Efficient Iris Recognition using Relational Measures

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Introduction

- Iris
  - universal
  - unique
  - permanent
  - acceptable
  - less circumvential
- Challanges
  - occlusions
  - quality degradation
  - sensor interoperability

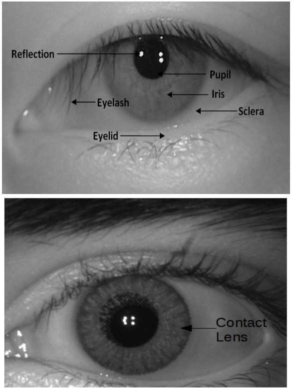
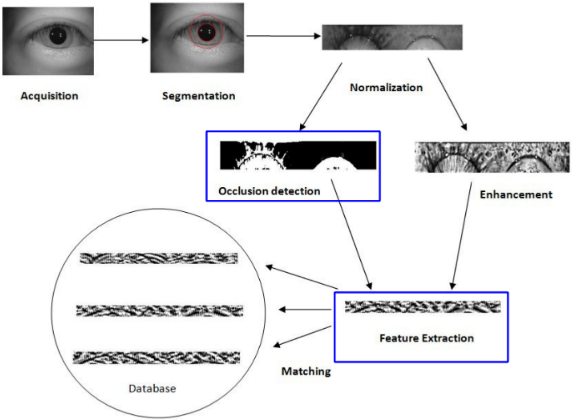


Figure: Iris Anatomy

General Iris Recognition System



Eyelid detection

- Lower and Upper Eyelids
- Traditional techniques
  - Parabola Fitting
- Stratagic Seed Points
- May leak out due to lack of contrast
  - Re-assigning the threshold

(a) Normalized image

(b) Eyelid mask

Eyelash detection

- Separable and multiple.
- Separable eyelashes $\longrightarrow$ high local variance
- Multiple eyelashes $\longrightarrow$ have low average intensity
- Varience and Intensity mapped for each pixel
- Otsu threshold

(c) Normalized image

(d) Eyelash mask

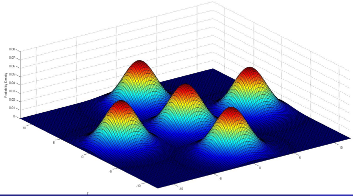
Relational Measures

- Traditional mathematical operations are **computationally intensive** e.g. using complex mathematical filters like Gabor.
- Relational Measures are calculated by comparing multiple entities in an image and encoding only the “order” between them.
- The “order” relationship is more stable than the actual difference because it is an intrinsic and robust property.

- A central region of size $b \times b$ is chosen. Its four neighbor regions of size $b \times b$ are selected at a particular distance d where $d \geq b$.
- A symmetric 2D gaussian filter centrally clipped to size $b \times b$ is put and convoluted over each of these five regions.

$$G(\vec{\mu}, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{(\vec{X}-\vec{\mu})(\vec{X}-\vec{\mu})^T}{2\sigma^2}} \tag{1}$$

where $\vec{\mu}$ is the spatial location of the peak, σ is the standard deviaton of the gaussian and $\vec{X}$ is the spatial location.
- Response compared with four neighbouring regions. Based on the result, 1 or 0 bit is generated and concatenated for each of the four regions.



Feature extraction cntd...

- Vertically and horizontally overlapping rectangular patches over the entire image are chosen as candidates for the central region.
- All the resultant bits are concatenated spatially to generate 2-D binary template. If the central block in feature extraction has more than 50% occlusion, then the corresponding mask bits are set, to generate a second level mask.

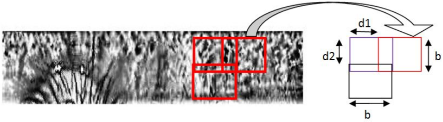


Figure: Choice of central regions

Matching

- Match using Hamming Distance

$$HD(t_1, t_2, m_1, m_2) = \frac{\Sigma_{i=1}^{M}\Sigma_{j=1}^{N}[t_1(i,j) \ \oplus \ t_2(i,j)] \mid [m_1(i,j) + m_2(i,j)]}{M \times N - \Sigma_{i=1}^{M}\Sigma_{j=1}^{N}[m_1(i,j) + m_2(i,j)]} \tag{2}$$

  where operators $\oplus$, $|$, and $+$ stand for binary XOR, NAND and OR operations. $a \oplus b = 1$ if a and b are not same, else 0.
- If the minimum HD for a probe image comes out to be with a gallery image belonging to same class, it is considered a hit else miss.
- Identification accuracy is the proportion of hits among all possible matchings of gallery and probes sets.

Rotational Invariance in Matching

- To account for head tilt
- Rotation of the eye corresponds to horizontal translation in the normalized image.
- Take minimum/best Hamming Distance

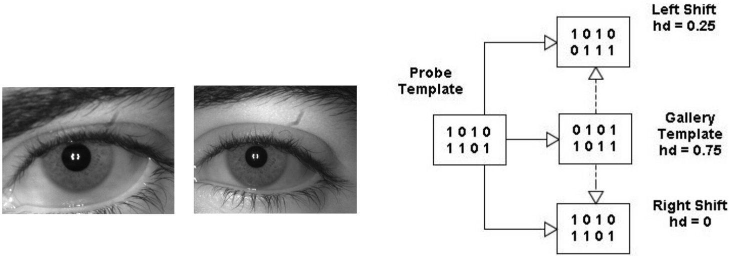


Figure: Calculation of minimum HD

Databases

Database	Size	Subjects	Sessions	Characteristic
CASIA-4.0 Interval	2,639	249	2	Clear Texture
CASIA-4.0 Lamp	16,212	411	1	Variable Illumination
IITK	20,420	1021	2	Quality Images

Table: Test Databases

Images from Databases

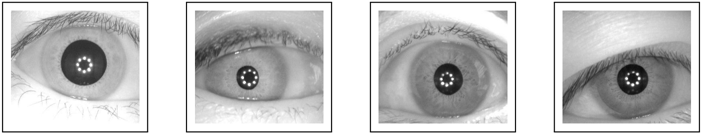


Figure: Images from CASIA 4.0-Interval Subset

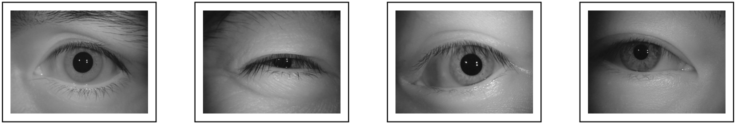


Figure: Images from CASIA 4.0-Lamp Subset

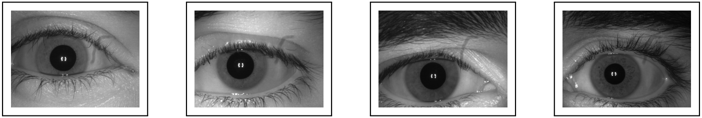


Figure: Images from IITK Database

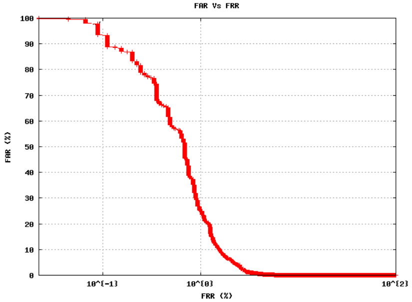
Recognition Results

Database	CRR	EER
CASIA-4.0 Interval	99.07%	2.26%
CASIA-4.0 Lamp	98.7%	4.2%
IITK	98.66%	2.12%

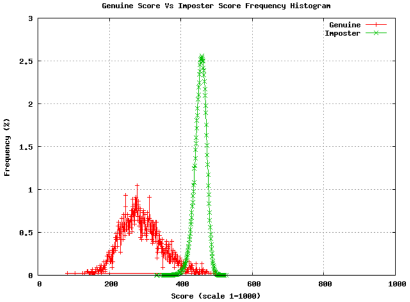
Table: Recognition Performance on Various Databases

- The EER on Lamp database is higher because there is severe occlusion present in its images as compared to other databases.
- The best EER obtained is on IITK database due to good image acquisition conditions.

ROC curves

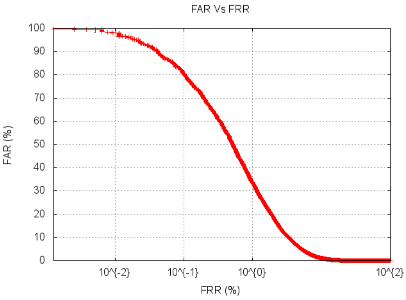


(a) False Accept Vs. False Reject Rate

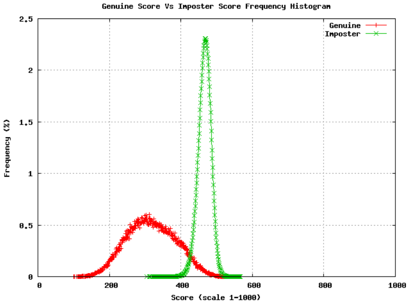


(b) Genuine-Impostor Dissimilarity Scores

Figure: Recognition Performance on CASIA-4.0 Interval Database

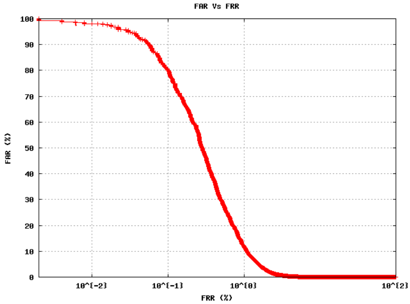


(a) False Accept Vs. False Reject Rate

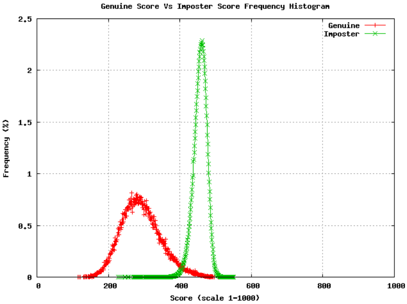


(b) Genuine-Impostor Dissimilarity Scores

Figure: Recognition Performance on CASIA-4.0 Lamp Database



(a) False Accept Vs. False Reject Rate



(b) Genuine-Impostor Dissimilarity Scores

Figure: Recognition Performance on IITK Database

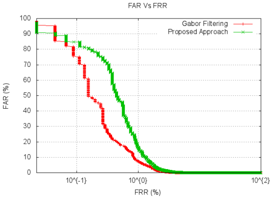
Comparison with Gabor filtering

- Preprocessing has been kept common

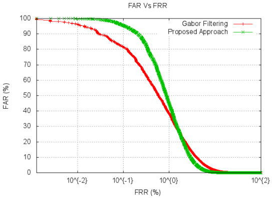
Database	CRR		EER	
	Gabor	Proposed	Gabor	Proposed
CASIA-4.0 Interval	99.47%	99.07%	1.88%	2.26%
CASIA-4.0 Lamp	98.90%	98.69%	5.59%	4.21%
IITK	98.85%	98.66%	2.49%	2.12%

Table: Comparative Results on Various Databases

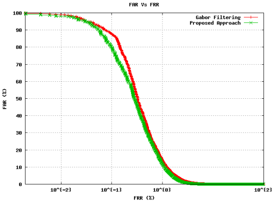
ROCs of Comparison



(a) Interval



(b) Lamp



(c) IITK

Figure: Comparison of Gabor Filtering with Proposed Approach

*

Database	Average Time Per Image (in sec)					
	Gabor			Proposed		
	Template	Matching	Total	Template	Matching	Total
Interval	1.491	0.020	1.512	1.483	0.014	1.497
Lamp	1.702	0.022	1.724	1.693	0.015	1.708
IITK	1.700	0.021	1.721	1.692	0.014	1.706

Table: Comparative Time Analysis on Various Databases

Conclusion

- Identification Rate (CRR) of 99.07% on CASIA-4.0 Interval, 98.7% on CASIA-4.0 Lamp and 98.66% on IITK database respectively. A Low EER of 2.26% on CASIA-4.0 Interval, 4.2% on CASIA-4.0 Lamp and 2.12% on IITK database respectively has been achieved.

References I

Adams, R., Bischof, L.
Seeded region growing
IEEE Transactions on Pattern Analysis and Machine Intelligence 16(6), 641647 (1994)

Alim, O., Sharkas, M.
Iris recognition using discrete wavelet transform and artificial neural networks
IEEE International Symposium on Micro- NanoMechatronics and Human Science. vol. 1, pp. 337340. IEEE (2003)

Bachoo, A., Tapamo, J.
Texture detection for segmentation of iris images
Proceedings of the 2005 annual research conference of the South African institute of computer scientists and information technologists on IT research in develop- ing countries. pp. 236243. South Africa

Institute for Computer Scientists and Information Technologists (2005)

Bendale, A., Nigam, A., Prakash, S., Gupta, P.
Iris segmentation using improved hough transform.
Emerging Intelligent Computing Technology and Applica- tions, pp. 408415. Springer Berlin Heidelberg (2012)

Daugman, J.
Biometric personal identification system based on iris analysis
(Mar 1 ,1994), uS Patent

Dorairaj, V., Schmid, N., Fahmy, G.
Performance evaluation of iris based recog- nition system implementing pca and ica encoding techniques.
Society of Pho-tographic Instrumentation Engineers (SPIE). vol. 5779, pp. 5158. Citeseer (2005)

He, Z., Tan, T., Sun, Z., Qiu, X.
Robust eyelid, eyelash and shadow localizationfor iris recognition.
15th IEEE International Conference on Image Processing(ICIP). pp. 265268. IEEE (2008)

Huang, Y., Luo, S., Chen, E.
An efficient iris recognition system.
Proceedings.2002 IEEE International Conference on Machine Learning and Cybernetics,. vol. 1,pp. 450454. IEEE (2002)

Ma, L., Tan, T., Wang, Y., Zhang, D.
Efficient iris recognition by characterizing key local variations.
IEEE Transactions on Image Processing 13(6), 739750 (2004)

Masek, L., et al.
Recognition of human iris patterns for biometric identification.
M. Thesis, The University of Western Australia (2003)

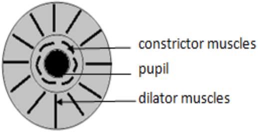
- Miyazawa, K., Ito, K., Aoki, T., Kobayashi, K., Nakajima, H.
  An efficient iris recognition algorithm using phase-based image matching.
  IEEE International Conference on Image Processing (ICIP). vol. 2, pp. II49. IEEE (2005)
- Monro, D., Rakshit, S., Zhang, D.
  Dct-based iris recognition.
  IEEE Transactionson Pattern Analysis and Machine Intelligence, 29(4), 586595 (2007)
- Sun, Z., Tan, T.
  Ordinal measures for iris recognition. IEEE Transactions on
  Pattern Analysis and Machine Intelligence, 31(12), 22112226 (2009)

Wildes, R.
Iris recognition: an emerging biometric technology.
Proceedings of the IEEE 85(9), 13481363 (1997)

Zuiderveld, K.:
Contrast limited adaptive histogram equalization.
Graphics gems IV. pp. 474485. Academic Press Professional, Inc. (1994)

Questions

Muscle Movements in Iris



- Two kind of muscles control the size of iris radial and circular direction

Effect of Enhancement

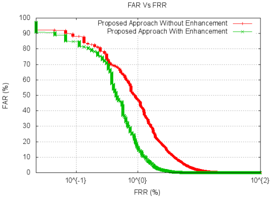


Figure: Effect of Enhancement on Proposed Approach