Iris Recognition Based on SIFT Features

Fernando Alonso-Fernandez, Pedro Tome-Gonzalez
Virginia Ruiz-Albacete, Javier Ortega-Garcia

Fernando Alonso-Fernandez
Biometric Recognition Group – ATVS
Escuela Politécnica Superior
Universidad Autónoma de Madrid, Spain
September 2009

Introduction

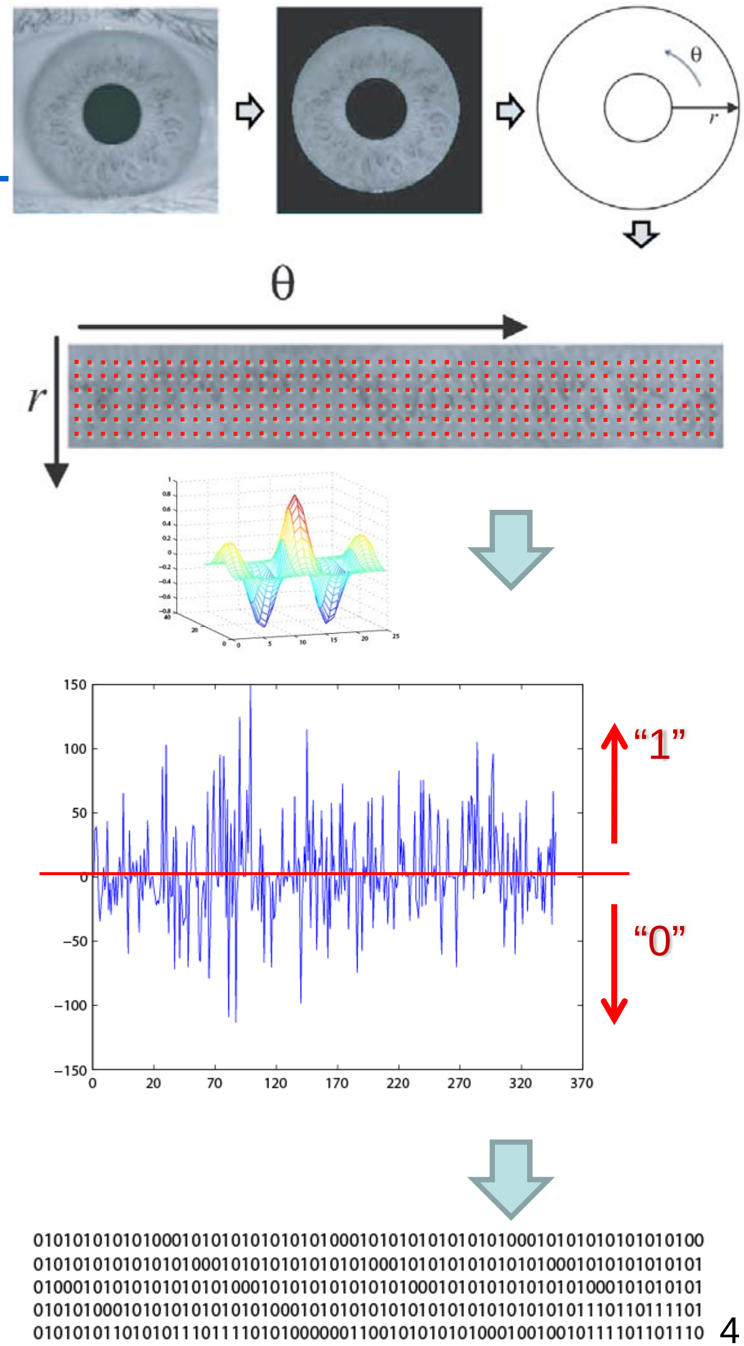
- **Biometrics** provide a convenient way of user recognition:
  - no tokens or keys to carry (which can be lost)
  - no passwords to remember (which can be forgotten)

Introduction

- Iris recognition is regarded as one of the most **reliable** and **accurate** biometric recognition system available
- Additionally, the iris is
  - highly **stable** over a person’s lifetime
  - **non-invasive** (externally visible organ)
- Explosion of interest in iris biometrics in recent years, with many applications developed

Introduction

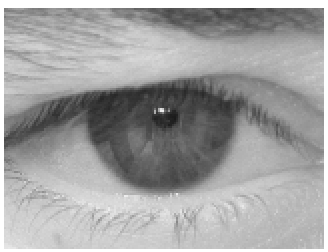
- Traditional iris recognition approaches approximates **iris boundaries as circles**.
    - Transformation of the ring-shaped region of the iris to a **rectangular** image
    - Features are then extracted from the **rectangular normalized iris pattern** (Gabor filters, log-Gabor filters, Gaussian filters, Laplacian-of-Gaussian filters, wavelet transforms, etc.)



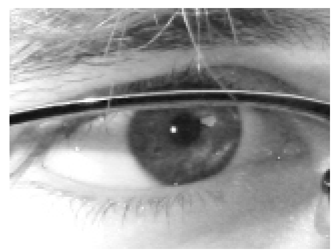
Introduction

- **Reliable transformation** to polar coordinates is **crucial**:
  - Highly accurate **segmentation** needed
  - Problems with **non-cooperative or low quality data** (changes in the eye gaze, non-uniform llumination, eyelashes/eyelids occlusion, etc.)

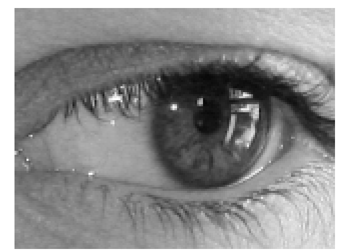
Occlusion



Glasses

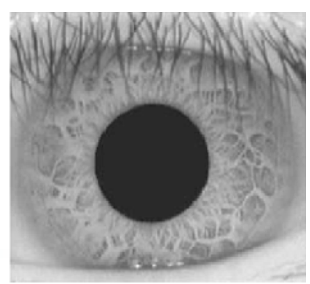


Gaze



Contact lens

Occlusion



Incomplete iris

Index

- This work is structured as follows:

Scale Invariant Feature Transformation (SIFT)

Database and protocol

Experimental results

Conclusions and Future Work

Scale Invariant Feature Transformation (SIFT)

Scale Invariant Feature Transformation (SIFT)

- Algorithm developed for **general purpose object recognition***

- SIFT detects **stable feature points** of an object such that the same object can be recognized with **invariance to illumination, scale, rotation and affine transformations**

- **Advantages** for iris recognition

  - Transformation to polar coordinates or highly accurate segmentation is **not needed**

  - Due to its invariance to illumination, scale and rotation, it is expected to be feasible its use with **unconstrained image acquisition conditions ->**
    - increased user **convenience**
    - applicability to **non-cooperative** environments

*** D. Lowe, "Distinctive image features from scale-invariant key points," Intl Journal of Computer Vision, vol. 60(2), 2004**

Scale Invariant Feature Transformation (SIFT)

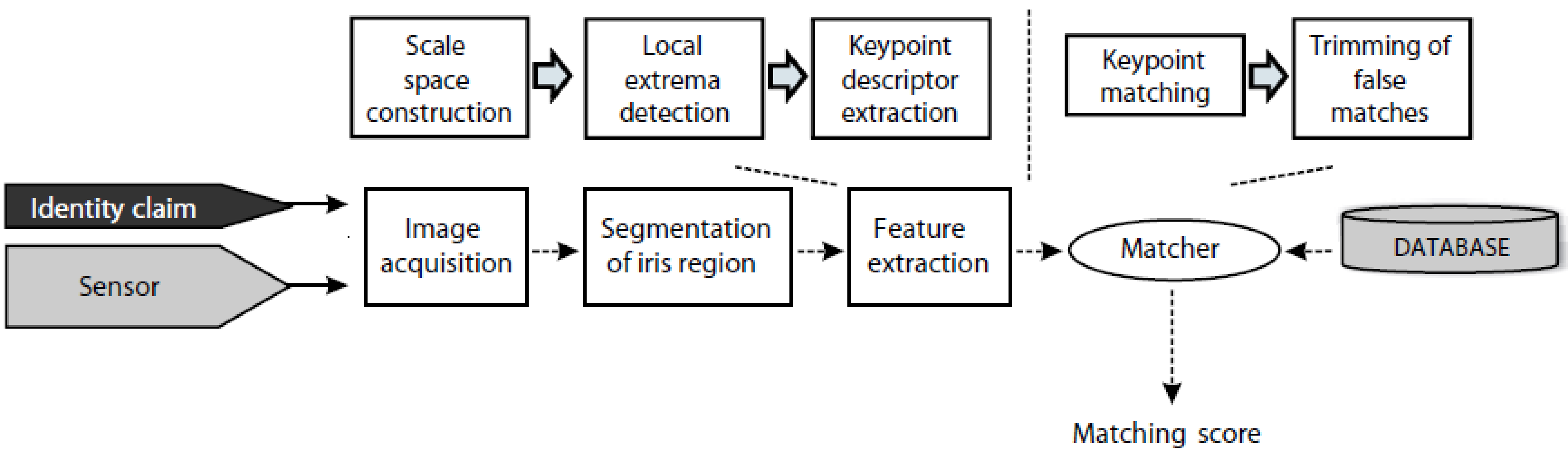
- **SIFT operation** for iris verification

FEATURE EXTRACTION

1. Scale space construction
2. Local extrema detection
3. Keypoint descriptor extraction

FEATURE MATCHING

4. Keypoint matching
5. Trimming of false matches

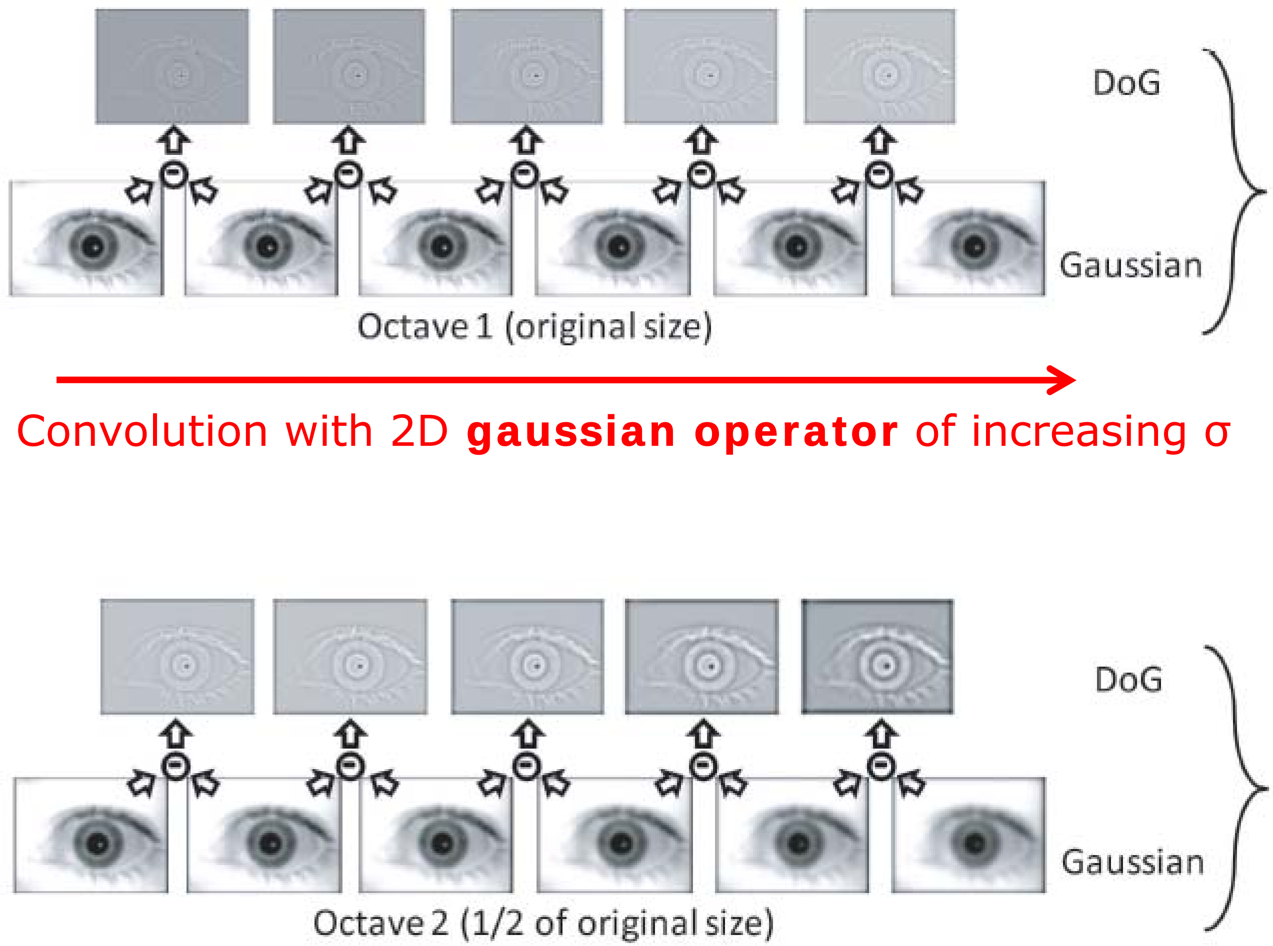


FEATURE EXTRACTION

1. **Scale space construction**

Substraction of consecutive images (DoG images)

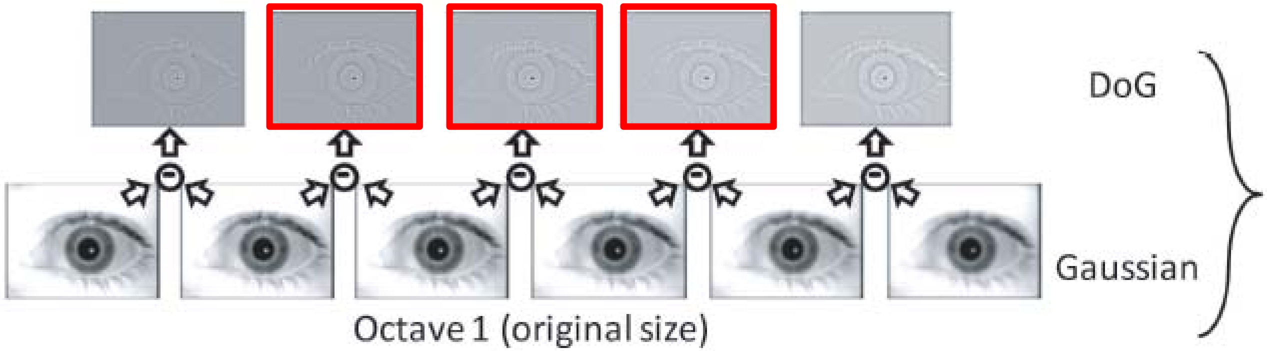
Image **downsampling** (scale invariance)



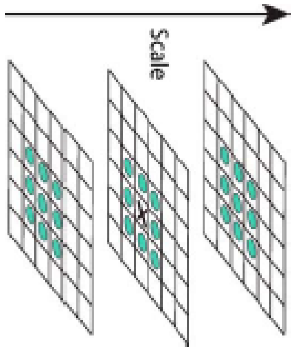
…….

FEATURE EXTRACTION

2. Local extrema detection (I)



- Detection of **local minimum or maximum** in the DoG images
- Comparison with its 8 neighbors in the current image and 9 neighbors in the two adjacent DoG images



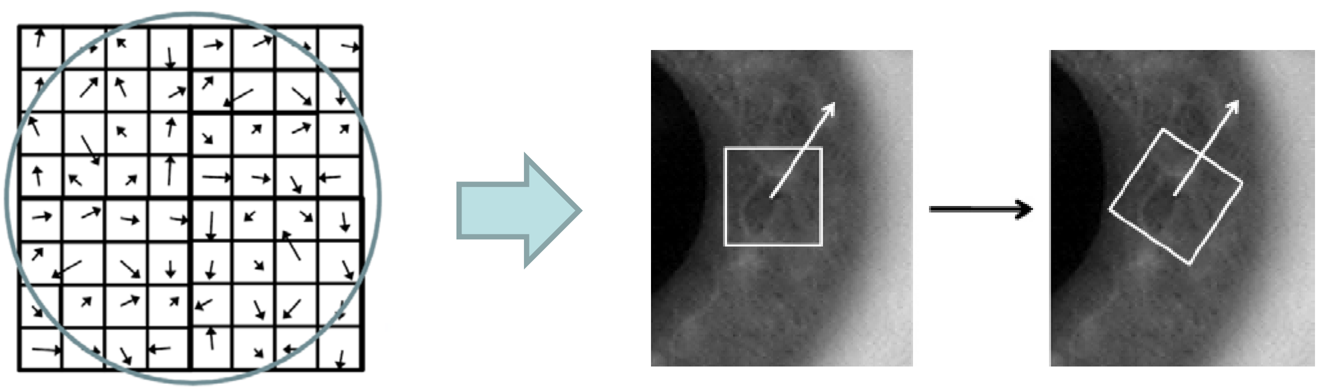
Scale Invariant Feature Transformation (SIFT)

FEATURE EXTRACTION

2. Local extrema detection (II)

- Removal of **unstable points** (two thresholds)
  - Points with **low contrast** (sensitive to noise)
  - Points **along an edge** (sensitive to viewpoint or lightning variation)

- **Orientation assignment** to each point (rotational invariance)
  - Histogram of **gradient orientations** around the point (36 orientation bins covering 360 degrees)
  - Detection of the histogram peak

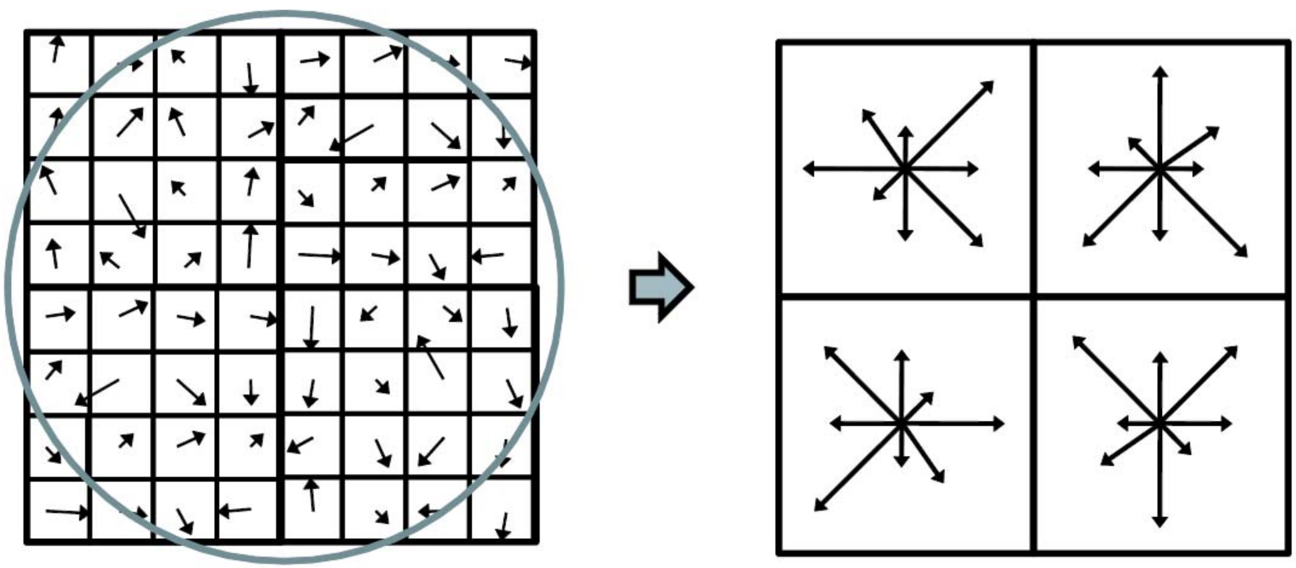


BIDS 2009

FEATURE EXTRACTION

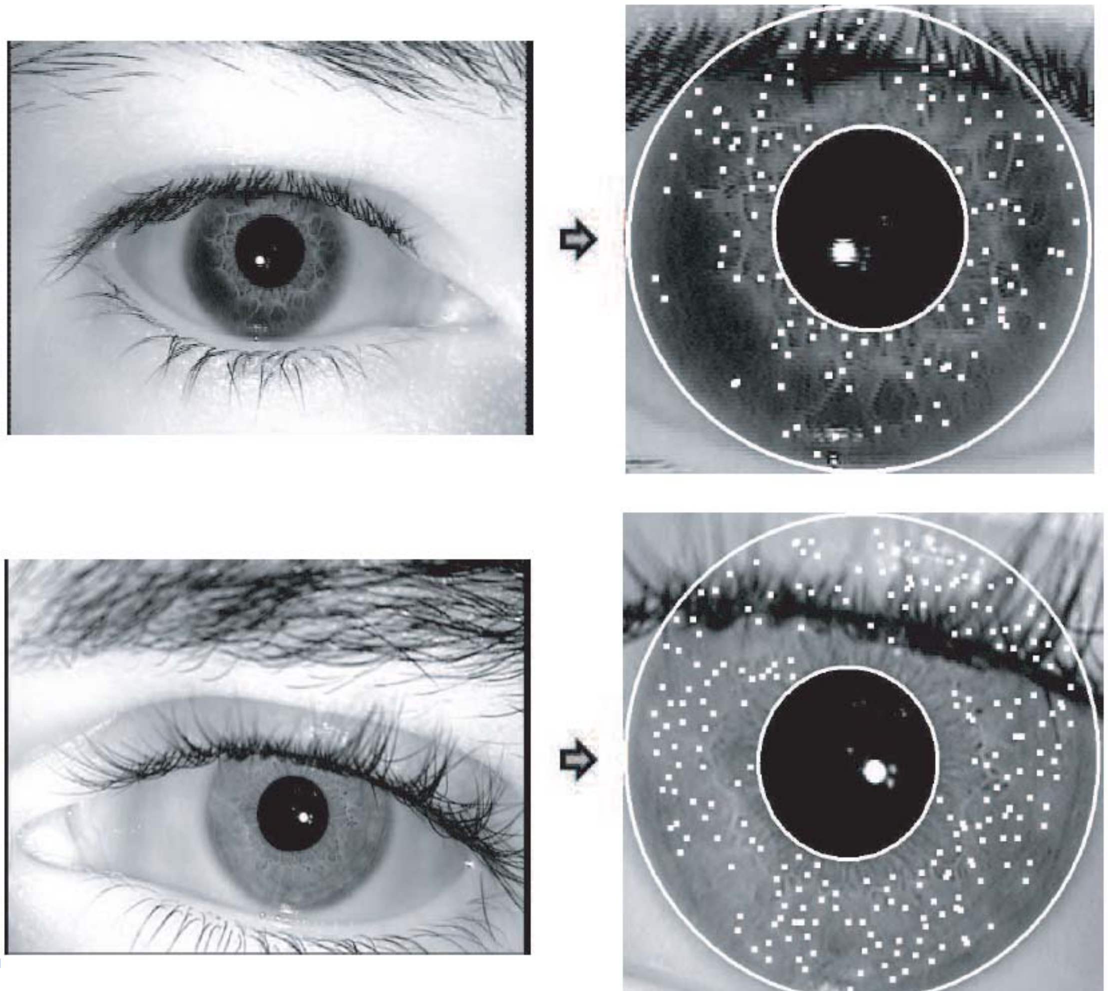
3. Keypoint descriptor extraction

- Histogram of **gradient orientations**, relative to the major orientation of the point (8 orientation bins covering 360 degrees)
- Computation in 4x4 sub-regions around the point
- **Vector** with all the histogram entries (4x4x8=128 elements)



Scale Invariant Feature Transformation (SIFT)

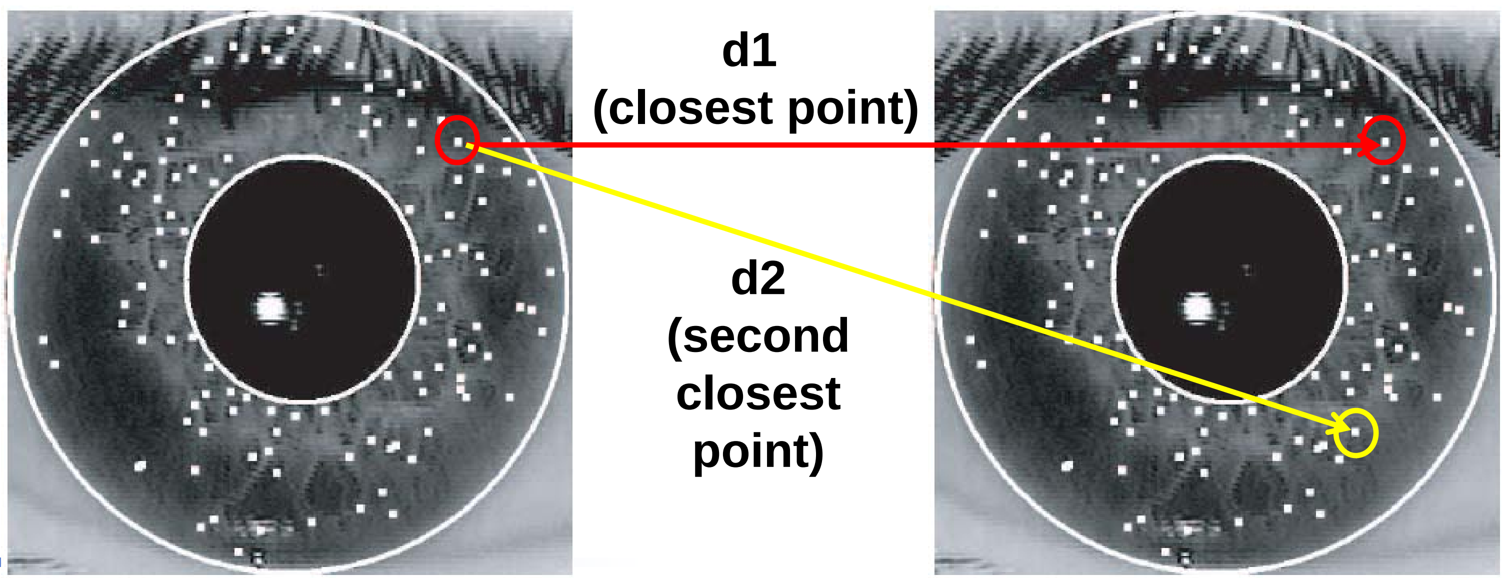
FEATURE EXTRACTION



FEATURE MATCHING

4. Keypoint matching

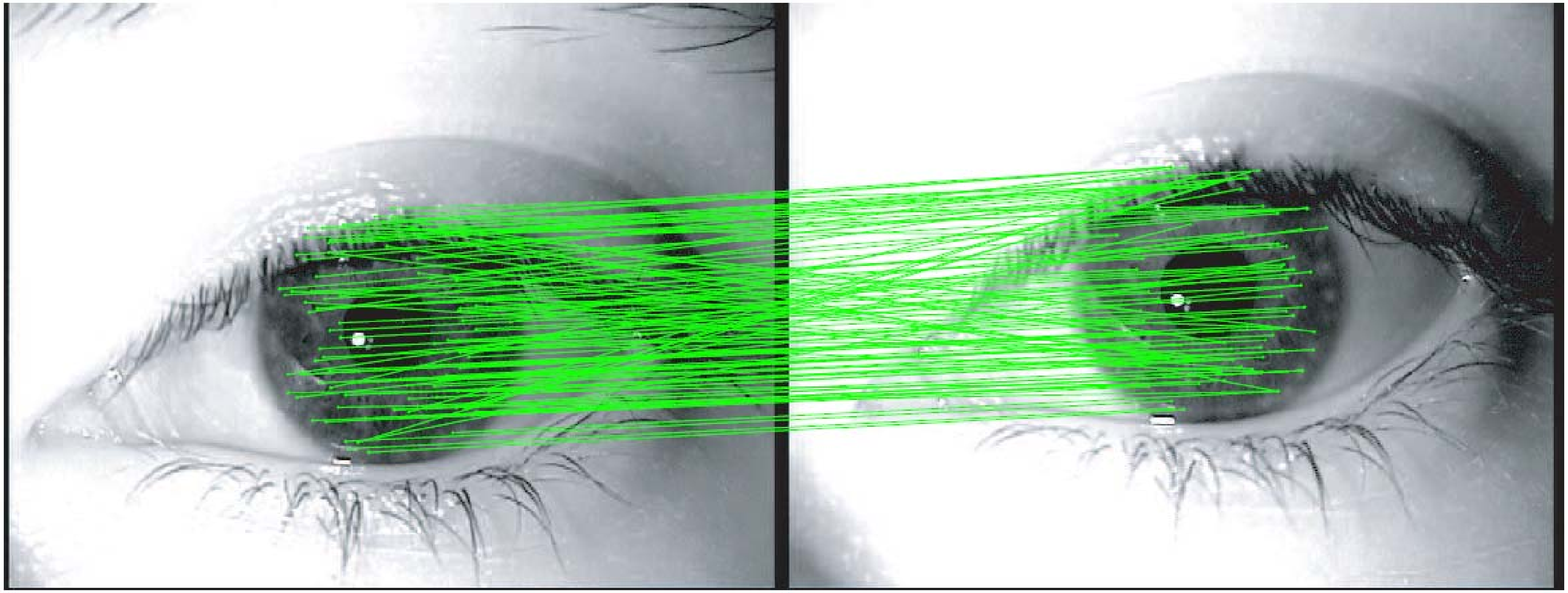
- Pairing of keypoints of two images based on the **Euclidean distance**
- **Matching of two points** if d1/d2 is sufficiently small



FEATURE MATCHING

4. Keypoint matching

- Pairing of keypoints of two images based on the **Euclidean distance**
- **Matching of two points** if d1/d2 is sufficiently small
- **Matching score** between two images=number of matched points



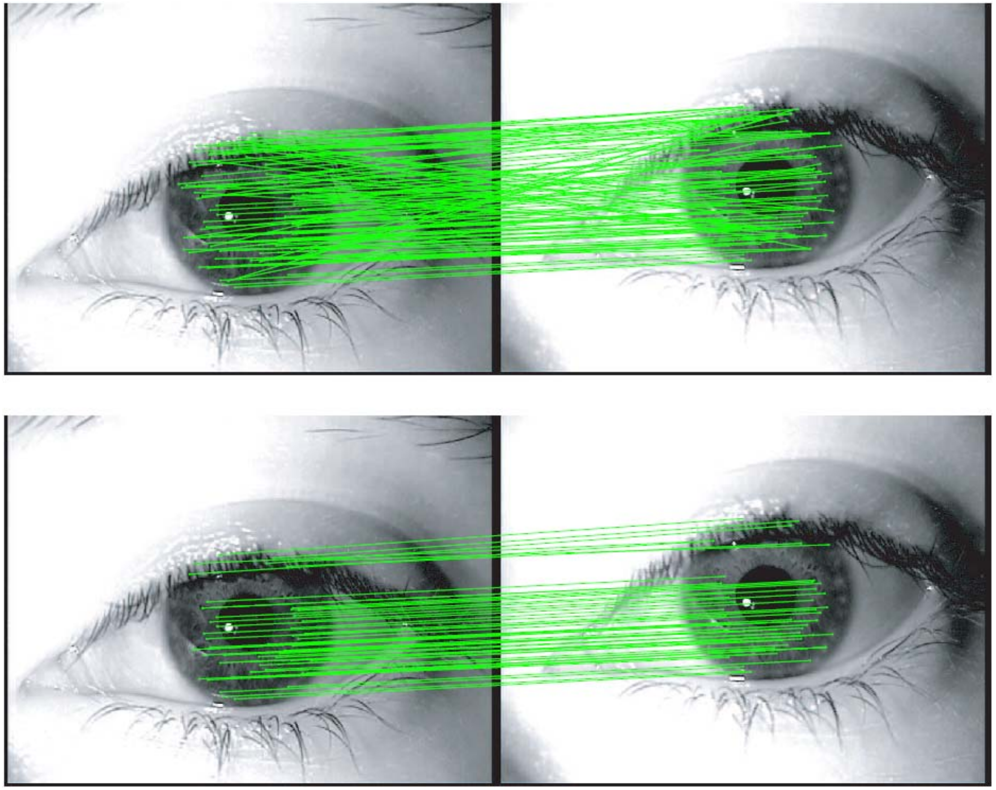
Scale Invariant Feature Transformation (SIFT)

FEATURE MATCHING

5. Trimming of false matches

- Removing erroneous matching points using **geometric constraints** by limiting typical geometric variations to **small rotations and displacements**

- Not proposed in the original algorithm, adapted from *

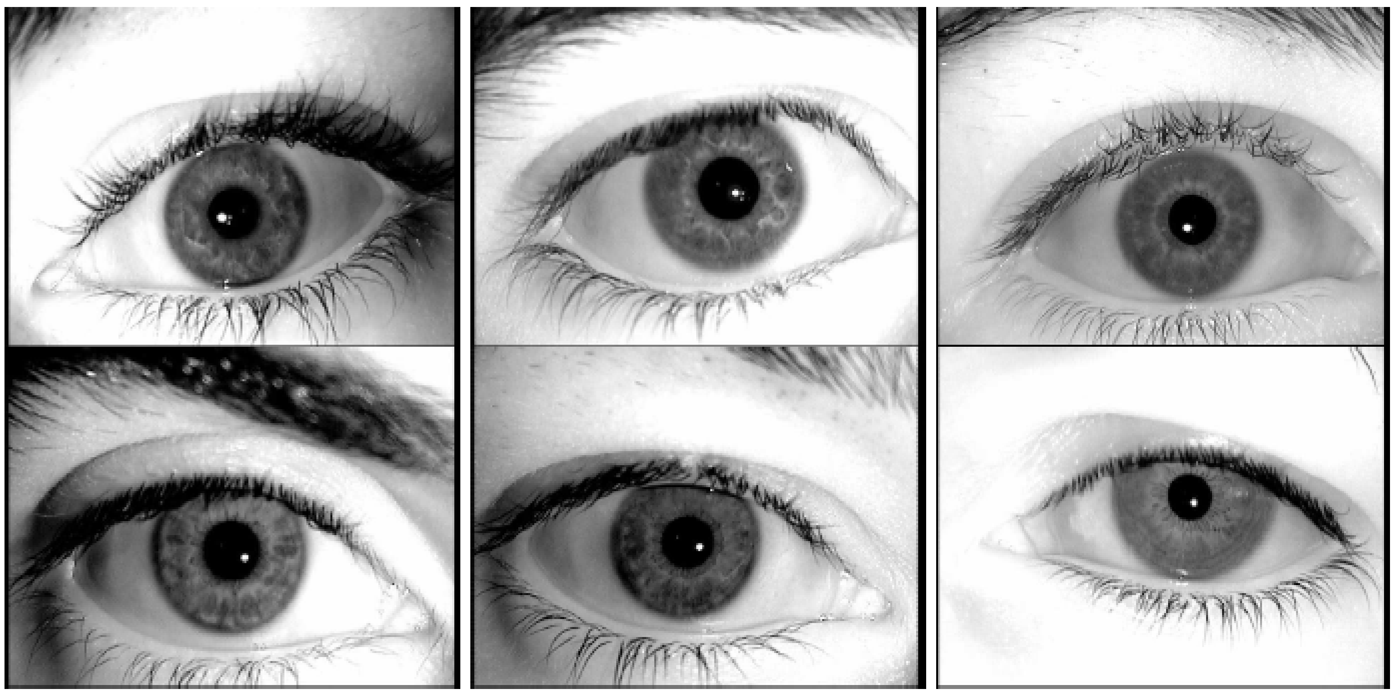


* U. Park, S. Pankanti, and A. K. Jain, “Fingerprint verification using SIFT features,” Defense and Security Symposium, Biometric Technologies for Human Identification, BTHI, Proc. SPIE, 2008.

Database and protocol

Database and protocol

- **200 subjects from the BioSec Multimodal Database (*)**
  - 2 acquisition sessions, office environment
  - Iris data with LG Iris Access 3000 sensor, image of 640x480 pixels
  - 200 individuals X 2 eyes X 4 images/eye x 2 sessions = 3200 images



*** J. Fierrez, J. Ortega-Garcia, D. Torre-Toledano, J. Gonzalez-Rodriguez, "BioSec baseline corpus: A multimodal biometric database," Pattern Recognition, vol. 40(4), 2007.**

Database and protocol

- **Protocol**
  - 50 individuals for training, 150 for testing
  - Each eye considered as a different user (total 400 users)

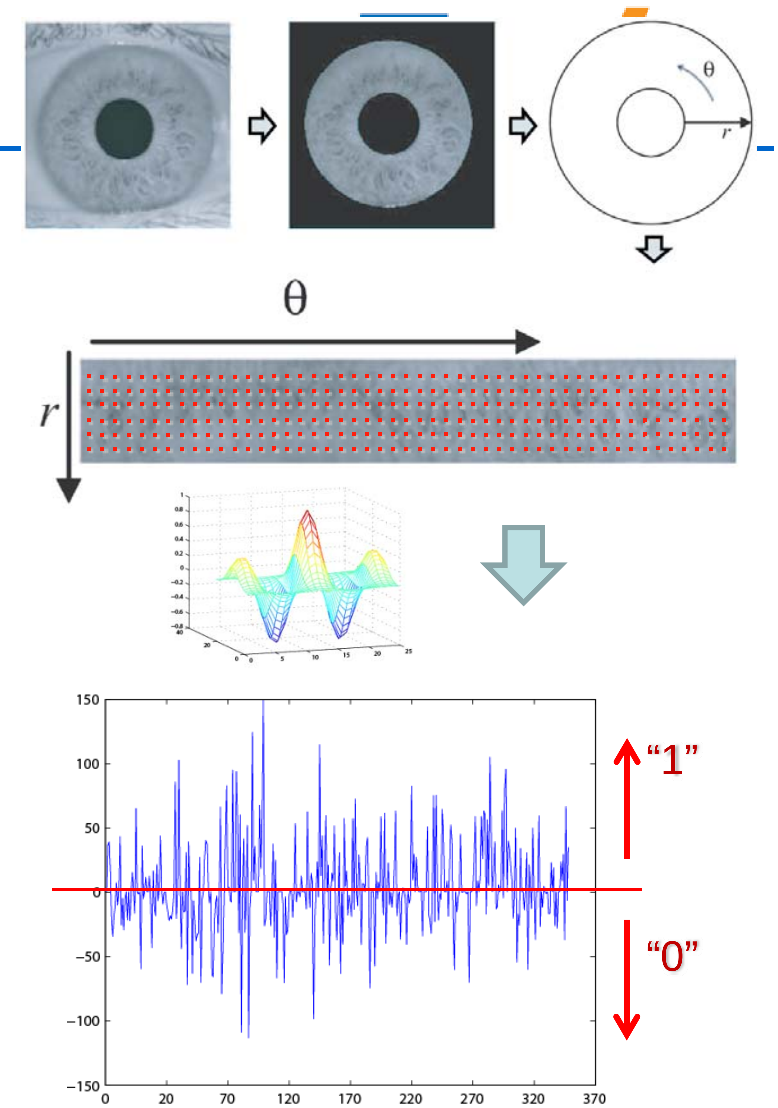
  - **Genuine matchings**= the 4 samples of the first session against the 4 samples of the second session
  - **Impostor matchings**= the 4 samples of the first session against 1 sample of the second session of the remaining individuals

  - **Images segmented automatically** using circular Hough transform + **manual correction** of incorrect images (to avoid bias in the performance due to incorrectly segmented images)

*** J. Fierrez, J. Ortega-Garcia, D. Torre-Toledano, J. Gonzalez-Rodriguez, "BioSec baseline corpus: A multimodal biometric database," Pattern Recognition, vol. 40(4), 2007.**

Database and protocol

- **Baseline iris matcher (*)**
  - For comparison with the proposed SIFT matcher
  - 1D implementation of the Daugman algorithm
  - Based on transformation to polar coordinates and Log-Gabor wavelets
  - Output of filtering is phase quantizied to binary level
  - Matching using the Hamming distance



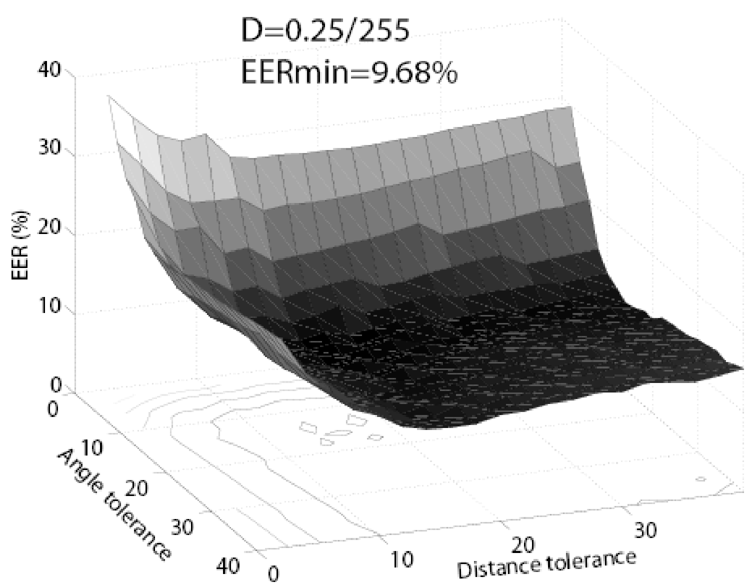

```
0101010101010001010101010101010001010101010101010001010101010101100
0101010101010101000101010101010101000101010101010101000101010101010101
0100010101010101010101000101010101010101010001010101010101010100010101010101
010101000101010101010101010100010101010101010101010101010101011101101111101
0101010110101011101111010100000011001010101010001001001011110110111 0
```

* L. Masek and P. Kovesi, “Matlab source code for a biometric identification system based on iris patterns,” The School of Computer Science and Software Engineering, The University of Western Australia, 2003.

Experimental Results

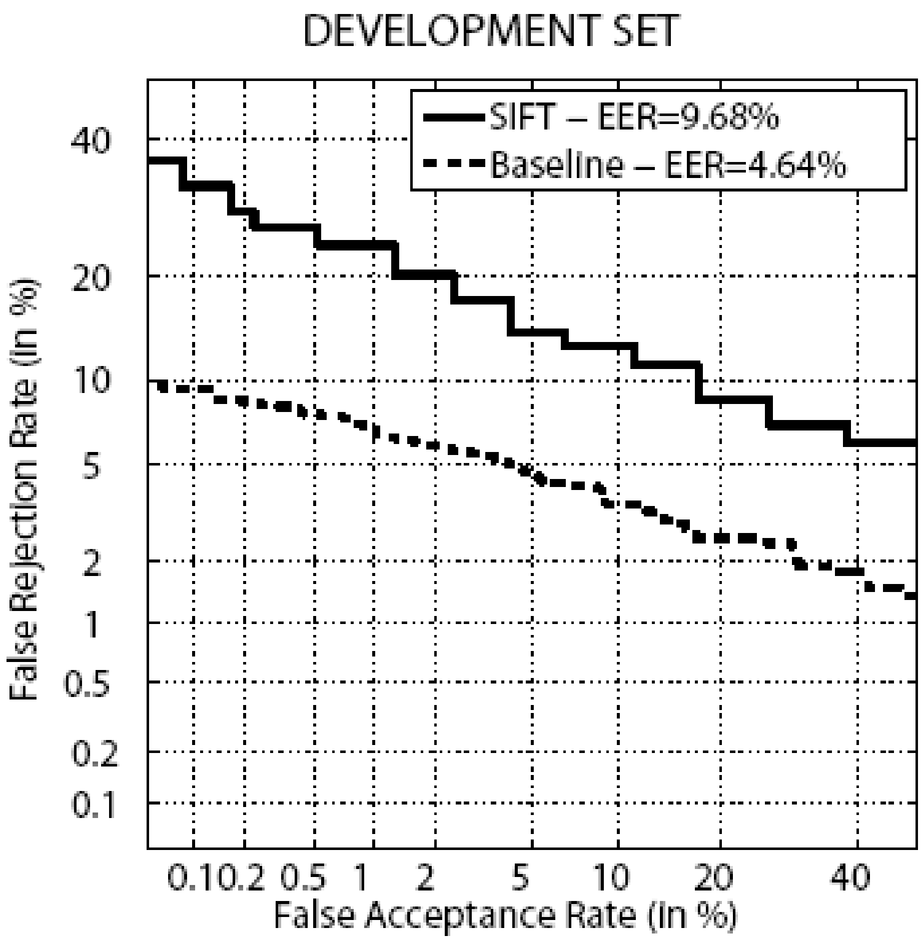
Results

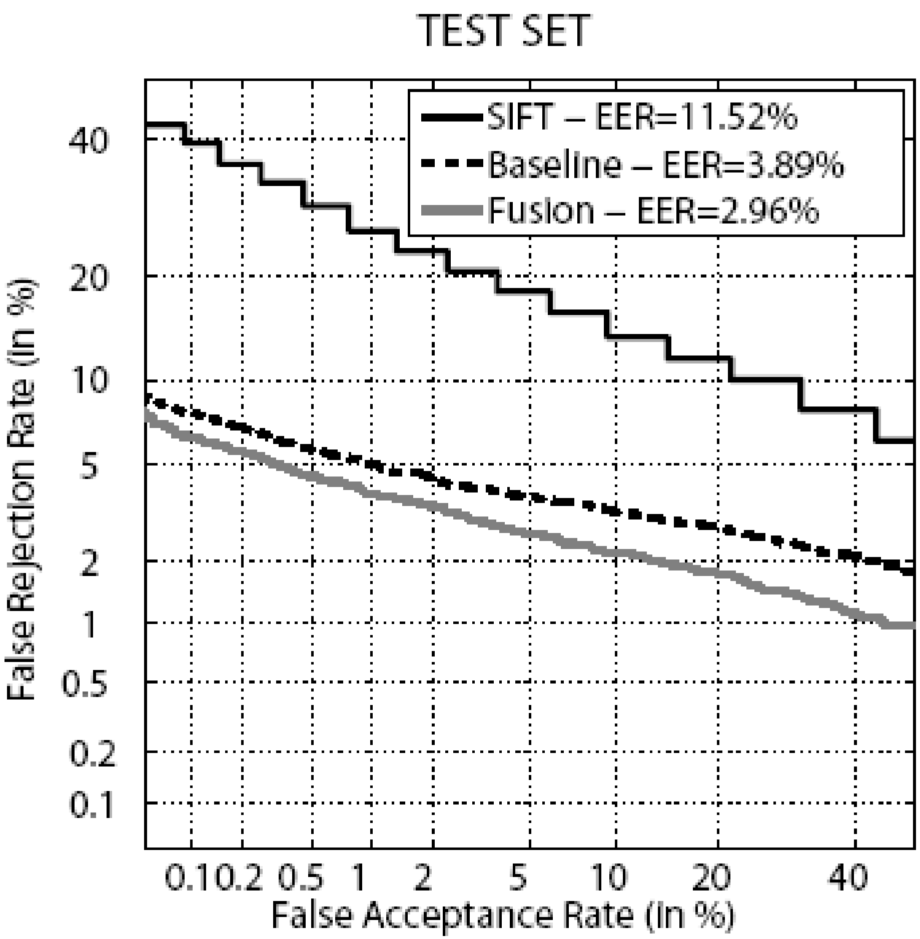
- **Optimization of SIFT parameters (training set)**
  - **Threshold D** for **discarding low contrast points** (the one proposed in the original paper discards most of the useful points in the iris region)
  - **Rotation and displacement tolerances** for **trimming of false matches**
  - Finding out the optimal combination of parameters (minimization of the EER in the training set):



D	ε_θ	ε_ℓ	EER
0.25	-	-	36.85%
0.25	**18**	**14**	**9.68%**
0.5	14	16	9.92%
0.75	18	14	10.96%
1	16	14	14.03%

- **RESULTS**


DEVELOPMENT SET
SIFT – EER=9.68%
Baseline – EER=4.64%
False Rejection Rate (in %)
False Acceptance Rate (in %)
0.1 0.2 0.5 1 2 5 10 20 40


TEST SET
SIFT – EER=11.52%
Baseline – EER=3.89%
Fusion – EER=2.96%
False Rejection Rate (in %)
False Acceptance Rate (in %)
0.1 0.2 0.5 1 2 5 10 20 40

Conclusions & Future Work

Conclusions

- **Proposal of the SIFT operator for iris feature extraction and matching**
  - Analysis of the influence of different SIFT parameters
  - Inclusion of an step for trimming of false matches

- Although the performance is (still) below popular approaches, we demonstrate its **feasibility** for iris recognition, as well as its **complementarity in the fusion**

- The SIFT operator:
  - Does not need transformation to **polar coordinates** or highly **accurate segmentation**
  - Due to its invariance to illumination, scale and rotation, it is expected to be feasible its use with **unconstrained image acquisition conditions**

Future Work

- Inclusion of **eyelids/eyelashes** detection

- Inclusion of **local quality measures** (*) to weight the contribution of each point to the matching score

- Applicability to datasets acquired in **unconstrained conditions** (**)

*** Y. Chen, S. Dass, and A. Jain, "Localized iris image quality using 2-D wavelets," Proc. International Conference on Biometrics, ICB, Springer LNCS-3832, 2006.**

**** NIST MBGC, NIST Multiple Biometric Grand Challenge http://face.nist.gov/mbgc, 2007.**

Iris Recognition Based on SIFT Features

Fernando Alonso-Fernandez, Pedro Tome-Gonzalez
Virginia Ruiz-Albacete, Javier Ortega-Garcia

Fernando Alonso-Fernandez
Biometric Recognition Group – ATVS
Escuela Politécnica Superior
Universidad Autónoma de Madrid, Spain
September 2009