Robust and Secure Iris Recognition

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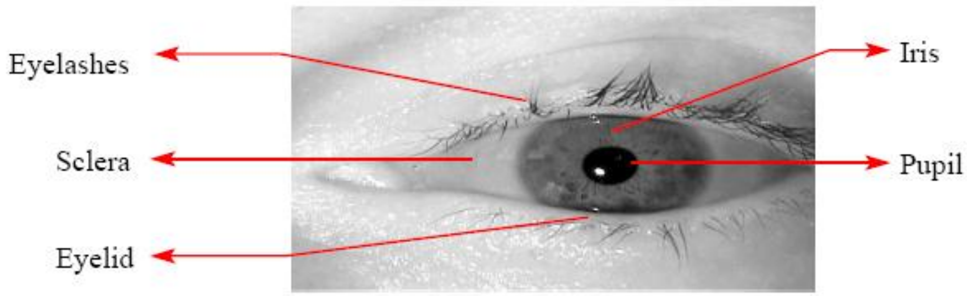
"Sparse Representation and Low-Rank Representation for Biometrics"

Outline

- Iris image selection and recognition
  - Bayesian fusion-based image selection and recognition
  - Iris recognition from video
- Secure iris biometric
  - Cancelability through random projections
- Analysis of results

Iris Recognition

- Recognize a person from the texture features on his iris image.



- Components of an iris recognition system ([Daugman 93])

- Existing algorithms ([Daugman 93]) give high recognition rates on well acquired iris images.

Unconstrained Iris Recognition

- Iris images acquired from unconstrained environments suffer from:
  - Specular reflections
  - Segmentation error
  - Occlusion
  - Blur

- Direct application of existing algorithms on these images give poor results.
- Select the good images and then do recognition.

Iris Image Selection and Recognition

- Sparse representation-based algorithm for iris image selection and recognition [Wright *et al.* 2009].

- Assume L classes and n images per class in gallery.
- The training images of the k^{th} class is represented as

$$\mathbf{D}_k = [\mathbf{x}_{k1}, ..., \mathbf{x}_{kn}]$$

- Dictionary $\mathbf{D}$ is obtained by concatenating all the training images

$$\begin{aligned}\mathbf{D} &= [\mathbf{D}_1, ..., \mathbf{D}_L] \in \mathbb{R}^{N \times (n.L)} \\ &= [\mathbf{x}_{11}, ..., \mathbf{x}_{1n} | \mathbf{x}_{21}, ..., \mathbf{x}_{2n} | ...... | \mathbf{x}_{L1}, ..., \mathbf{x}_{Ln}]\end{aligned}$$

- The unknown test vector can be represented as a linear combination of the training images as

$$\mathbf{y} = \sum_{i=1}^{L} \sum_{j=1}^{n} \alpha_{ij} \mathbf{x}_{ij}$$

Basic Formulation

- In a more compact form

$$\mathbf{y} = \mathbf{D}\alpha. \qquad \alpha = [\alpha_{11}, ..., \alpha_{1n} | \alpha_{21}, ..., \alpha_{2n} | ...... | \alpha_{L1}, ..., \alpha_{Ln}]^T$$

- The test image can approximately be written as a linear combination of the training images of the correct class.
- The coefficient vector **α** is sparse vector.
- **α** can be recovered by Basis Pursuit as

$$\hat{\alpha} = \arg\min_{\alpha'} \| \alpha' \|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{D}\alpha'.$$

- A measure of sparsity is the Sparse Concentration Index (SCI), defined by

$$SCI(\alpha) = \frac{\frac{L.\max \|\Pi_i(\alpha)\|_1}{\|\alpha\|_1} - 1}{L - 1}.$$

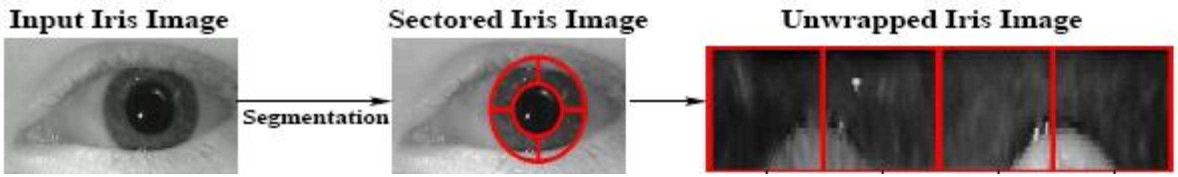
- Well acquired images will have high SCI.
- Reject the images having low SCI value.

Selection and Recognition Algorithm

- Given the gallery, construct the dictionary **D** by arranging the training images as its columns.
- Using the test image, by Basis Pursuit, obtain the coefficient vector $\boldsymbol{\alpha}$.
- Obtain the Sparsity Concentration Index.
- Compare SCI with a threshold to reject the poorly acquired images.
- Find the reconstruction error while representing the test image with coefficients of each class separately.
- Select the class giving the minimum reconstruction error.

Bayesian Fusion-based Image Selection and Recognition

- Different regions of the iris have different qualities.



- Recognize the different regions separately and combine the results depending on the quality of the region.
- Let C be the set of possible class labels and *M* be the number of sectors retained after rejection.
- *Let* $d_1, d_2, \ldots d_M$ be the class labels of the retained sectors.
- The final class label is given by

$$\tilde{c} = \arg\max_{c \in \mathbf{C}} \sum_{j=1}^{M} SCI(d_j).\delta(d_j = c)$$

$$CSCI(c_l) = \frac{\sum_{j=1}^{M} SCI(d_j).\delta(d_j = c_l)}{\sum_{j=1}^{M} SCI(d_j)}$$

$$\tilde{c} = \arg\max_{c \in \mathbf{C}} CSCI(c)$$

Recognition from Video

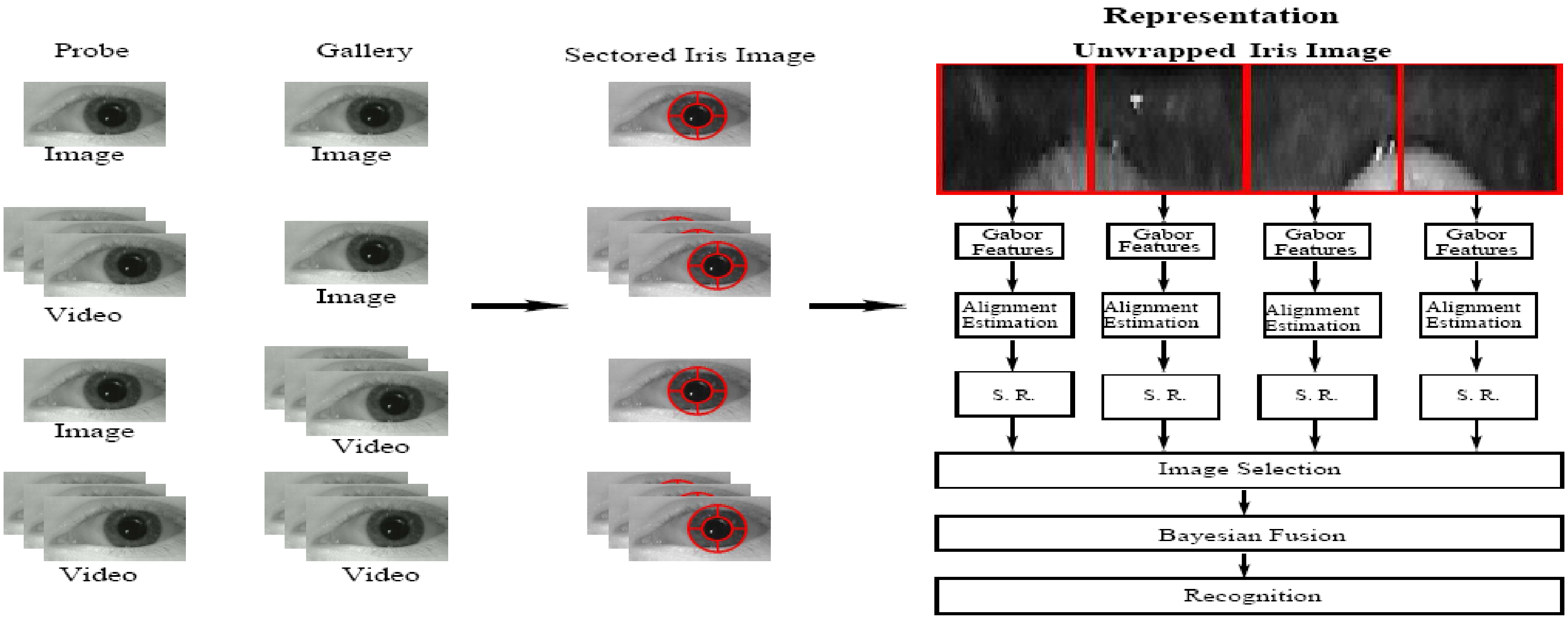
- The sectors of the different frames of the video can be combined based on their quality.
- Let $\boldsymbol{Y} = \{\boldsymbol{y}^1, \boldsymbol{y}^2, \ldots \boldsymbol{y}^J\}$ be the J vectorized frames in the test video.
- Let M_i be the number of sectors retained by the selection scheme in the i^{th} frame.
- Let $\boldsymbol{y}^i_j$ be the j^{th} retained sector in the i^{th} frame.
- The final class label is given by

$$\tilde{c} = \arg\max_{c \in \mathbf{C}} \sum_{i=1}^{J} \sum_{j=1}^{M_i} SCI(d^i_j).\delta(c = d^i_j) \qquad CSCI(c_l) = \frac{\sum_{i=1}^{J} \sum_{j=1}^{M_i} SCI(d^i_j).\delta(d^i_j = c_l)}{\sum_{i=1}^{J} \sum_{j=1}^{M_i} SCI(d^i_j)}$$

$$\tilde{c} = \arg\max_{c \in \mathbf{C}} CSCI(c)$$

where d^i_j is the class label assigned by the classifier to $\boldsymbol{y}^i_j$.

Iris Recognition



Different modes of operation. Both the probe and the gallery can be individual iris images or iris video.

Cancelable Biometrics

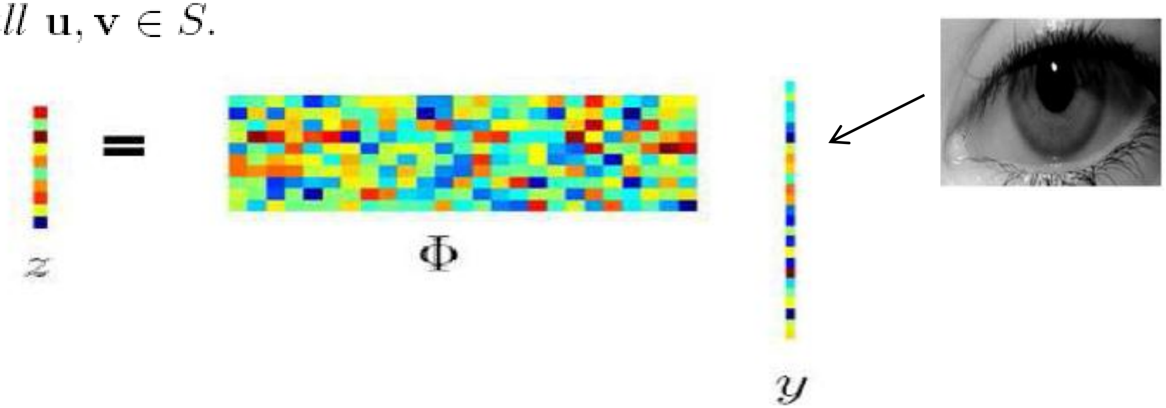
- Need for Secure Iris Biometric
  - Iris patterns are unique to each person
  - Iris patterns cannot be re-issued if stolen
  - Different patterns required for different applications
- Cancelable Biometrics – Apply a revocable and non invertible transformation on the original one.
- Requirements:
  - Different templates should be used in different applications to prevent cross matching.
  - Template computation has to be non-invertible to prevent illegal recovery of biometric data.
  - Revocation and reissue should be possible in the event of compromise.
  - Recognition performance should not degrade when a cancelable biometric template is used.

Johnson-Lindenstrauss Lemma

Lemma 1. *(Johnson-Lindenstrauss) Let $\epsilon \in (0,1)$ be given. For every set S of $\sharp(S)$ points in $I\!R^N$, if n is a positive integer such that $n > n_0 = O\left(\frac{\ln(\sharp(S))}{\epsilon^2}\right)$, there exists a Lipschitz mapping $f : R^N \rightarrow R^n$ such that*

$$(1-\epsilon)\|\mathbf{u}-\mathbf{v}\|^2 \leq \|f(\mathbf{u})-f(\mathbf{v})\|^2 \leq (1+\epsilon)\|\mathbf{u}-\mathbf{v}\|^2$$

for all $\mathbf{u}, \mathbf{v} \in S$.



- J-L Lemma - A set of points in a high-dimensional space can be embedded into a space of much lower dimension in such a way that distances between the points are nearly preserved.

Random Projection (RP) Matrices

- The following are some of the matrices that can be used for cancelability.
  - $n \times N$ random matrices Φ whose entries $\phi_{i,j}$ are independent realizations of Gaussian random variables $\phi_{i,j} \sim \mathcal{N}\left(0, \frac{1}{n}\right)$.
  - Independent realizations of ± 1 Bernoulli random variables

$$\phi_{i,j} \doteq \begin{cases} +1/\sqrt{n}, & \text{with probability } \frac{1}{2} \\ -1/\sqrt{n}, & \text{with probability } \frac{1}{2}. \end{cases} \quad (1)$$

  - Independent realizations of related distributions such as

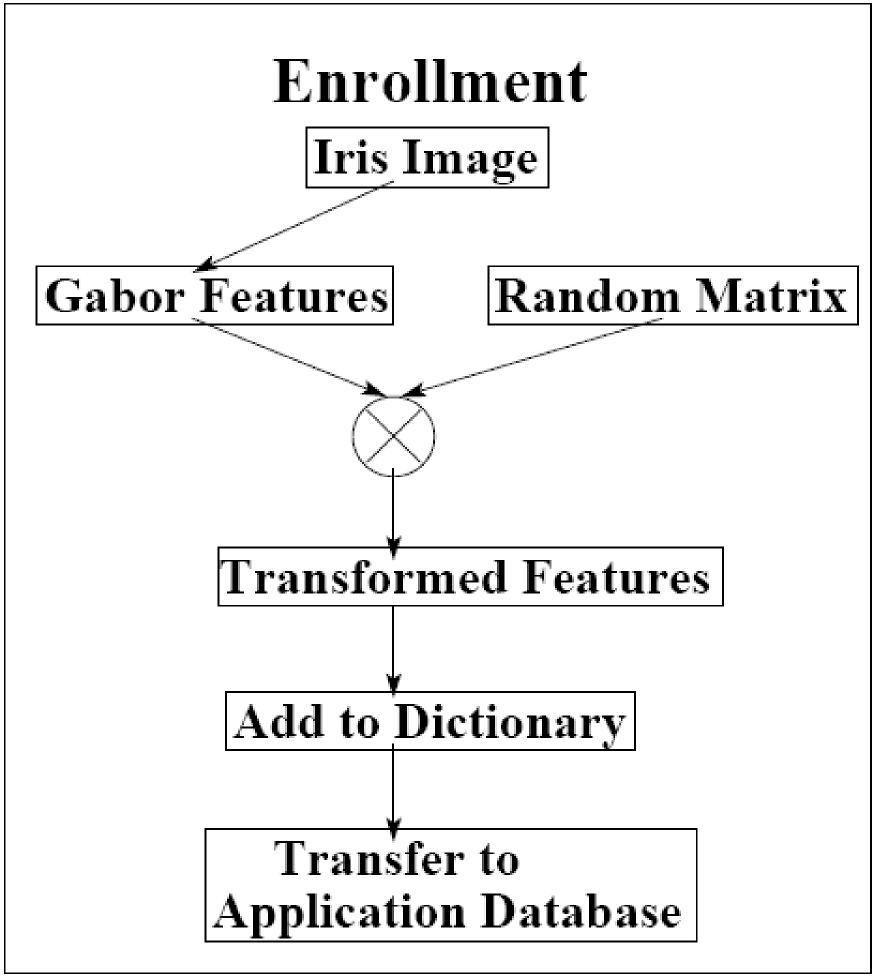
$$\phi_{i,j} \doteq \begin{cases} +\sqrt{3/n}, & \text{with probability } \frac{1}{6} \\ 0, & \text{with probability } \frac{2}{3} \\ -\sqrt{3/n}, & \text{with probability } \frac{1}{6}. \end{cases} \quad (2)$$

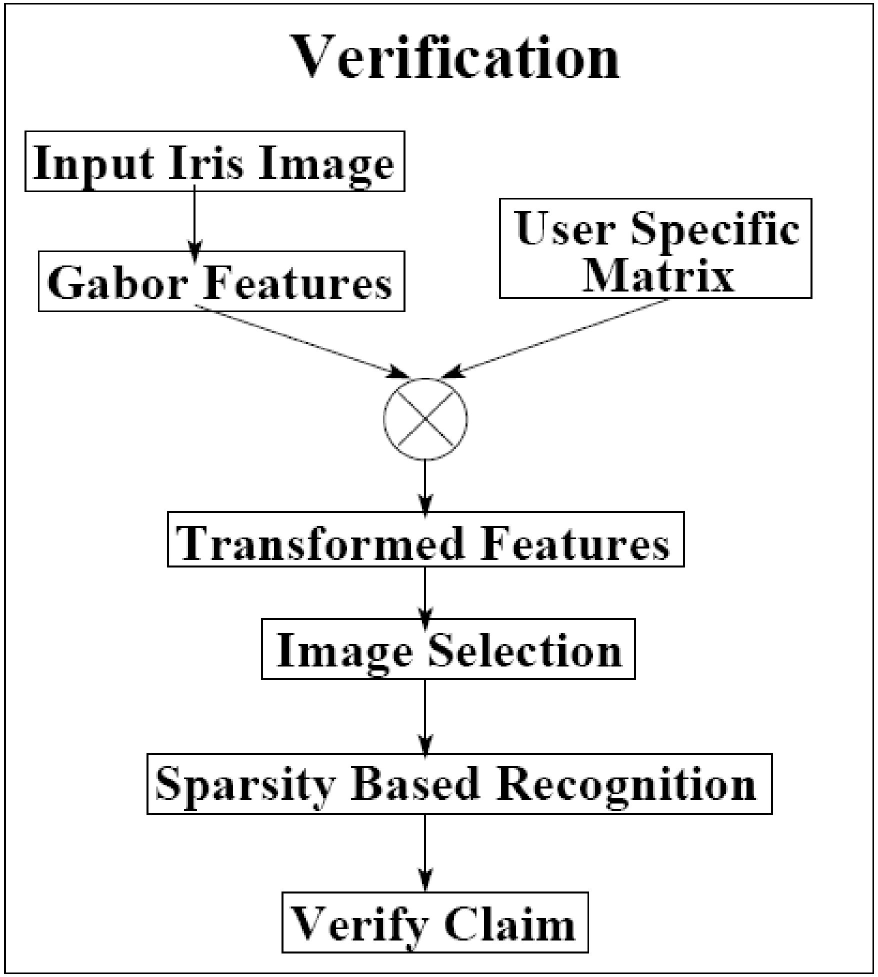
  - Multiplication of any $n \times N$ random matrix Φ with a deterministic orthogonal $N \times N$ matrix $\mathbf{D}$, i.e. $\Phi\mathbf{D}$.

Sectored Random Projections (SRP)

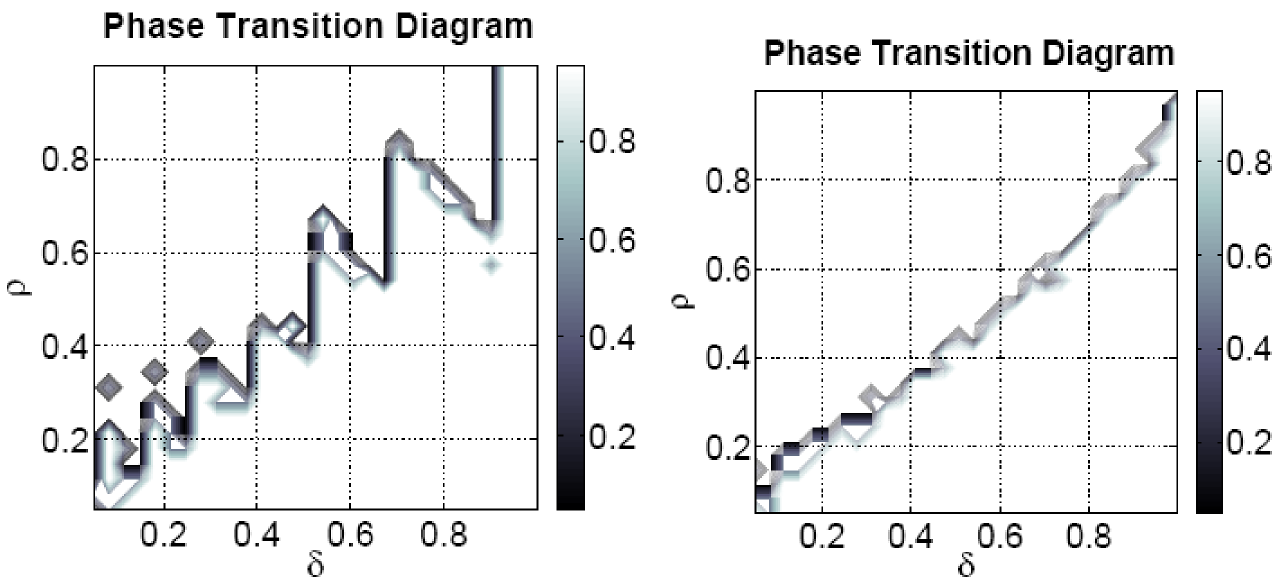
- Apply RP to different iris sectors separately.
- Advantages:
  - Bad regions cannot corrupt the whole image.
- Cancelability requirements:
  - **Performance** - does not drop after applying SRP.
  - **Non-Invertibility** - due to RP and dimension reduction.
  - **Revocability** – Apply a new RP if the old patterns are lost.
  - **Different Applications** – Assign a different matrix for each application.
  - **Compatibility** – Only a single matrix multiplication stage has to be added to existing algorithms.

Random Projections-based Cancelable System





Phase Transition Diagrams

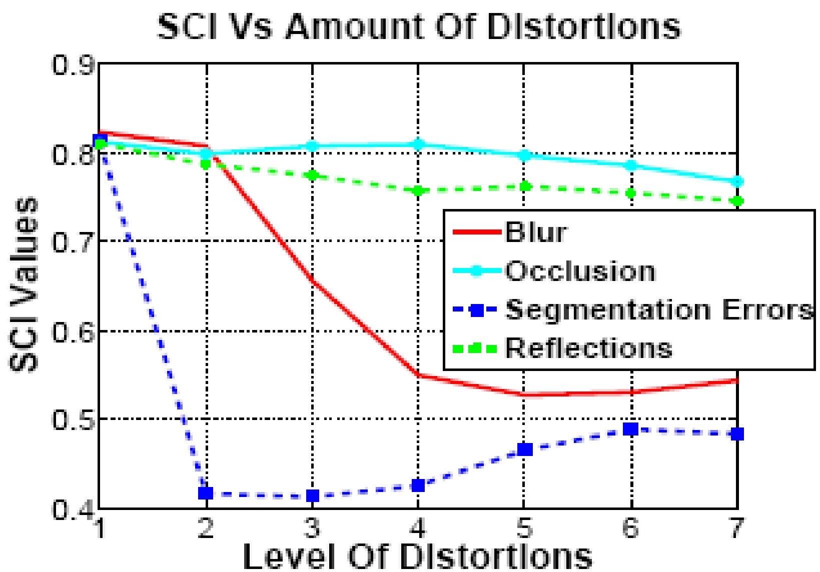


(a) (b)

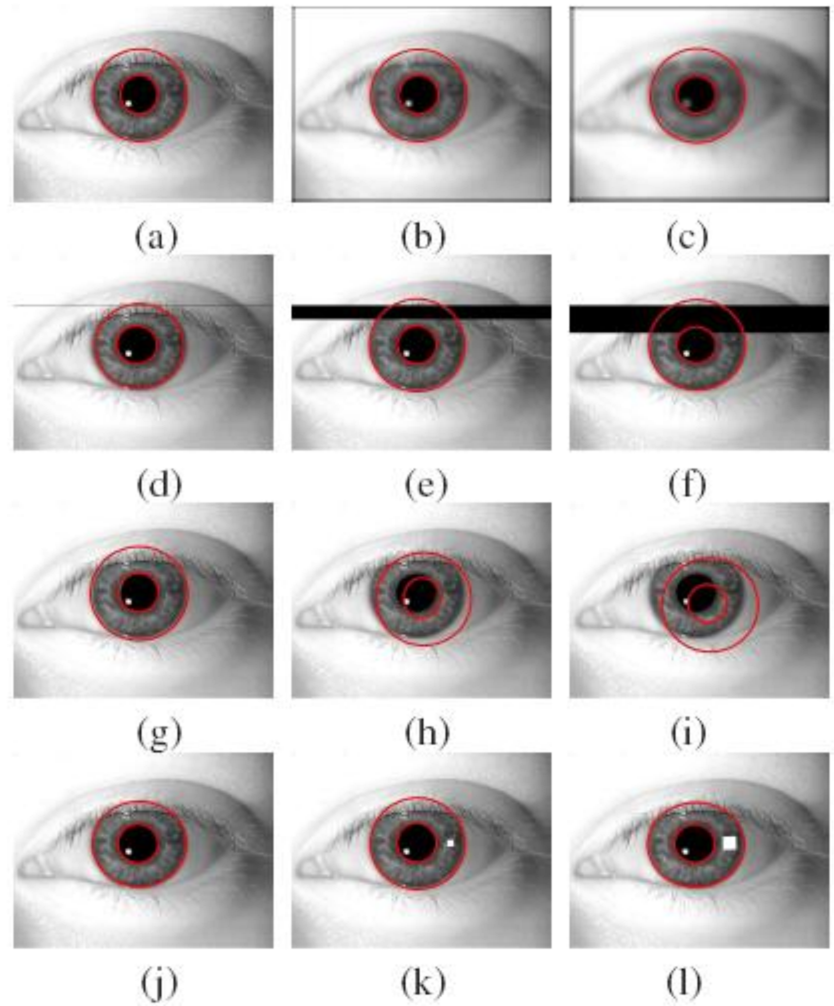
Phase transition diagrams corresponding to the case when the dictionary is (a) $\mathbf{GD}$ and (b) $\Phi\mathbf{GD}$, where $\mathbf{G}$ is the Gabor transformation matrix and Φ is the random projection matrix for cancelability. In both figures, we observe a phase transition from lower region where the ℓ_0/ℓ_1 equivalence holds, to the upper region, where one must use combinatorial search to recover the sparsest solution.

$$\hat{\alpha} = \arg\min_{\alpha'} \| \alpha' \|_1 \quad \text{subject to} \quad \mathbf{y} = \mathbf{D}\alpha'.$$

SCI Values – ND Dataset

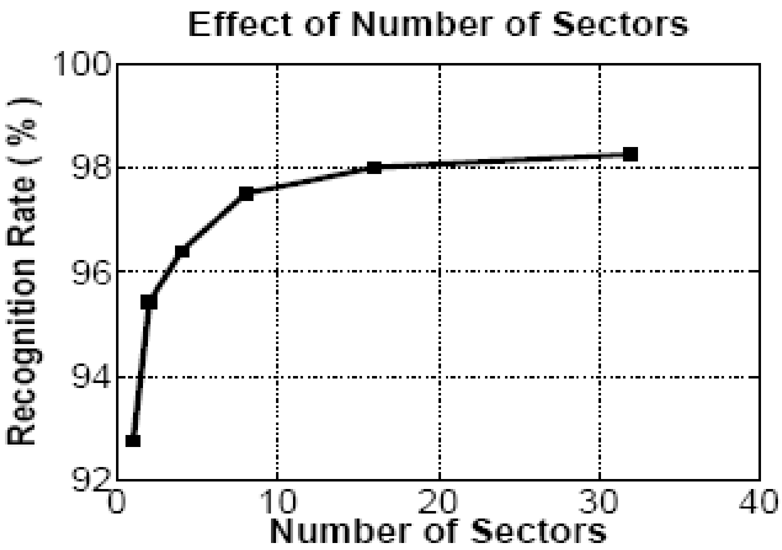


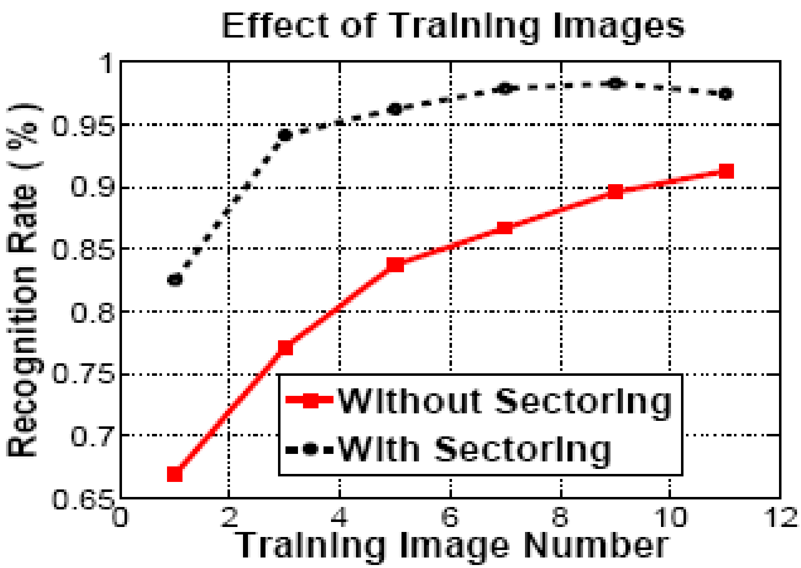
- 15 clean iris images of the left eye of 80 people.
- 12 images per person formed the gallery.
- The SCI falls with increasing levels of distortions.



Simulated Distortions on the images from the ND dataset. The detected pupil and iris boundaries are indicated as red circles.

Recognition – ND Dataset



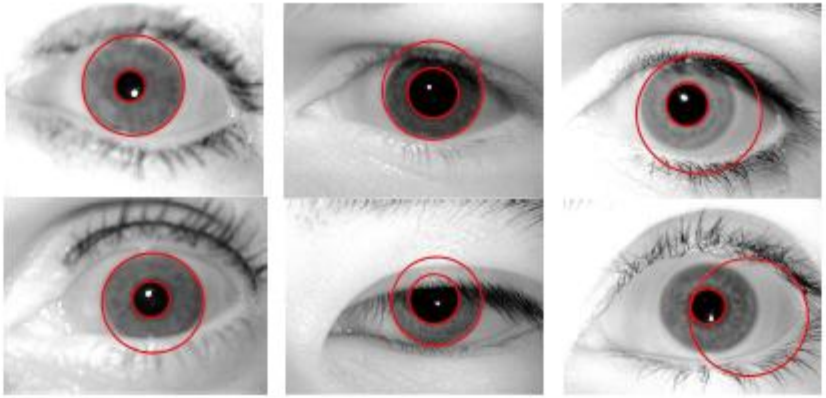


- The performance improves significantly as the number of sectors is increased.
- The recognition rate increases with the number of training images.
- Sectoring enhances the recognition performance.

Recognition Performance – ND Dataset

Table 1: Recognition Rate on ND Dataset

Image Quality	NN	Masek's Implementation	Sparsity-based
Good	98.33	97.5	99.15
Blured	95.42	96.01	98.18
Occluded	85.03	89.54	90.44
Seg. Error	78.57	82.09	87.63



(a) (b) (c)

Iris images with low SCI values in the ND dataset. Note that the images in (a), (b) and (c) suffer from high amounts of blur, occlusion and segmentation errors respectively .

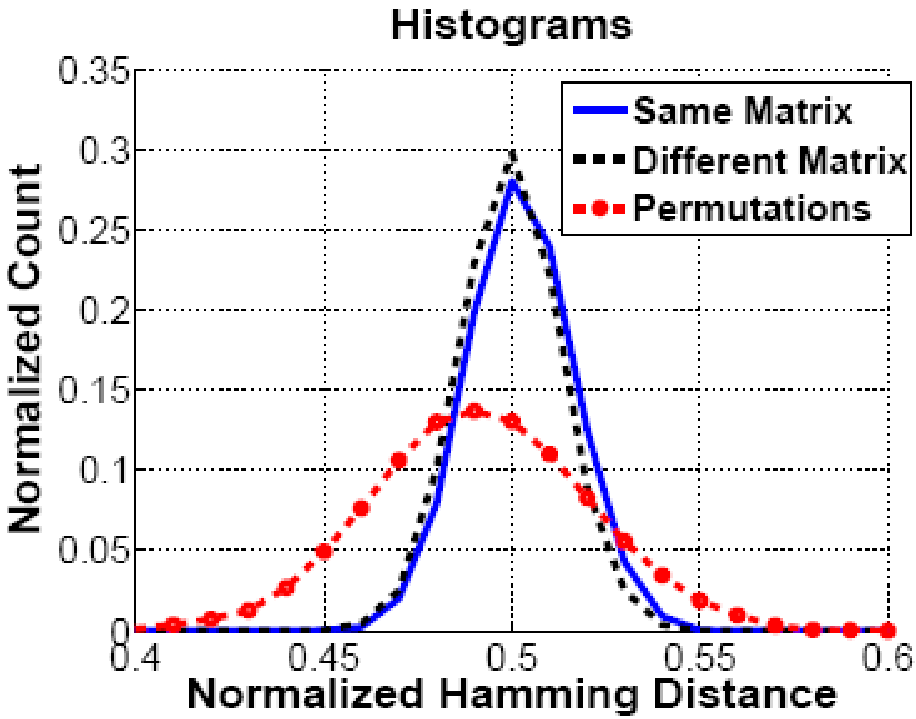
Recognition Performance – ICE 2005 Dataset

Table 2: Verification rate at an FAR of 0.001 on the ICE 2005 dataset

Method	Verification Rate (%)
Pelco	96.8
WVU	97.9
CAS 3	97
CAS 1	97.8
CMU	99.5
SAGEM	99.8
Sparsity-based	98.13

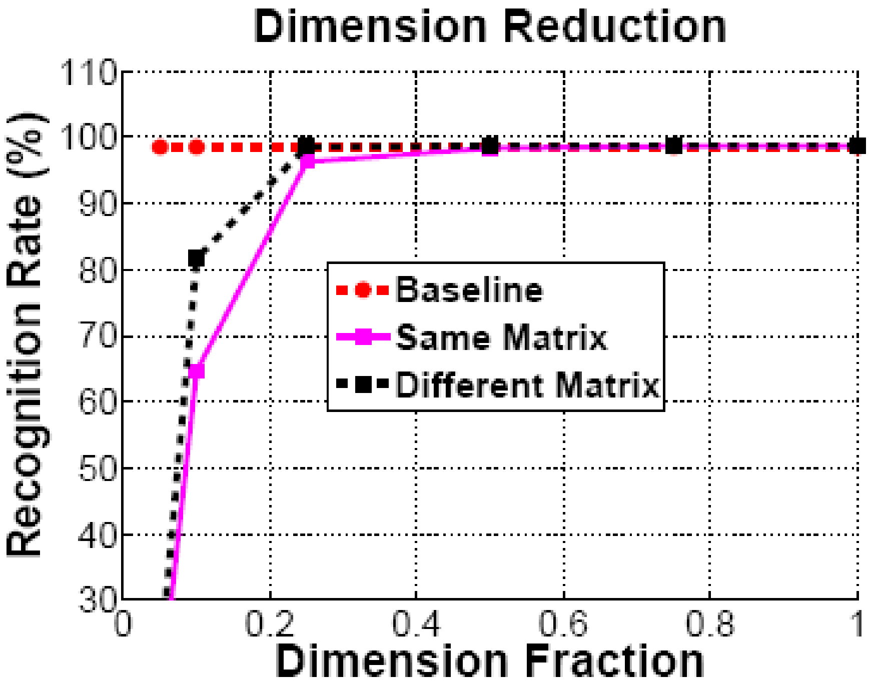
- Experiment 1: 1425 iris images corresponding to 120 different classes.
- 10 images per person in gallery and remaining as the test set.

Normalized Hamming Distance



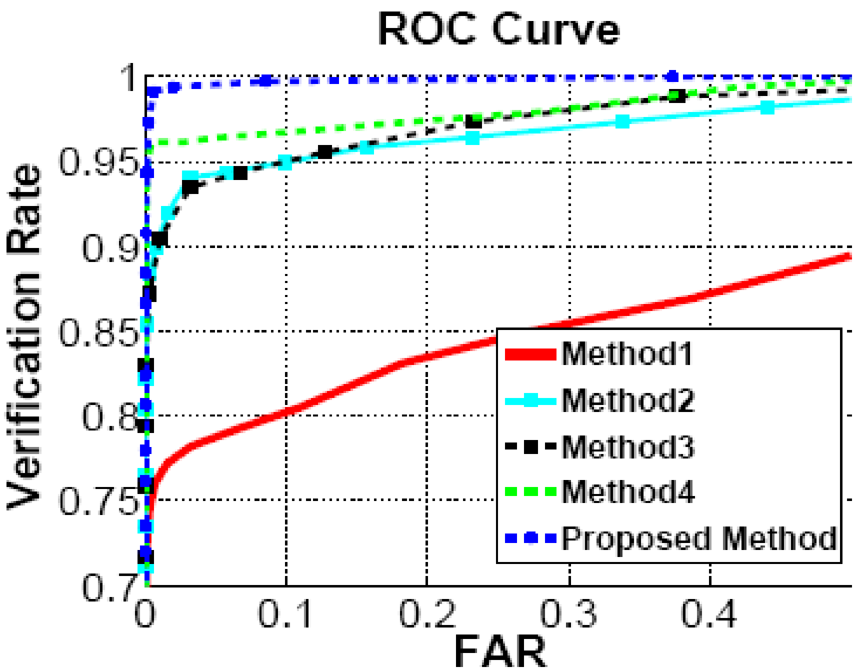
- Normalized Hamming distance histogram peaks at 0.5, indicating that the original and transformed vectors are independent.
- It is impossible to extract original vector from the transformed ones.

Cancelability Results



- The performance stays the same up to 30% of the original dimension.
- Same matrix – Apply the same random Gaussian matrix for all the users.
- Different matrix – Apply different random matrices for different users.

Results on Iris Videos - MBGC



- Method 1 – Consider each frame of the video as a different probe.
- Method 2 – Average the intensity of the different iris images.
- Method 3 and 4 – All possible pairwise Hamming distances between the video frames of the probe videos and the gallery videos belonging to the same class are computed.
- Method 3 uses the average of these Hamming distance as the score.
- Method 4 uses the minimum of the pairwise Hamming distance as the score.

Collaborators:

- Jaishanker K. Pillai, UMD
- Prof. Rama Chellappa, UMD
- Dr. Nalini K. Ratha, IBM

Publications:

- J. K. Pillai, V. M. Patel, R. Chellappa and N. K. Ratha, "Secure and Robust Iris Recognition using Random Projections and Sparse Representations," *IEEE PAMI*, 2011.
- J. K. Pillai, V. M. Patel, R. Chellappa and N. K. Ratha, "Sectored Random Projections for Cancelable Iris Biometric," *ICASSP*, 2010.
- J. Wright, A. Y. Yang, A. Ganesh, S. S. Sastry, Y. Ma, "Robust face recognition via sparse representation," *IEEE PAMI*, 2009.

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