On Iris Quality, Quality Based Segmentation and Quality of Large Biometric Databases

by

Natalia Schmid, WVU

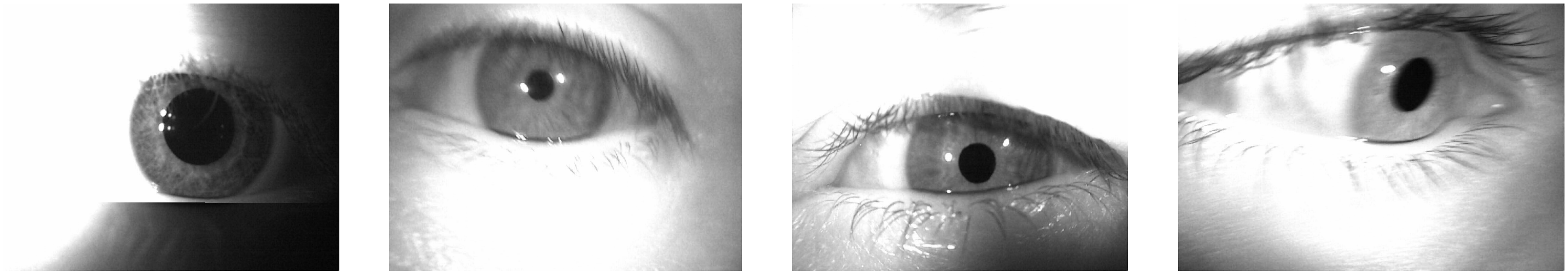
Sponsors: Center for Identification Technology Research,
Lockheed Martin

Outline

- On Iris Quality
  - Evaluation Methodology
  - Performance of quality evaluation algorithm
- Quality based restitution
  - Quality based segmentation
  - Other developments
- Biometric-Based Capacity as a global Quality measure

On Iris Quality

Motivation



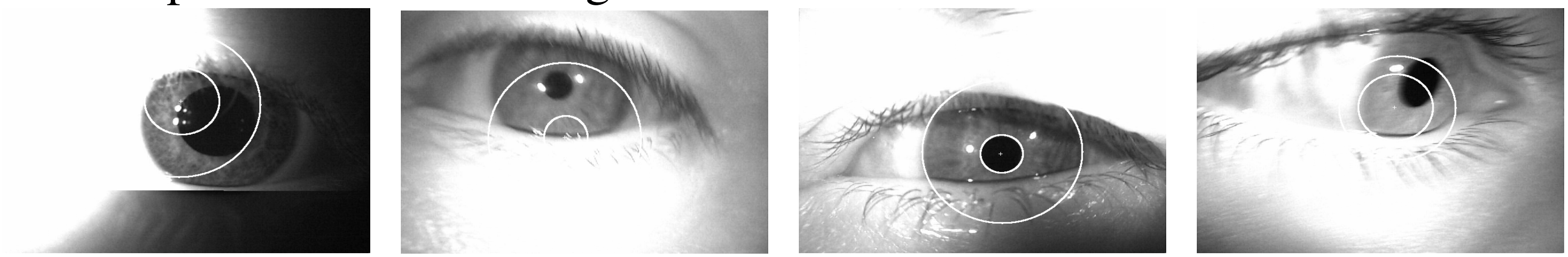
Images from an OKI camera collected at WVU

Sources of noise:

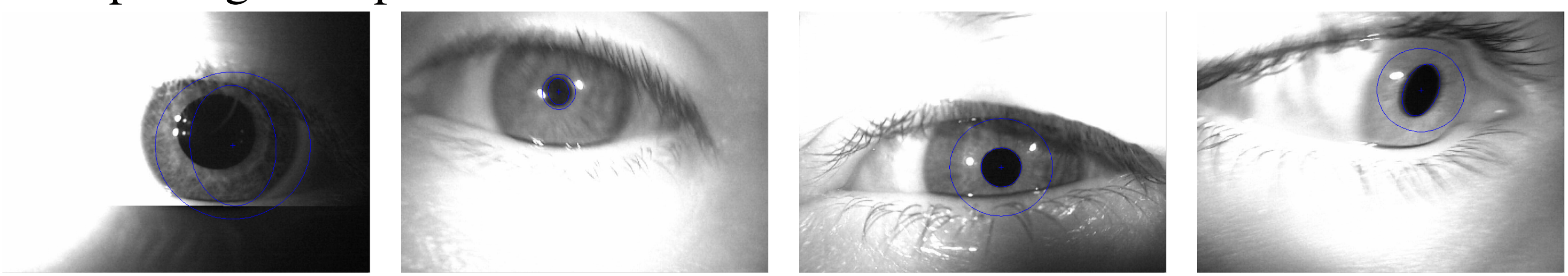
- Irregular Lighting
- Smear due to movement of camera or user
- Bad camera focus
- Physiology of the eye (Convexity of iris surface; Natural position and geometry of the eye)
- CCD shot noise

Motivation: Segmentation

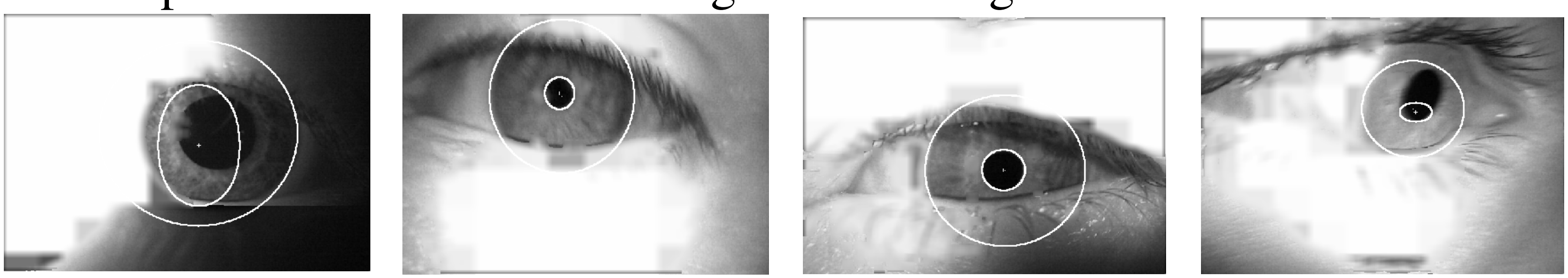
Our implementation of Daugman's Method



Morphological Operators



Our implementation of Wildes' segmentation algorithm.



Objective

Design quality assessment tool

- that allows adaptive recognition system
- that provides online feedback regarding image quality (fast feedback).

- Factors:
  - Defocus Blur
  - Motion Blur
  - Off-Angle
  - Lighting
  - Occlusion
  - Specular Reflection
  - Pixel Counts

Previous Works

(Zhu et al. 2004) - evaluate quality by analyzing the coefficients of particular areas of iris texture by employing discrete wavelet decomposition.

(Chen et al. 2006) - Classify iris quality by measuring the energy of concentric iris bands obtained using 2-D wavelets.

(Zhang and Salganicaff 1999) - examine the sharpness of the region between the pupil and the iris.

(Ma et al. 2003) - analyze the Fourier spectra of local iris regions to characterize defocus, motion and occlusion.

(Daugman 2004) and (Kang and Park 2005) - characterize quality by quantifying the energy of high spatial frequencies over the entire image region.

Features of Previous Works:

Estimation of a single or pair of factors such as defocus, motion blur, and occlusion

Combination Rule: Dempster-Shafer

Based on evidential reasoning (belief functions).
Applications: artificial intelligence, software engineering, and pattern classification.

Consider 3 beliefs (Estimated factors) A1, A2, A3 such that $A1 \leq A2 \leq A3$ then min confidence can be calculated by the following expression:

$$M(A1\ ,\ A2) = \frac{(A1 * A2)^n}{(A1 * A2)^n + (1 - A1)^n\,(1 - A2)^n}$$

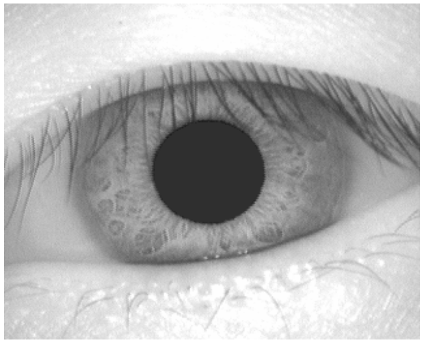
n ~ correlation

$$M(\ M(A1\ ,\ A2)\ ,\ A3) = \frac{(M(A1\ ,\ A2) * A3)^n}{(M(A1\ ,\ A2) * A3)^n + (1 - M(A1\ ,\ A2)\ )^n\,(1 - A3)^n}$$

Similarly, max confidence can be found by sorting the factors in increasing order and evaluating the same expressions.

R. Murphy, “Dempster-Shafer Theory for Sensor Fusion in Autonomous Mobile Robots,” IEEE Trans. Robotics and Automation, vol. 14, no. 2, Apr. 1998.

Belief Function: Example



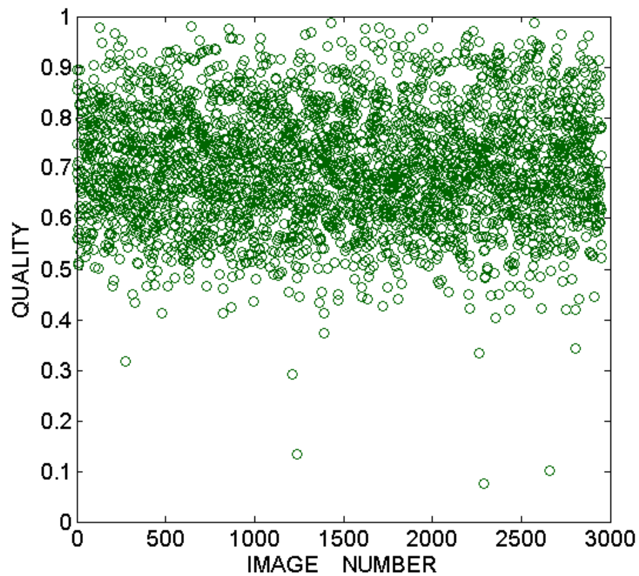
Defocus	Motion Blur	Occlusion	Max Conf.	Min Conf.
0.11524	0.0125	0.45122	.94	.85

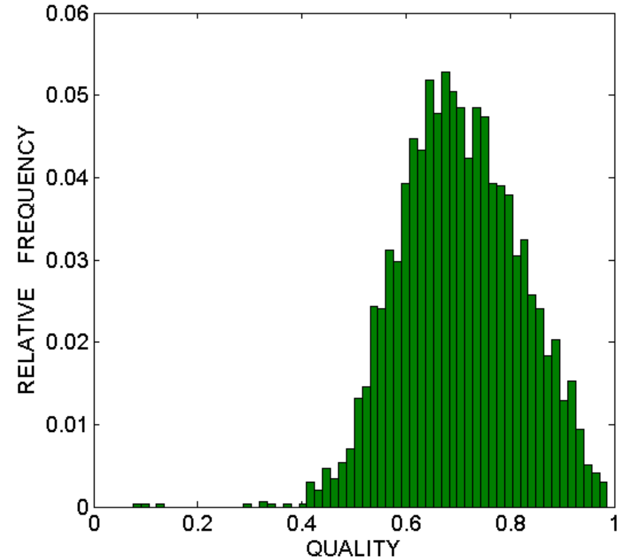
- A sample CASIA image, and confidence bounds for image quality.
- Scores are between [0,1] with 0 corresponding to the lowest error and 1 corresponding to highest error.

Defocus	Motion Blur	Occlusion	Max Conf.	Min Conf.
0.68843	0.0125	0.38889	.89	.69

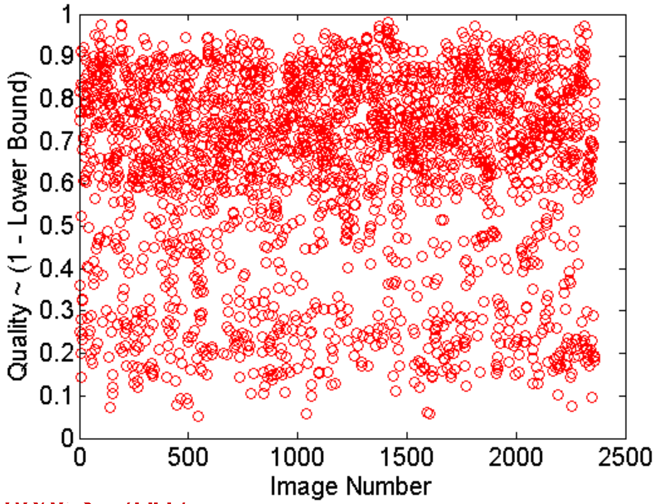
With a bad quality image, the bounds are not tight. The image is characterized by high Occlusion and Defocus blur.

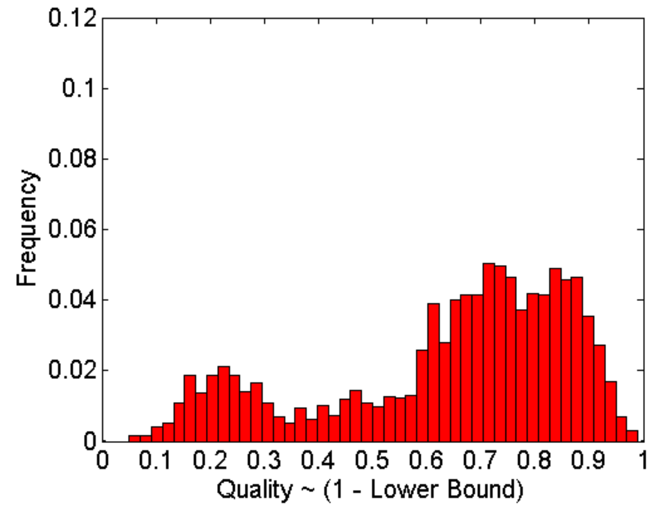
Quality per Image





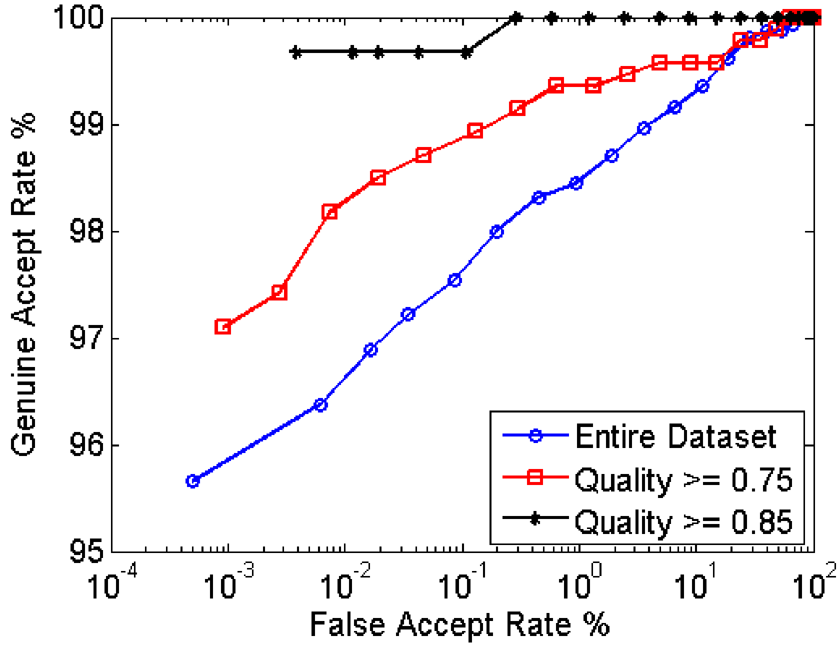
ICE 2005





WVU

Performance: Gabor based



Interval	EER	Dprime	Quality	Images
All	1.30	2.63	0.79	738
Quality $\geq$ 0.75	0.63	2.79	0.85	556
Quality $\geq$ 0.85	0.11	3.13	0.89	273

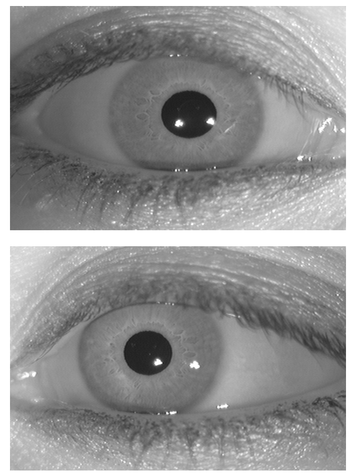
Quality Based Restitution

Options for Adaptive Restitution

Regular Quality Feedback

Data Acquisition

Enhancement



Use more bits,

More filters, etc.

Encoding

Adaptive Deblurring, Restoration, Mosaicking Superresolution, etc.

Adaptive Metrics or Threshold

Matching

Multiple Algorithms Multiple Metrics, etc.

Adaptive Score or Decision Fusion

Robust Segmentation

Introduction

Previous Segmentation Methods

- J. Daugman @ University of Cambridge (efficient integro-differential operators)

- R. P. Wildes @ The Sarnoff Corporation (circular Hough transform)
- X. Liu etc. @ University of Notre Dame
- Q. Tian, Q. Pan, Y. Cheng, and Q. Gao

- J. De Mira Jr. and J. Mayer (morphological operators)
- E. Sung, X. Chen, J. Zhu, and J. Yang from Nanyang Technological University and Carnegie Mellon University (ellipse fitting)

- H. Proença and L.A. Alexandre @ Universidade da Beira Interior (texture segmentation)

- C. Fancourt etc. @ The Sarnoff Corporation (distance, off-angle and eyewear)

- V. Dorairaj, N. A. Schmid, and G. Fahmy @ WVU (off-angle)
- A. Abhyankar, L. A. Hornak, and S. Schuckers from Clarkson University and WVU (off-angle)

Introduction

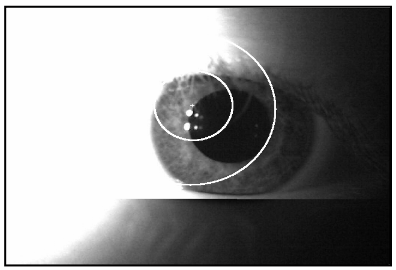
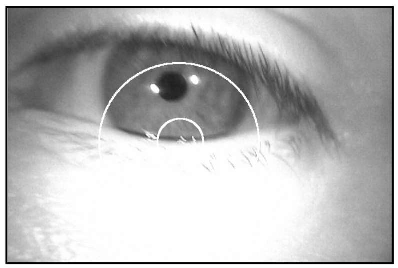
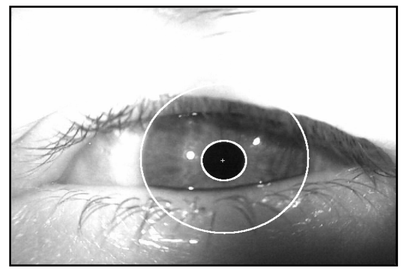
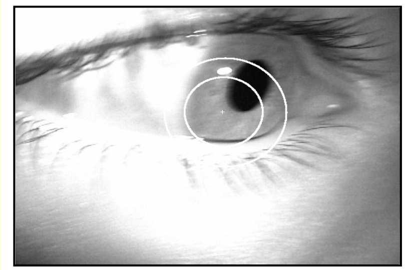
occlusion
specular reflections
lighting problem

occlusion
specular reflections
motion blur

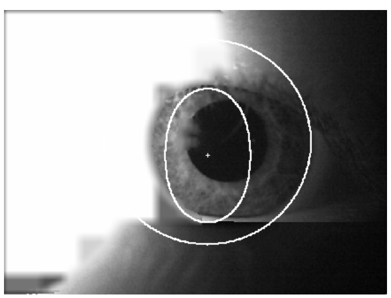
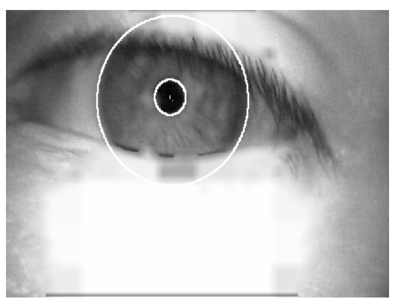
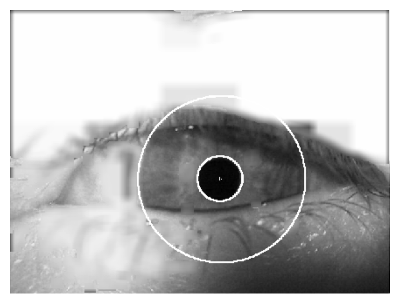
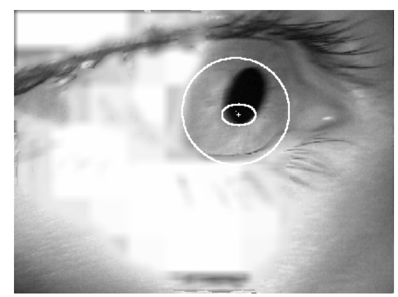
occlusion
specular reflections

occlusion
specular reflections
motion blur
off-angle

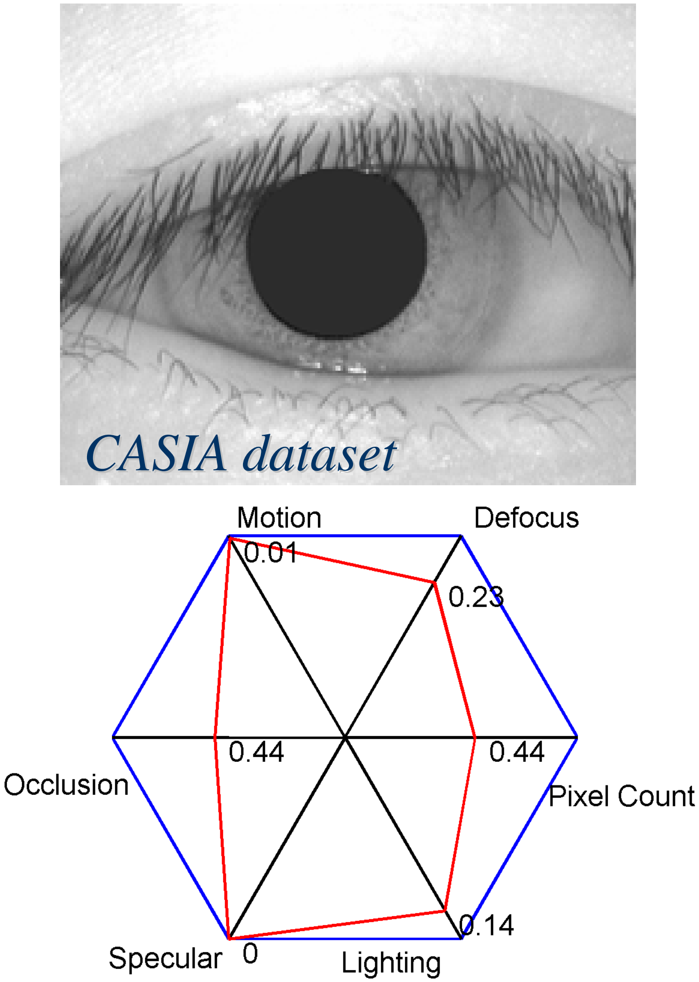
Our implementation of Daugman's segmentation algorithm

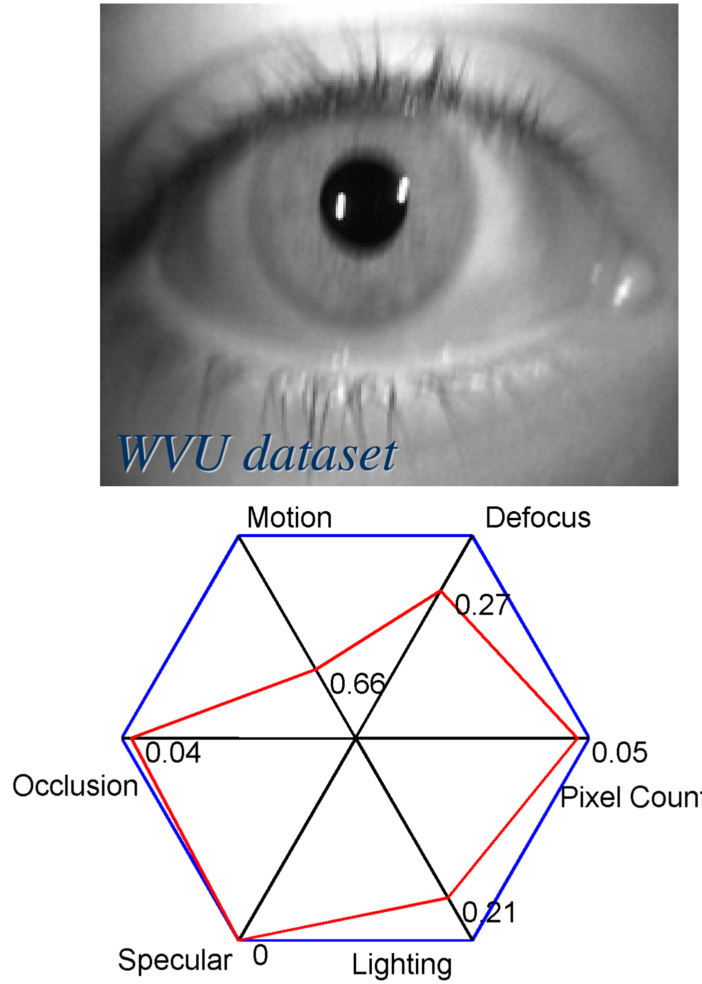





Our implementation of Wildes's segmentation algorithm

Quality Factors



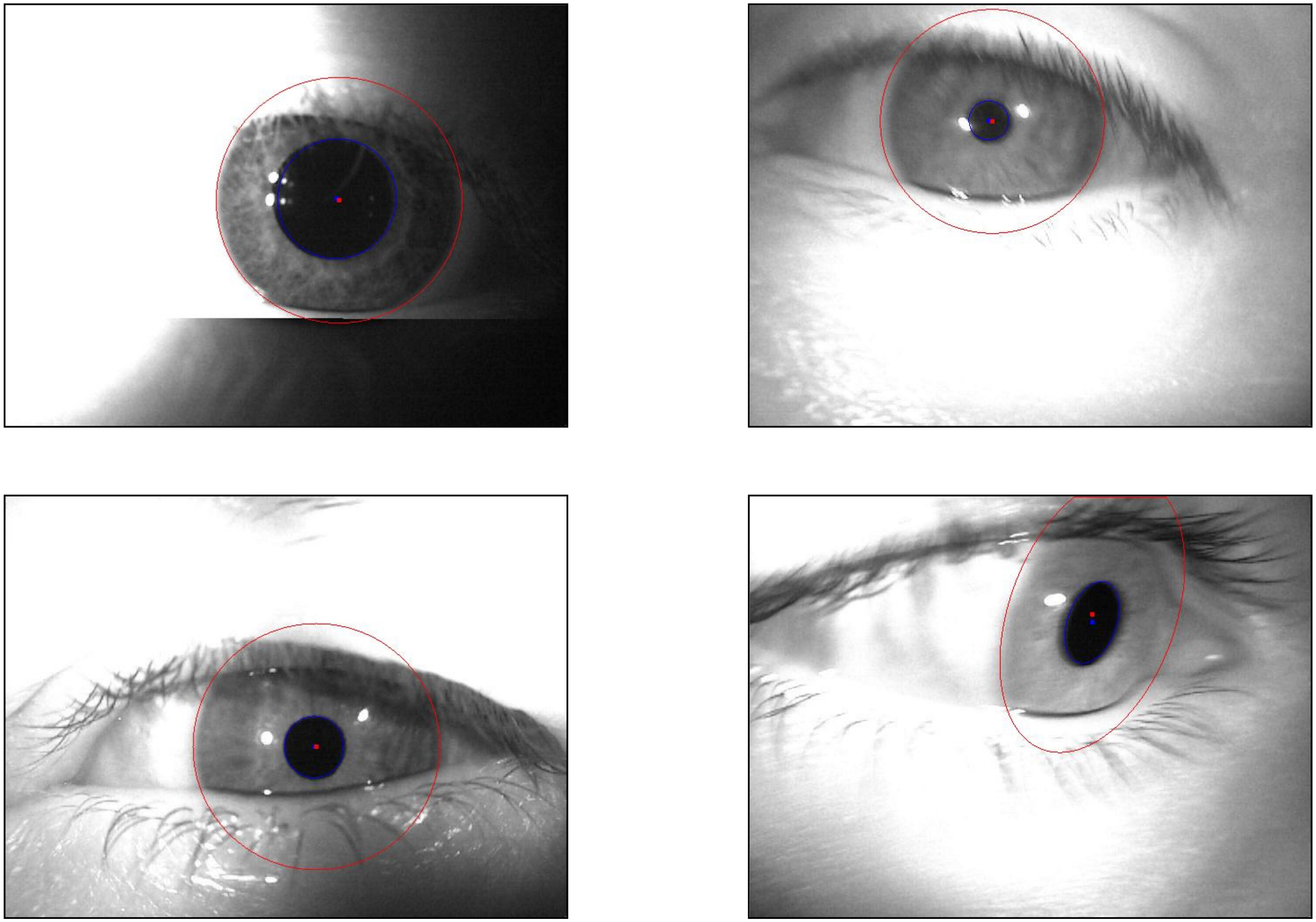


N. D. Kalka, J. Zuo, N. A. Schmid, and B. Cukic, "Image quality assessment for iris biometric," Proc. of 2006 SPIE Conf. on Biometric Technology for Human Identification III, vol. 6202, pp. 62020D–1 – 62020D–11, Apr 2006.

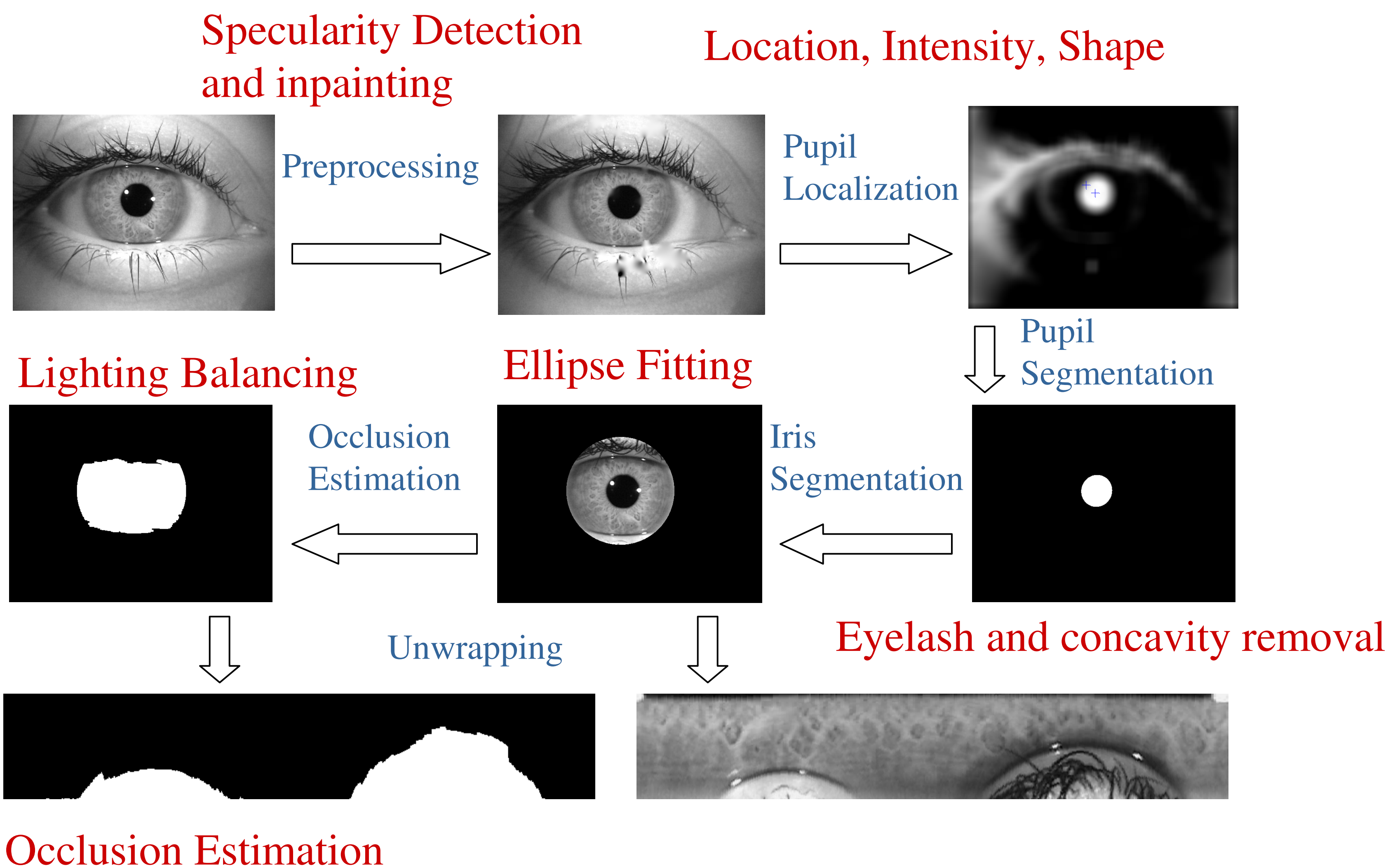
Inclusion of Quality Factors

Quality factors	Our solutions
Occlusion	A new occlusion estimation method
Specular reflections	They are masked and inpainted
lighting problem	Contrast weight compensation
Out-of-focus blur and **motion blur**	
Pixel count	Intensity based pupil segmentation
Off-angle	Ellipse fitting

Results of Segmentation

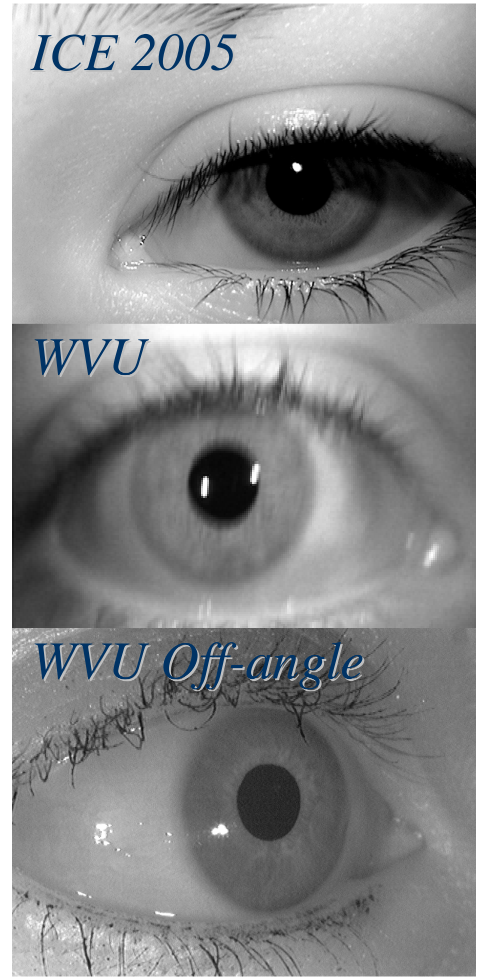


Main Block Diagram



Segmentation Performance

Database name	Database size	# of Classes	# of images per class	Main quality factors
ICE 2005	**2953**	**244**	**1 - 43**	**ALL**
WVU	**2453**	**359**	**2 - 17**	**ALL**
WVU Off-Angle	**560**	**140**	**4**	**Occlusion, out-of-focus blur, specular reflection, pixel count, off-angle**

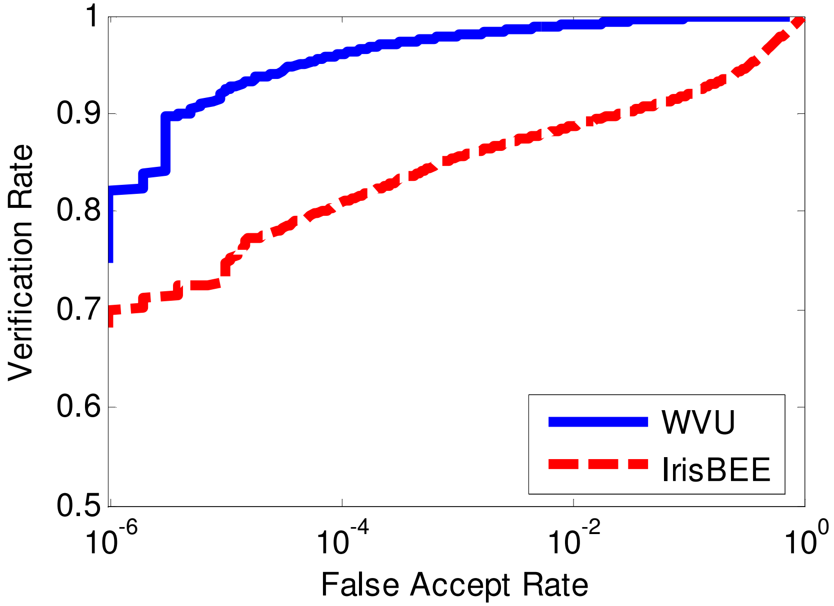


Segmentation Performance (continue)

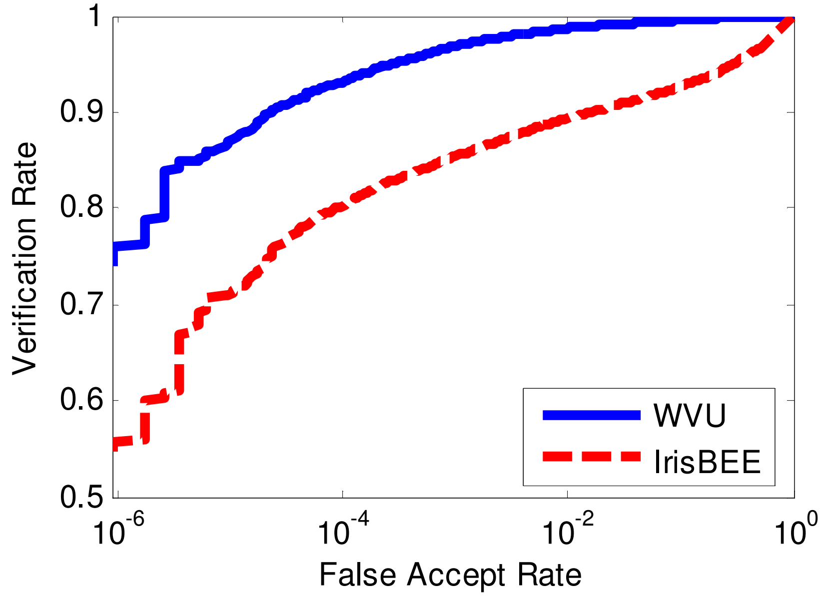
Database name	Masek	Camus and Wildes (our implementation)	Proposed
CASIA I	86.90 %	98.54 %	99.74 %
ICE 2005	91.20 %	90.79 %	99.15 %
WVU	64.77 %	85.24 %	95.84 %
WVU Off-Angle	71.43 %	70.00 %	97.32 %

Recognition Performance

ICE 2005:



Right eyes

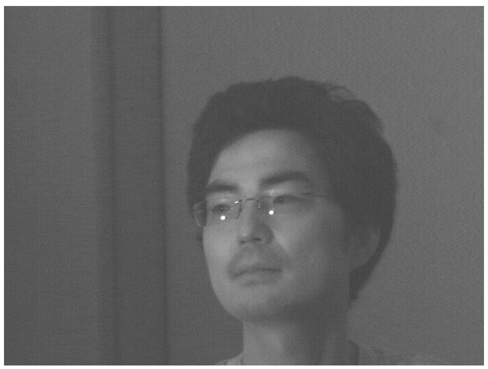


Left eyes

Large Databases: Quality Measure

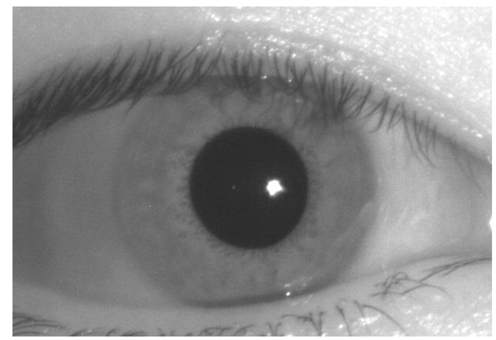
Model Based Approach

If **probabilistic model** is well fitted to describe experiment, fundamental limits (in design procedure) can be achieved.



3D world

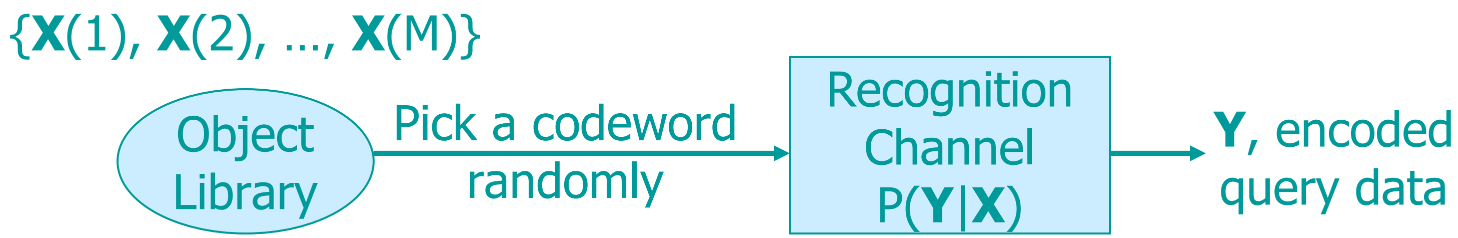
channel, transformation, acquisition device, etc.



measurement

Recognition Channel (Communication Theory Approach)

Given an encoding technique, the remaining factors can be attributed to a recognition channel [Schmid04,Westover05].



- templates {**X**(1), **X**(2), ..., **X**(M)} are i.i.d. random vectors.
- **Y** is a distorted, noisy realization of one template in the library.

• N. A. Schmid and J. A. O'Sullivan, "Performance prediction methodology for biometric systems using a large deviations approach," *IEEE Trans. On Signal Processing*, Supplement on Secure Media, vol. 52, no. 10, pp. 3036-3045, Oct 2004.
• M. B. Westover and J. A. O'Sullivan, "Achievable rates for pattern recognition: Binary and Gaussian cases," in *International Symp. On Information Theory (ISIT)*, Adelaide, Australia, 2005, pp. 28-32

Recognition Capacity

- Process data such that templates of different individuals are weakly dependent or independent and have similar distributions.
- From Information Theory, the constrained capacity

$$\bar{I}(X,Y) = \lim_{n\to\infty} \frac{1}{n} E\left[\log \frac{p(X^n, Y^n)}{p(X^n)\,p(Y^n)}\right],$$

- X^n and Y^n are one of templates and a query template.
- The results are valid for ideal case: everything is known.

Practical Case

- The parameters of distributions or distributions are estimated using training labeled data.
- The limiting empirical capacity becomes

$$\lim_{n\to\infty,\quad M\to\infty} \frac{1}{n} E\left[\log \frac{\hat{p}(X^n, Y^n)}{\hat{p}(X^n)\hat{p}(Y^n)}\right],$$

- "Hat" indicates estimated distribution functions
- Estimates depend on the size of the training set, M.
- The capacity can be found only if the sequence is ergodic.

PCA and ICA-based Capacity

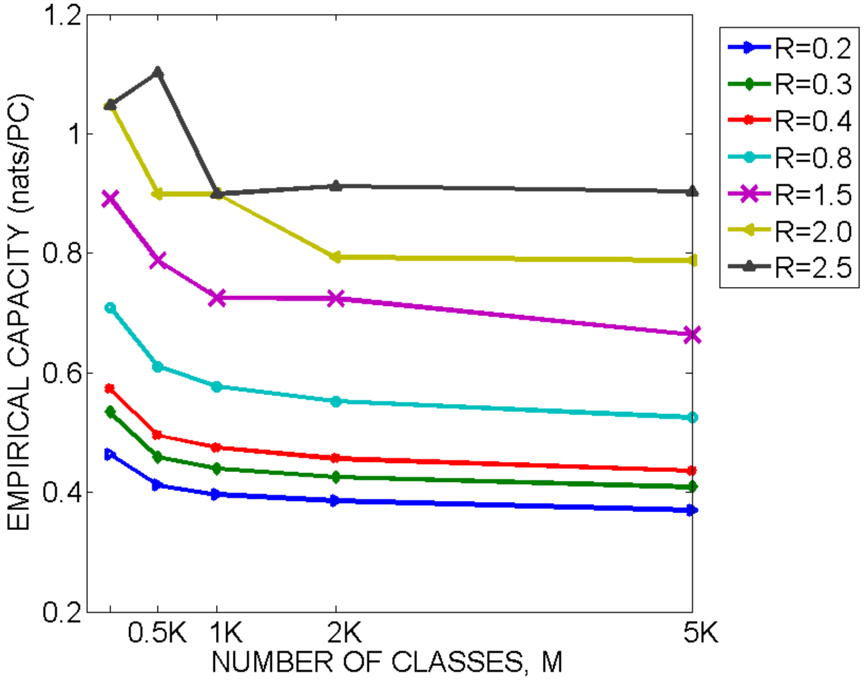
M<<resolution

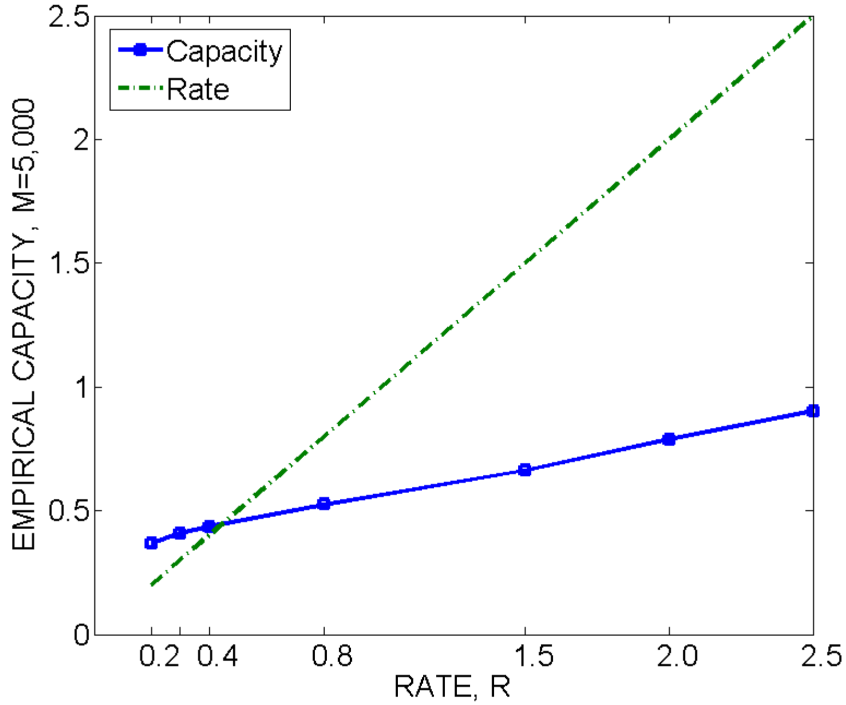
Iris Database	PCA Empirical Capacity (bits per component)	ICA Empirical Capacity (bits per component)
WVU	0.3198	0.5301
CASIA III	0.5030	0.8102
BATH	1.1284	2.9483

Interpretation: Let the length of templates be n=100. Let the capacity be C=0.5301. Then the number of users that can be recognized asymptotically with a small probability of error is $M = 9.0698 \times 10^{15}$.

PCA and ICA-based Capacity

Resolution << M





- Rate: R=log(M)/n
- PCA capacity is 0.4466.
- ICA capacity is 0.4325.

Ongoing Research

- Quality Based Restitution of Iris Features in High Zoom Images for Less Constrained Iris Recognition System
- Fusion at the Score Level using Dempster-Shafer Network
  - Adaptive fusion based on iris image quality
  - Capacity at the Match Score Level

Contact Information

Natalia.Schmid@mail.wvu.edu

Phone: (304) 293-0405 x 2557