Iris recognition at 20 years: from zero to 150 trillion iris comparisons per day

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Professor of Computer Vision and Pattern Recognition

University of Cambridge

IAPR Keynote Lecture

International Conference on Biometrics

New Delhi, 1 April 2012

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A 20-year anniversary (1992—2012):

October 21, 1992

IEEE COMPUTER SOCIETY

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SUBJECT: YOUR MANUSCRIPT "HIGH CONFIDENCE RECOGNITION...", PAMI #92-08-31

Dear Professor Daugman:

Enclosed are three reviews of your manuscript which was submitted for publication in the IEEE Trans. PAMI. All the three reviews are positive and recommend publication after minor revisions. I have also quickly read the manuscript and found it to be very

1148 IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, VOL. 15, NO. 11, NOVEMBER 1993

High Confidence Visual Recognition of Persons by a Test of Statistical Independence

John G. Daugman

Sincerely,

Anil K. Jain

Anil K. Jain
Editor-in-Chief, TPAMI

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Today, some 200 papers per year are published on this topic

(chart from survey chapter by Bowyer et al., in Handbook of Iris Recognition, 2012):

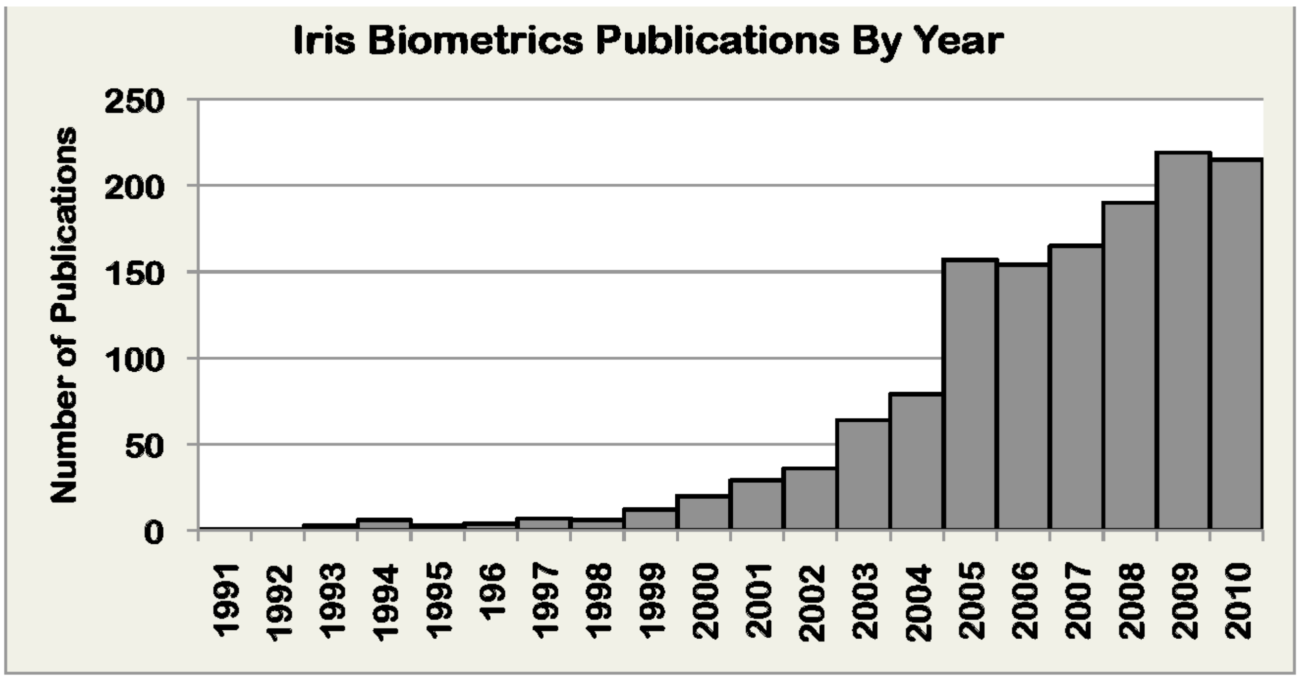

Fig. 1 Iris Biometrics Papers in Google Scholar from 1990 through 2010. This data was taken using Google Scholar's "advanced search" facility, searching for "iris biometrics pupil" appearing in articles, excluding patents, in the Engineering, Computer Science and Mathematics literature.

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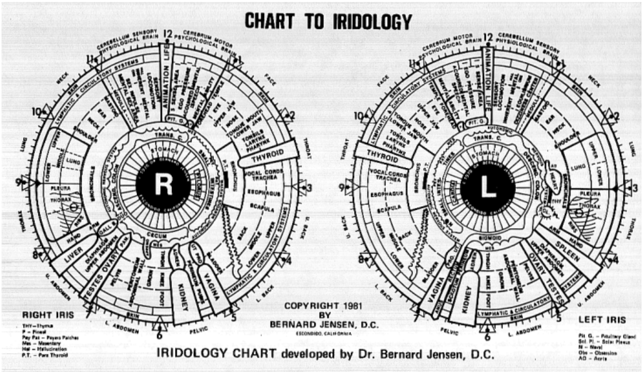
Deeper origins of iris recognition

- Adler (*Physiology of the Eye,* 1952): *"In fact, the markings of the iris are so distinctive that it has been proposed to use iris photographs as a means of identification, instead of fingerprints."*
- Doggart (*Ocular Signs in Slip-Lamp Microscopy,* 1949): *"Just as every human has different fingerprints, so does the minute architecture of the iris exhibit variations in every subject examined."*

  (The proposals of Doggart and of Adler were patented in 1987 by Flom and Safir, but without any actual algorithm for iris recognition.)
- Bertillon (*"Tableau de l'iris humain",*1892) documented nuances
- Divination of all sorts of things based on iris patterns goes back to ancient Egypt, Babylonia, and Greece. Iris divination persists today, as "Iridology."



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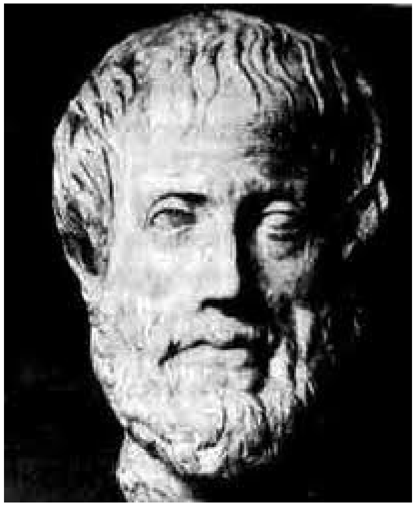
Philosophy of Biometrics



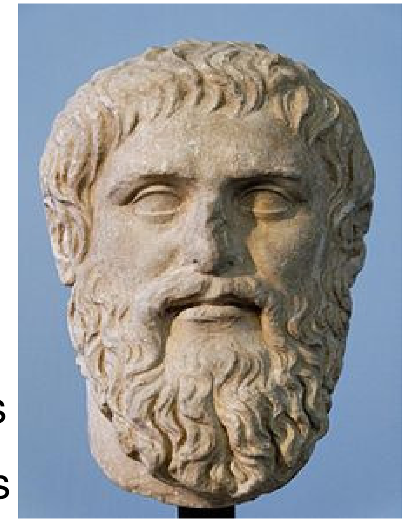
Aristotle (384 BC – 322 BC)

The **universal** and the **particular**:

- need to detect first that this object is a **generic** object (a face, iris, etc); and then, that this is a **specific** individual instance.

Face detection; iris segmentation: → **universal** features

Face/iris identification: → analysis of **particular** features



Plato (424 BC – 348 BC)

Ancient philosophical question about essences:
"What makes something **different from everything else?**"

universal forms: ειδε (a face, an eye) particular forms: ουσια (this face, this eye)

Iris recognition works by the **Failure of a test of statistical independence**: you are (statistically) guaranteed to pass this test of independence against all other irises; but to fail this test only against another image of your same eye.

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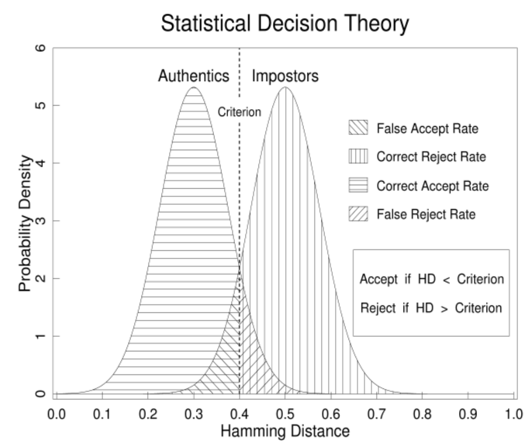
Biometrics, fuzzy-matching, and a 7-valued logic in Jainism (a 3000+ year old Indian philosophy)

Biometric decision-making maps ambiguous or fuzzy similarity into Aristotelian "same/different" classes. But in the "Age of Jain Logic" (4th-16th century) there were 7:

1. Syād-asti — "in some ways it is"
2. Syād-nāsti — "in some ways it is not"
3. Syād-asti-nāsti — "in some ways it is and it is not"
4. Syād-asti-avaktavya — "in some ways it is and it is indescribable"
5. Syād-nāsti-avaktavya — "in some ways it is not and it is indescribable"
6. Syād-asti-nāsti-avaktavya — "in some ways it is, it is not and it is indescribable"
7. Syād-avaktavya — "in some ways it is indescribable"

Mahavira (599 BCE)



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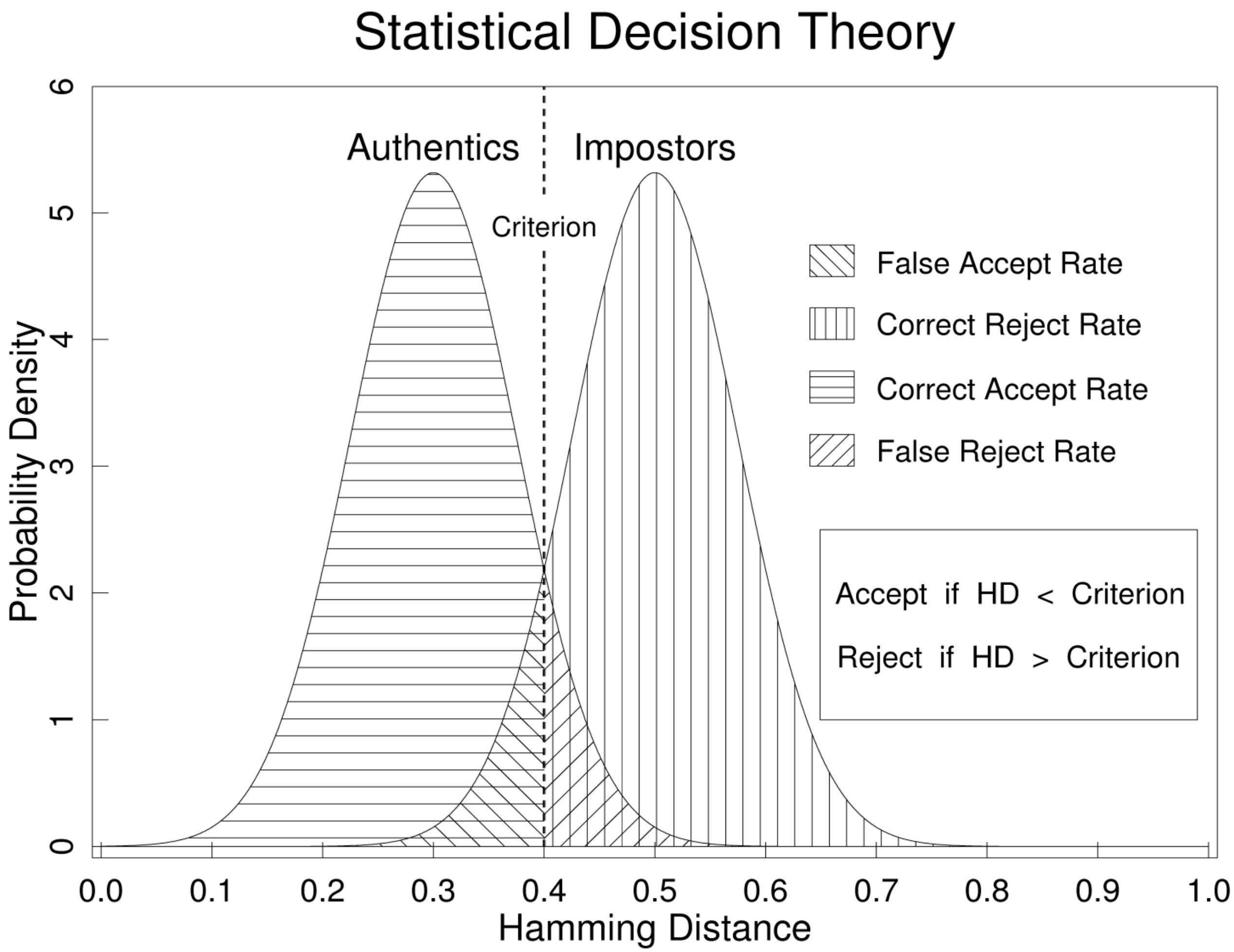

Biometric decision power depends on the magnitudes of within-person variability and between-person variability

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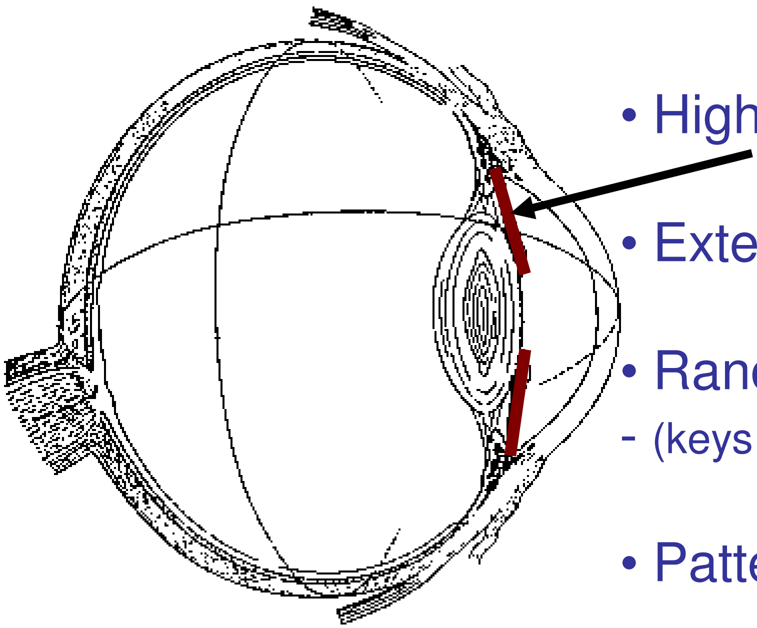
Properties of the Iris as an Identifier



- Highly protected, internal organ of the eye
- Externally visible, from distance up to some meters
- Random pattern of great complexity & uniqueness
  - (keys to uniqueness are randomness + complexity)
- Pattern is epigenetic (not genetically determined)
- Presumed stable, apart from pigmentation changes
  - (no evidence of any visible pattern changes, although there is some evidence that computed IrisCode templates may "age")

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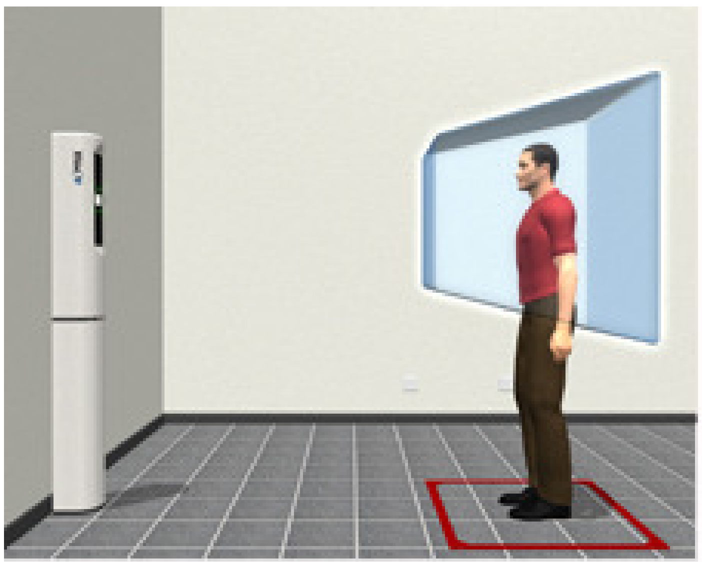
In early iris recognition systems, sometimes the user interface was not always as convenient and user-friendly as it might or should have been...



Today: 2 meter stand-off distance, capture volume ≈ 1 cubic meter

(courtesy Aoptix)

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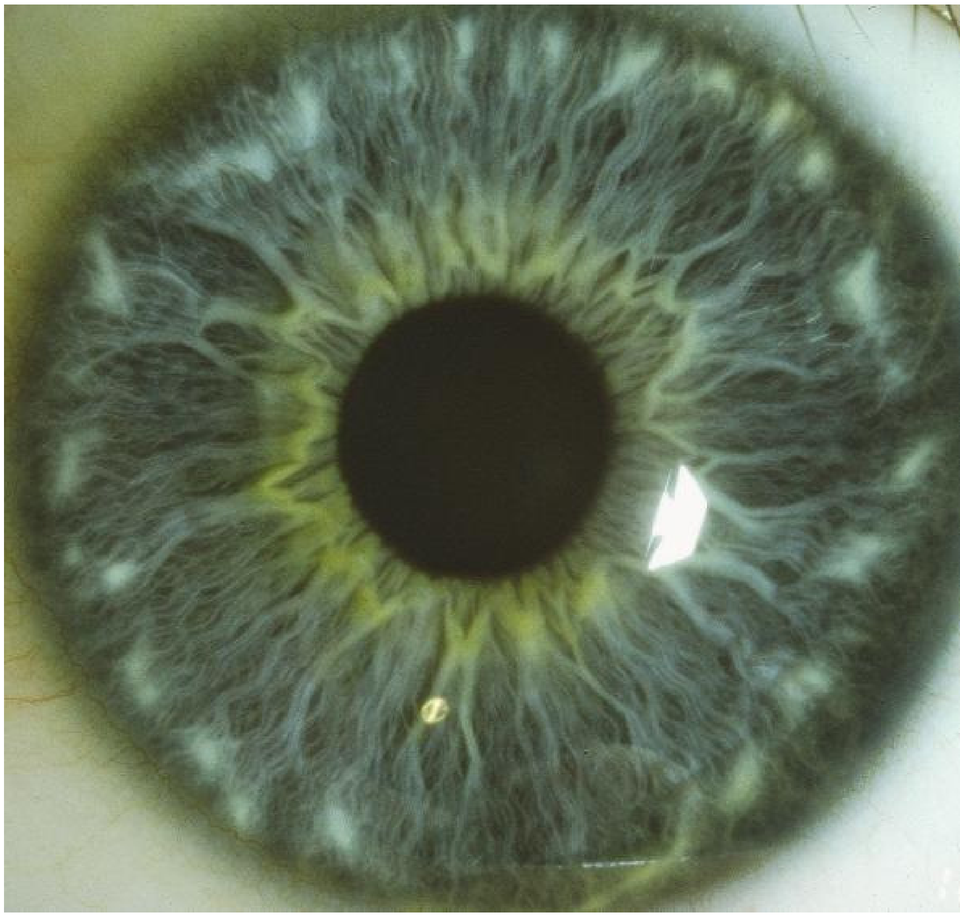
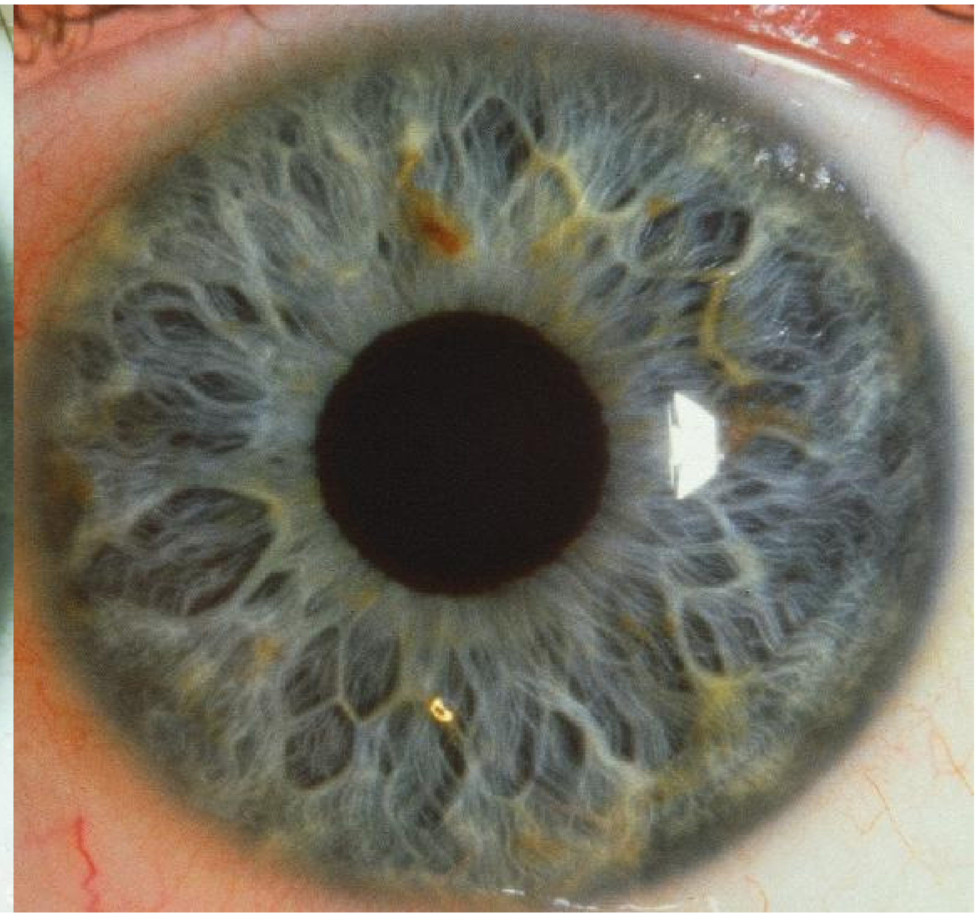
In the visible band of light, the iris reveals a very rich, random, interwoven texture (the *"trabecular meshwork"*)





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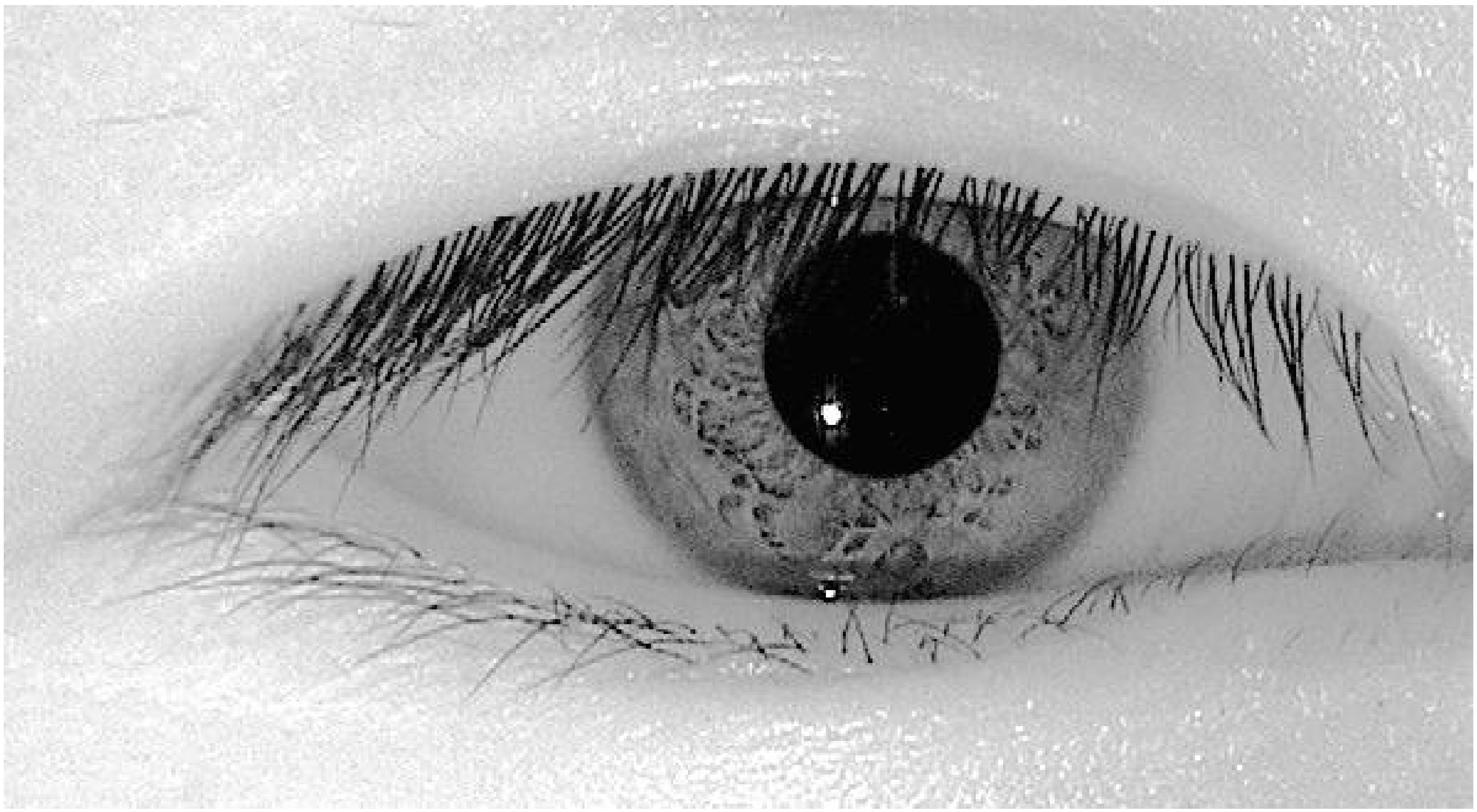
But even "dark brown" eyes show rich texture when images are captured in infrared illumination



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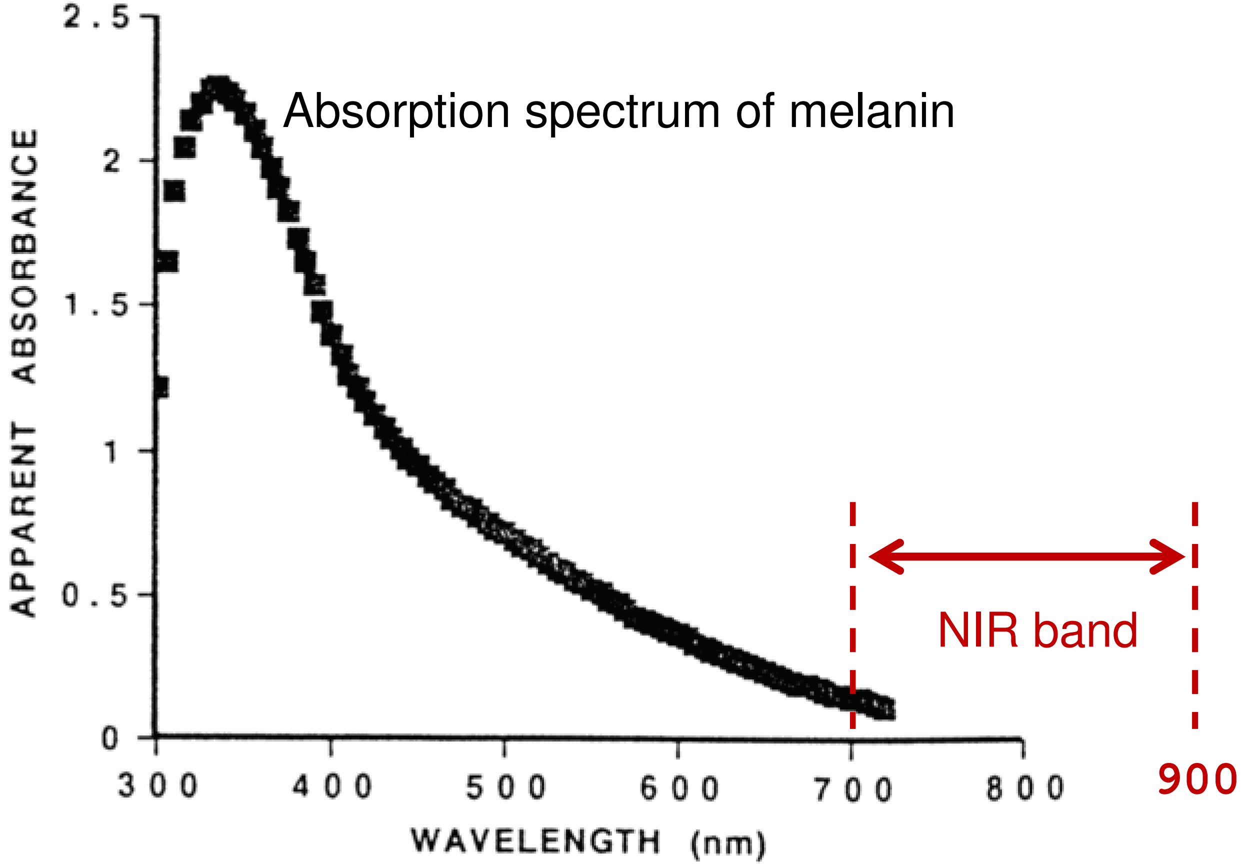
All pigmentation variations are due to melanin density. This can sometimes change (e.g. growth of freckles, or pigment blotches); but these are invisible in the NIR (near infrared: 700nm – 900nm) band of light used in all publicly deployed iris cameras, because melanin is almost completely non-absorbing beyond 700nm.



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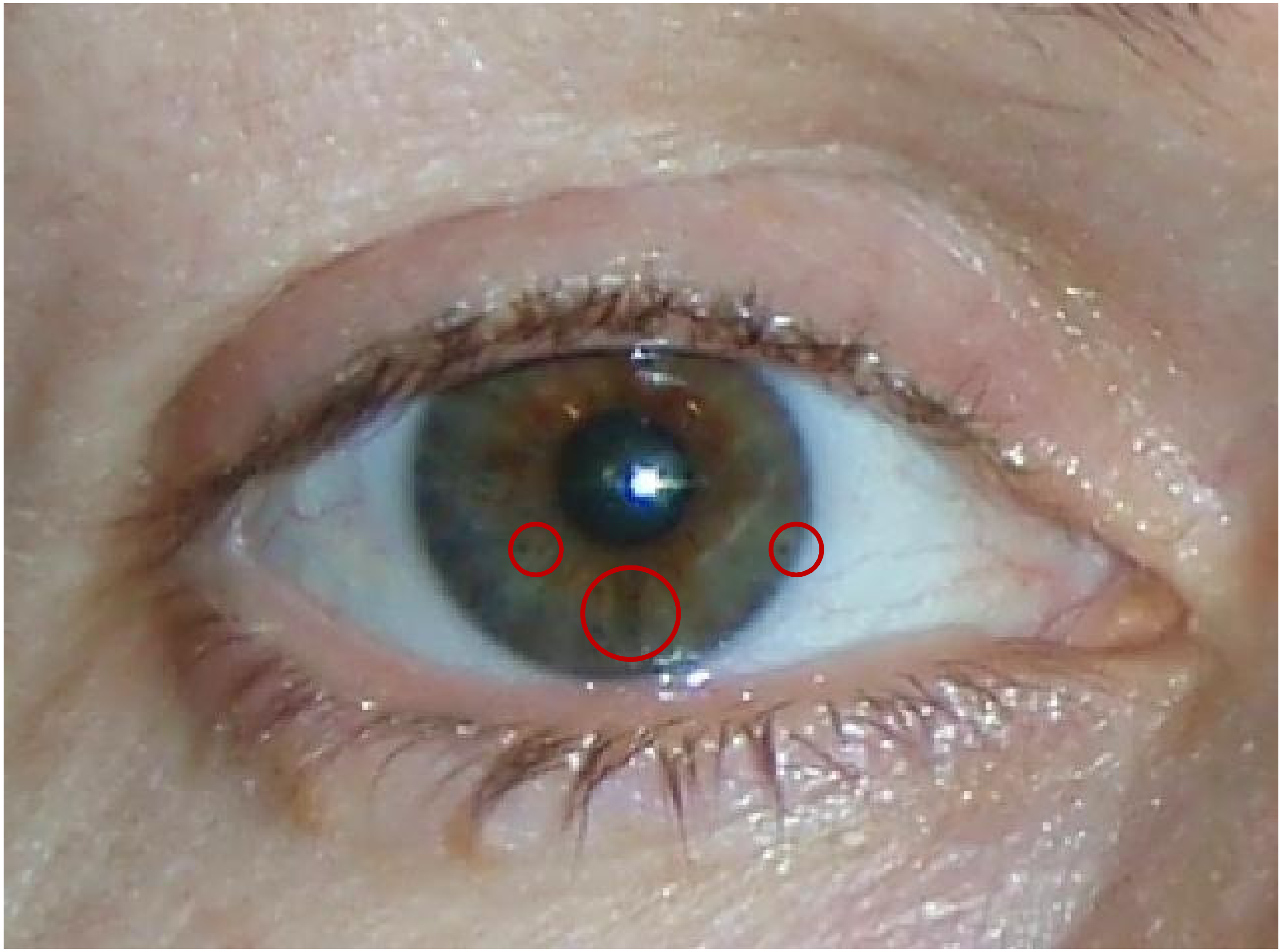
Example of an iris imaged in the visible band of illumination (400nm–700nm), showing freckles



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The same iris, imaged (almost simultaneously) in the NIR band (700nm–900nm): freckles become invisible

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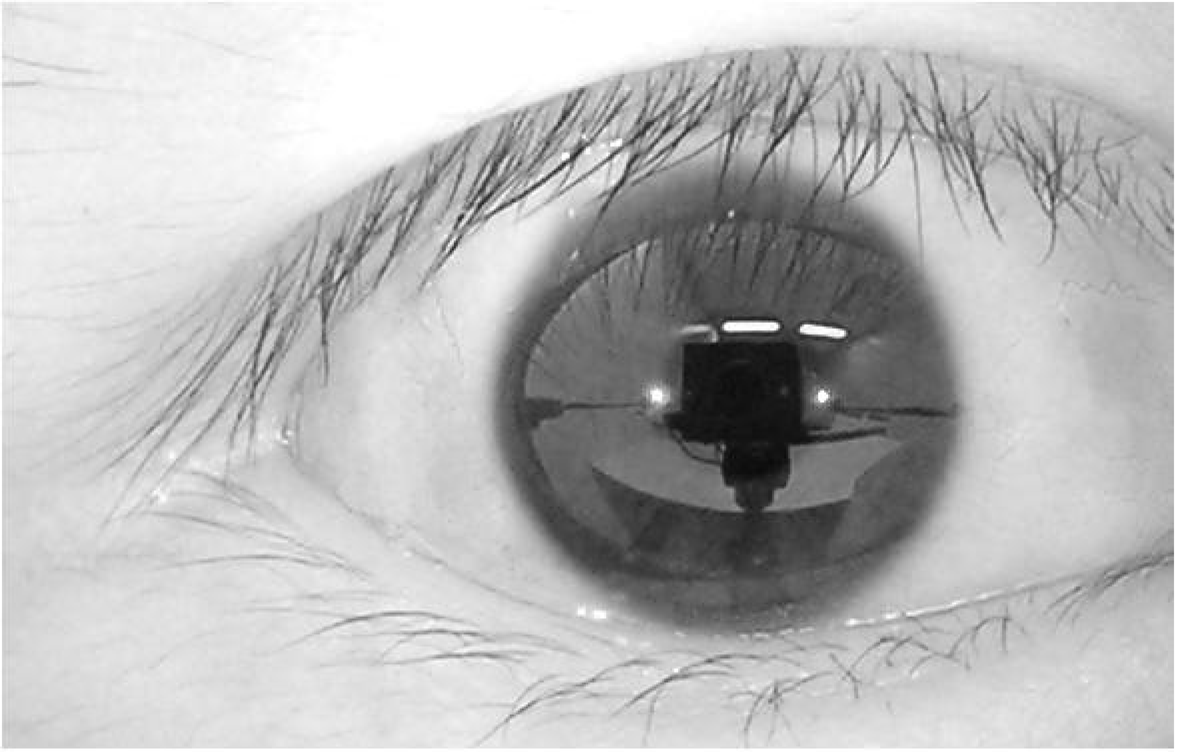
In the visible band of light in unconstrained environments (e.g. outdoors), ambient corneal reflections are common. An iris acquired in the visible band often looks like this:



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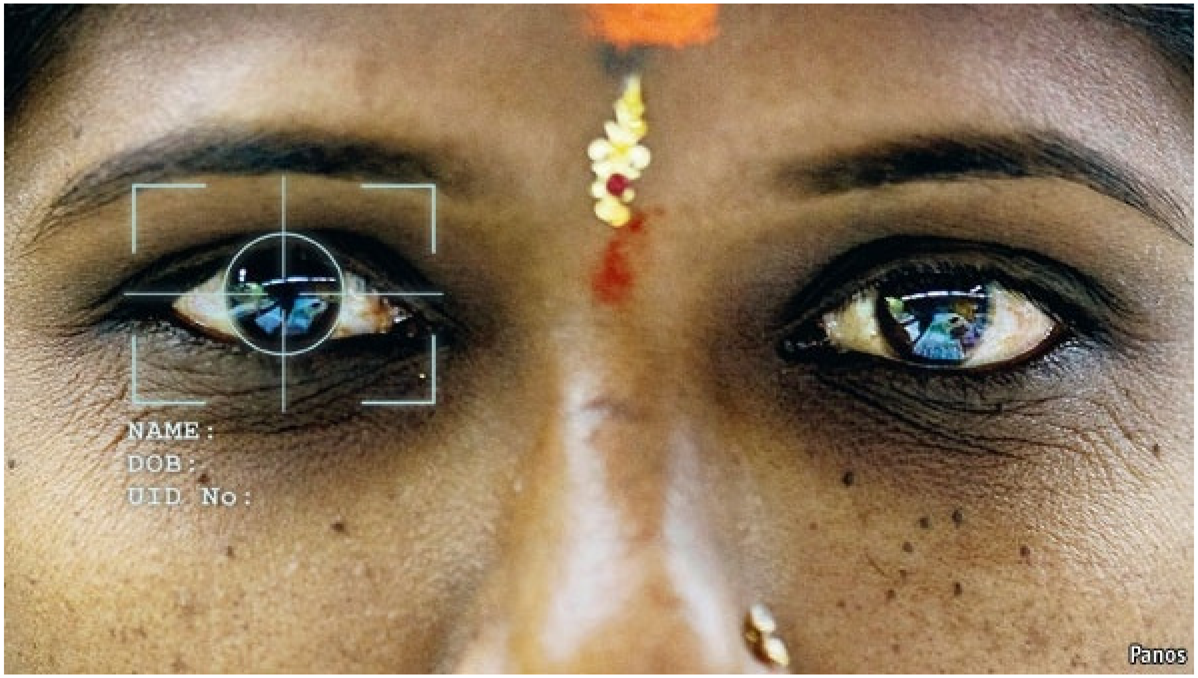
Example of how an iris with low albedo (i.e. dark brown) looks in the visible band: the corneal specular reflections completely dominate the Lambertian iris image. (From *The Economist*, 14 January 2012.)



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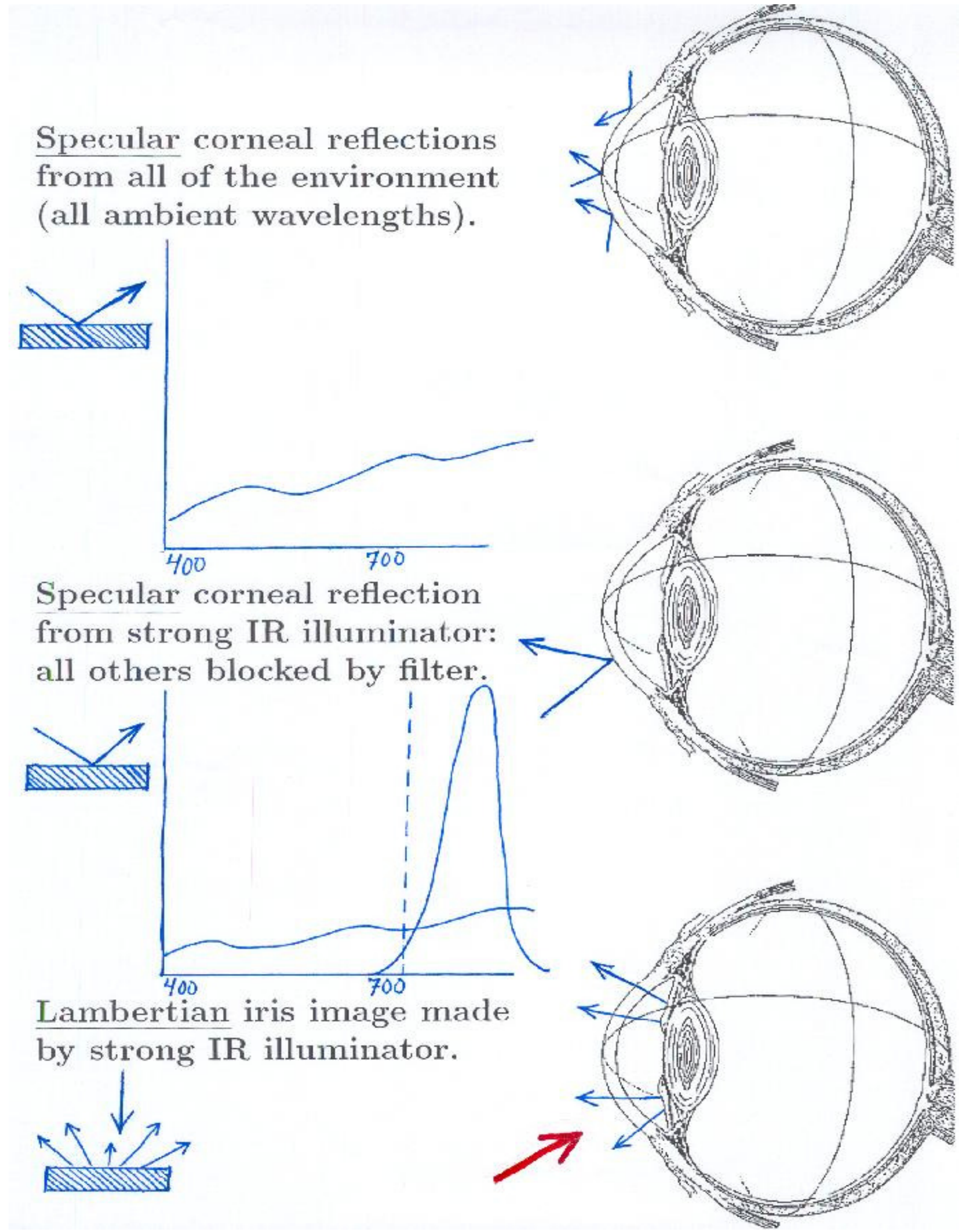
All surfaces lie somewhere between specular (mirror-like) and Lambertian (scattering light equally in all directions).

The cornea is a specular surface; the iris is Lambertian. This fact can be exploited to separate out the ambient environmental corneal reflections, which are broadband but weak, from the more narrow-band light in a nominated band projected by the camera onto the eye to obtain a Lambertian image of the iris.

By allowing back into the camera only that same nominated narrow band of light that the iris camera emitted, a band in which there is much more spectral power than in the broadband ambient corneal reflections, these two sources can be separated.



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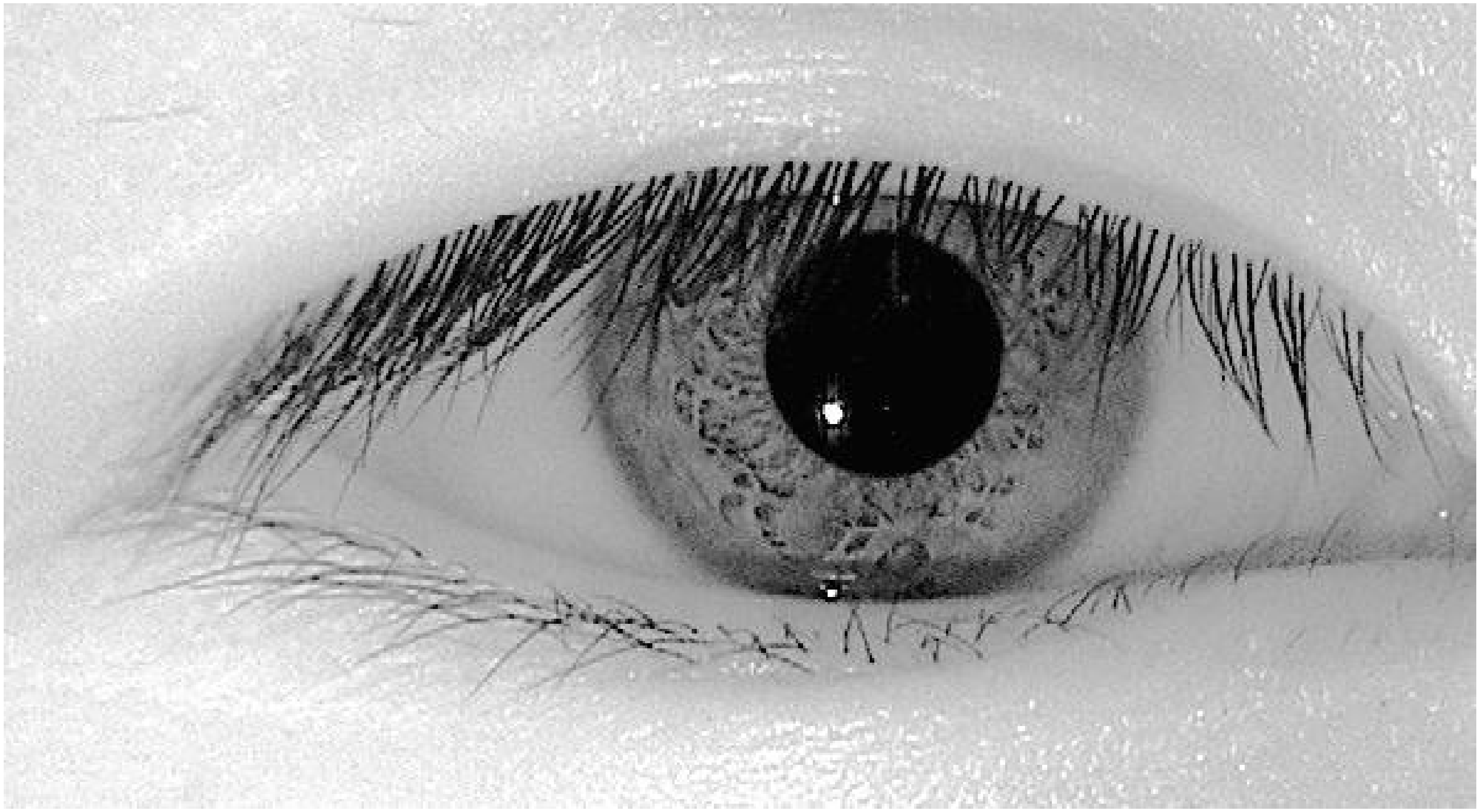
The result is an image acquired in narrowband near-infrared light, from which almost all ambient environmental corneal reflections (except for that of the illuminator) have been "scrubbed."



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Entropy: the key to biometric collision avoidance

- The discriminating power of a biometric depends on its entropy
- Entropy measures the amount of random variation in a population:
  - the number of different states or patterns that are possible;
  - the probability distribution across those possible states
- Entropy H (in bits) corresponds to 2^H discriminable states or patterns
- Surviving large database searches requires large biometric entropy
- Epigenetic features (not genetically determined) make best biometrics

About 1 percent of persons have a monozygotic ("identical") twin

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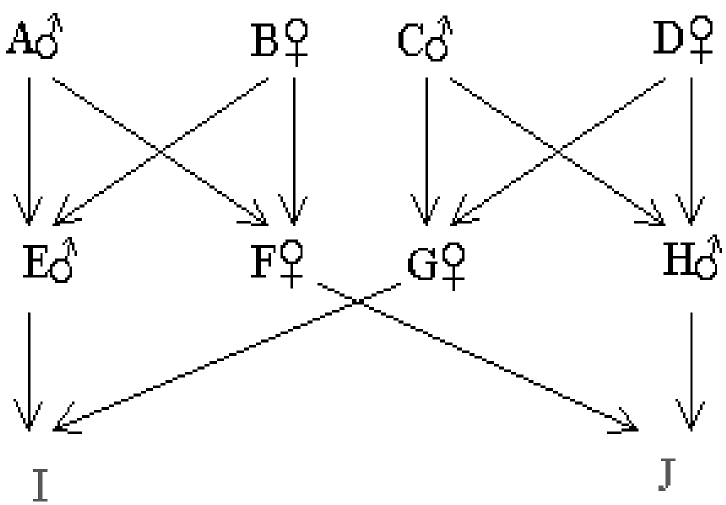
Epigenetic biometric features are vital if de-duplication of a large national database is required, as in the UID programme in India.

The epigenetic biometric property is especially important in cultures with high rates of group inbreeding (*e.g.* cousin marriage), so that genetically related persons do not collide in their biometrics.



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Iris Patterns are Epigenetic

Every biometric lies somewhere on a continuum between being genetically determined (genotypic) or not (epigenetic)

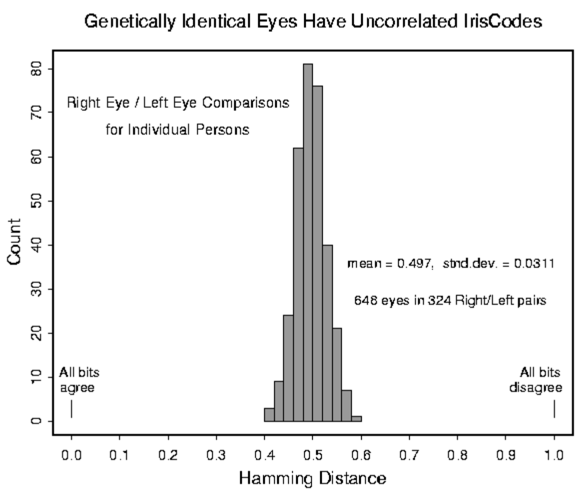
Examples of genotypic traits: DNA, blood type, gender, race

Examples of epigenetic traits: fingerprints (except for type correlations); and iris patterns (except for eye colour)

Example at middle of continuum: facial appearance. (Identical twins look identical, but they both change over time like everyone, yet they track each other as they age.)

Genetically identical eyes have iris patterns that are uncorrelated in detail:

Monozygotic Twins A
(6 year-old boys)



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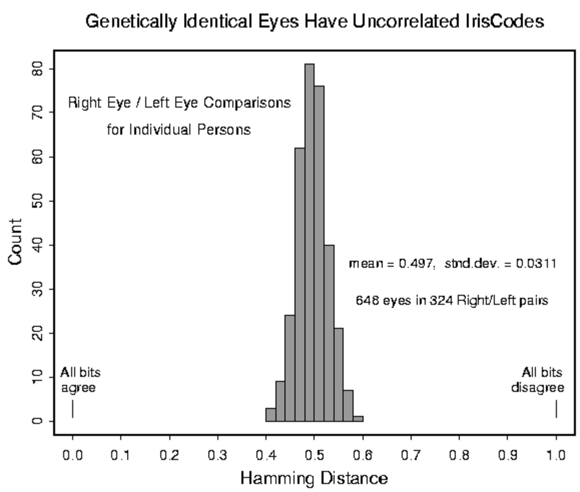
Genetically identical eyes have iris patterns that are uncorrelated in detail:

Monozygotic Twins B
(18 year-old women)



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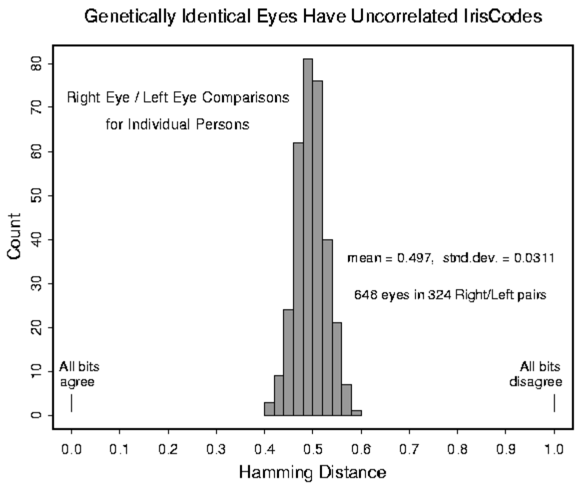
Genetically identical eyes have iris patterns that are uncorrelated in detail:

Monozygotic Twins C
(78 year-old men)



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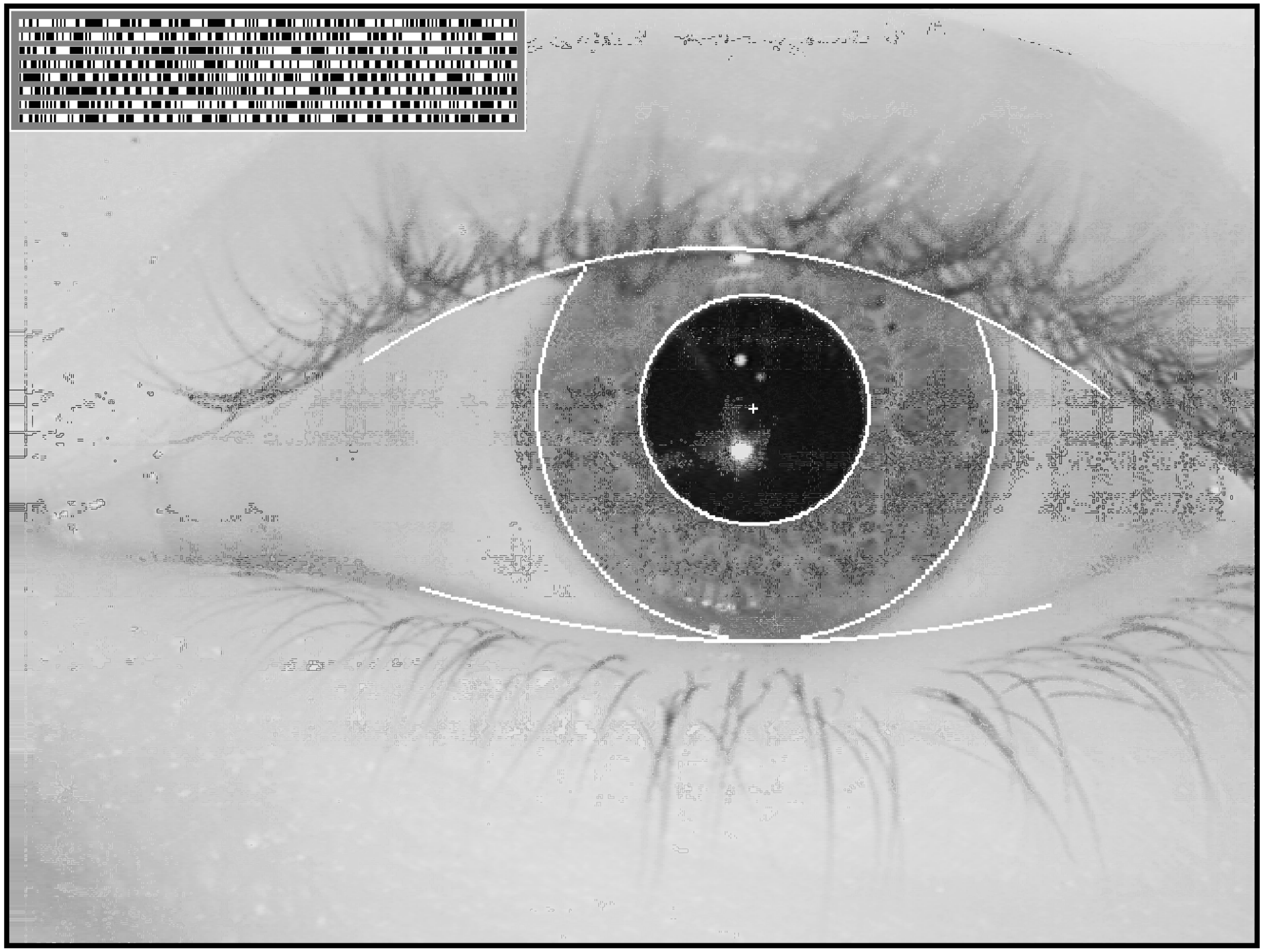

$$\max_{(r,x_0,y_0)} \left| G_\sigma(r) * \frac{\partial}{\partial r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} ds \right|$$

Localizing the iris boundaries by integro-differential operators

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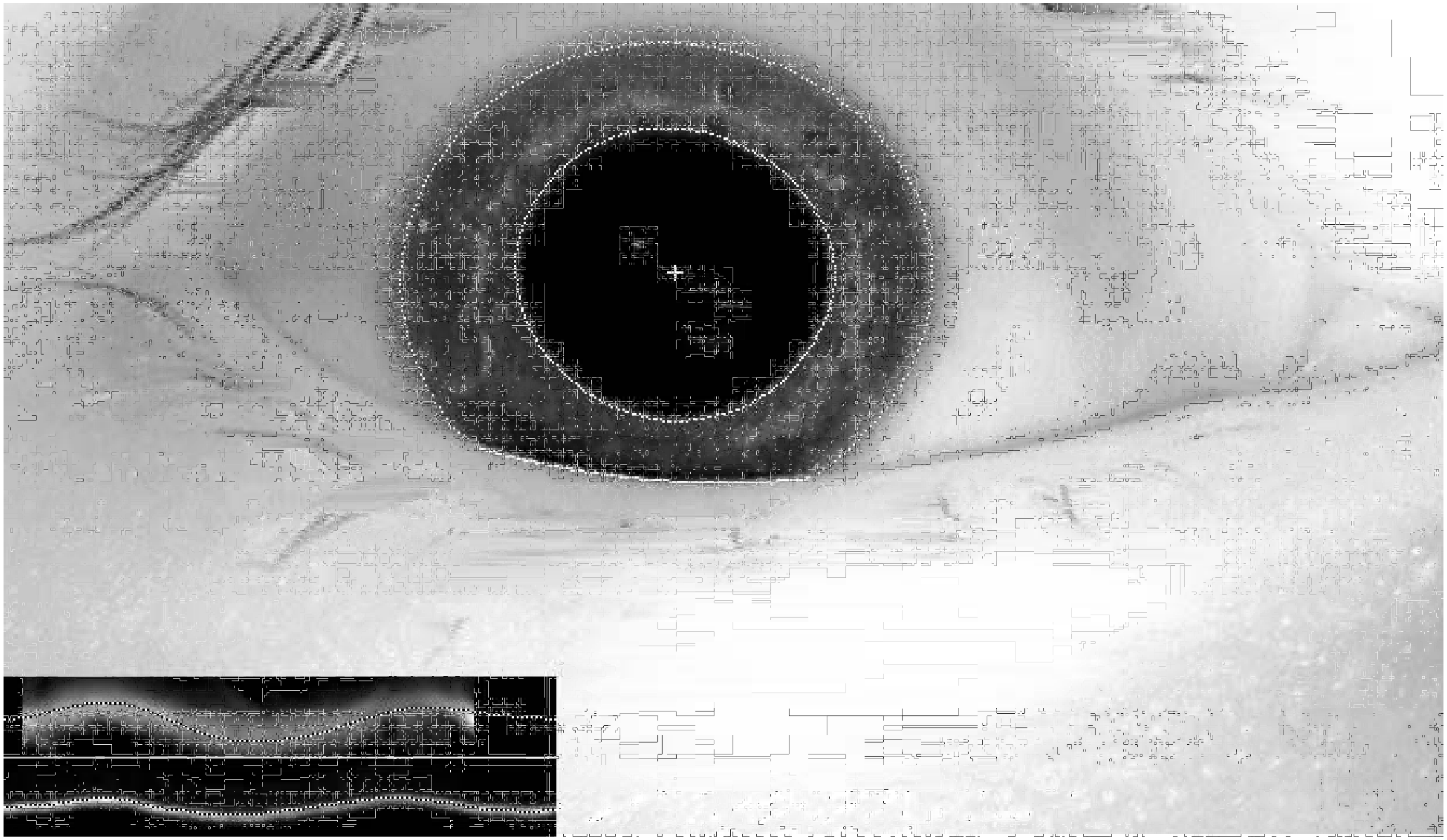

Iris boundaries are often non-round. The coordinate system must...

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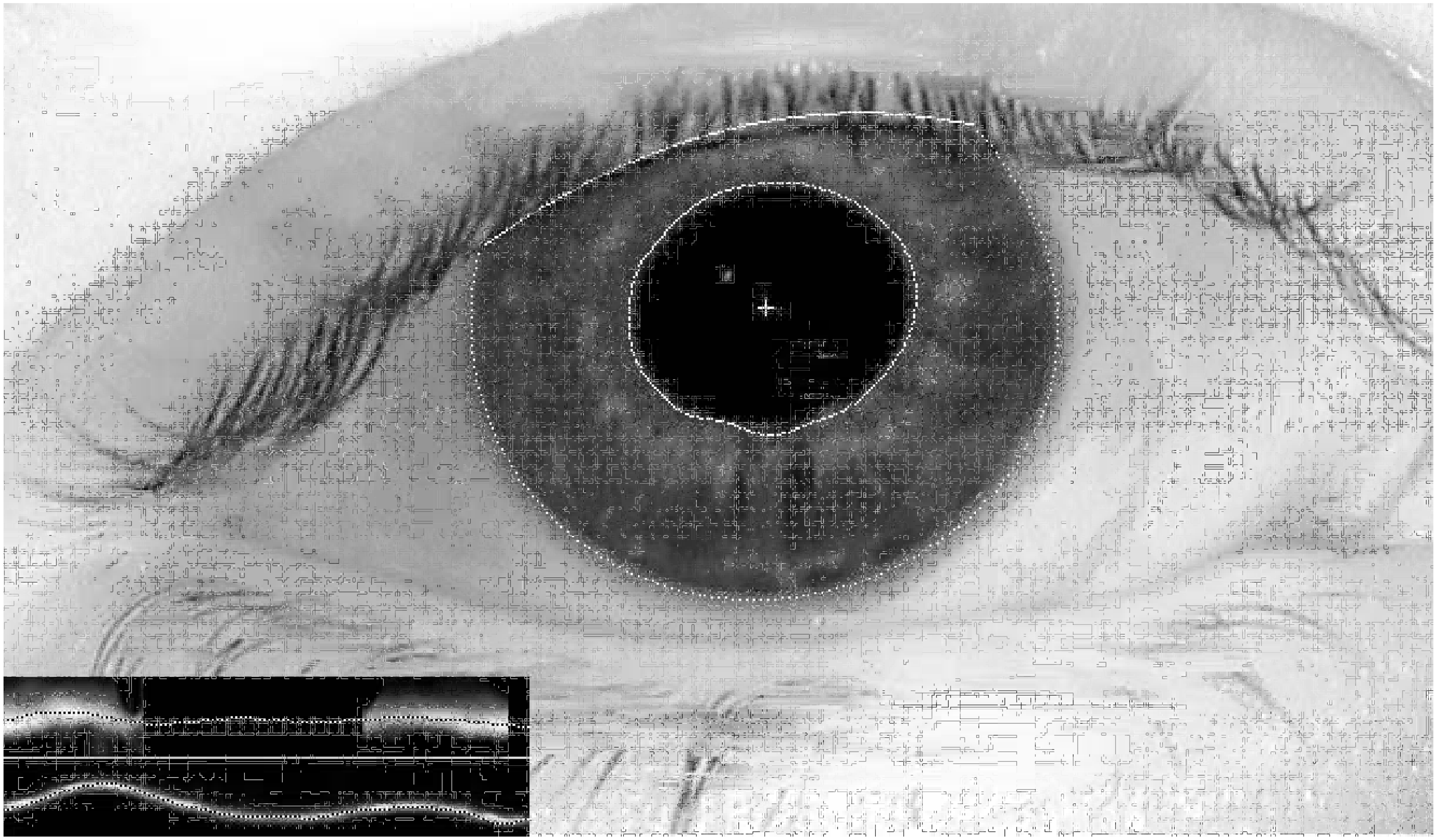

...create a deformed, non-concentric, doubly-dimensionless iris mapping

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Active Contours and non-Circular Iris Coordinates

- Iris boundaries are rarely true circles. Performance is much enhanced by encoding the boundary shapes accurately when mapping iris patterns.

- So: compute a Fourier expansion of N angular samples of radial gradient edge data $\{r_\theta\}$ for $\theta = 0$ to $N-1$ spanning $[0, 2\pi]$. A set of M discrete Fourier coefficients $\{C_k\}$ are derived from the data sequence $\{r_\theta\}$ as follows:

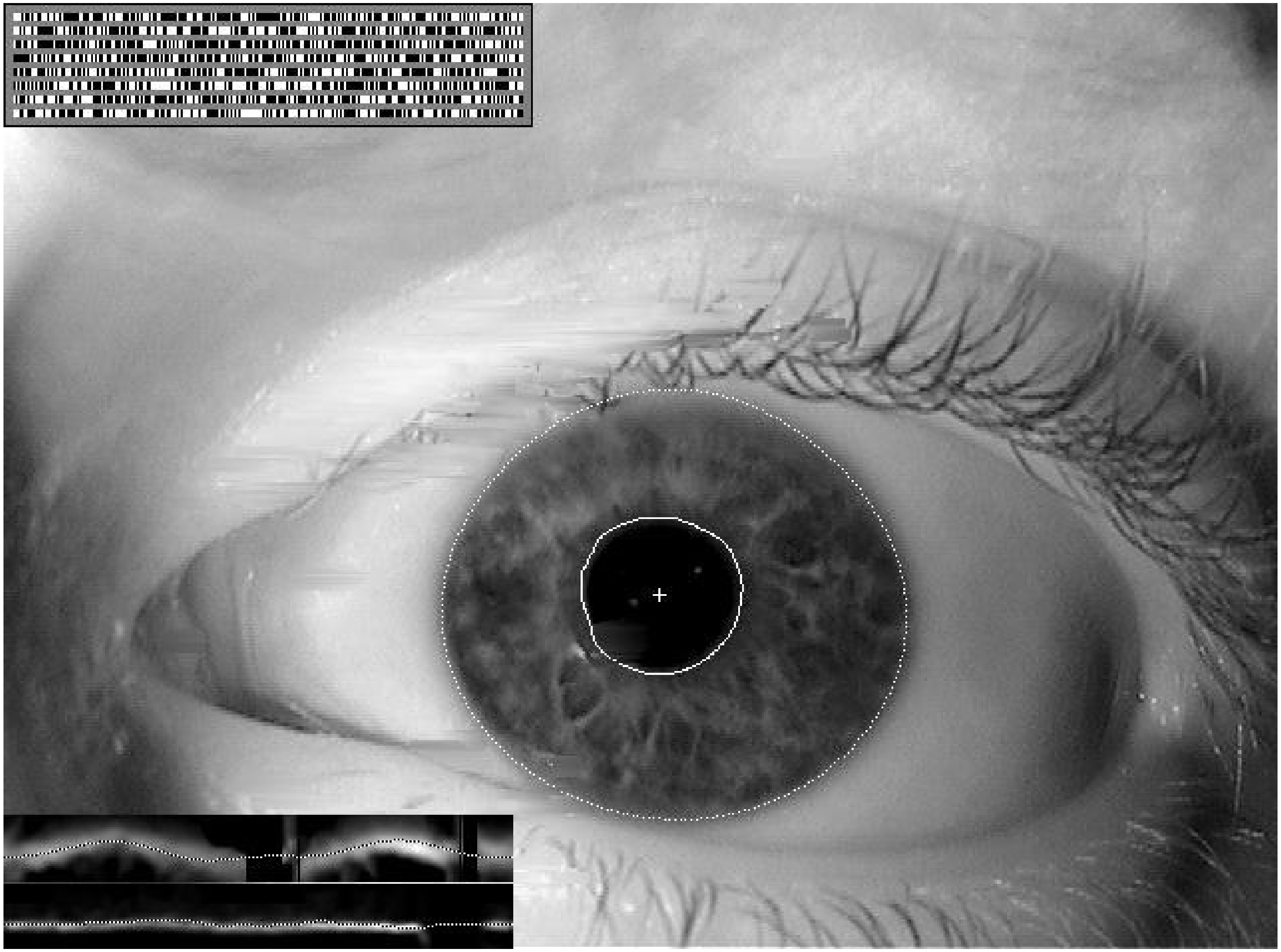
$$C_k = \sum_{\theta=0}^{N-1} r_\theta e^{-2\pi i k\theta/N}$$

- Note that the zeroth-order coefficient or "DC term" C_0 extracts the average curvature of the boundary: its radius if modelled simply as a circle.

- From these M discrete Fourier coefficients, an approximation to the inner or outer iris boundary (now spanning occlusion interruptions, and at a resolution determined by M) is obtained by the Fourier series $\{R_\theta\}$:

$$R_\theta = \frac{1}{N} \sum_{k=0}^{M-1} C_k e^{2\pi i k\theta/N}$$

- The trade-off between fidelity to the true boundary, and the stiffness of the Active Contour, is set by M, the number of Fourier components used.



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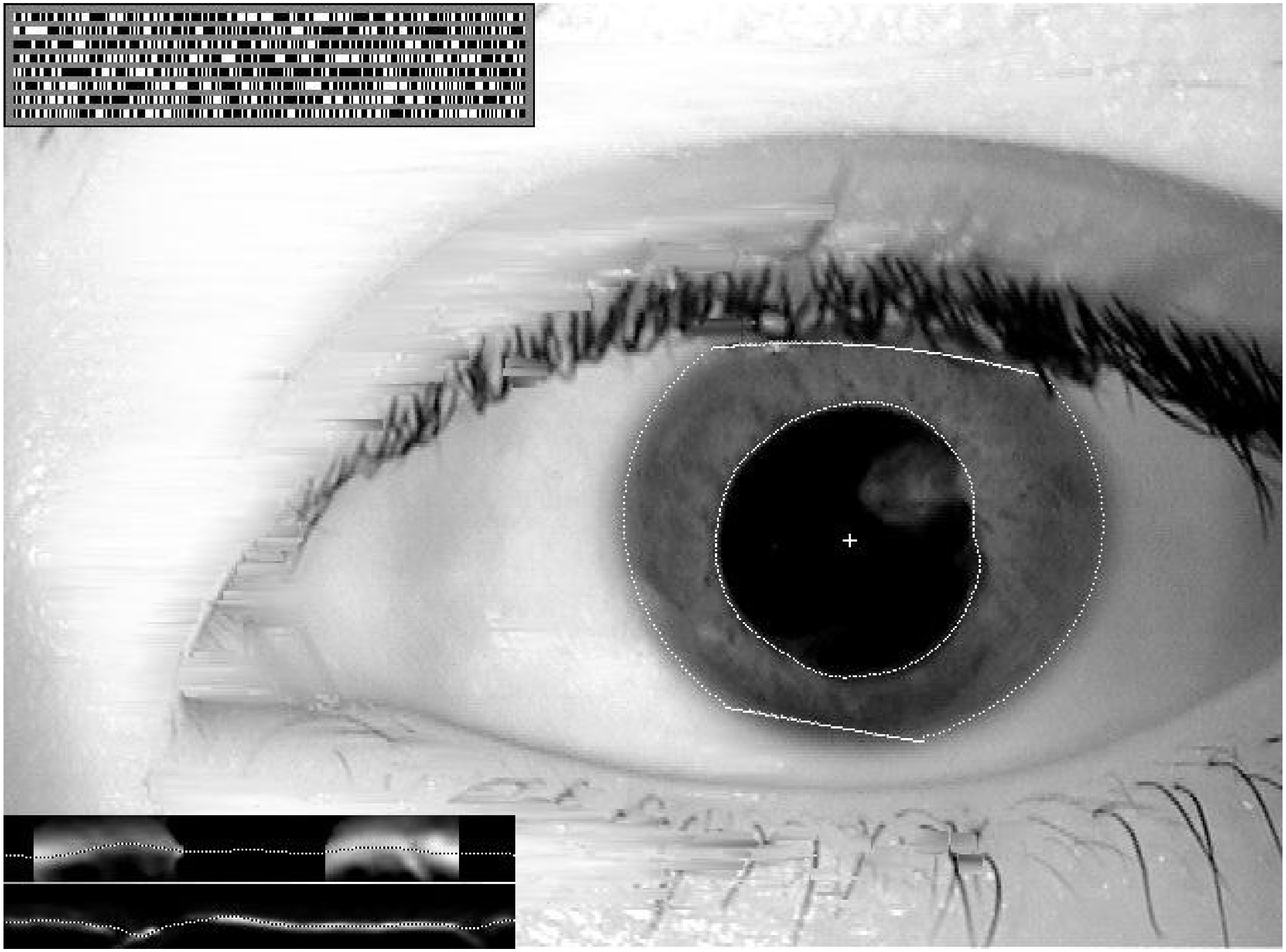

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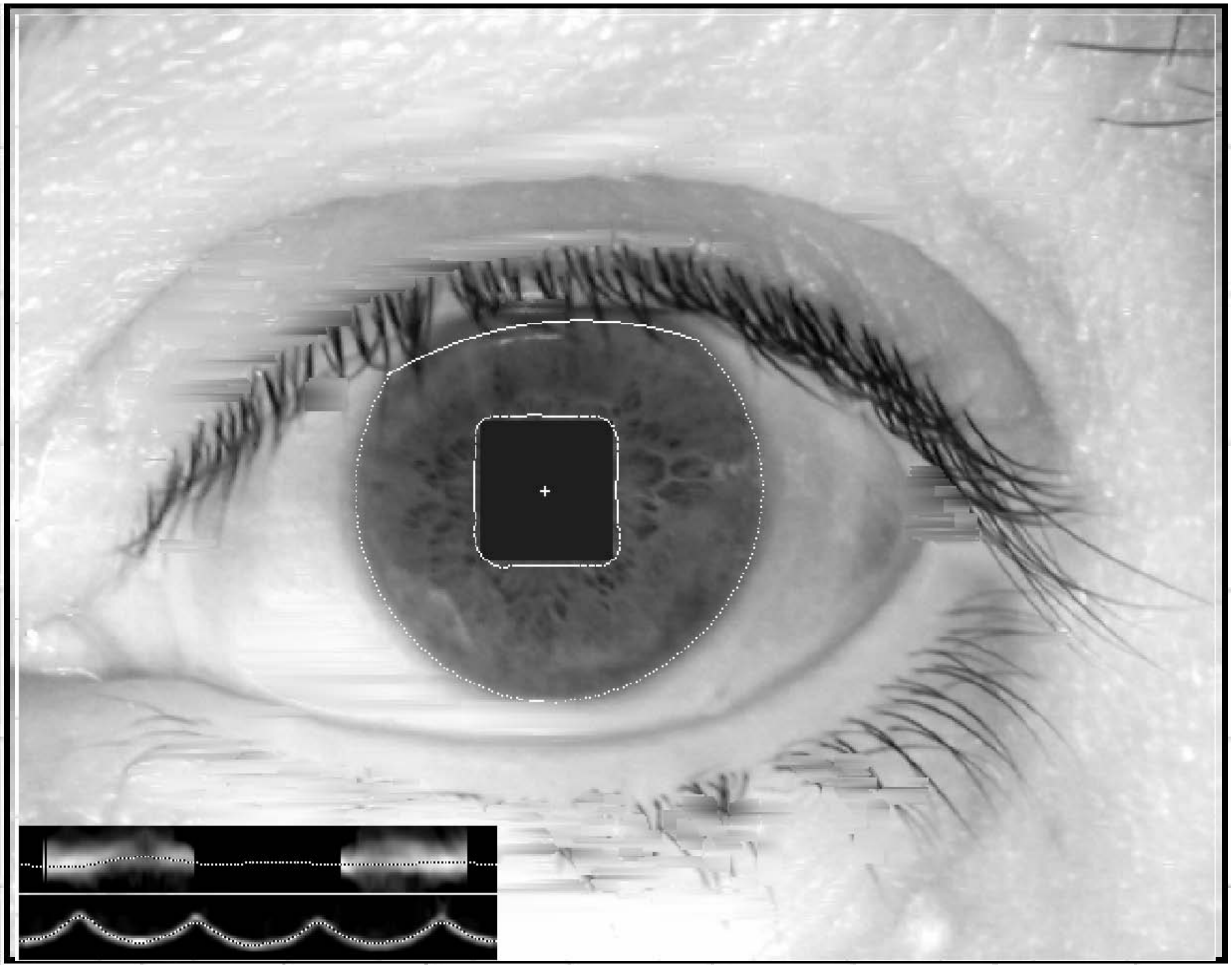

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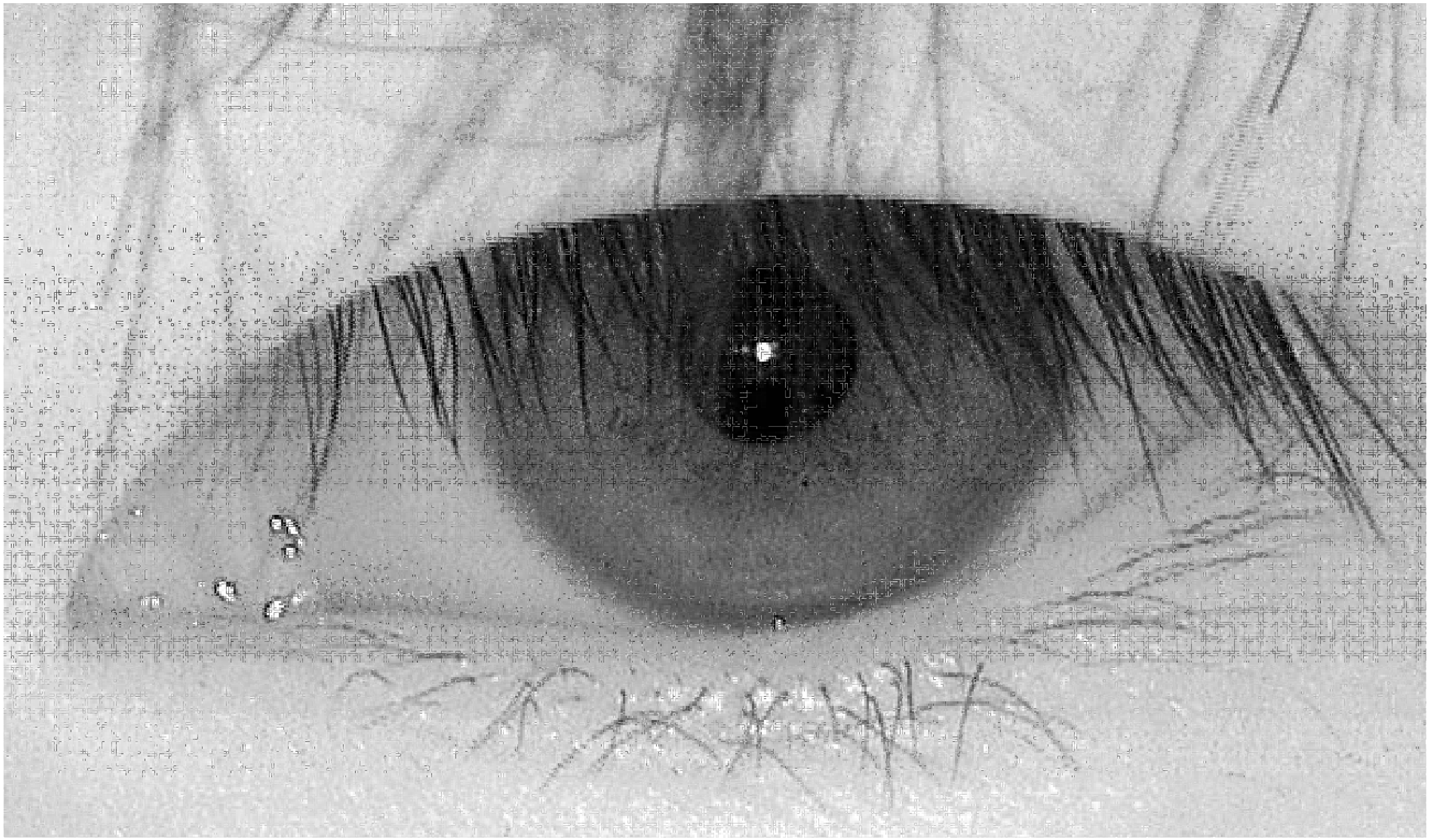
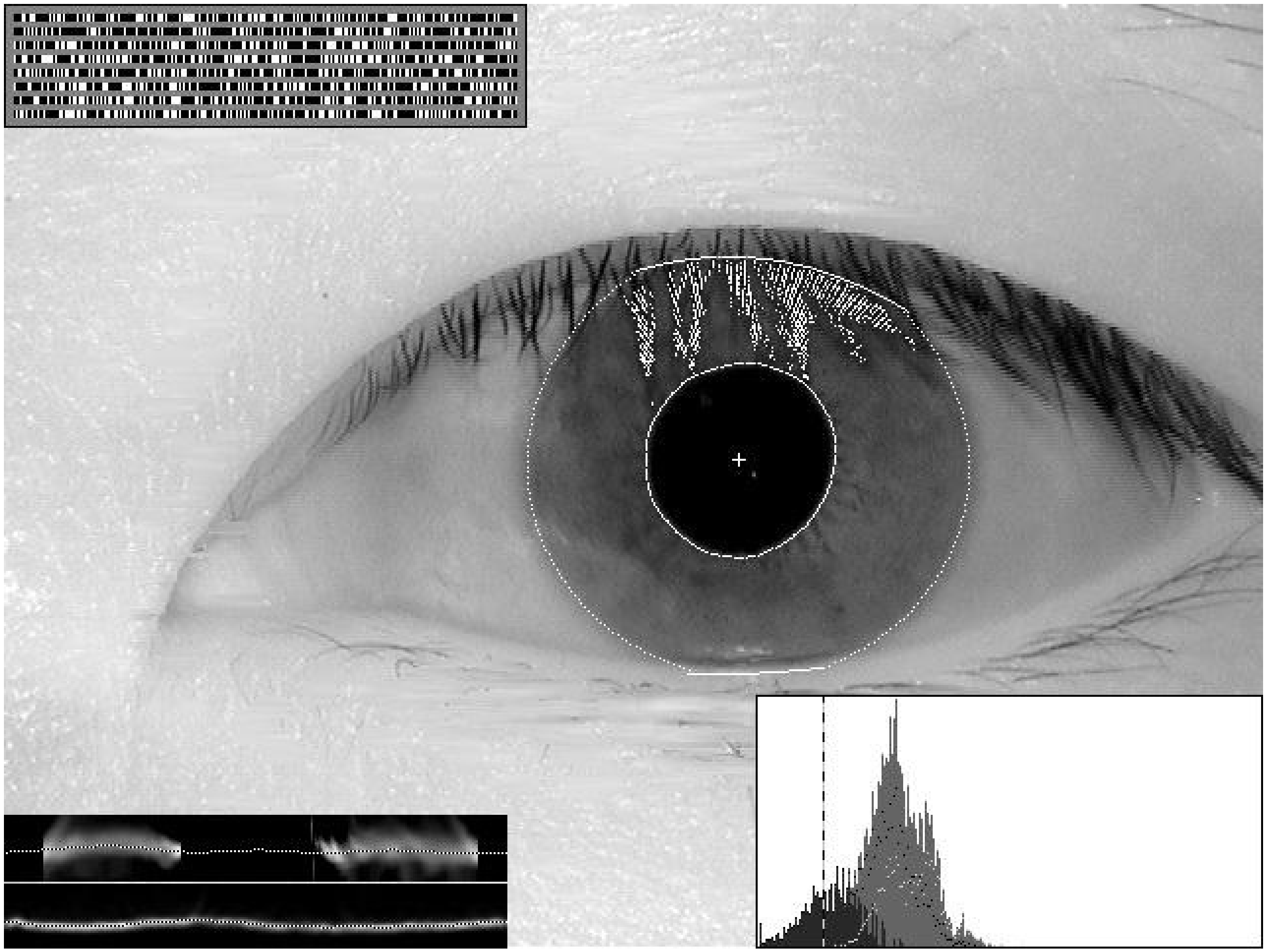


Often the iris (especially in Oriental persons) is covered by eyelashes...

Occluding eyelashes are detected and masked out (prevented from influencing the IrisCode) by statistical



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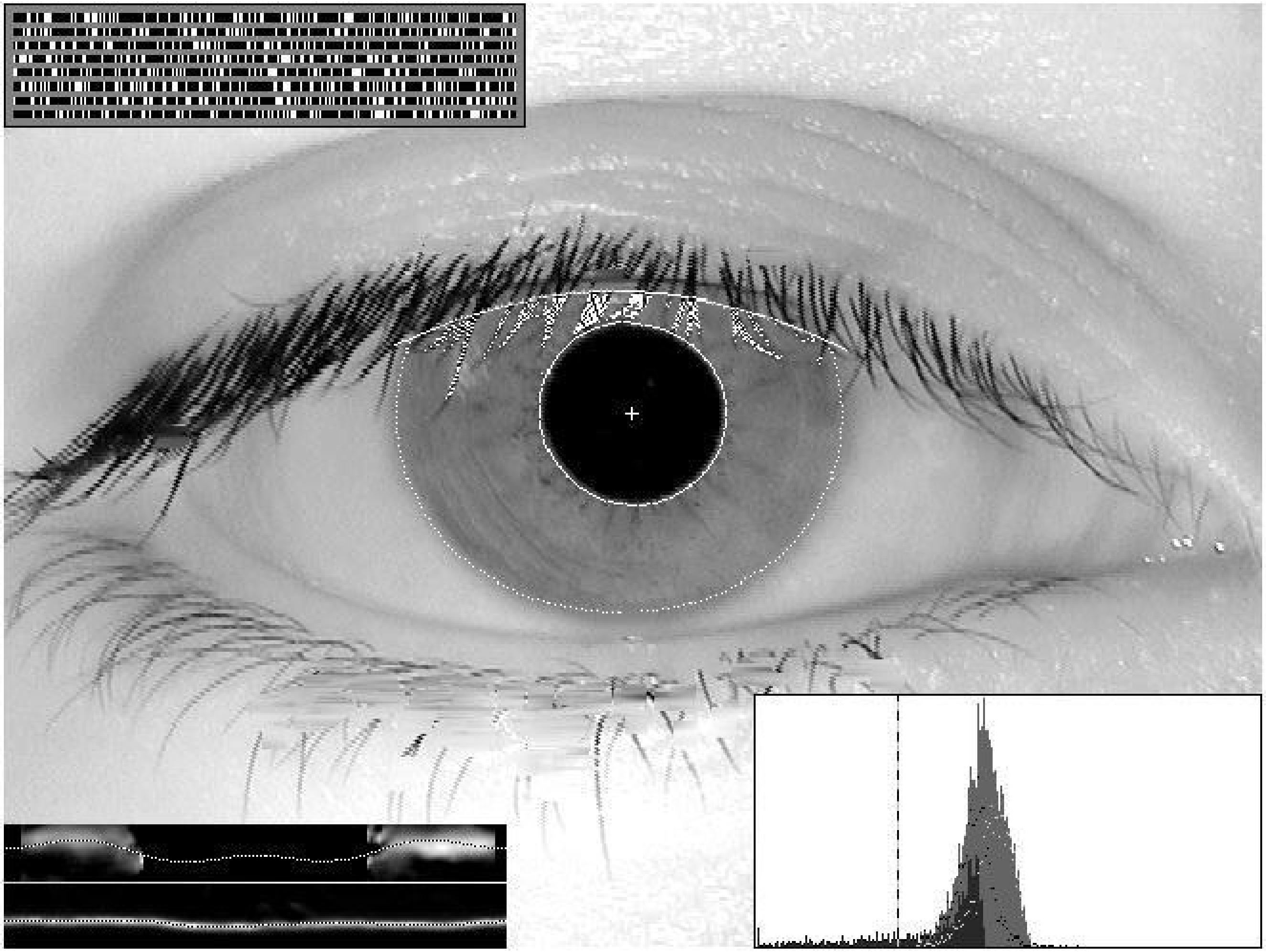
hypothesis testing on the distribution of iris pixels, seeking evidence of a sub-population passing a test.



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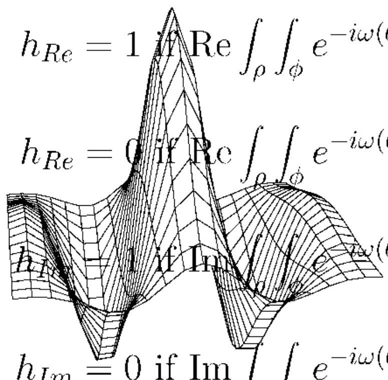
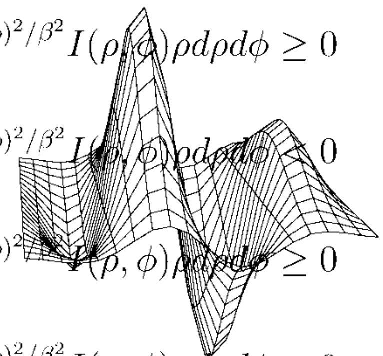
Setting Bits in an IrisCode by Wavelet Demodulation



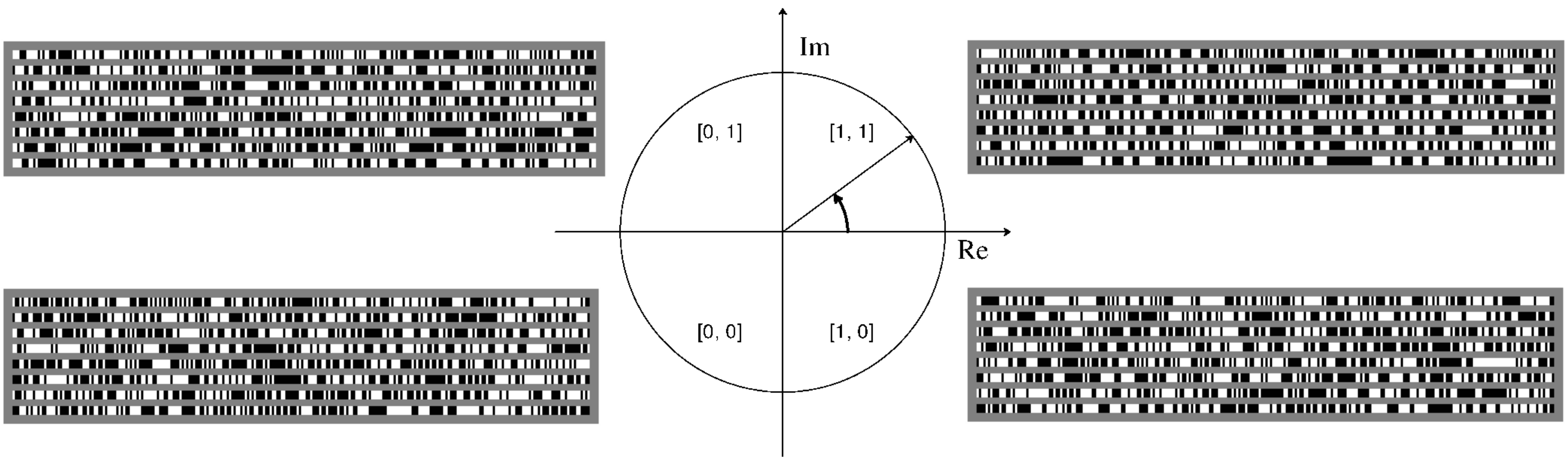


$$h_{Re} = 1 \text{ if } \mathrm{Re} \int_\rho \int_\phi e^{-i\omega(\theta_0-\phi)} e^{-(r_0-\rho)^2/\alpha^2} e^{-(\theta_0-\phi)^2/\beta^2} I(\rho,\phi)\rho d\rho d\phi \geq 0$$

$$h_{Re} = 0 \text{ if } \mathrm{Re} \int_\rho \int_\phi e^{-i\omega(\theta_0-\phi)} e^{-(r_0-\rho)^2/\alpha^2} e^{-(\theta_0-\phi)^2/\beta^2} I(\rho,\phi)\rho d\rho d\phi < 0$$

$$h_{Im} = 1 \text{ if } \mathrm{Im} \int_\rho \int_\phi e^{-i\omega(\theta_0-\phi)} e^{-(r_0-\rho)^2/\alpha^2} e^{-(\theta_0-\phi)^2/\beta^2} I(\rho,\phi)\rho d\rho d\phi \geq 0$$

$$h_{Im} = 0 \text{ if } \mathrm{Im} \int_\rho \int_\phi e^{-i\omega(\theta_0-\phi)} e^{-(r_0-\rho)^2/\alpha^2} e^{-(\theta_0-\phi)^2/\beta^2} I(\rho,\phi)\rho d\rho d\phi < 0$$



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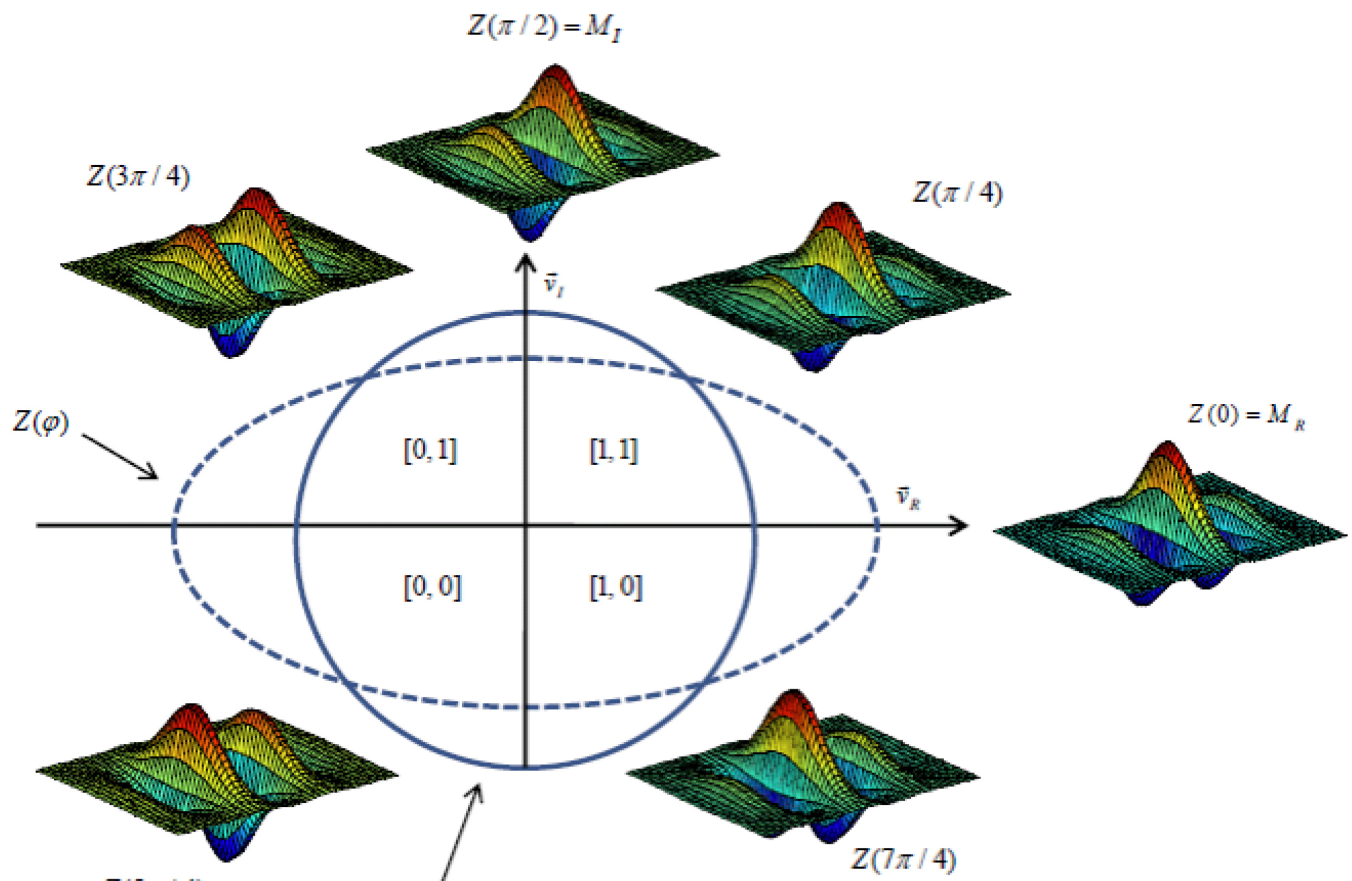
2D Gabor wavelets as phase-steerable detectors

D. Gabor (1900-1979)



(Adams Kong)

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Why phase is a good variable for biometric encoding

- Phase encodes <u>structural</u> information, independent of contrast
- Phase encoding thereby achieves some valuable invariances
- Phase information has much higher entropy than amplitude
- In harmonic (Fourier) terms, phase "does all the work"
- Phase can be very coarsely quantised into a binary string
- Phase is equivalent to a clustering algorithm (c.f. Adams Kong)
- Question: what is the best quantisation of phase (2, 4, 8... sectors)?
- Phase can be encoded in a scale-specific, or a scale-invariant, way

Gabor wavelets encode phase naturally, but in a scale- (or frequency)-specific way

Alternatives exist that encode phase in a total way (independent of scale/frequency), such as the Analytic function (the signal minus its Hilbert Transform $i\ f_{Hi}(x)$ cousin):

$f(x) - i\ f_{Hi}(x)$, which is a complex function whose 2 parts are "in quadrature"

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Why IrisCode matching is so fast, parallelisable, and scalable

Bit streams A and B are data words of two IrisCodes.
Bit streams C and D are their respective mask words.

(data) A	1	0	0	1	0	1	1	0	0	0	1	0	1	1	1	0	$\cdots$
(data) B	0	1	0	1	1	1	0	0	1	0	0	1	0	1	1	0	$\cdots$
$A \oplus B$	1	1	0	0	1	0	1	0	1	0	1	1	1	0	0	0	$\cdots$
(mask) C	1	1	1	0	1	0	1	1	0	0	1	1	1	0	1	1	$\cdots$
(mask) D	0	1	1	1	1	1	0	1	0	1	1	1	0	1	1	1	$\cdots$
$C \cap D$	0	1	1	0	1	0	0	1	0	0	1	1	0	0	1	1	$\cdots$
$(A \oplus B) \cap C \cap D$	0	1	0	0	1	0	0	0	0	0	1	1	0	0	0	0	$\cdots$

Note that for these 16 bit chunks, only 8 data bits were mutually unmasked by $C \cap D$.

Of those 8, they agreed in 4 and disagreed in 4, so raw Hamming distance is $4/8 = 0.5$ which is typical for comparisons between "Impostors" (unrelated IrisCodes).

Bit-parallel logic programming allows all of this to be done in a single line of C-code, operating on word lengths up to the word-length of the CPU (*e.g.* 64 bits at once):

```
result = (A ^ B) & C & D;
```

Each of the 3 logical parallel operators executes in a single "clock tick" (*e.g.* at 3 GHz).

Different use scenarios have different speed requirements

- **Real-time image processing speed** is needed for “iris-on-the-move” applications (*e.g.* must process 30 frames per second if the Subject is walking at 1 meter/second, with camera depth-of-field ~6 cm).

- **Matching speed** may need to survey the entire enrolled database ($10^6 – 10^9$?) per second, but matching is intrinsically parallelisable across platforms, is intrinsically very fast anyway because it is based on bit-parallel logic, and finally it is greatly expedited by Indexing.

- **De-duplication** is highly compute-intensive, because the number of pairings to be considered grows as N^2 for a population of size N. *E.g.* Indian UID: $N = 10^9$, so $N^2 = 10^{18}$. But de-duplication is generally an off-line process, performed as the enrolled database is built, and again it is expedited by parallelisation and Indexing.

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Speed benchmarks for the publically deployed algorithms

- All image processing operations, including segmentation and template extraction, are performed within 30 milliseconds.

- The bit-parallel matching algorithm allows as many bits as the word-length of the computer (*e.g.* 64 bits) to be compared in a single operation (1 machine instruction) between two IrisCodes.

- Exploitation of ergodicity in (non-identical) IrisCode comparisons by subsampling and “early exit”, further accelerates matching.

- Routine matching speeds are a million IrisCodes per second, per ordinary (single-core) CPU. Indexing accelerates this by 1 or 2 orders-of-magnitude, *e.g.* 50 nanoseconds including all rotations.

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But:

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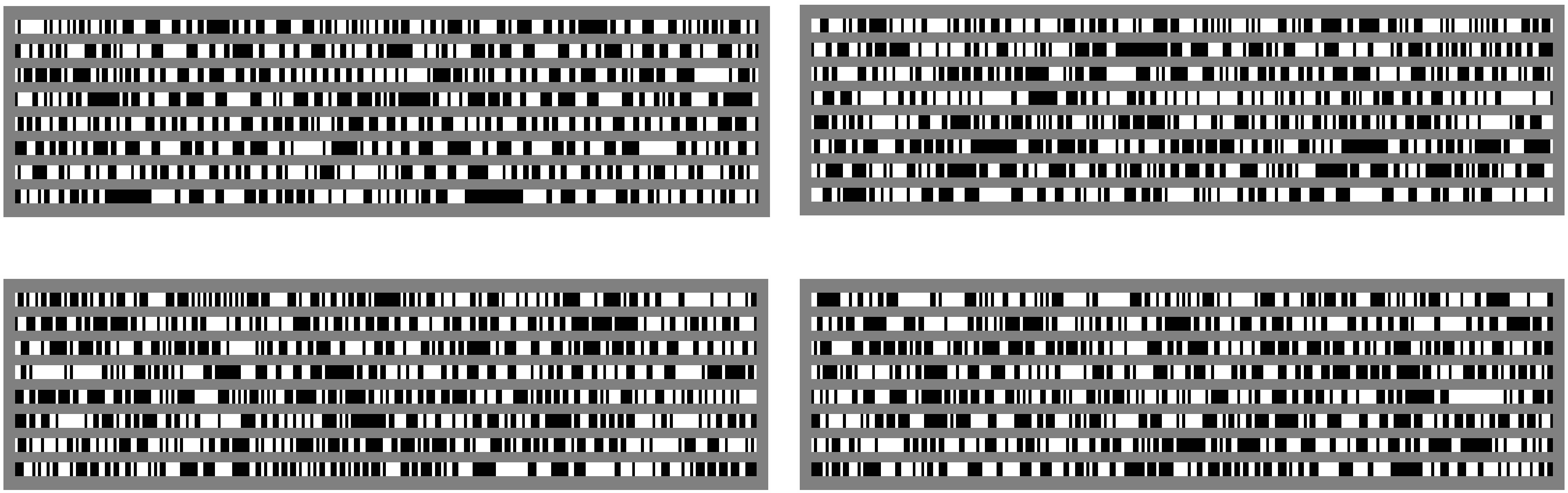
Entropy gives resistance against False Matches



The probability of two different people colliding by chance in so many bits (*e.g.* disagreeing in only one-third of their IrisCode bits) is infinitesimal. Thus the False Match Rate is easily made minuscule.

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But it’s like looking for one of these...

...in one of these.

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Example of the importance of high entropy

- UIDAI (Unique Identification Authority of India) in 2011 began enrolling iris images of all **1.2 billion** citizens
- As of February 2012, **150 million** had been enrolled
- Currently enrolling **1 million persons per day**
- Each enrolled person is compared against all of those enrolled so far, to detect duplicates (*"de-duplication*"). This requires (1 million x 150 million) = **150 trillion** x 2 iris cross-comparisons daily: **3 x 10^{14} per day**

The avoidance of biometric collisions among comparisons on this scale requires high biometric entropy, as possessed by IrisCode phase bits, ensuring very rapidly attenuating tails of the distribution obtained when comparing different eyes.

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3 x 10^{14} iris comparisons per day! A typical galaxy contains "just" 100 billion stars (10^{11})... So UIDAI daily iris workflow equates to the number of stars in 3,000 galaxies combined

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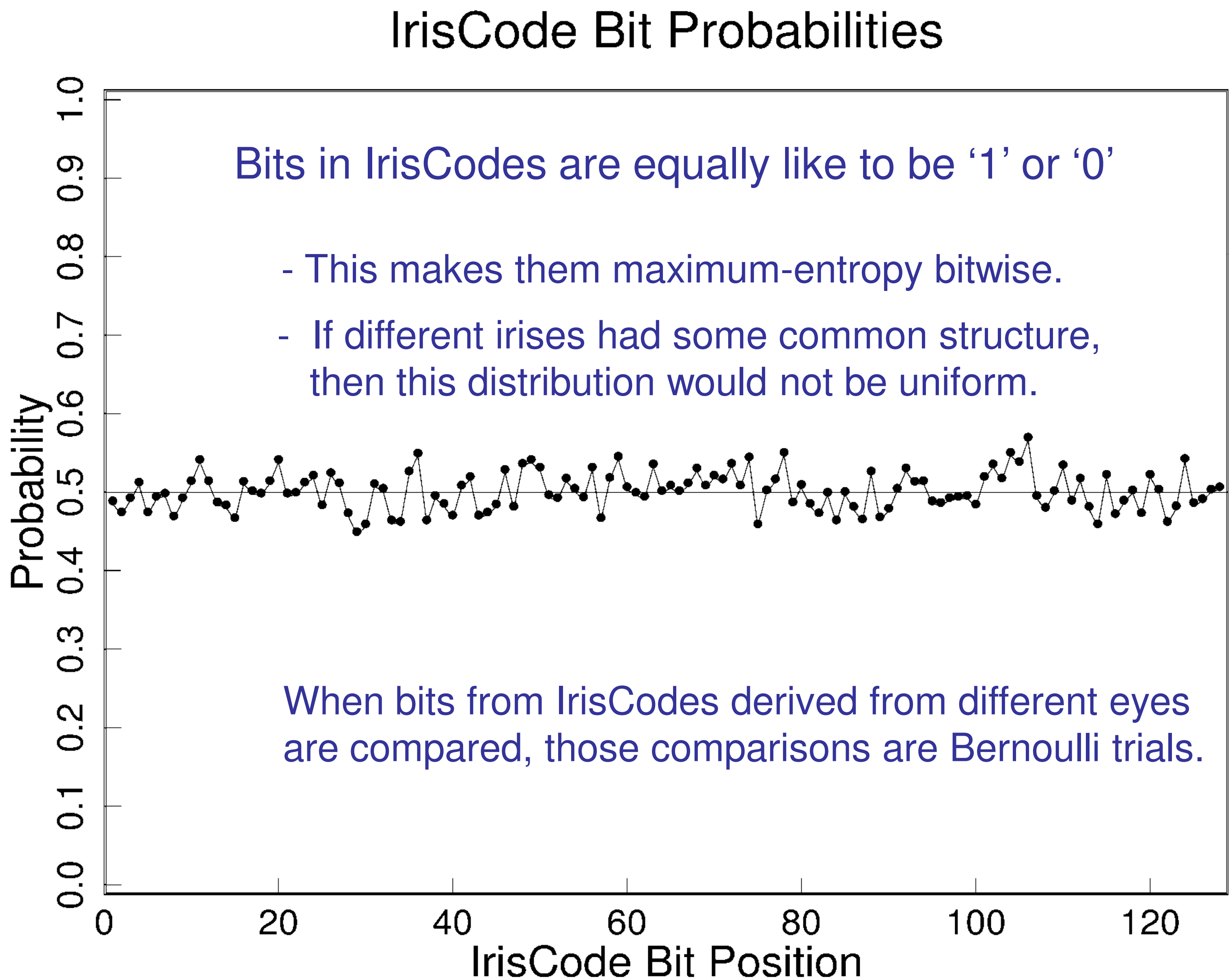

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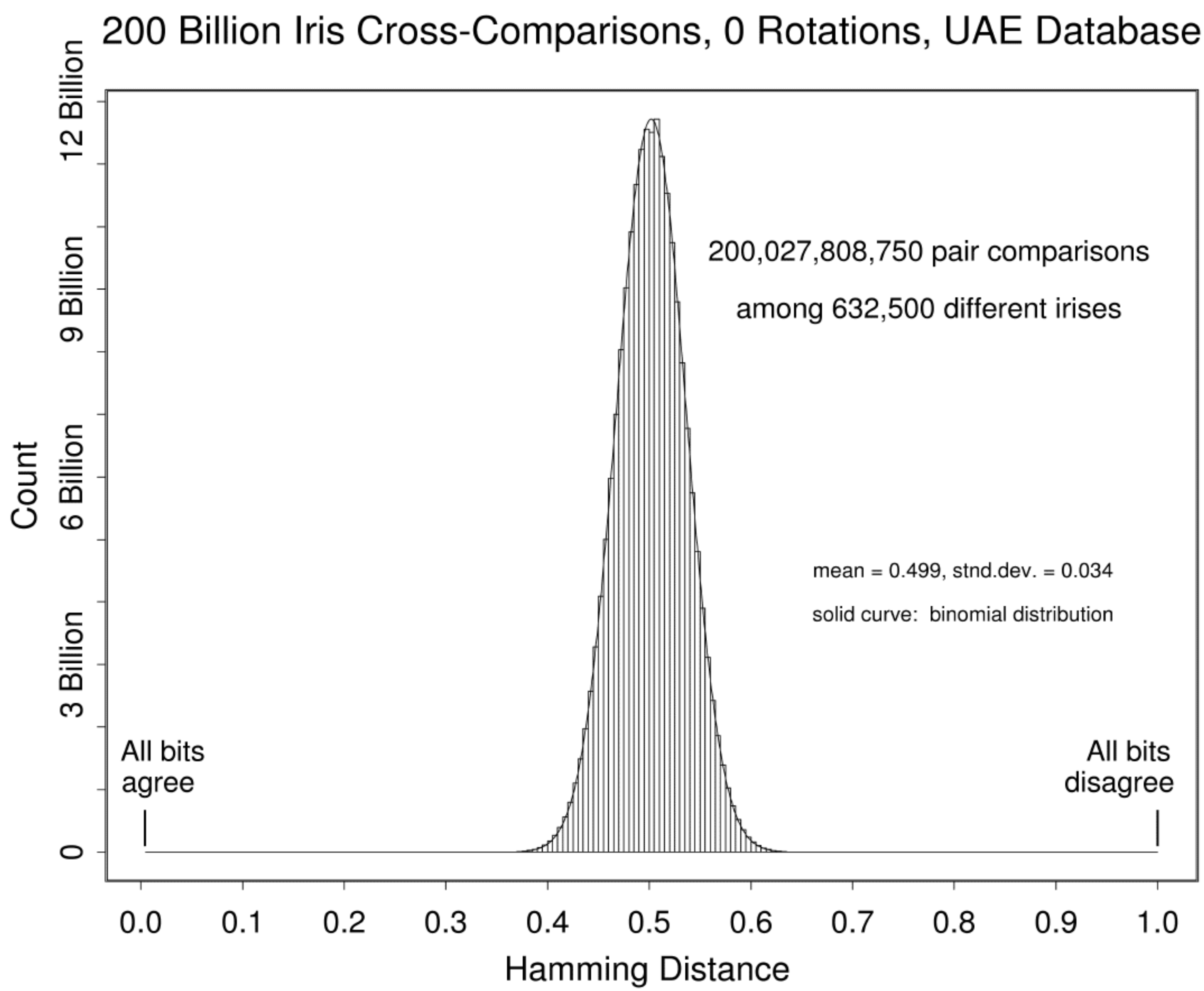

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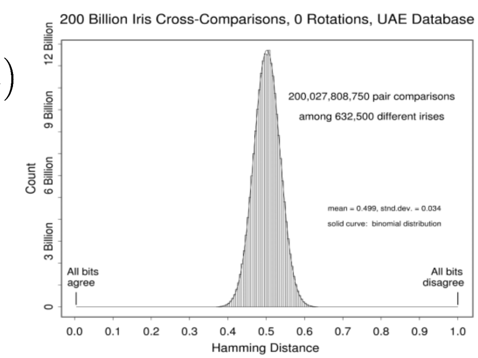
IrisCode Bit Comparisons are Bernoulli Trials

Jacob Bernoulli (1645-1705) analyzed *coin-tossing* and derived the binomial distribution. If the probability of "heads" is p, then the likelihood that a fraction $x = m/N$ out of N tosses will turn up "heads" is:

University of Groningen

$$P(x) = \frac{N!}{m!(N-m)!}\, p^m\,(1-p)^{(N-m)}$$



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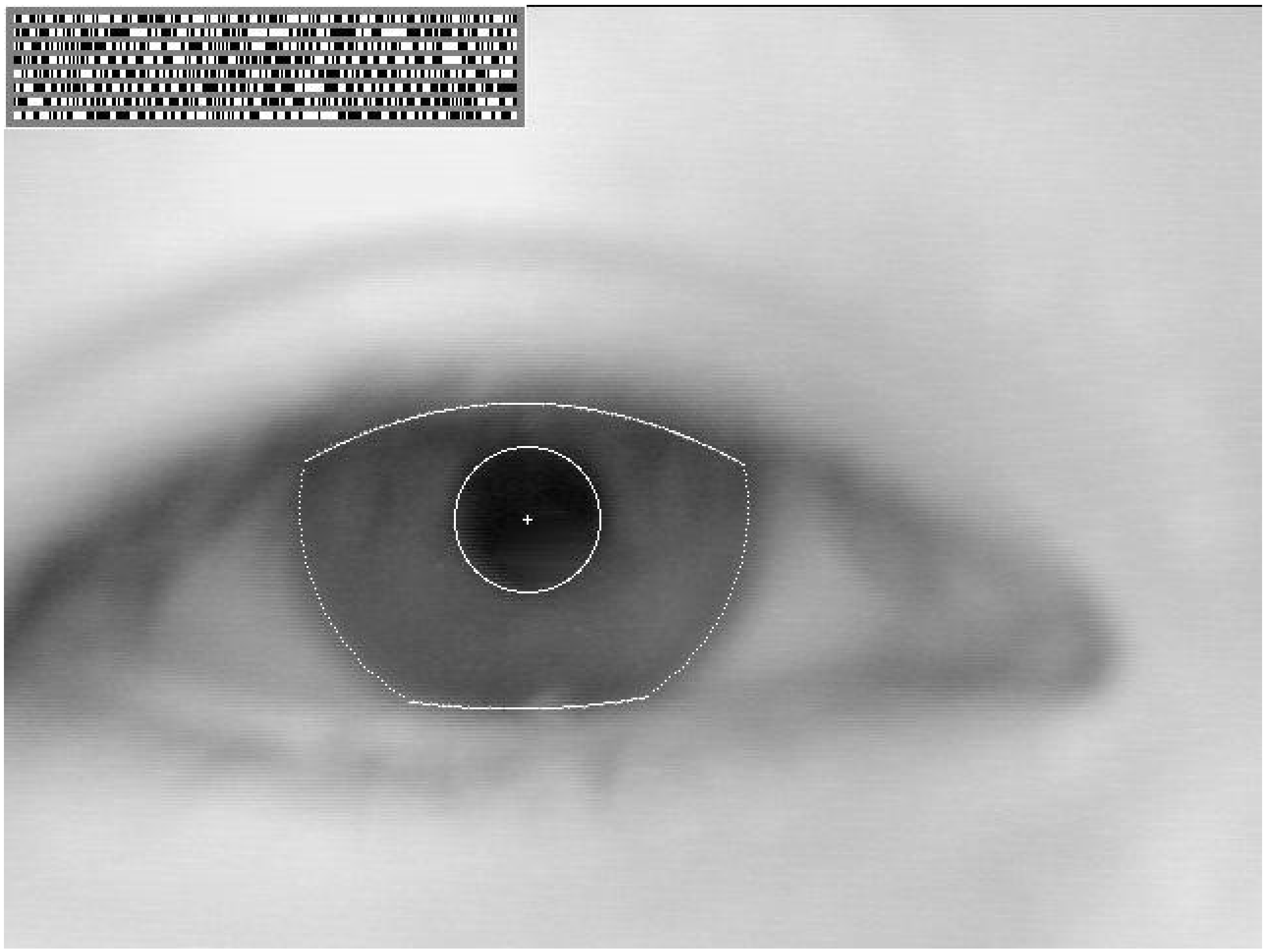
Badly defocused iris images do not cause False Matches, because the IrisCode phase bits then just become random, determined by pixel noise. This is an advantage of phase over correlation-based coding methods.



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IrisCode Logic and Normalizations

Logic for computing raw Hamming Distance scores, incorporating masks:

$$HD_{\text{raw}} = \frac{\|(codeA \otimes codeB) \cap maskA \cap maskB\|}{\|maskA \cap maskB\|}$$

where $\otimes$ is Exclusive-OR, $\cap$ is AND, and $\|\quad\|$ is the count of 'set' bits.

Score re-normalisation to compensate for number of bits compared:

$$HD_{\text{norm}} = 0.5 - (0.5 - HD_{\text{raw}})\sqrt{\frac{n}{911}}$$

Decision Criterion normalisation by database size and query rate:

$$HD_{\text{Crit}} \sim 0.32 - 0.012\ \log_{10}(N \times M)$$

where N is the search database size, M is the number of queries to be compared against the full database, while requiring nil False Matches

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False Match Rate without Score Normalization: Dependence on Number of Bits Compared and Criterion

HD_{Crit}	400 bits	500 bits	600 bits	700 bits	800 bits	900 bits	1000 bits
0.260	$2 \cdot 10^{-9}$	$5 \cdot 10^{-10}$	$3 \cdot 10^{-10}$	$1 \cdot 10^{-10}$	0	0	0
0.265	$3 \cdot 10^{-9}$	$8 \cdot 10^{-10}$	$5 \cdot 10^{-10}$	$2 \cdot 10^{-10}$	$4 \cdot 10^{-11}$	0	0
0.270	$4 \cdot 10^{-9}$	$1 \cdot 10^{-9}$	$9 \cdot 10^{-10}$	$5 \cdot 10^{-10}$	$2 \cdot 10^{-10}$	0	0
0.275	$7 \cdot 10^{-9}$	$2 \cdot 10^{-9}$	$1 \cdot 10^{-9}$	$9 \cdot 10^{-10}$	$5 \cdot 10^{-10}$	$3 \cdot 10^{-11}$	0
0.280	$1 \cdot 10^{-8}$	$4 \cdot 10^{-9}$	$2 \cdot 10^{-9}$	$2 \cdot 10^{-9}$	$1 \cdot 10^{-9}$	$2 \cdot 10^{-10}$	0
0.285	$2 \cdot 10^{-8}$	$7 \cdot 10^{-9}$	$4 \cdot 10^{-9}$	$3 \cdot 10^{-9}$	$2 \cdot 10^{-9}$	$5 \cdot 10^{-10}$	$2 \cdot 10^{-11}$
0.290	$3 \cdot 10^{-8}$	$1 \cdot 10^{-8}$	$8 \cdot 10^{-9}$	$7 \cdot 10^{-9}$	$4 \cdot 10^{-9}$	$1 \cdot 10^{-9}$	$1 \cdot 10^{-10}$
0.295	$4 \cdot 10^{-8}$	$2 \cdot 10^{-8}$	$1 \cdot 10^{-8}$	$1 \cdot 10^{-8}$	$9 \cdot 10^{-9}$	$3 \cdot 10^{-9}$	$4 \cdot 10^{-10}$
0.300	$6 \cdot 10^{-8}$	$3 \cdot 10^{-8}$	$3 \cdot 10^{-8}$	$2 \cdot 10^{-8}$	$2 \cdot 10^{-8}$	$7 \cdot 10^{-9}$	$9 \cdot 10^{-10}$
0.305	$9 \cdot 10^{-8}$	$6 \cdot 10^{-8}$	$5 \cdot 10^{-8}$	$4 \cdot 10^{-8}$	$4 \cdot 10^{-8}$	$1 \cdot 10^{-8}$	$2 \cdot 10^{-9}$
0.310	$1 \cdot 10^{-7}$	$1 \cdot 10^{-7}$	$8 \cdot 10^{-8}$	$8 \cdot 10^{-8}$	$7 \cdot 10^{-8}$	$3 \cdot 10^{-8}$	$5 \cdot 10^{-9}$
0.315	$2 \cdot 10^{-7}$	$2 \cdot 10^{-7}$	$1 \cdot 10^{-7}$	$2 \cdot 10^{-7}$	$1 \cdot 10^{-7}$	$6 \cdot 10^{-8}$	$1 \cdot 10^{-8}$
0.320	$3 \cdot 10^{-7}$	$3 \cdot 10^{-7}$	$2 \cdot 10^{-7}$	$3 \cdot 10^{-7}$	$3 \cdot 10^{-7}$	$1 \cdot 10^{-7}$	$2 \cdot 10^{-8}$

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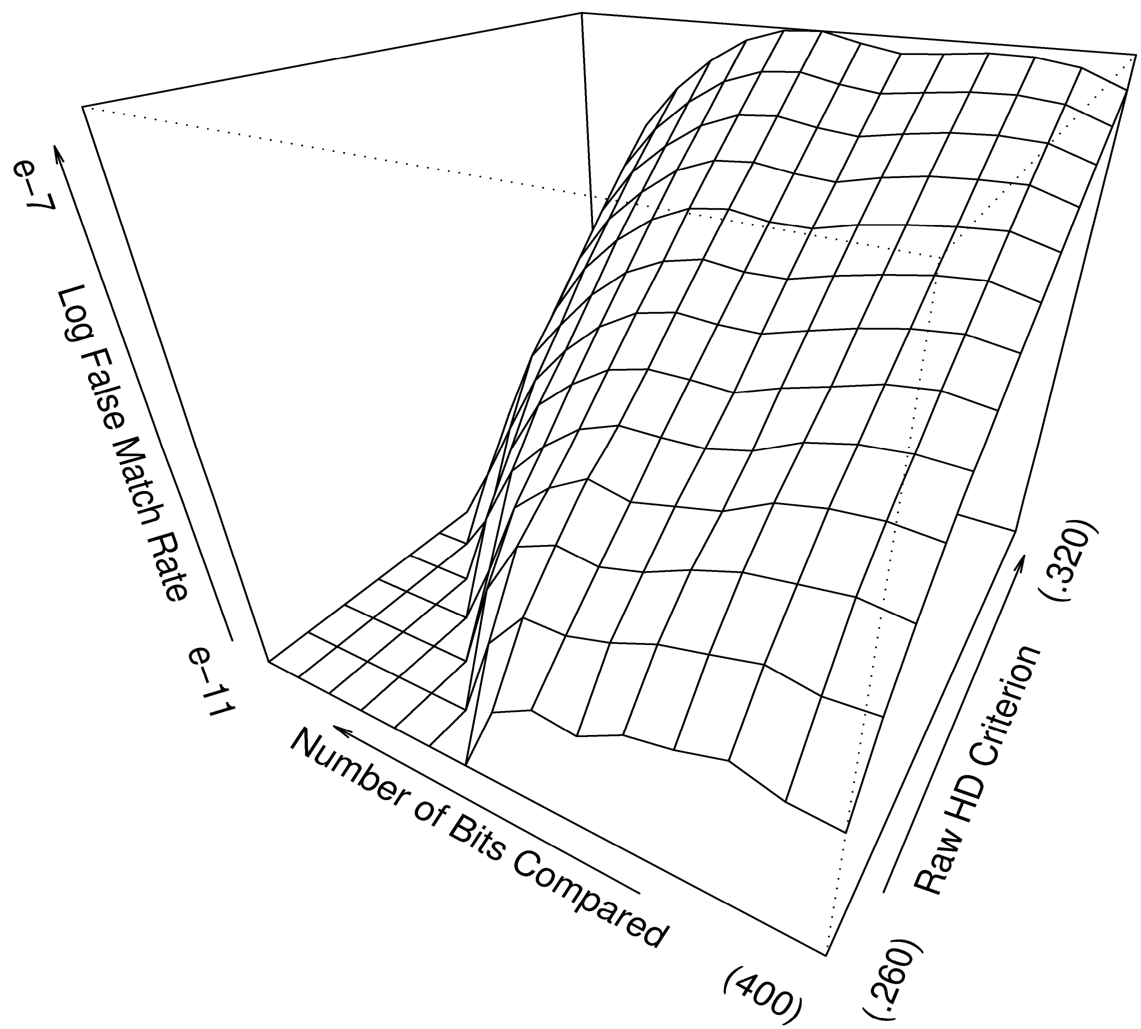
Log False Match Rates versus HD_crit and Number of Bits Compared

for 200 Billion Iris Comparisons, non−Normalised Scores



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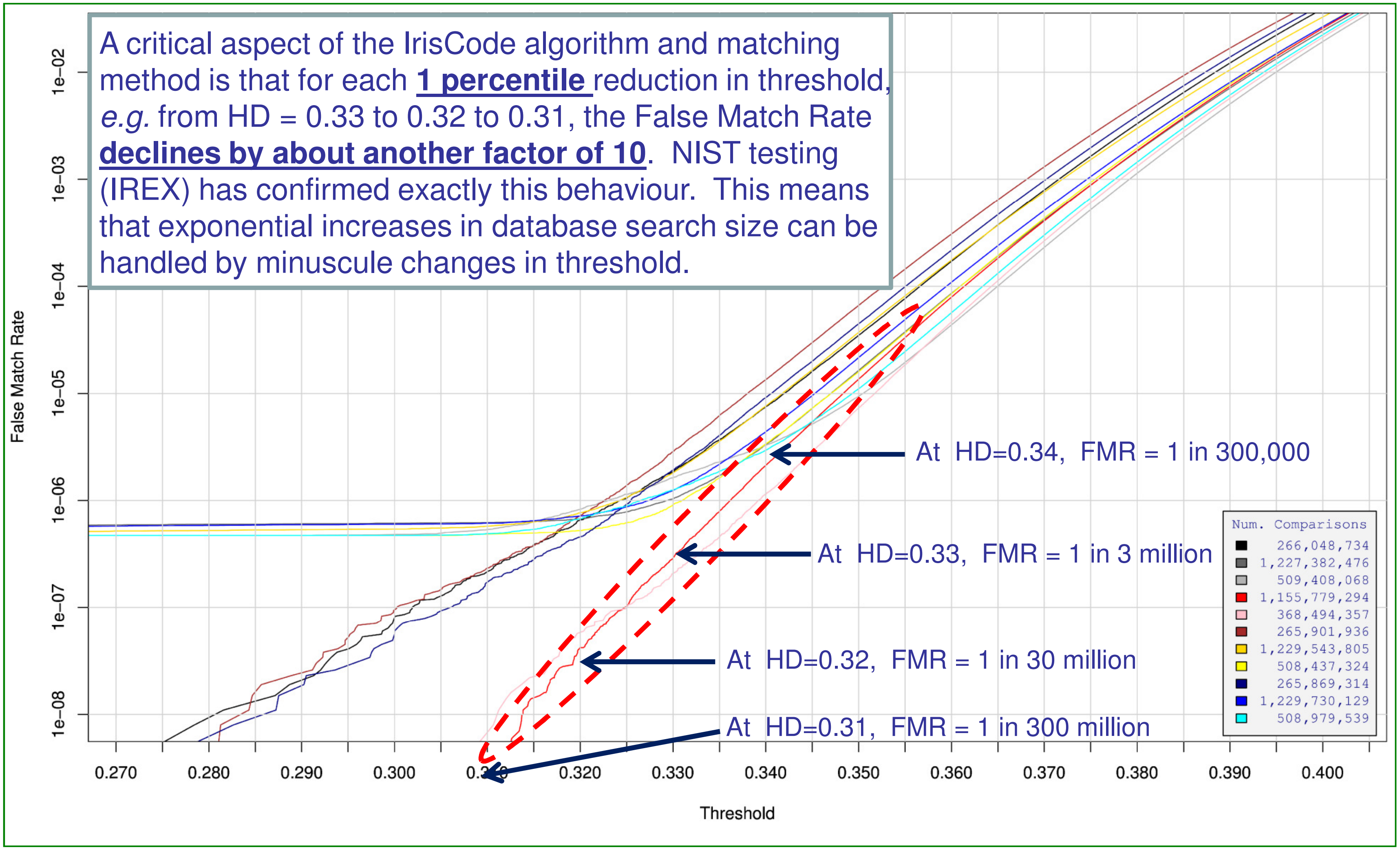
Effect of the "Amount of Iris Visible"

- If eyelids occlude much of the iris, fewer IrisCode bits are available for comparison with other IrisCodes
- Decision criterion then becomes correspondingly more demanding
- Renormalisation is based on equal-confidence contours for binomial combinatorics, whatever the number of bits compared
- All of the matches in this table are equivalently decisive:

number of bits compared	*approximate percent of iris visible*	*maximum acceptable fraction of bits disagreeing*
200	17%	0.13
300	26%	0.19
400	35%	0.23
500	43%	0.26
600	52%	0.28
700	61%	0.30
800	69%	0.31
911	79%	0.32
1000	87%	0.33
1152	100%	0.34

NIST (IREX-1) confirmation of the exponential decline in False Match Rate with minor threshold reductions



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False Match Rates with HD_{norm} Score Normalization:
Dependence on Criterion (200 Billion Comparisons, UAE Database)

HD Criterion	*Observed False Match Rate*
0.220	0 (*theor: 1 in* 5×10^{15})
0.225	0 (*theor: 1 in* 1×10^{15})
0.230	0 (*theor: 1 in* 3×10^{14})
0.235	0 (*theor: 1 in* 9×10^{13})
0.240	0 (*theor: 1 in* 3×10^{13})
0.245	0 (*theor: 1 in* 8×10^{12})
0.250	0 (*theor: 1 in* 2×10^{12})
0.255	0 (*theor: 1 in* 7×10^{11})
0.262	1 in 200 billion
0.267	1 in 50 billion
0.272	1 in 13 billion
0.277	1 in 2.7 billion
0.282	1 in 284 million
0.287	1 in 96 million
0.292	1 in 40 million
0.297	1 in 18 million
0.302	1 in 8 million
0.307	1 in 4 million
0.312	1 in 2 million
0.317	1 in 1 million

The benefit of fusion:

This entire range of False Match probabilities can be squared, if both eyes are used ("AND "rule), because they are independent. *E.g.*. If both eyes give HD scores below 0.28 (for which FMR~10^{-9}), then their joint FMR is ~10^{-18}

Empirical performance in this range was confirmed also by IBG's ITIRT Report (2005) testing these algorithms.

In 1.7 billion comparisons between different irises, the smallest HD score observed by IBG was in the vicinity of 0.28 (consistent with this Table).

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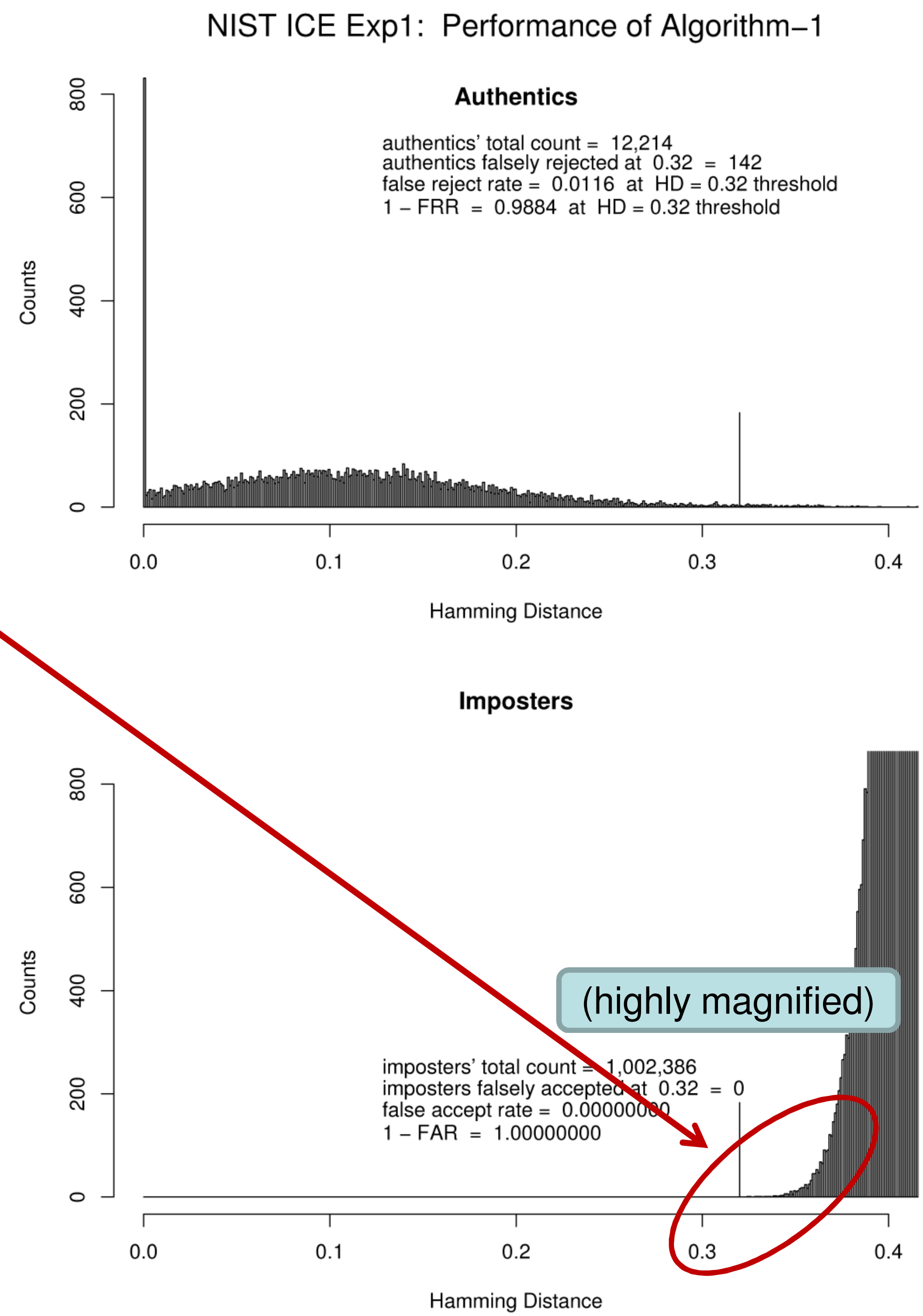
In biometrics, it is the tail attenuation that matters!

The key to iris recognition's resistance to False Matches is the very rapid attenuation of the tail of the distribution for Impostor iris comparisons.



This property seems to be unique to this biometric, and it reflects the great entropy of the iris code.

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Some funny hiccups which delayed recognition that iris has extraordinary resistance against False Matches:

(1.)

- In 2000, the "**National Biometric Test Center**" (USA) reported that testing an iris recognition prototype had generated "lots of False Matches."
- The images were sent to me; - at first I confirmed their apparent finding....
- But then I found that they were actually all TRUE matches (*i.e.,* ground-truth errors).
- The Director of the "National Biometric Test Center" then generously acknowledged:

```
From: JLWayman@aol.com "Jim Wayman"
Sent: Wednesday, September 06, 2000 2:32 PM

...clearly we were getting scammed by some of our
volunteers (at $25 a head, they were changing names
and coming through multiple times).

JLW
```

NB: International Standard ISO/IEC 19795-1,-6: *"Best Practices in Biometric Testing and Reporting"*, under development now; - see Tutorial here at ICB

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(2.)

• In 2006, the NIST "Iris Challenge Evaluation" (ICE) evaluated iris recognition algorithms at a threshold making FMR=0.001 (False Match Rate = 1 in a thousand).

• They concluded that (at this ROC point), iris FnMR was about the same as for face.

• (In such very **non-demanding** regions of an ROC plot, most biometrics will appear equally powerful. At FMR = 0.01, length of one's big toe would be as discriminating.)

• Based on FMR=.001 evaluation, E. Newton and J. Phillips (2007) therefore dismissed *"the conventional wisdom that iris is a very powerful biometric."*

• They overlooked the **flatness of ROC** curves for iris. (ROC slope = "likelihood ratio.")

• Minuscule reductions in threshold allow FMR to reduce by 4 or 5 orders-of-magnitude, while FnMR hardly changes at all.

(*source:* NIST presentation, London, 2011)

• **NIST IREX-III (2011)** conclusions for iris : *"there is little variation in FnMR across the five decades of FMR"* [= 5 orders-of-magnitude change in FMR via threshold].

• "For any plausible FMR target, **<u>iris makes 100,000 fewer False Matches than face</u>**."

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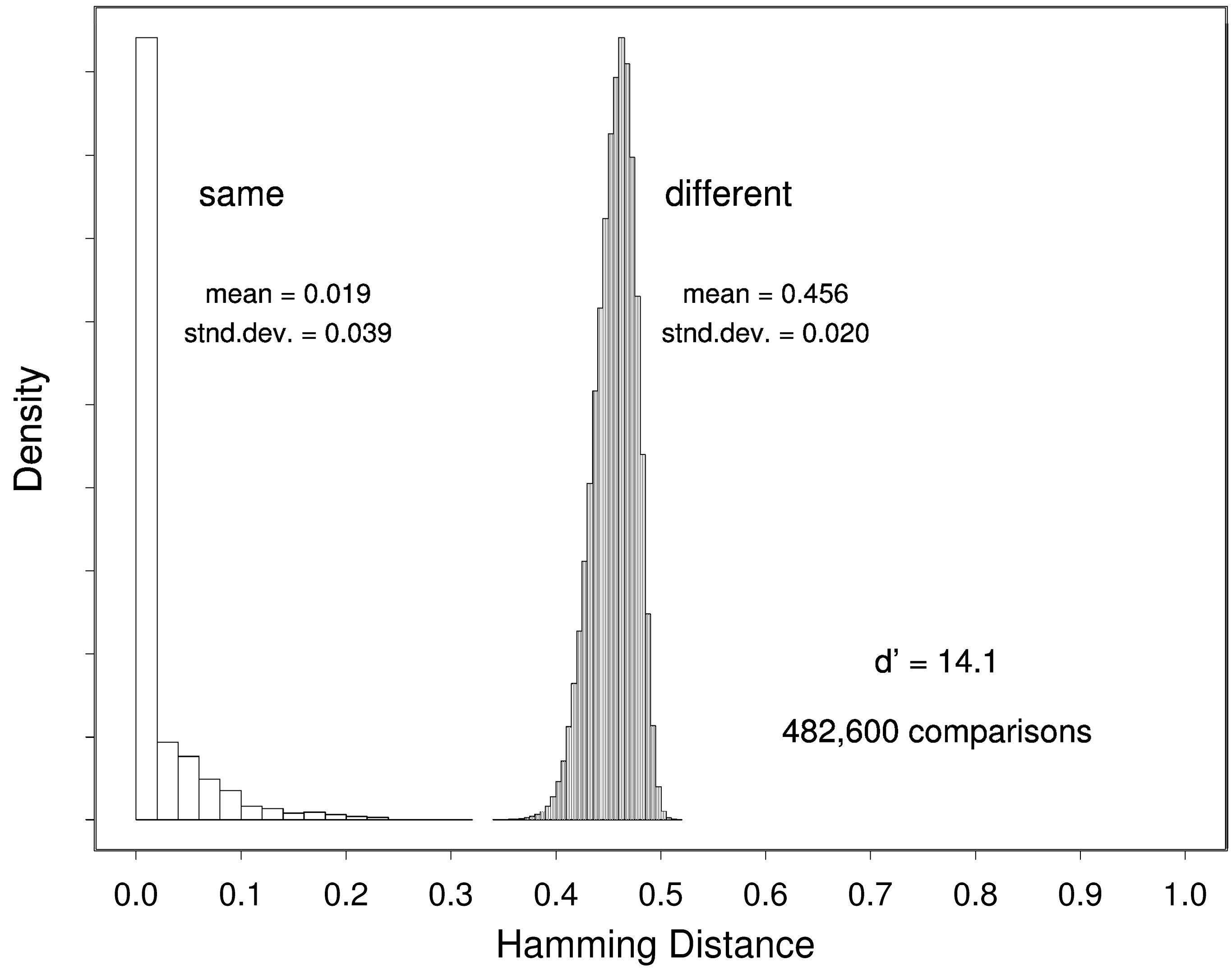
Decision Environment for Iris Recognition: Ideal Imaging



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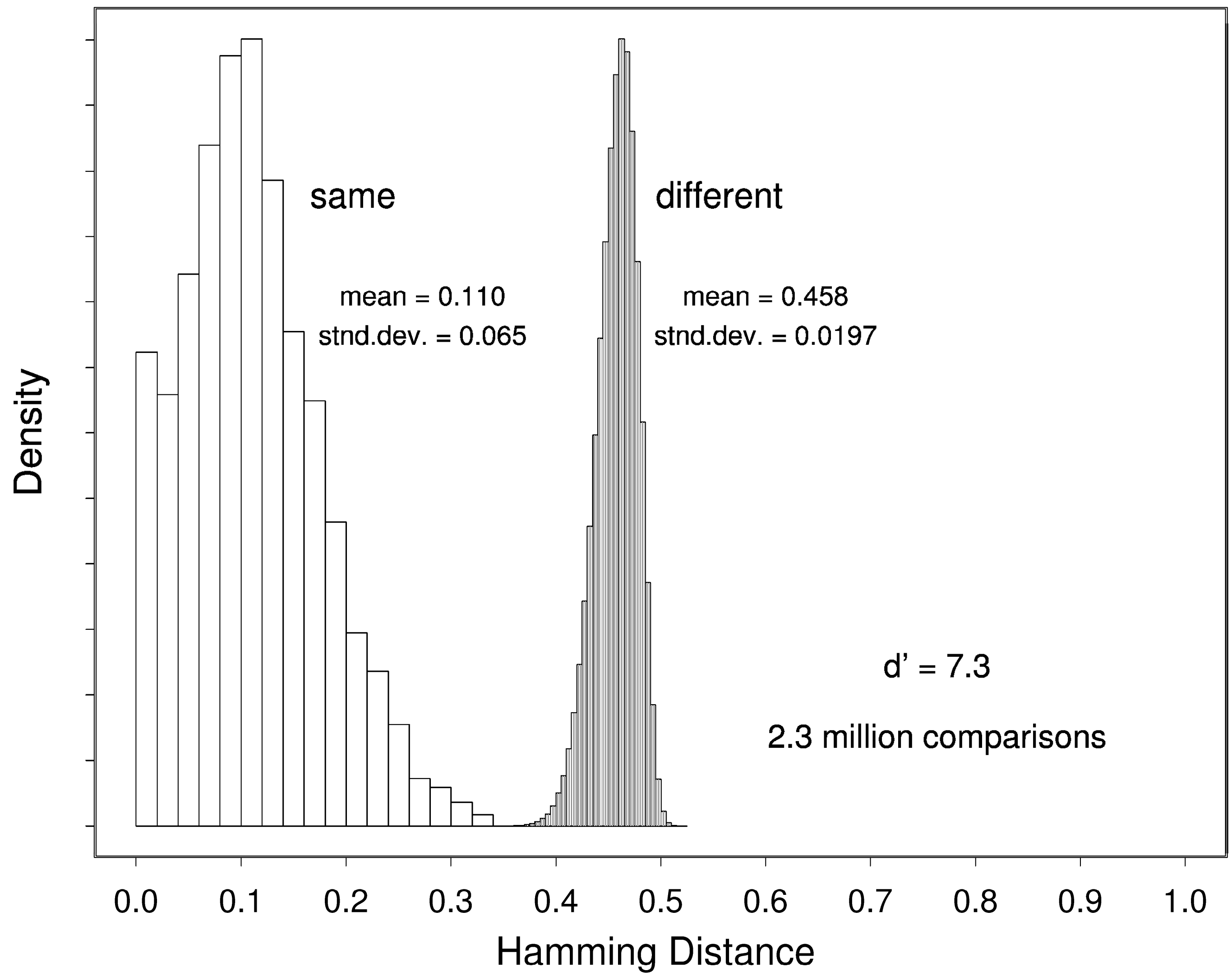
Decision Environment for Iris Recognition: Non-Ideal Imaging



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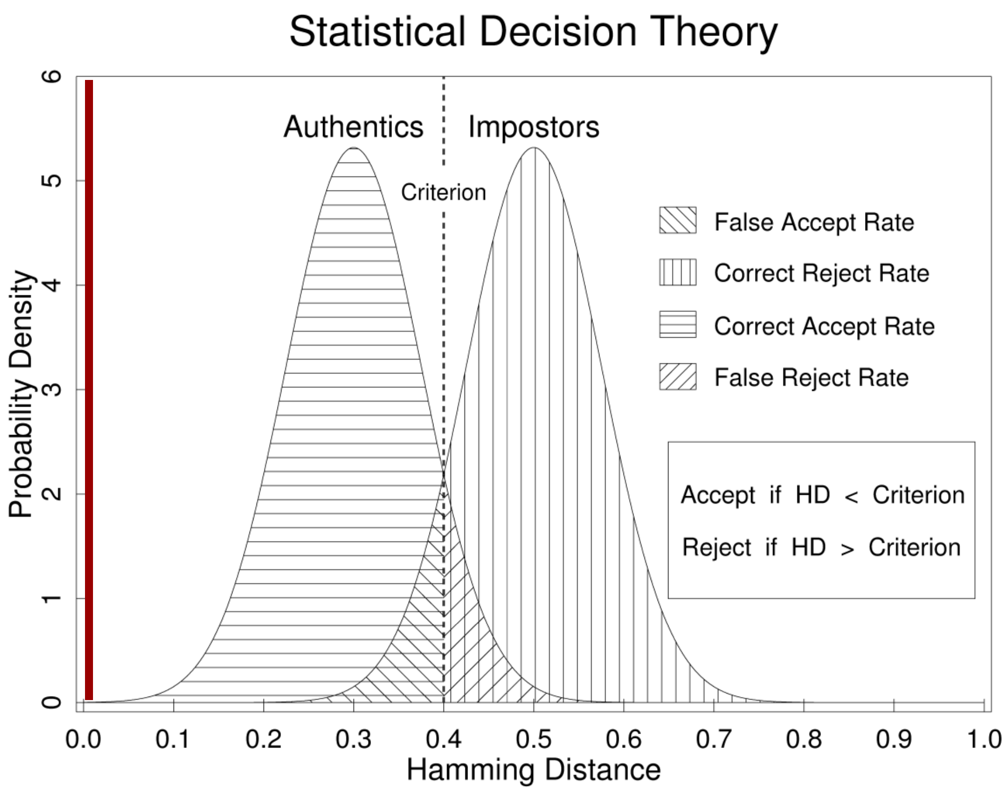

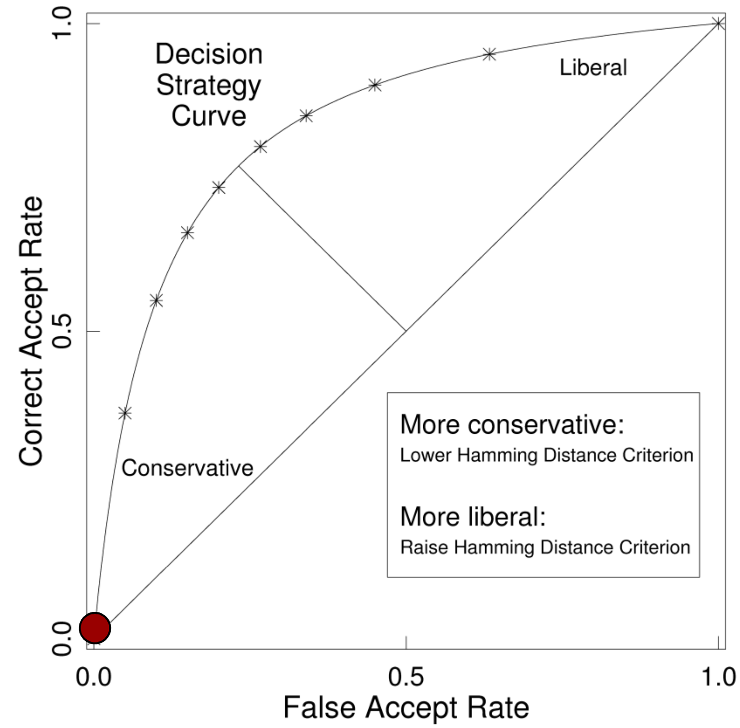

Generating ROC (or DET) curves requires moving the decision threshold, from conservative to liberal, to see the trade-off between FMR and FnMR errors.

The slope of the ROC curve is the likelihood ratio: ratio of the two density distributions at a given decision threshold criterion. Flat ROC curves permit FMR to be greatly reduced by small threshold changes, at little cost to FnMR.

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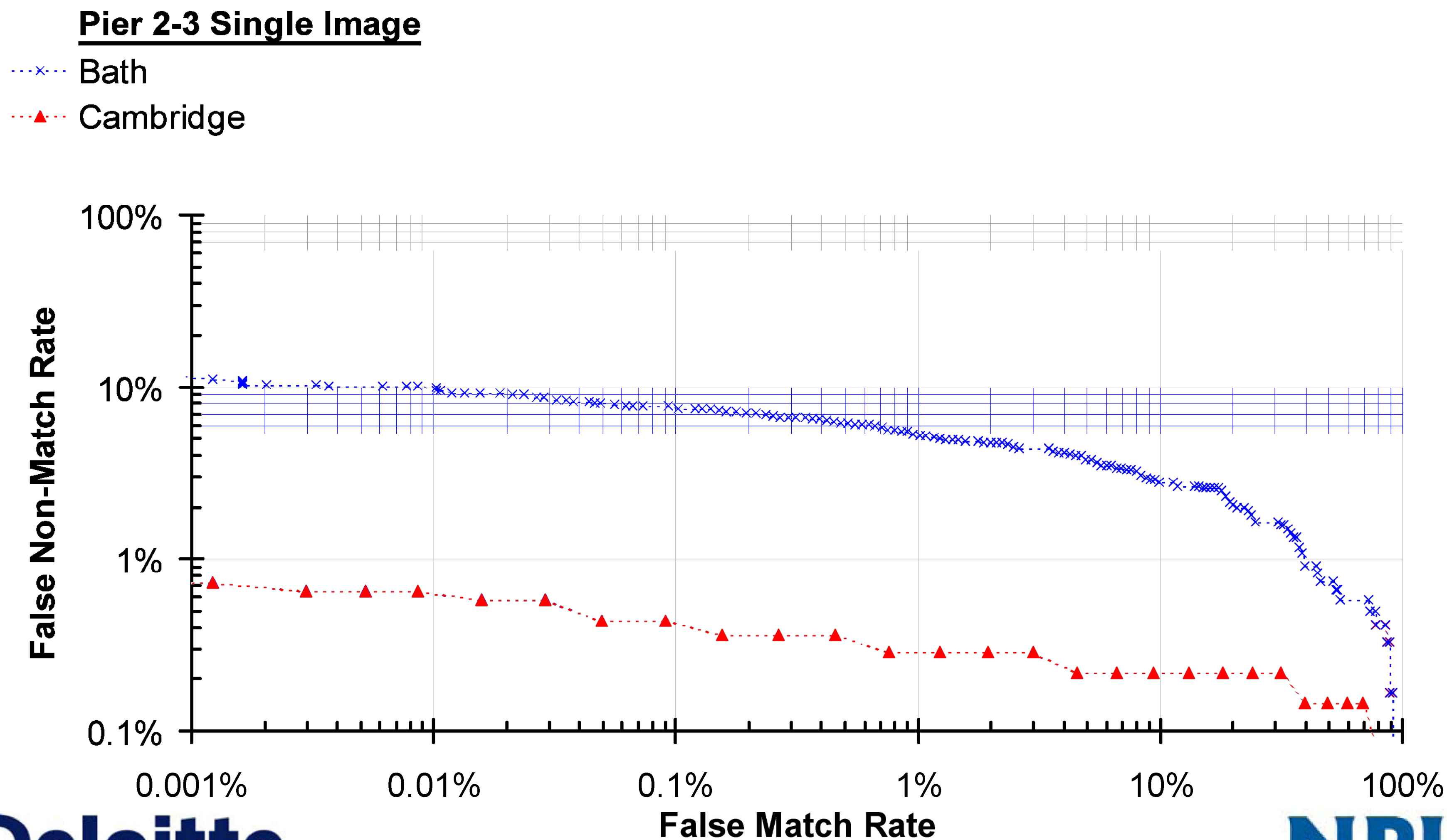
Performance of iris comparison algorithms



Deloitte.

NPL

7.7.1 Intra-Visit Enrollment Comparison DETs (Single-Attempt)

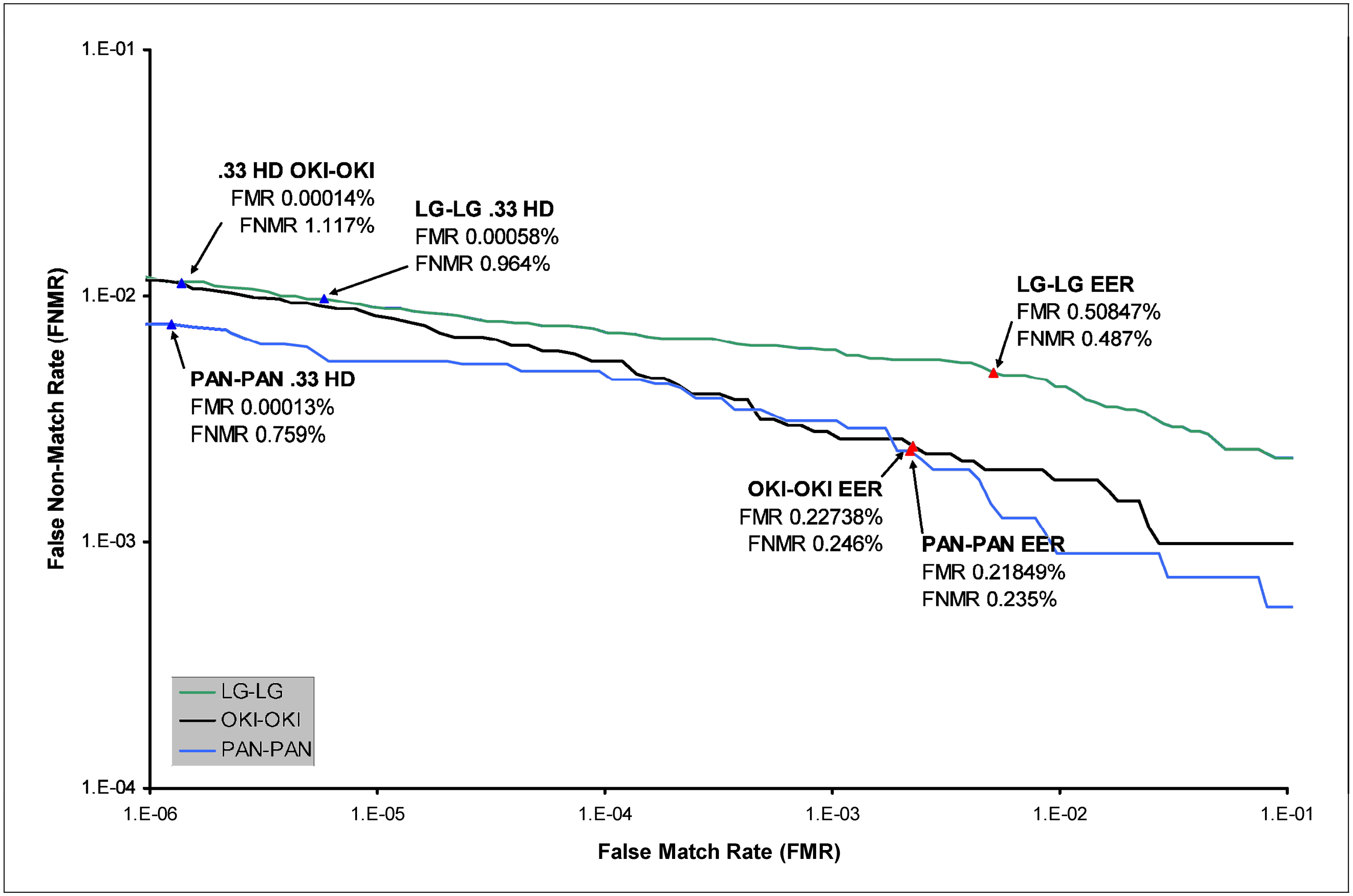


Figure 55: Intra-Visit Enrollment Comparison DETs (Single-Attempt)

Progression of iris cameras (2001 – 2012)

Schiphol Airport (NL):
iris recognition in lieu of passport presentation

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Access to condominium building, and programming the lift(!), in Japan

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Automated entry into UK without Passport presentation

- UK Project IRIS: Iris Recognition Immigration System

A "frequent flier" programme that allows enrolled participants to enter the UK from abroad without passport presentation, and without asserting their identity in any other way. Cameras at automated gates operate in identification mode, searching a centralised database exhaustively for any match.

Home Office
Border & Immigration Agency

What is IRIS?
The Iris Recognition Immigration System (IRIS) is a much more efficient and convenient way to clear immigration.
iris

IRIS statistics as of June 2009:

" > 1 million frequent travellers have been enrolled, growing by 2,000 per week, and there have been about 4 million IRIS automated entries since January 2006, with currently almost 20,000 IRIS arrivals into the UK per week."

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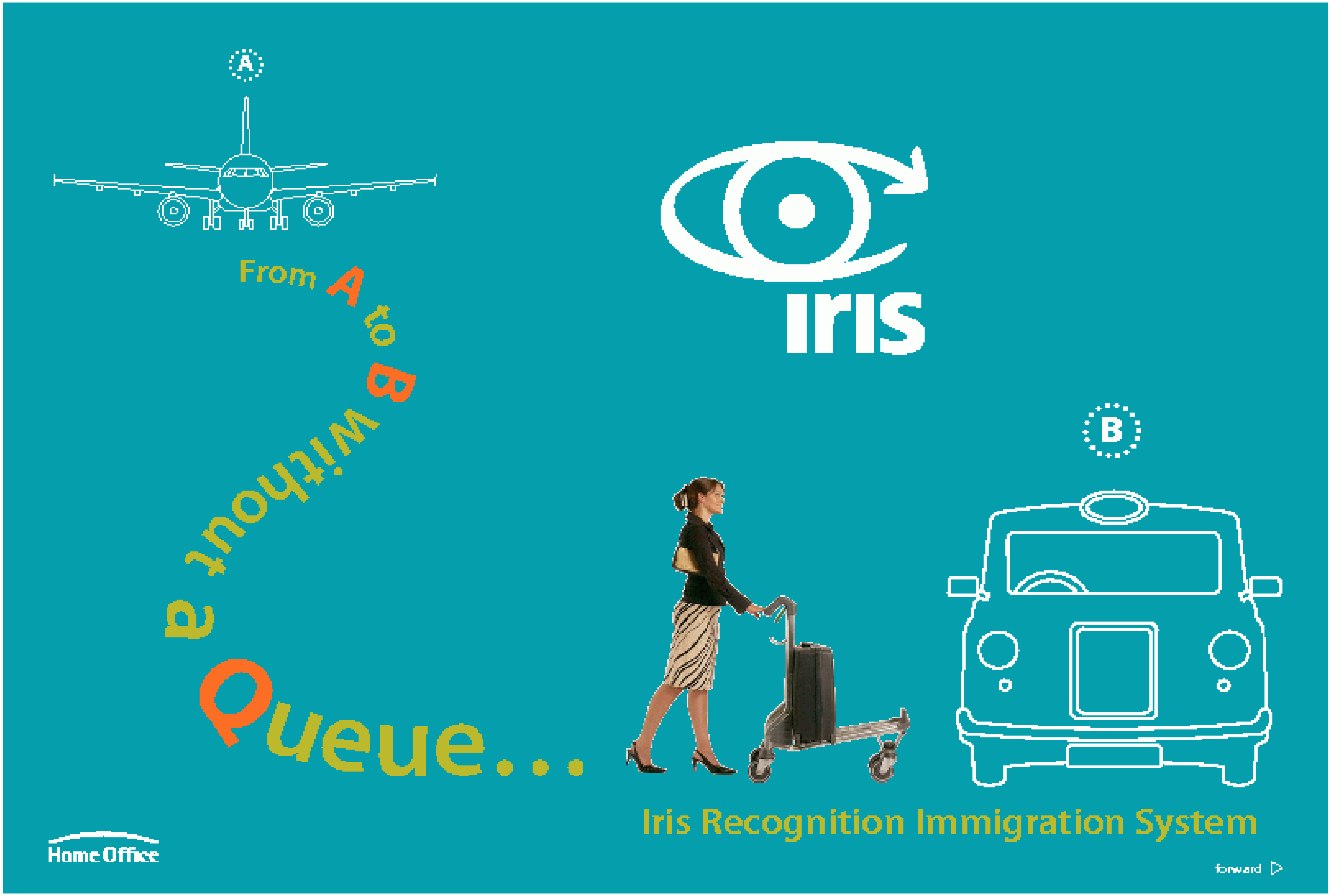

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IRIS gates at 10 UK airport terminals for registered
frequent travellers in lieu of passport presentation

US-Canadian border crossing in lieu of passports

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Takhtabaig Voluntary Repatriation Centre, Pakistan-Afghan border

The United Nations High Commission for Refugees (UNHCR) administers cash grants for returnees, using iris identification.

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- The United Arab Emirates iris-based border security system

- Deployed at all 32 air, land, and sea-ports
- 1,190,000 IrisCodes registered in a watch-list
- On a typical day 12,000 irises are compared to all on the watch-list (14 billion comparisons/day)
- Each exhaustive search takes < 2 seconds
- About 30 trillion (30 million-million) comparisons of irises have been done since 2001
- After an amnesty for violators of work permit laws or other offences in 2001, expellees' iris patterns were encoded. About 150,000 persons have since been caught trying to re-enter illegally.

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Visa application and registration, UAE

(Officer-operated and controlled camera)

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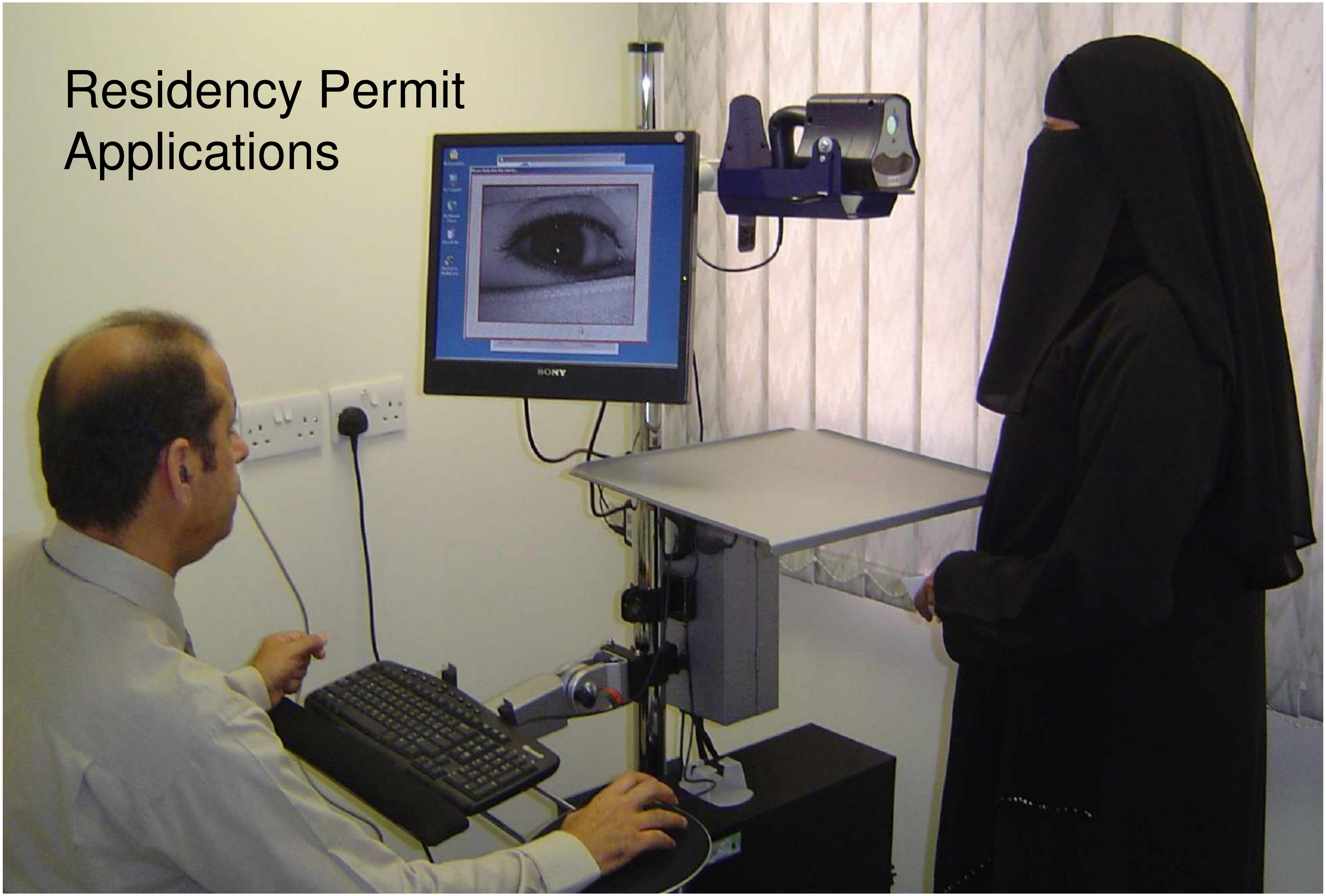
Residency Permit Applications



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Handheld and portable iris cameras

U.S. Police Departments:
bookings and releases

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Handheld, portable, wireless cameras (radio linked to database)
- deployed in Iraq and Afghanistan

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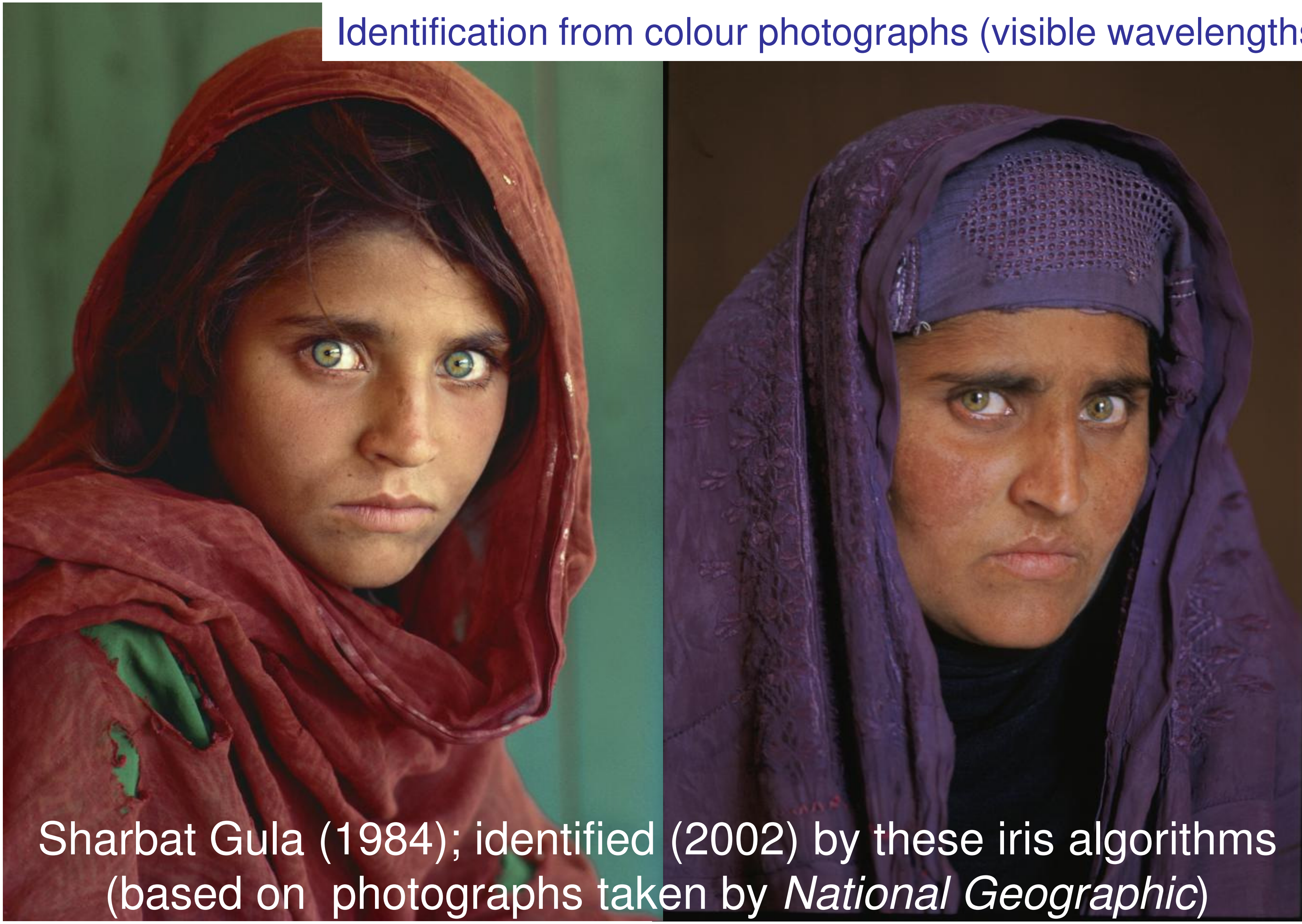
Identification from colour photographs (visible wavelengths)



Sharbat Gula (1984); identified (2002) by these iris algorithms (based on photographs taken by *National Geographic*)

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Today's state-of-the-art public iris cameras: at-a-distance, and/or on-the-move:
Airport check-in: 2 meter distance from camera; capture volume $\approx$ 1 cubic meter

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Iris image standard; data formats; compressibility

- ISO/IEC 19794-6:2011 Iris Image Data Interchange Format Standard (2nd gen. revision published in 2011)
- Inter-operable image formats were needed, instead of proprietary IrisCode templates; vendor neutral
- NIST IREX study endorsed new compact formats: iris image compression to as little as 2 KB using JP2K (not JPEG), with cropping and ROI masking; or lossless compression using PNG container
- Revision process was **empirically-based** (process led by Prof. C. Busch, and driven by NIST tests)

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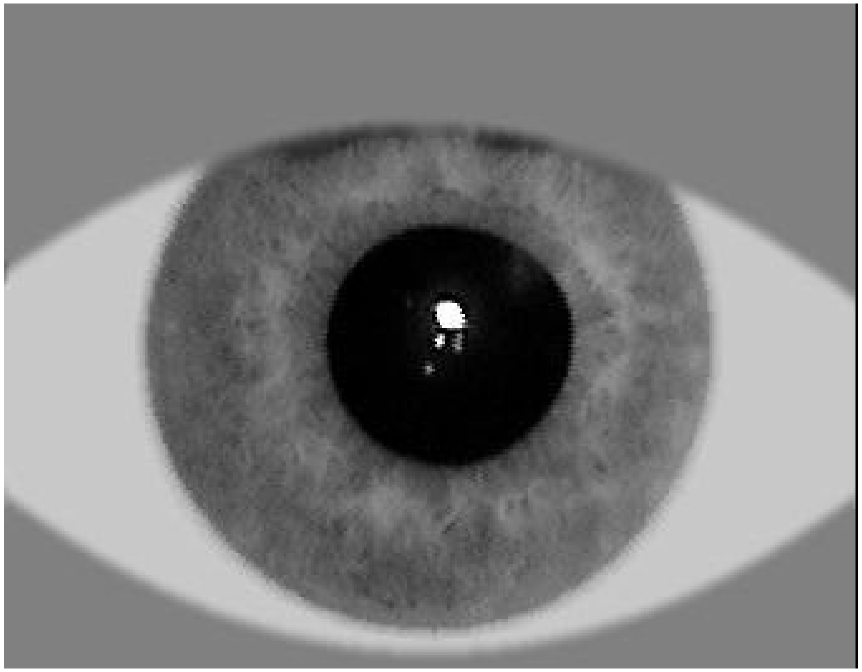
New ISO Standard: highly compact iris image format, compressed to as little as 2,000 bytes



- Cropping, and masking non-iris regions, preserves the coding budget
- Pixels outside the ROI are fixed to constant values, for normal segmentation
- Softening the mask boundaries also preserves the coding budget
- At only 2,000 bytes, iris images are now much more compact than fingerprints

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Several major research areas today

1. Metrics for assessing iris image Quality (empirically driven by NIST; steering development of an ISO Standard)
2. Improving the user interface: more fluid, less intrusive: iris-at-a-distance (3+ meters), iris-on-the-move (1 meter/sec), iris recognition with unconstrained illumination / wavelengths
3. Tolerating off-axis gaze (detecting & compensating for it)
4. Countermeasures against spoofing
5. How much can resolution requirements be relaxed?
6. Indexing for fuzzy databases (matching without search)

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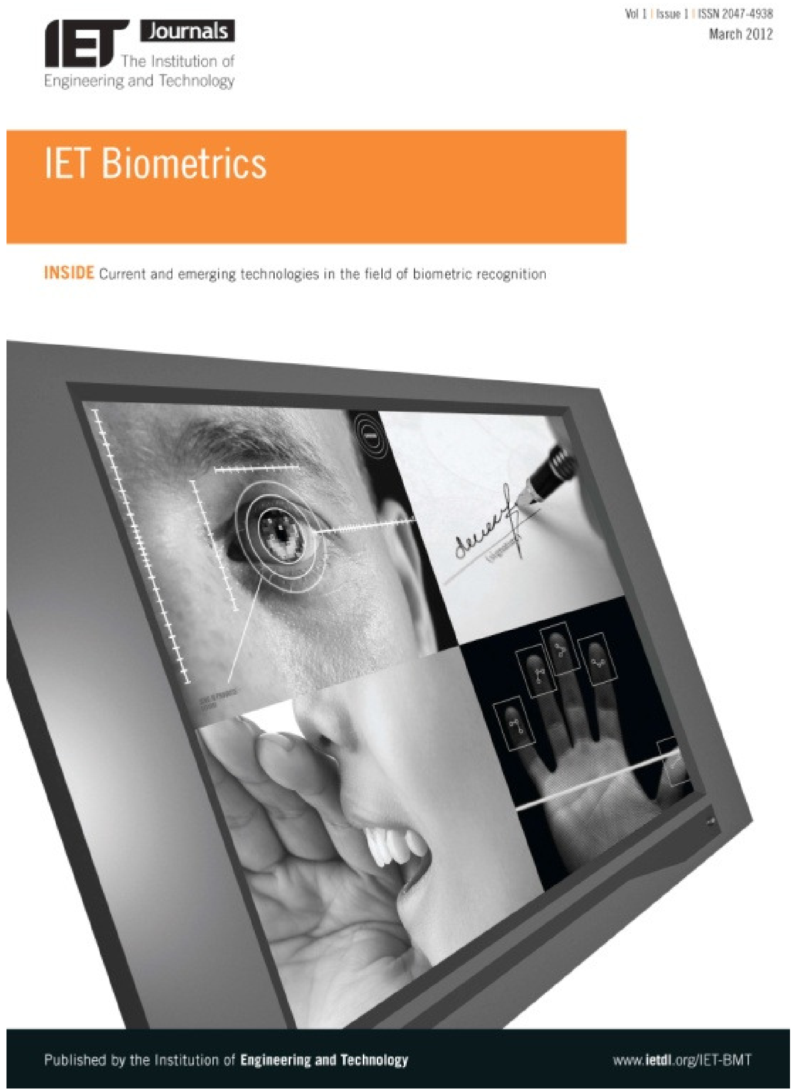
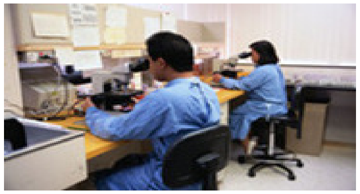
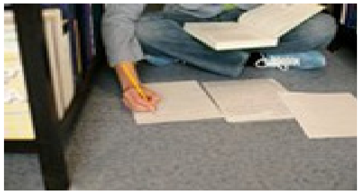
A new forum for research publications in these areas

A new Journal for the biometrics community



About the IET

- One of the world's leading professional societies for the engineering and technology community
- Formerly The Institution of Electrical Engineers (The IEE) established 1871
- Over 150,000 members in 127 countries
- Offices in the UK, USA, China and India

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1. Metrics for assessing iris image quality

- By assessing quality of each image frame, better quality iris enrollments are possible, and time is not wasted on poor images.
- Real-time image quality metrics include: focus; iris texture energy; eyelid occlusion; pupil boundary contrast; number of valid bits.
- If an image fails these quality metrics, it is rejected and a new image is captured.
- A new ISO/IEC Standard (29794-6) for iris image quality is being developed (E.Tabassi, ed.)

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Quality metrics in IQCE with nonlinear veto powers

Veto power is important because otherwise some aspects of quality (such as good focus) might seem to "compensate for" other, fatal, problems (e.g. the eyelids are completely closed).

General approach proposed for ISO/IEC 29794-6 Standard:

- Map each quality vector element onto [0, 1] unit interval with a normalising function such as $x \rightarrow x^2/(x^2 + c^2)$ or $(1 - e^{-x/c})$
- Combine those normalised vector elements (say x, y, z) which should have veto powers into a single actionable quality scalar, Q, as a product of various power functions: $Q = x^{\alpha} y^{\beta} z^{\gamma}$
- Fit the exponents (α, β, γ) empirically by nonlinear regression to maximise the ability of Q to predict recognition performance, e.g. inverse relation to Hamming distance for authentics.

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NIST IREX-II *(IQCE: "Iris Quality Calibration and Evaluation")* confirmation that the best Quality metric for iris (= most predictive of performance), is a product of power functions:

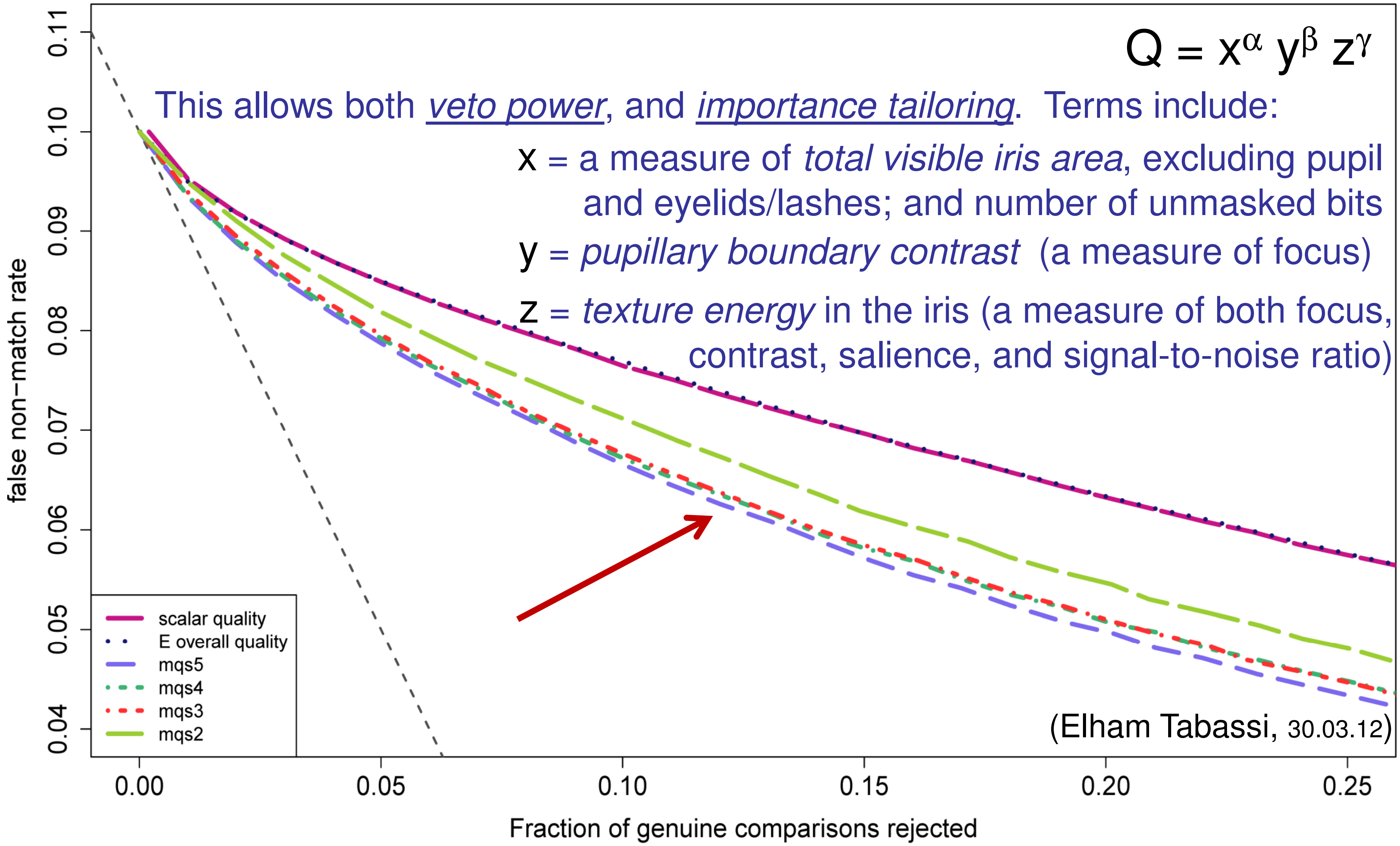

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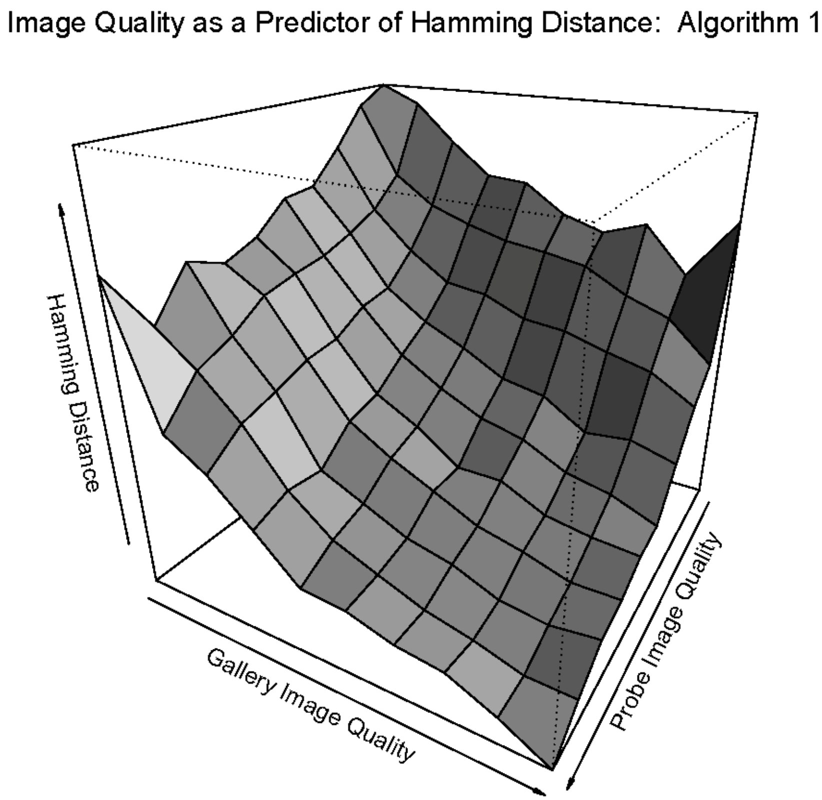
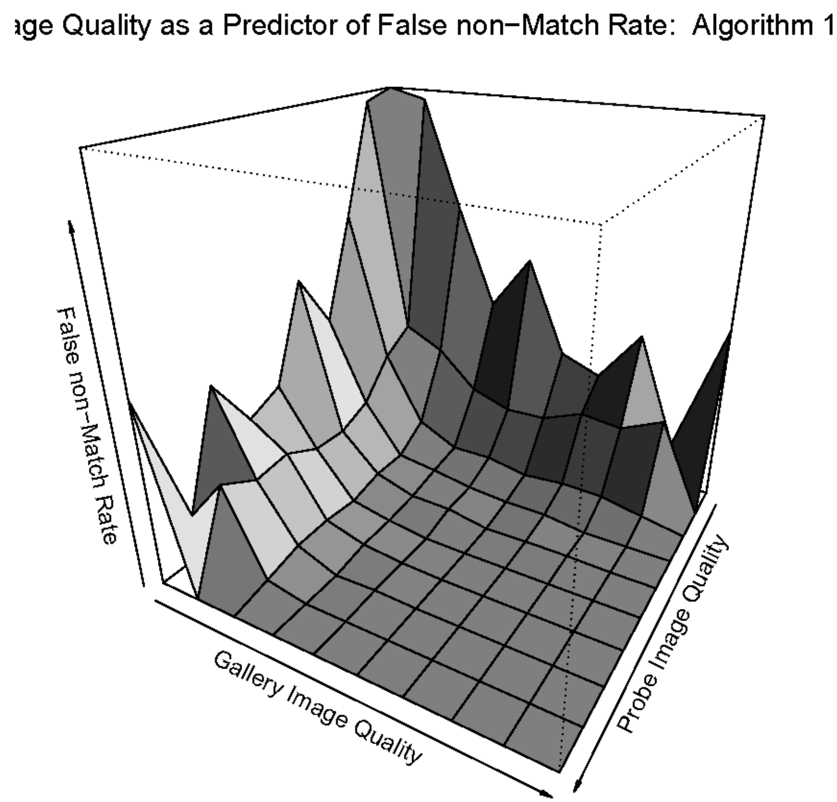
Image Quality scores can predict failures-to-match



Hamming Distances of same-eye images predicted by their joint Q scores.



non-Match Rate for same-eye images predicted by their joint Q

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2. Improving the user interface

In early iris recognition systems, sometimes the user interface was not always as convenient and user-friendly as it might or should have been...

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Iris-on-the-Move, Iris-at-a-Distance

Parameters of Sarnoff IoM system
(Matey et al., *Proc IEEE*, 94, Nov. 2006)

- camera distance: 3 meters, hidden
- capture rate: 15 frames/sec
- subject walking speed: 1 meter/sec
- inter-frame travel distance: ~ 6 cm
- sensor: 2048 x 2048 pixels (Pulnix)
- resolution at subject: 0.1 mm/pixel

- (so iris diameter is about 100 pixels)

- lens focal length: 210 mm
- illumination: NIR LEDs on portal
- capture volume: 20 cm x 20 cm x 10cm (depth of field), so one or two well-focused images can be captured at a walking speed of 1 meter/sec

Fig. 6. ***Illustration of the concept of operation for the IOM system. The panels behind the subject are the sides of a commercial metal detector. The stanchions just in front of the subject support an array of NIR illuminators. The camera package is at the far right of the subject.***

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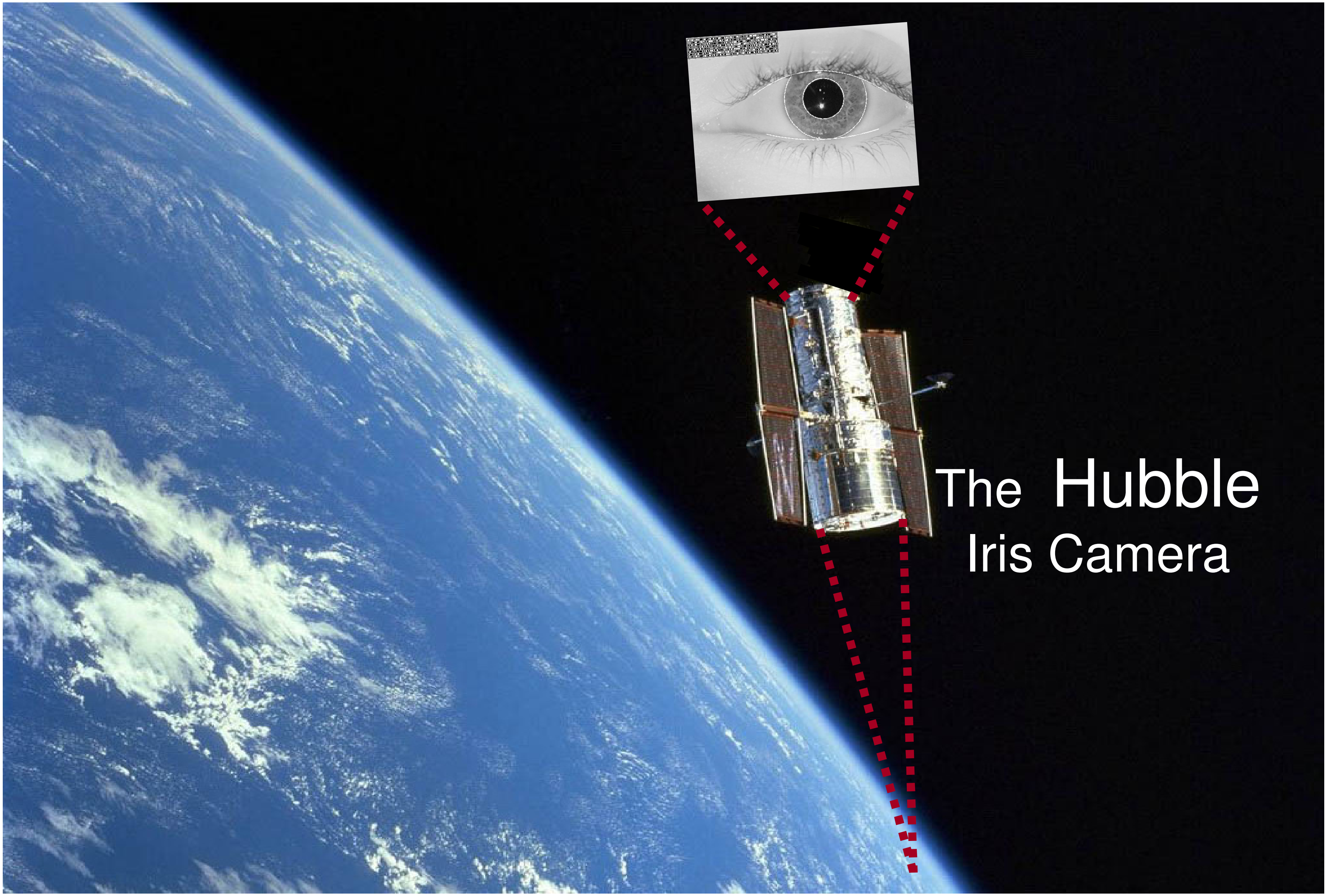

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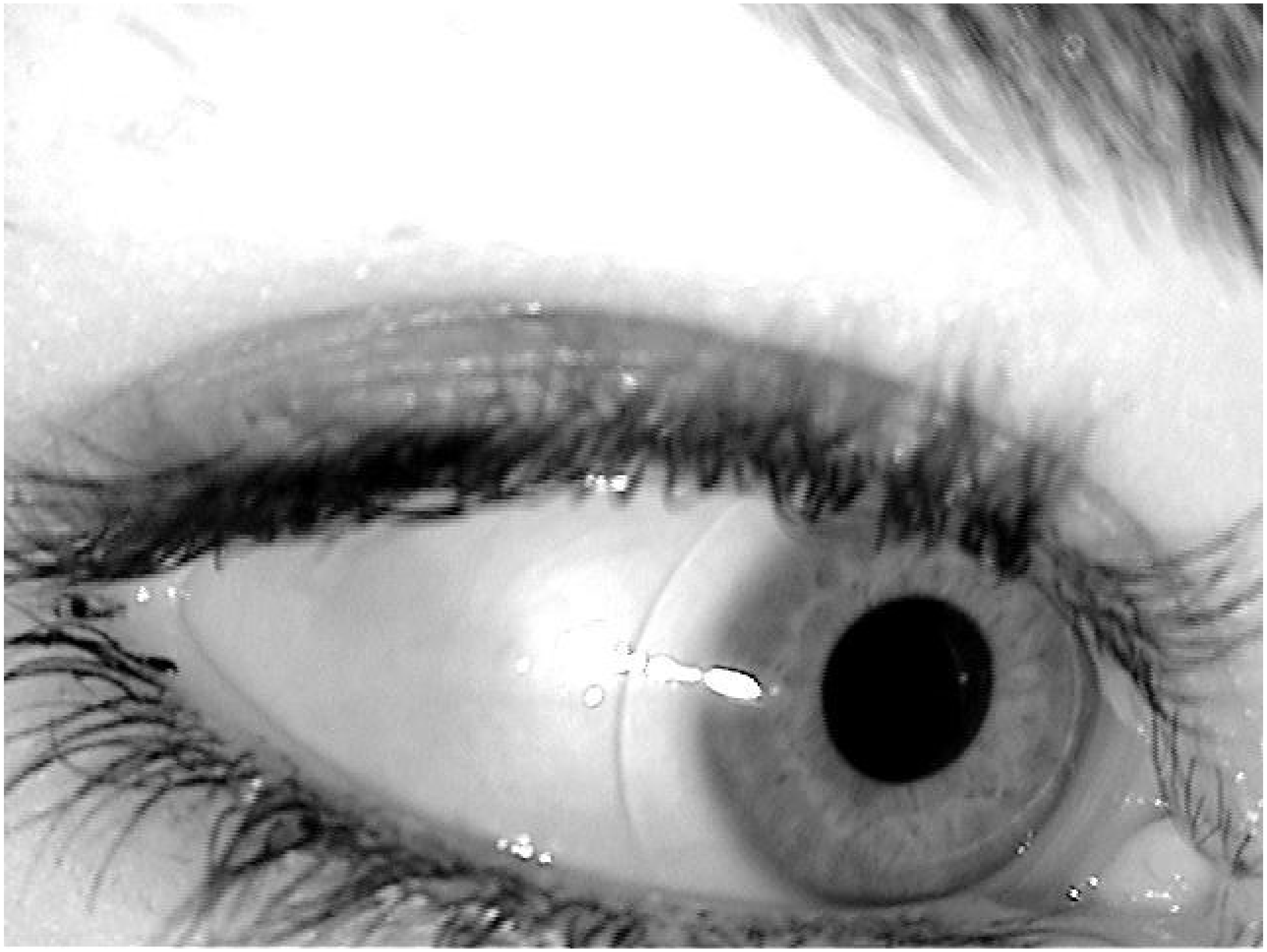
3. Tolerating off-axis gaze:
Iris images acquired off-axis…



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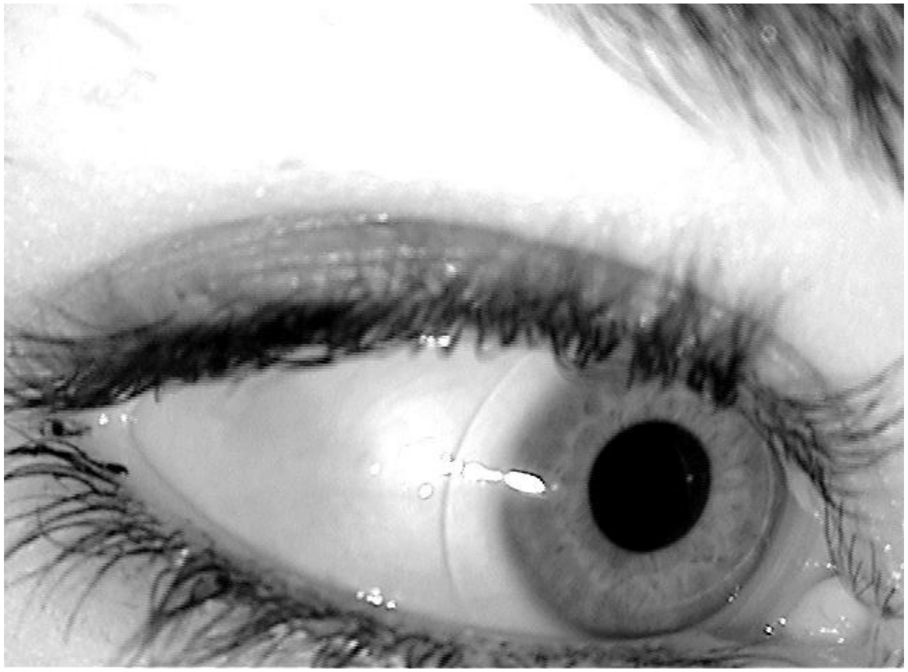
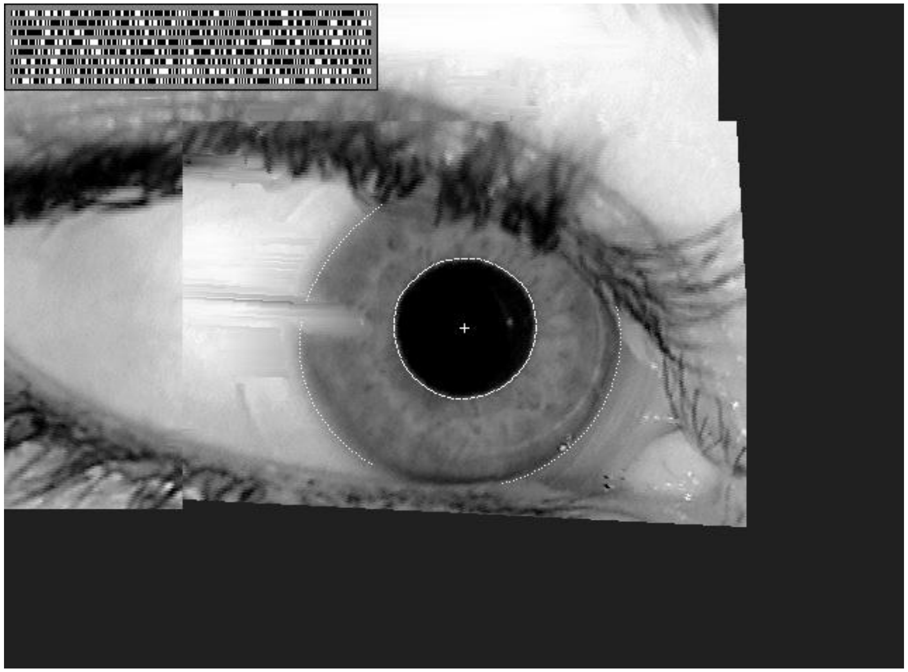
…can be "corrected" by Fourier-based trigonometry to estimate the gaze angle and make a corrective affine transformation, effectively "rotating the eye in its socket, towards the camera:"





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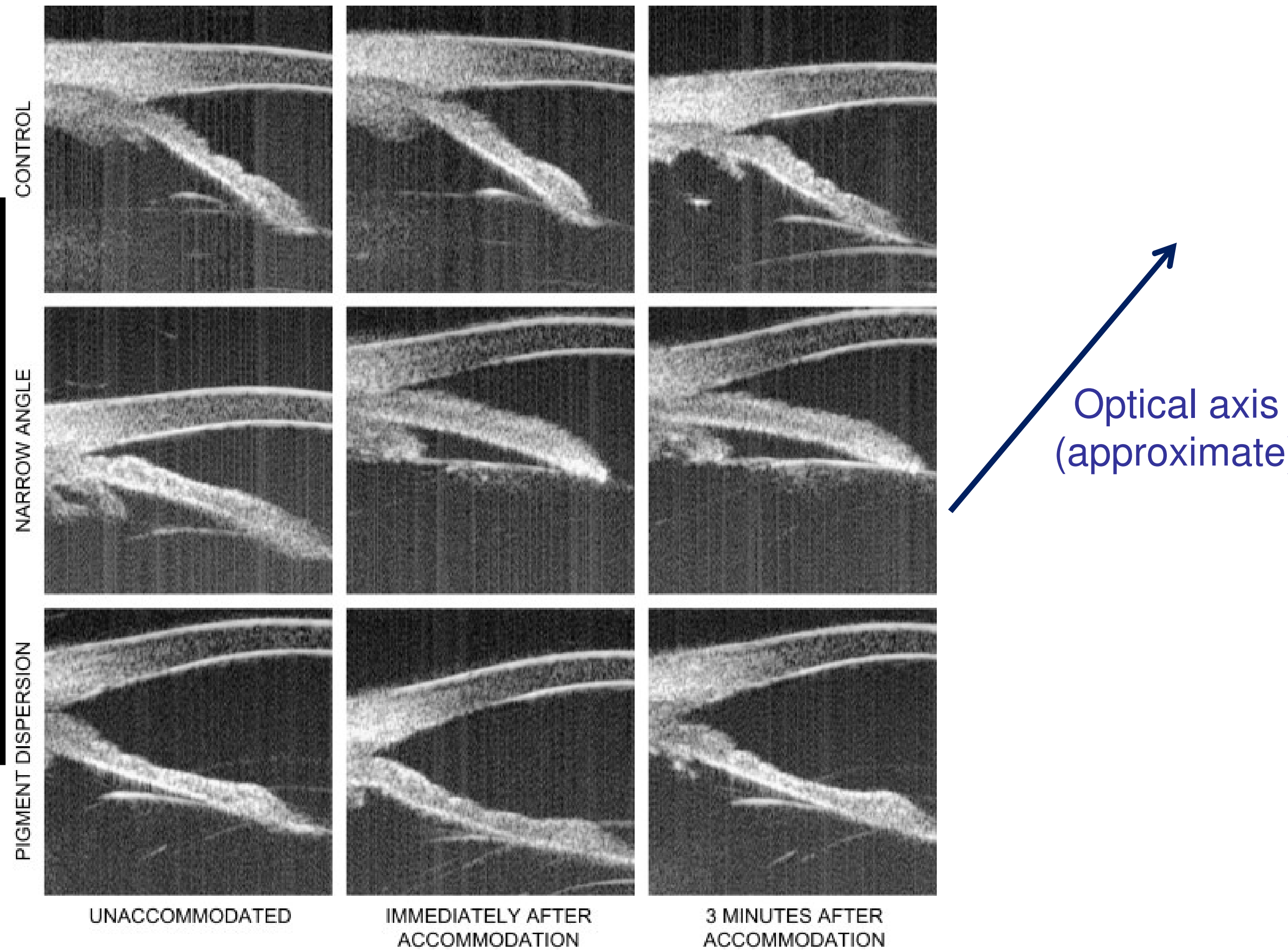
Complication: Ultrasound images of the iris in cross-section reveal that it is not planar, and that its curvature changes with lens accommodation. Also, ultrasound reveals that it “bunches” when it dilates (non-elastic deformation).

Violations of the assumptions of “rubber-sheet” elasticity, and of planarity, limit the validity of an affine correction for the projective geometry of off-axis gaze, and of pupil dilation.



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4. Countermeasures against spoofing

All biometrics are vulnerable to spoof attacks, either to conceal an identity, or to impersonate another.

No biometric pattern is a secret.
How can iris vitality be proven?

- spectrographic and photonic countermeasures

- behavioural countermeasures

- detection of analog attacks

- permutation of IrisCode bytes to invalidate digital replay attacks

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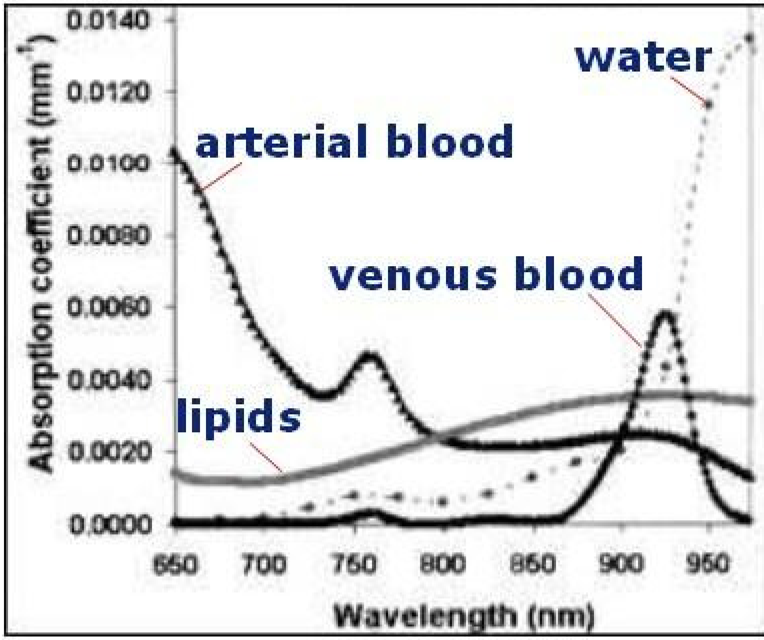
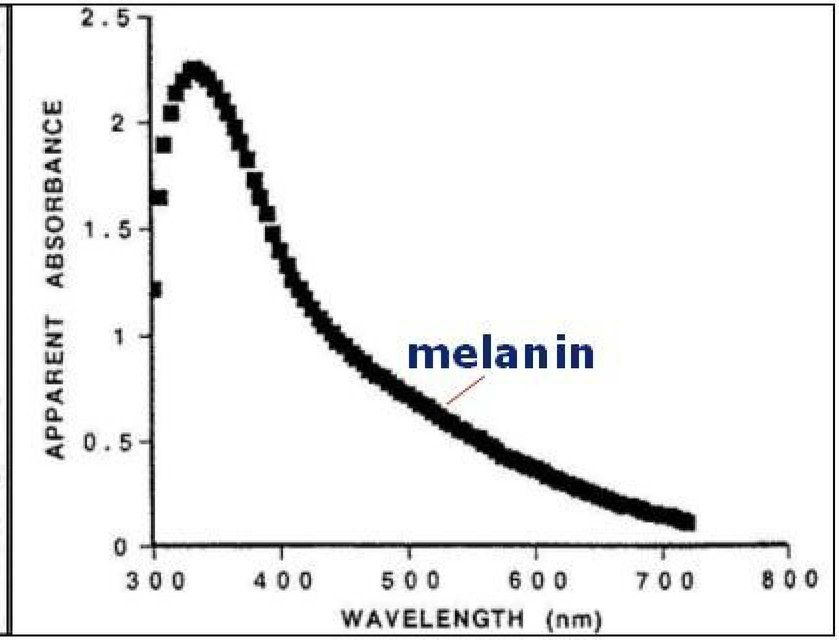
Photonic properties of living tissue (wavelength dependence of reflected light) may help distinguish a living eye from a fake artefact in a “spoofing” attack.





Other possibilities: pupillary light response (dilation / constriction / hippus); dynamic specular reflections from cornea; cavity optics properties (retinal back-reflection; 4 Purkinje reflections); eye blinks and movement challenges; etc.

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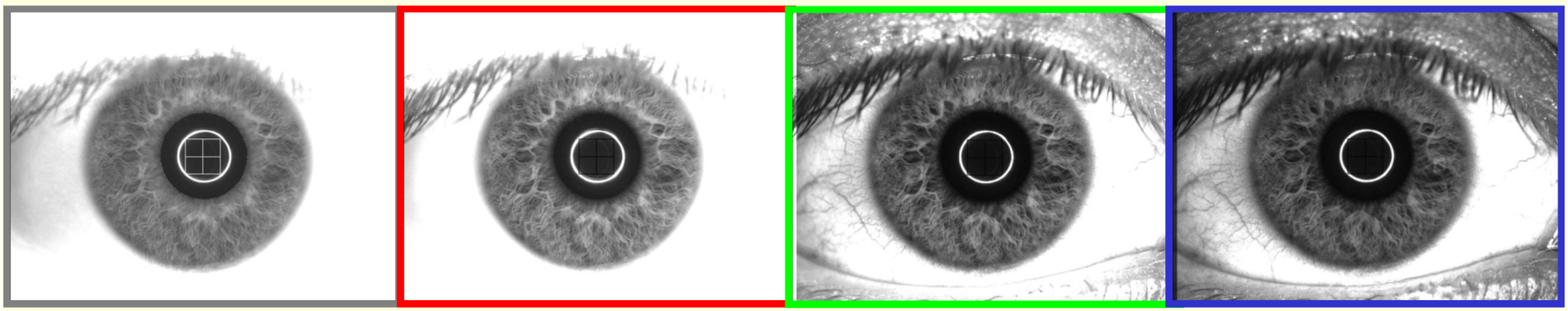
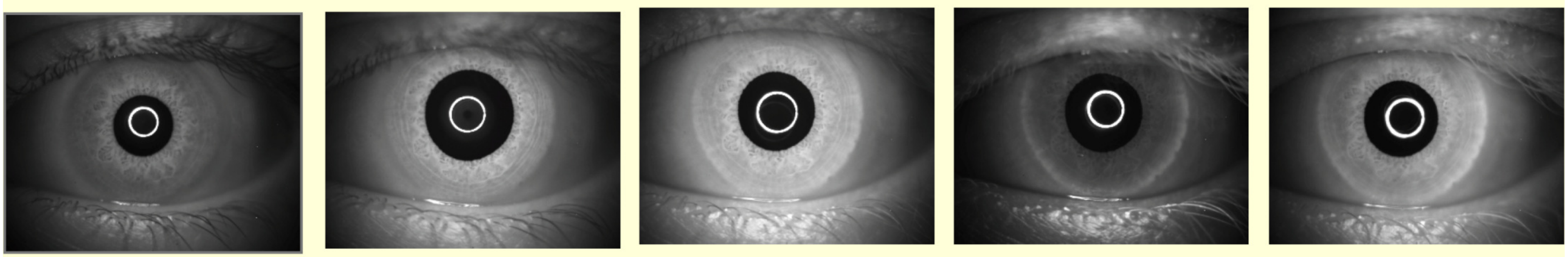
Biophotonics as a countermeasure against spoofing with an artificial iris:

living tissue responds differently to different wavelengths of light

- Boyce et al, “Multispectral Iris Analysis: A Preliminary Study,'' CVPR Workshop on Biometrics, June 2006





(Multispectral iris photographs from Laboratory of Arun Ross)

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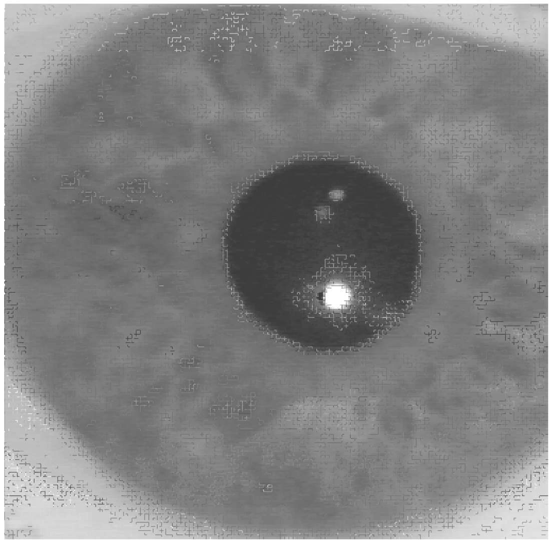
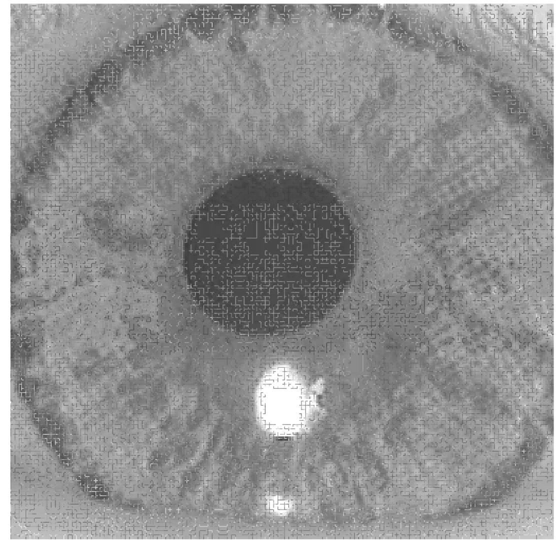
Detecting the presence of a printed, fake, patterned contact lens by the 2D Fourier spectrum of the printing dot matrix.

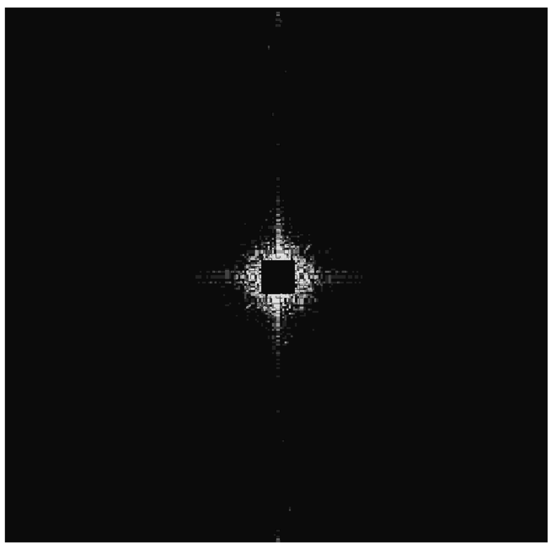
Such lenses are popular as cosmetic accessories to change one's natural eye colour.



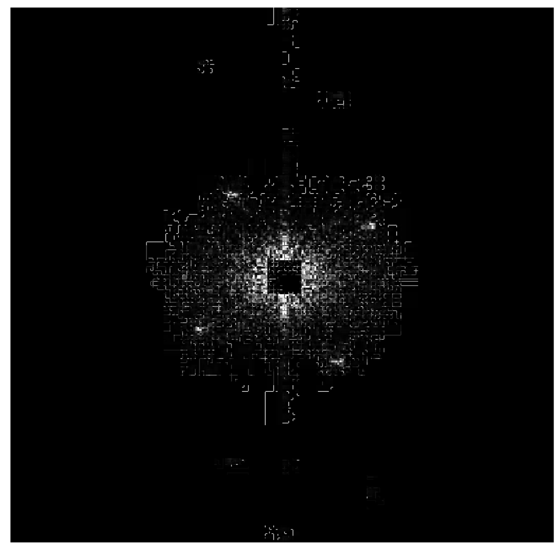
Natural iris



Fake iris printed on a contact lens



2D Fourier spectrum of natural iris



2D Fourier spectrum of fake iris

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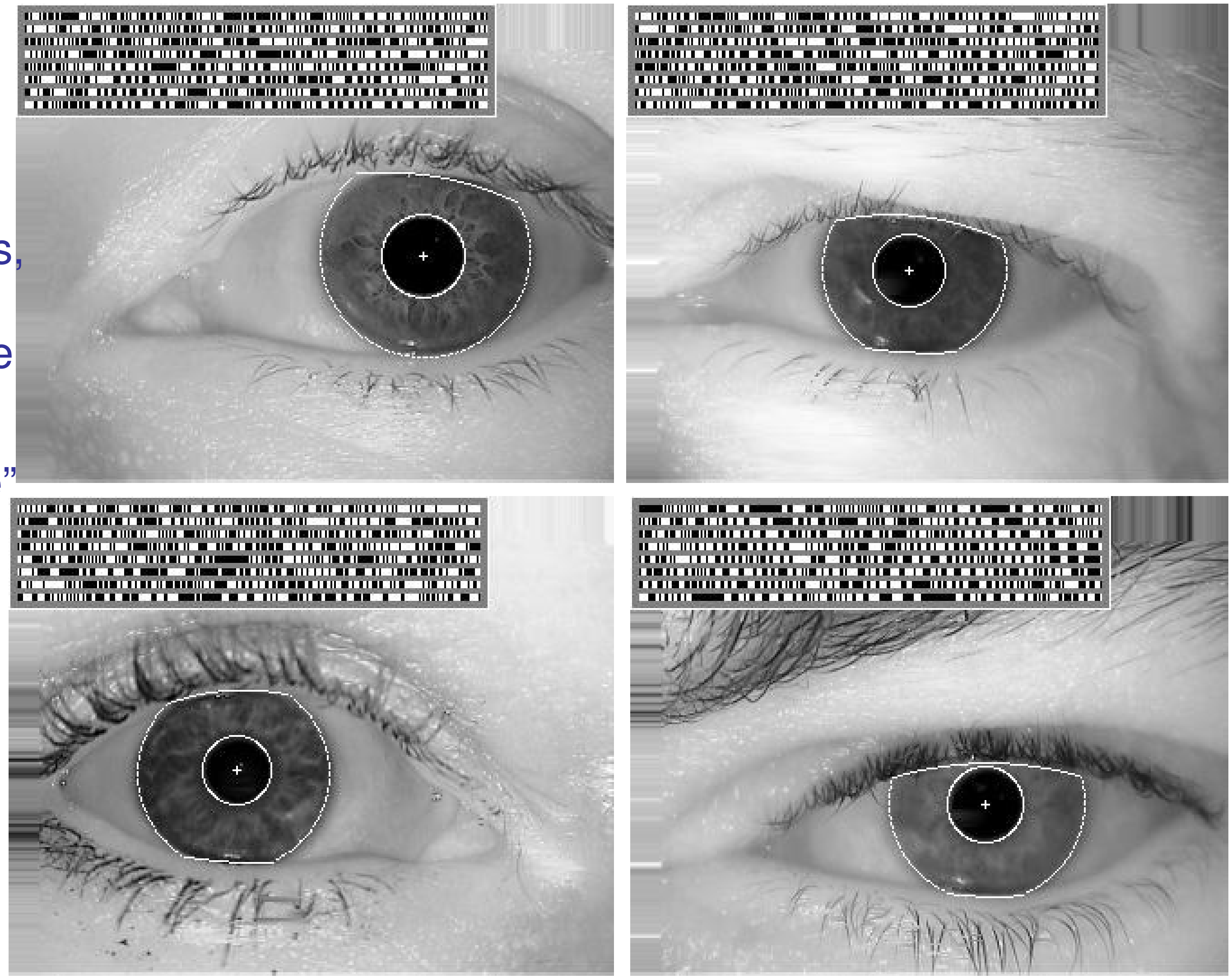
5. How much can resolution requirements be reduced?

Half-size resolution in QCIF (Quarter Common Intermediate Format), in which the iris radius may typically be only 50 pixels, seems acceptable. No impact on FMR; but there is a small cost in FnMR.

Sarnoff “iris-on-the-move” and “iris-at-a-distance” acquires iris images at this resolution, and then up-samples.

How much further can reduction in resolution requirement be pushed?



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6. Fuzzy database matching with a Codex

Use *indexing* for large databases, instead of *exhaustive search*.

The concept is similar to Content-Addressable Memory (CAM), in which the data itself is used as an address.

A Codex is constructed, listing IrisCodes containing various bit patterns. When enough collisions, or "suspicious coincidences" occur between IrisCodes, they (and *they alone*) are considered candidates for matching. Speed-up arises from ignoring others.

Pruning factor (therefore speed-up factor) approaches ~ 100:1. Adoption of Indexing should be gated by Quality Assessment, because indexing fails for lower-quality images.

(based on Technical Report circulated in March 2006: Hao, Daugman, and Zielinski, *"A fast search algorithm for a large fuzzy database"*, published in *IEEE T-IFS*, **3**(2), pp. 203-212.)

The Doctrine of Suspicious Coincidences

When the recurrence of patterns just by chance is a highly improbable explanation, it is unlikely to be a coincidence.

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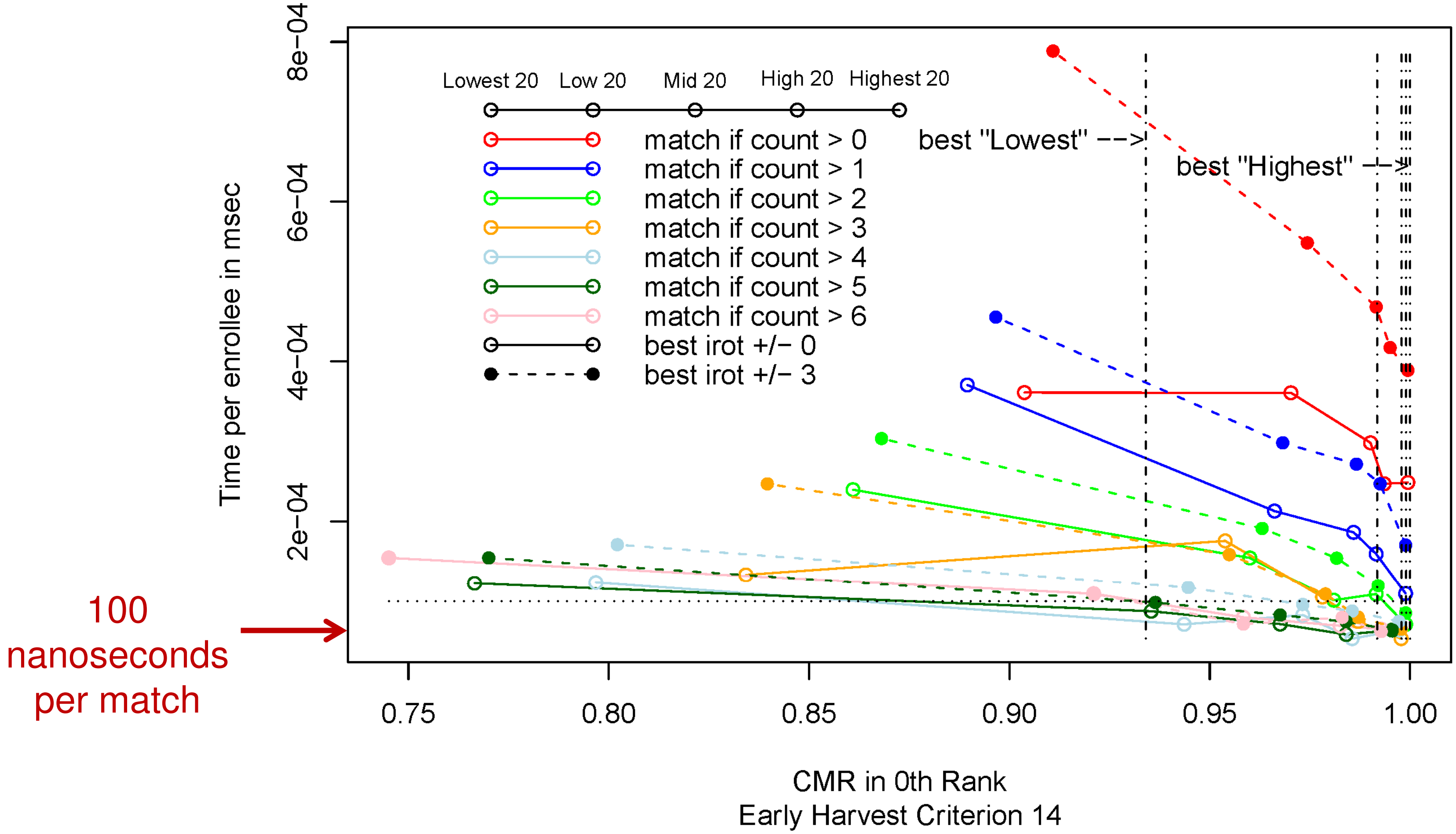
The quality scalar Q is useful for gating the application of indexing methods, which perform well only for high-quality images. These plots show Speed-Accuracy profiles for 5 quantiles (lowest 20%, ..., highest 20%) of UIDAI image Q scores, allowing up to 10 million matches/sec/CPU.



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Makes it POSSIBLE to
FIND one of these...

...in one of these!

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"Synthetic biometrics," minimal description length, and Kolmogorov complexity

Kolmogorov (1903-1987)

Kolmogorov introduced a new definition for the complexity of a string of data: it is *the **length** of the shortest program that could **generate** the data.*

Creating that program "compresses" the data; executing that program "decompresses" (generates) the data.

If the shortest program that can generate a data string is essentially a data statement containing it, then the data is its own shortest possible description ("K-incompressible").

Today iris images can be compressed to about 2 kB, which is about the same size as standard iris templates.

Synthetic biometrics (creating an image indistinguishable from an actual sample) are programs that serve to "compress" biometric samples in Kolmogorov's sense. In the future, will biometric recognition operate by **comparing such programs**?

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