of the window. A square window also puts equal emphasis on all intensity variation measures regardless of their distance from the center of the window. Instead more weight should be put on values made closer to the center of the window. So it is suggested in [5] to use circular window like Gaussian. (x,y) is defined as an interest point in an image if the matrix M has two significant eigenvalues, that is if the determinant Det and trace Trace , of this matrix verify a measure of cornerness

$$\begin{aligned} R(x,y) &= \text{Det}(M) - k(\text{Trace}(M))^2 \\ \text{Det}(M) &= AB - C^2 \\ \text{Trace}(M) &= A + B \end{aligned} \quad (4)$$

Here k is lying between 0.04 and 0.06. The intensity map, $R(x,y)$, is compared against a threshold T and intensity values below T are set to zero. Positive values of R occur in corner regions, negative values in edge regions, and small values in flat regions. From the thresholded image a pixel is selected as an interest/corner point if it is local maxima in the block. Order statistic filter is used for finding the local maxima.

The feature set is formed using every detected corner points (x,y) in an image. At each detected corner point i centered at location (x_i, y_i) a window (w_i) of size $(k \times k)$ is formed. Using w_i the entropy information is obtained. Entropy is defined in terms of its probability distribution and is a good measure of randomness or uncertainty for evaluating structures and patterns. An important characteristic is to find the minimum amount of data that is sufficient to describe completely an input pattern without any loss of information. In accordance with this proposition entropy can be defined as

$$H_i = -\left(\sum_{j=0}^{N-1} p_j \log_2 p_j \right) \quad (5)$$

where p_j is the probability of the j^{th} quantiser level being used (often obtained from histogram of image intensities) and j is the possible intensity levels in the range from 0 to $N-1$.

For each detected corner point (i) the following information is recorded to form feature vector

1. (x, y) are the coordinates of i^{th} corner point
2. H_i is the entropy information of window w_i

The value of i ranges from 1 to m , where m is the total number of corner points detected in an image.

V. DUAL STAGE APPROACH

For matching the corner points a traditional Euclidean distance approach has been used. The coordinates centered

on corresponding corners are paired using 2D translation. But the approach fails due to lack of image statistics for finding similarity. This paper proposes a novel method for matching that combines distance based approach with information theoretic local similarity measure. Here matching is done serially using dual stage approach. At first stage the matching between the two iris images is done using Euclidean distance. To compute distance for each corner from the first image, all second image corners are used. These distance values are compared against a threshold and the points satisfying the criteria are taken into consideration as candidate points for the second stage. In the next stage, the actual corner mate is found by estimating Mutual Information (MI) [11] locally on a small window around candidate corner points. MI measures the amount of information of one image is contained into another image. This is a measure of how well one random variable explains another variable. MI based approach has not been taken into consideration earlier for biometric template matching. The window with maximum value of MI is chosen and compared against some predefined threshold. If it matches the criteria then corresponding points are paired and removed from the list of unpaired corners.

Let $A = \{m_1, \dots, m_m\}$ and $B = \{m_1, \dots, m_n\}$ be the set of interest points extracted from database and live query image respectively where m_i is a 3-tuple comprising of $\{x_i, y_i, H_i\}$, x_i and y_i are the coordinates at particular interest point and H_i is the entropy obtained as given in (5). At the first level of matching the Euclidean distance between coordinates of one 3-tuple in A is compared to all 3-tuples in B using

$$sd_l = \sqrt{(x_d - x_q)^2 + (y_d - y_q)^2} \quad (6)$$

where sd_l refers to the spatial distance for two points and (x_d, y_d) are the coordinates of the database tuple while (x_q, y_q) are the coordinates of the query tuple.

The corner points with distances below a specified threshold τ are taken as potential corners. To find an optimal pair, MI between the entropies around potential corners is computed. MI (J) corresponding to the two entropy values H_d and H_q is defined as

$$J(d, q) = H_d + H_q - H(d, q) \quad (7)$$

where H_d and H_q are the entropies derived from window at one corner point in database image and another corner point in query image respectively. Moreover, $H(d, q)$ is the joint entropy defined by

$$H(d, q) = - \sum_d \sum_q p(d, q) \log_2 p(d, q) \quad (8)$$

where $p(d, q)$ is joint probability distribution of values around d and q . The value of J is maximized to find an optimal pair between database and query image. A true pair/mate contains the maximal amount of information about each other. The maximum value of MI is compared against another threshold φ and if it passes the criteria, the two interest points are paired and removed from the list.

Similarly, the steps are repeated for the remaining corner points to find an appropriate mate. Finally the total number of mates are counted and compared against threshold. Paired corner points between a gallery and probe iris image is shown in Fig. 2. Solid lines indicate the correct pairing of corners points. Dotted line indicates that the corner points are wrongly paired.

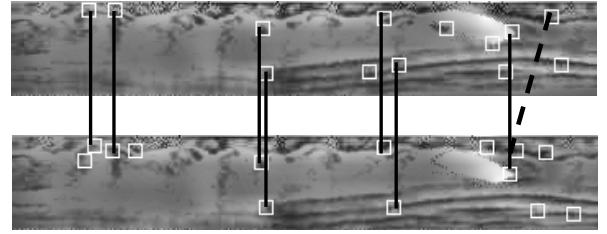


Fig. 2. Interest Point Pairing. Solid lines indicate true pairs whereas dotted line indicates wrong pairing of points

VI. EXPERIMENTAL RESULTS

The results are evaluated on three standard databases i.e., CASIA version 3 [12], BATH University [13] and Indian Institute of Technology Kanpur (IITK) [14]. CASIA database comprises 2255 distinct images from 249 subjects. BATH database comprises of 2160 images taken from 54 subjects and IITK database comprises of 5400 images from 1800 subjects (1800×3). The results are noted down for all the three datasets and Receiver Operator Characteristic (ROC) curve is plotted. For evaluation all images pertaining to an individual falls in the gallery set except one image is taken in the probe set.

In first session results were obtained using Euclidean distance only. However through results it has been inferred that the system does not give satisfactory performance.

In the second session MI based approach has been used independently to measure performance. From the results it has been found that the individual classifiers results in higher FAR and FRR.

In third session, an attempt has been made to reduce the error rates using dual stage matching approach by combining Euclidean distance and MI in a hierarchical fashion. ROC curve for all three approaches on CASIA database is shown in Fig. 3. Similar experiments have been done for BATH and IITK datasets. Table I presents the comparative analysis of results using the three classifiers. From the experiments it is evident that the Euclidean distance between the points in the scale space does not promise satisfactory results. The system performs poorly for BATH database and gives an accuracy of approximately 75% for CASIA and IITK database. A small change in viewpoint or orientation may spatially translate the corner points. To overcome limitations of location based approaches, texture information around the corner point is obtained using MI. However, MI independently gives an accuracy of 73%, 84% and 87% for BATH, IITK and CASIA databases respectively. These values were still not satisfactory and hence a combined

approach using spatial as well texture details has been implemented.

The dual stage system gives an accuracy of 87% and 92% for BATH and CASIA datasets which symbols an improvement over the other two approaches. The system outperforms with an accuracy of 98.69% with FRR of 0.0% and lower FRR of 2.61% on IITK database. From the results it is inferred that dual stage approach performs much better compared to individual approaches.

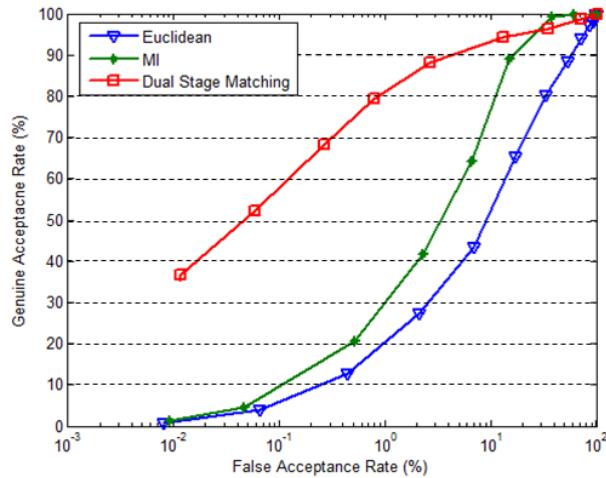


Fig. 3 ROC Curve for Euclidean, MI and Dual Stage approach on CASIA Dataset

VII. CONCLUSION

This paper proposes a novel feature extraction technique using spatial location of interest point and entropy information of window around interest point. The interest points are detected using Harris Corner approach. These points clearly represents the texture features and remains invariant to scale and illumination. For matching a dual stage approach is proposed. This approach serially combines Euclidean distance between corner points followed by Mutual Information between the windows around the candidate corner points. Simulation results are obtained for individual classifiers and dual stage matcher. The individual

classifiers result in higher error rates whereas proposed approach outperforms available recognizers. Dual stage matcher gives an accuracy of more than 98%. Furthermore the proposed approach reduces error rates compared to individual matchers by fusion.

REFERENCES

- [1] K. W. Bowyer, K. Hollingsworth, and P. J. Flynn, "Image understanding for iris biometrics: A survey", *Computer Vision and Image Understanding*, Vol. 110 (2), 2008, pp. 281-307.
- [2] D. J. Kerbyson, and T. J. Atherton, "Circle detection using Hough transform filters", *Fifth International Conference on Image Processing and its Applications*, 1995, pp. 370-374.
- [3] J. Daugman, "How iris recognition works", *IEEE Transactions on Circuits and Systems for Video Technology*, Vol. 14, 2004, pp. 21-40.
- [4] L. Ma, T. Tan, Y. Wang, and D. Zhang, "Efficient iris recognition by characterizing key local variations", *IEEE Transactions on Image Processing*, Vol. 13, 2004, pp. 739-749.
- [5] C. Harris, and M. Stephens, "A Combined Corner and Edge Detection", *Proceedings of Fourth Alvey Vision Conference*, 1998, pp. 147-151.
- [6] R. P. Wildes, "Iris Recognition: An Emerging Biometric Technology", *Proceedings of the IEEE*, Vol. 85, 1997, pp. 1348-1363.
- [7] D. M. Monro, S. Rakshit, and D. Zhang, "DCT-Based Iris Recognition", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 29 (4), 2007, pp. 586-595.
- [8] C. Tisse, L. Martin, L. Torres, and M. Robert, "Person Identification Technique Using Human Iris Recognition", *Proceedings of Vision Interface*, 2002, pp. 294-299.
- [9] W. Boles, and B. Boashash, "A human identification technique using images of the iris and wavelet transform", *IEEE Transactions on Signal Processing*, Vol. 46 (4), 1998, pp. 1185-1188.
- [10] J. Gan, and Y. Liang, "Applications of wavelet packets decomposition in iris recognition", *In International Conference on Biometrics*, 2006, pp. 443-449.
- [11] M. I. A. Lourakis, A. A. Argyros, and K. Marias, "A Graph-Based Approach to Corner Matching Using Mutual Information as a Local Similarity Measure", *17th International Conference on Pattern Recognition*, Vol. 2, 2004, pp. 827-830.
- [12] <http://www.cbsr.ia.ac.cn/english/IrisDatabase.asp>
- [13] <http://www.bath.ac.uk/elec-eng/research/sipg/irisweb/>
- [14] <http://www.cse.iitk.ac.in/users/biometrics/>
- [15] R. Zhu, J. Yang, and R. Wu, "Iris Recognition Based on Local Feature Point Matching," *International Symposium on Communications and Information Technologies*, 2006, pp. 451-454.

TABLE I
FAR, FRR AND ACCURACY VALUES FOR INDIVIDUAL AND COMBINED CLASSIFIERS USING BATH, CASIA AND IITK DATASETS

Datasets	Euclidean Distance			MI			Dual Stage		
	FAR (%)	FRR (%)	Accuracy (%)	FAR (%)	FRR (%)	Accuracy (%)	FAR (%)	FRR (%)	Accuracy (%)
BATH	29.04	39.03	65.97	22.61	31.61	72.89	14.91	10.25	87.42
CASIA	17.18	34.73	74.05	14.91	10.89	87.09	02.64	11.80	92.78
IITK	24.95	21.95	76.55	08.65	22.43	84.46	02.61	00.00	98.70