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Introduction to Biometric Recognition Technologies and Applications

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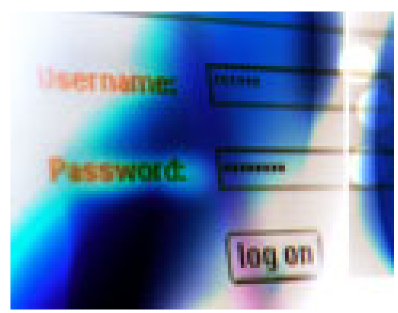
What are Biometrics?

- The term "biometrics" is derived from the Greek words bio (life) and metric (to measure).
- For our use, biometrics refers to technologies for measuring and analyzing a person's physiological or behavioral characteristics. These characteristics are unique to individuals hence can be used to verify or identify a person.

Also Look at report by *Duane M. Blackburn, Federal Bureau of Investigation*
http://www.biometricscatalog.org/biometrics/biometrics_101.pdf or biometrics_101.pdf

Problems with current security systems…

- Based on Passwords, or ID/Swipe cards
- Can be Lost.
- Can be forgotten.
- Worse! Can be stolen and used by a thief/intruder to access your data, bank accounts, car etc….



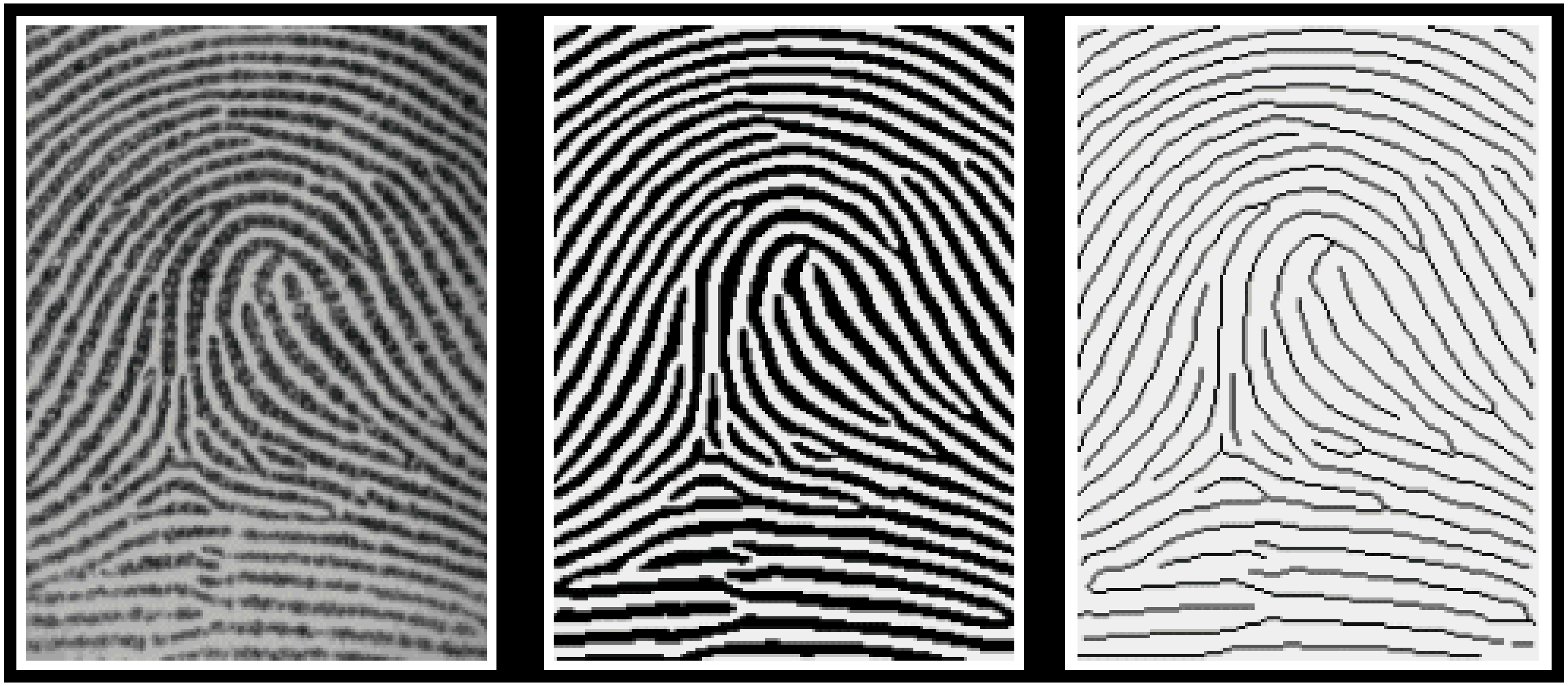
Some Examples of Different Biometrics

- Face
- Fingerprint
- Voice
- Palmprint
- Hand Geometry
- Iris
- Retina Scan
- Voice
- DNA
- Signatures
- Gait
- Keystroke

Minutiae base fingerprint Matching

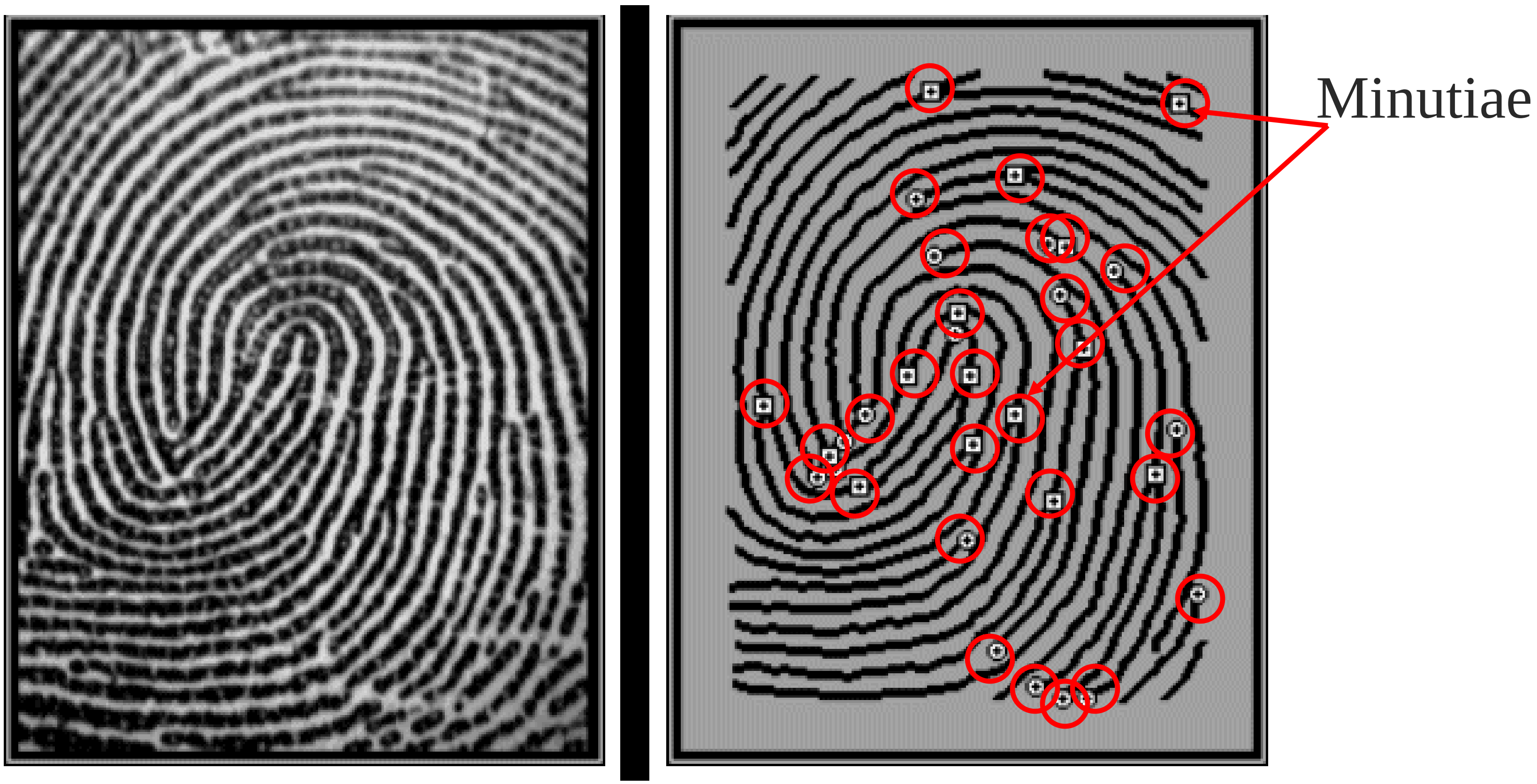
- This is one of the most commonly used algorithms for extracting features that characterizes a fingerprint.
- The different Minutiae feature locations and types can identify different individuals.
- These are what are stored in the Biometric template.
- We at CMU have other technologies based on Distortion-Tolerant Advanced Correlation Filters (we will talk about these later on)

Fingerprint Minutiae Extraction



Original → Processed → Thinning

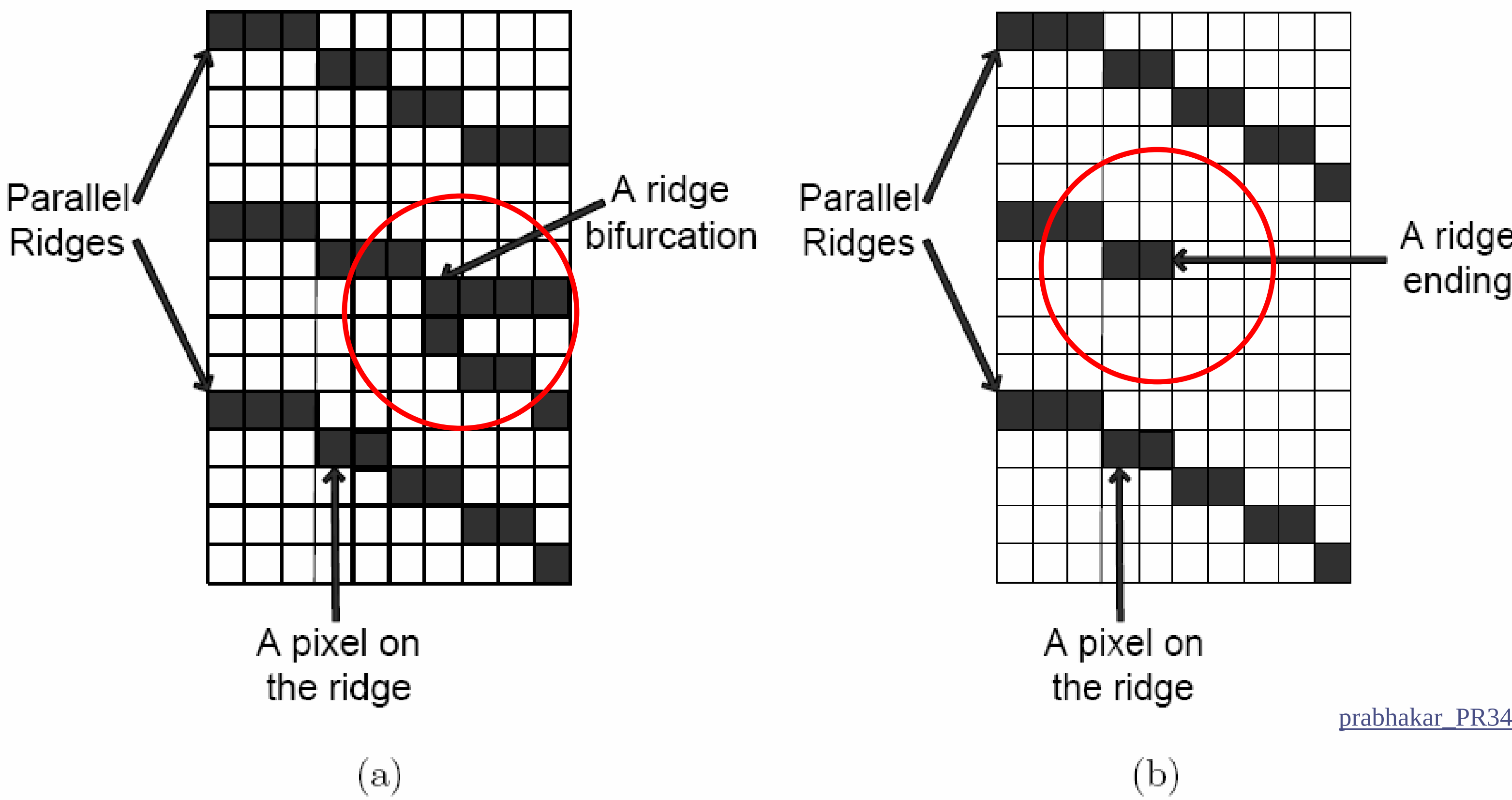
Fingerprint Minutiae Extraction



Original

Final Processed with
Fingerprint Minutiae Detected

Some example Minutiae types



prabhakar_PR3465.pdf

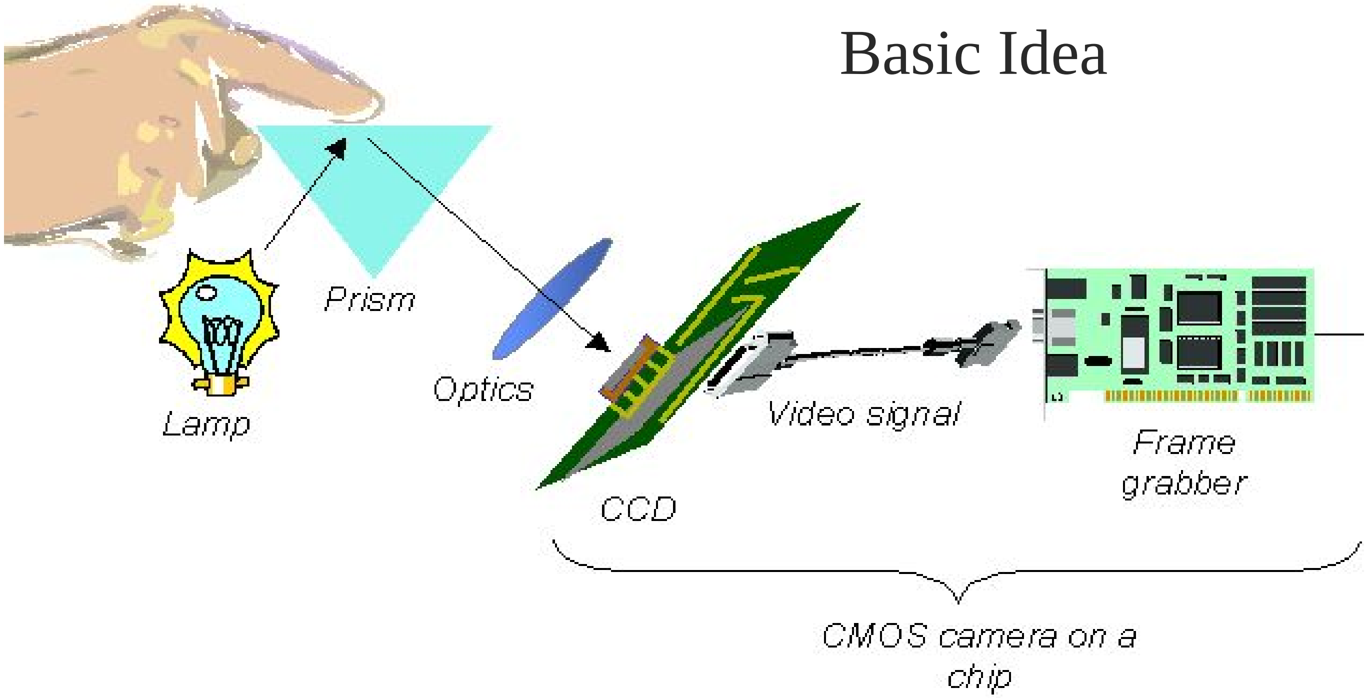
Ref: Salil Prabhakar, Anil K. Jain, Sharath Pankanti: Learning fingerprint minutiae location and type. Pattern Recognition 36(8): 1847-1857 (2003)

Minutiae Based Matching

- Enrollment: Minutiae are extracted and stored in database (or could be smart-card)

- Verification: Minutiae are extracted during the test phase and matched against those stored in database.

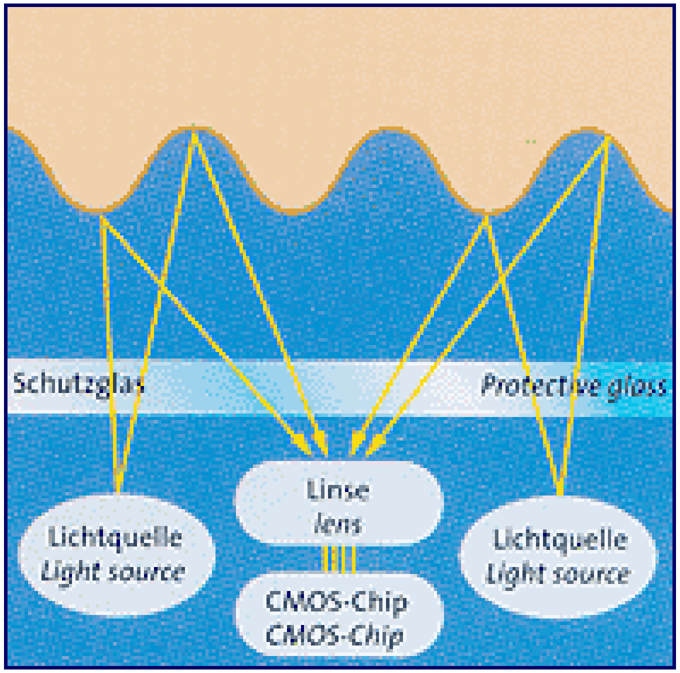
How Optical Sensors work



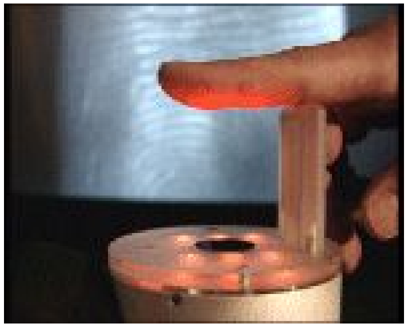
• Fingerprint touches the prism. It is illuminated from one side from the lamp and is transmitted to the CCD camera through the lens using total internal reflection.

- http://perso.wanadoo.fr/fingerchip/biometrics/types/fingerprint_sensors_physics.htm#thermal

Touchless (reflection) Fingerprint Sensors



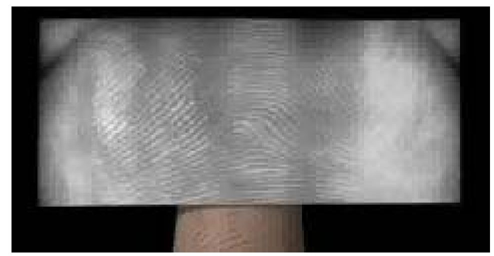
- Light is reflected from the fingerprint itself onto the CMOS sensor to form the fingerprint image.



- http://perso.wanadoo.fr/fingerchip/biometrics/types/fingerprint_sensors_physics.htm#thermal

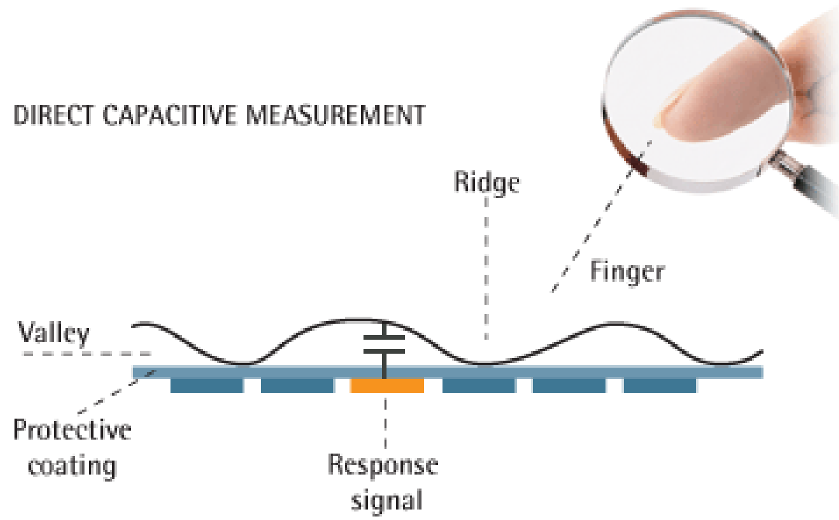
Touch-less Sensors can be used to provide a surround fingerprint

http://www.tbsinc.com/products/finger_sensor/index.php



- Surround Fingerprint is captured

Capacitative Sensors



- These sensors measure the capacitance between the skin and the sensor to acquire fingerprints.
- Ridge and valleys of a fingerprint have different capacitance which provide a signature to output a fingerprint image.
- These sensors are typically very cheap but are prone to damage by electro-static discharge (ESD).

Companies with Capacitative Sensors

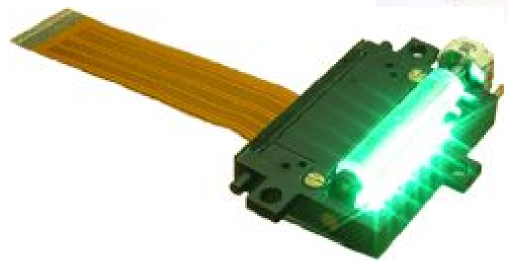
- Upek (spin-off from ST-Microelectronics): www.upek.com

- Fujitsu: http://www.fma.fujitsu.com/biometric/
- LighTuning: http://www.lightuning.com/
- SONY: http://www.sony.net/Products/SC-HP/sys/finger/
- Infineon (formerly Siemens): http://www.infineon.com/cgi/ecrm.dll/jsp/home.do?lang=EN
- Atrua: http://www.atrua.com/index.html
- Melfas: http://www.melfas.com/

Companies with Optical Fingerprint Sensors

- TesTech (electro-optical)

http://www.testech.co.kr/



- Digital Persona

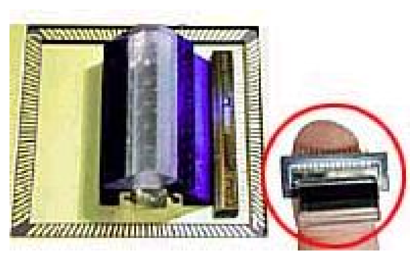
http://www.digitalpersona.com/

- CASIO:

http://www.casio.co.jp/ced/english/fingerprint.html

- **Sannaedle / Cecrop / Kinetic Sciences**

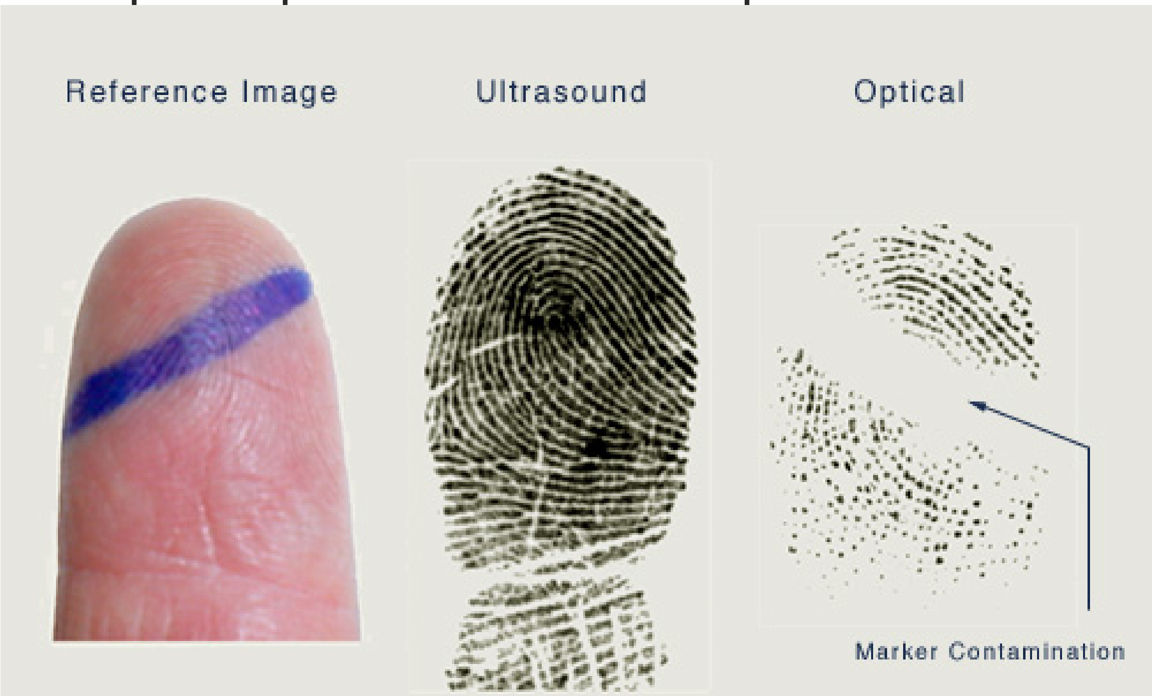
http://www.cecrop.com/



Companies with Ultrasound Sensor

- UltraScan: http://www.ultra-scan.com/

-"They claim superior performance over optical sensors"



Source: http://www.ultra-scan.com/technology/index.html

Cellphones with Fingerprint Sensors

- LG’s rolling out their latest handset with a built-in biometric fingerprint scanner, the LG-LP3550 (Apr, 2005)
- Has a 3.24 megapixel digital camera
- MP3 playback software
- Dual 3D stereo speakers
- miniSD card slot.

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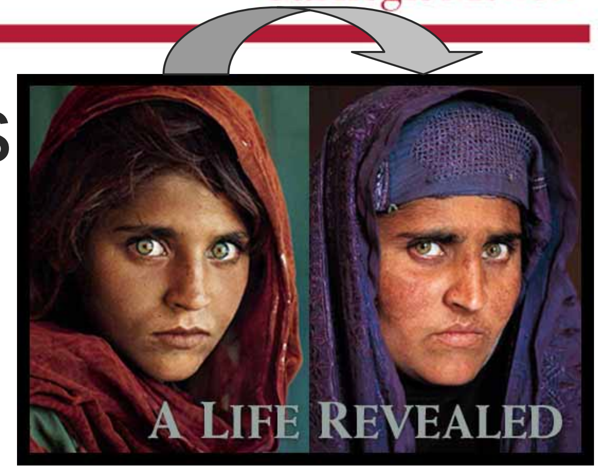
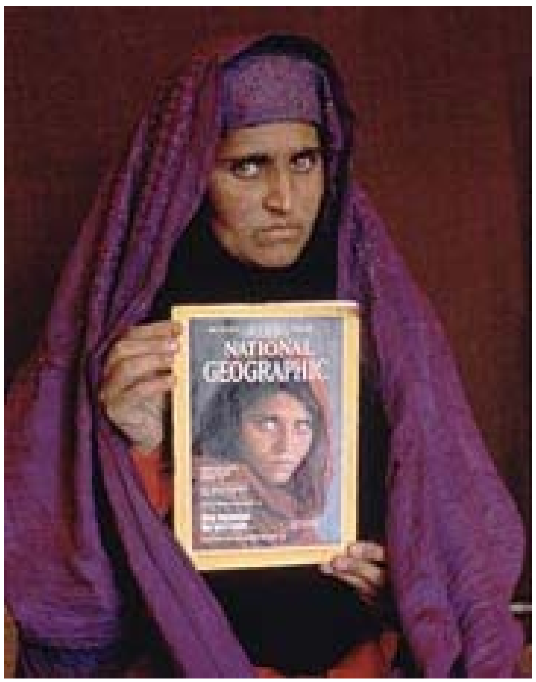
Iris Biometrics

Iris Biometric got really famous in the lost Afghan girl story..



Source: National Geographic Magazine



- In 1994 National Geographic photographer Steve McCurry took a picture of a little Afghan girl called Sharbat Gula in refugee camp in Pakistan.
- Her photo (she had amazing green eyes) made it to National Geographic 100 best Pictures!
- McCurry later tried to trace and find the girl, until finally 17 years later he located a girl with those same haunting green eyes.

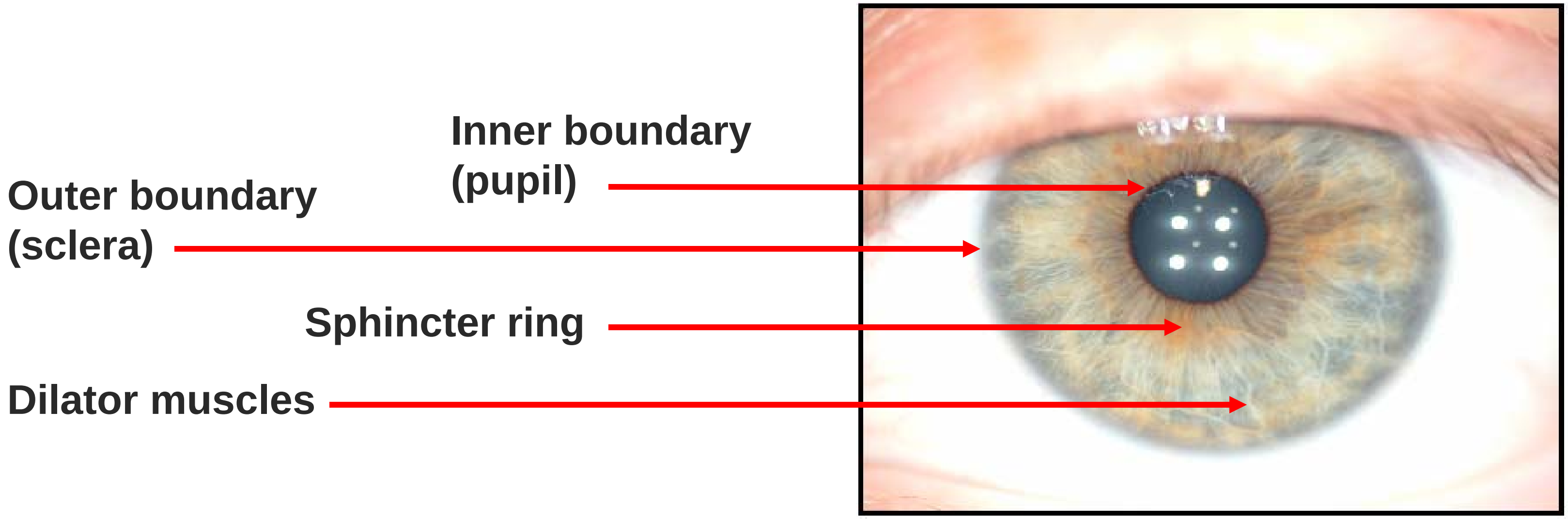
http://news.nationalgeographic.com/news/2002/03/0311_020312_sharbat.html

17 years passed…how to verify if this was the same girl?

- Hard-ship changed the girl’s appearance. But she had those same haunting green eyes…
- The Explorer team got verification using U.S. FBI iris scanning technology. They used iris image from old taken photograph and compared to the new one.
- Iris code declared a ‘match’!
- This was indeed the same girl! Iris biometric made it possible to verify this.

Iris as Biometric

The iris is the colored portion of the eye surrounding the pupil. Its pattern results from a meshwork of muscle ligaments, and its color and contrast are determined by pigmentation.



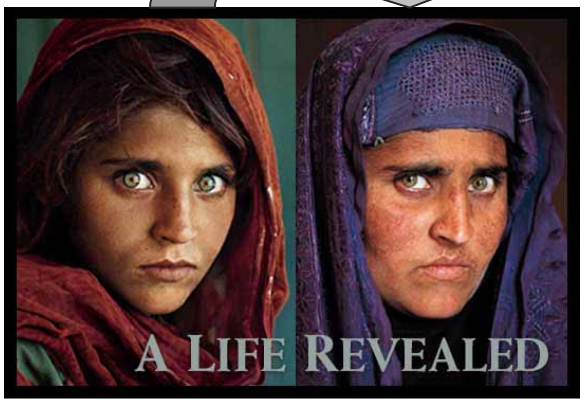
Biometric Advantages

- thought to be very unique, potentially more discriminate than fingerprints
- remains stable over an individual's lifetime
- for cooperating subjects, iris pattern is captured quickly in an image

Iris as a Biometric

The iris is the colored portion of the eye surrounding the pupil. Its pattern results from a meshwork of muscle ligaments and pigmentation.

18 years later



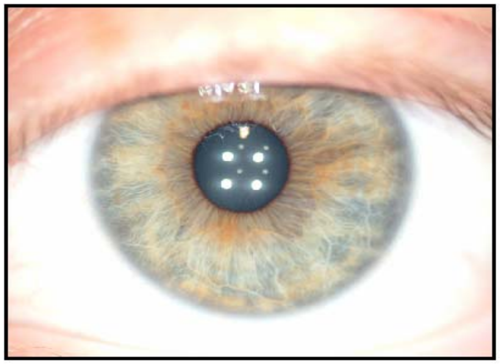
Source: National Geographic Magazine

Biometric Advantages

- thought to be very unique, potentially more discriminate than fingerprints.
- remains stable over an individual's lifetime (does not change with aging)
- captured quickly in a cooperative scenario

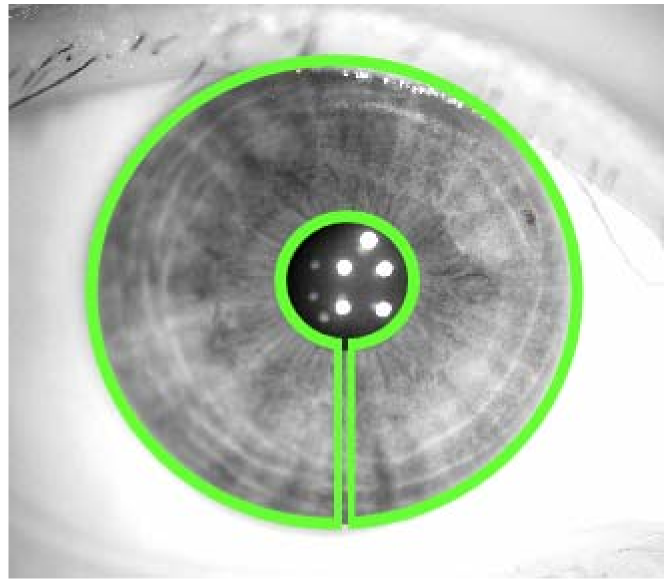
Iris Camera Equipment

- We acquire images using equipment built around a Fuji S1 Pro digital camera (pictured left).
- Images are taken at close range under normal illumination, and at very high resolution (12 megapixels).

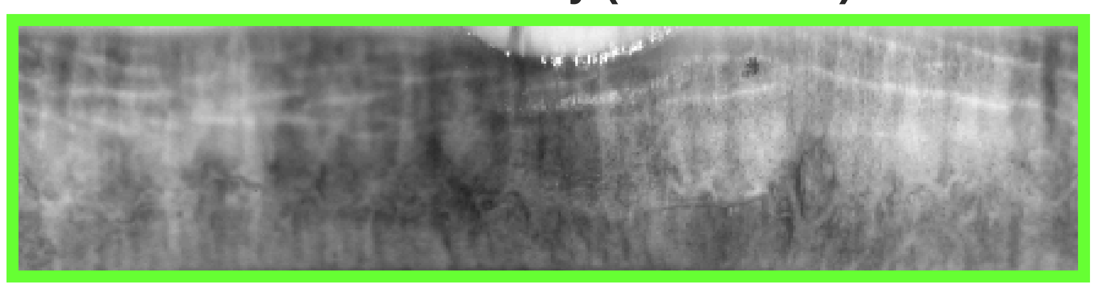


First Step: Iris Segmentation

"Unwrapping" the iris

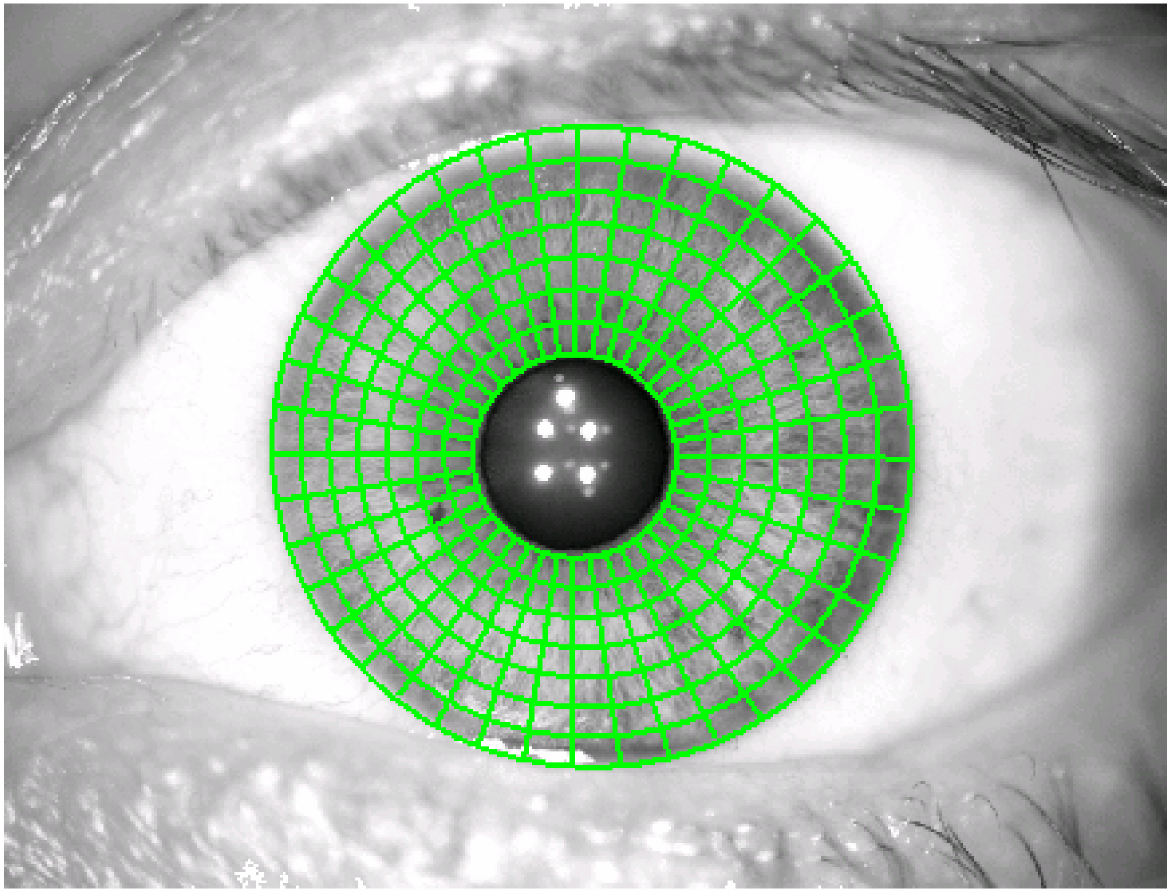


Outer boundary (with sclera)

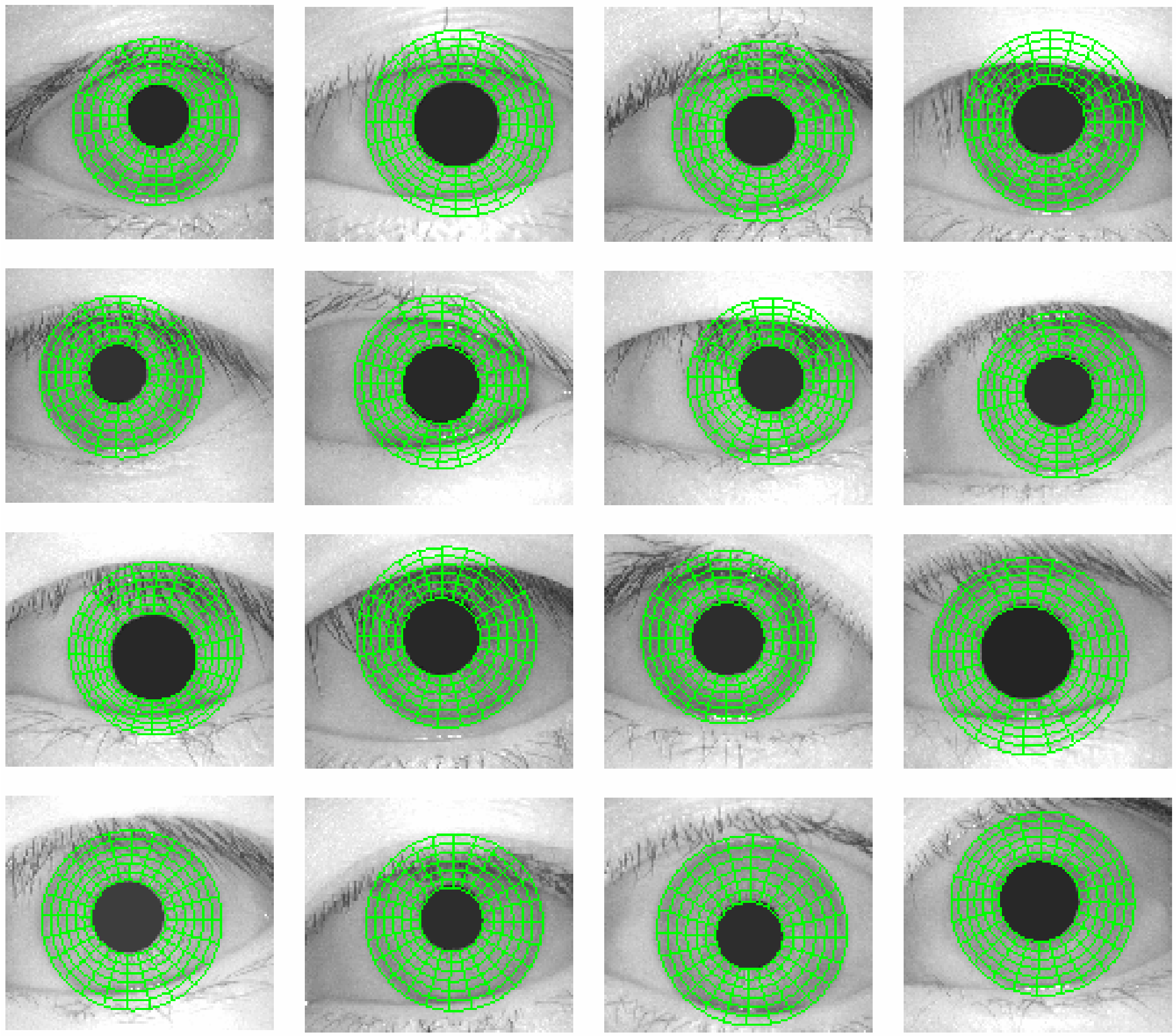


Inner boundary (with pupil)

Boundary Detection: Example

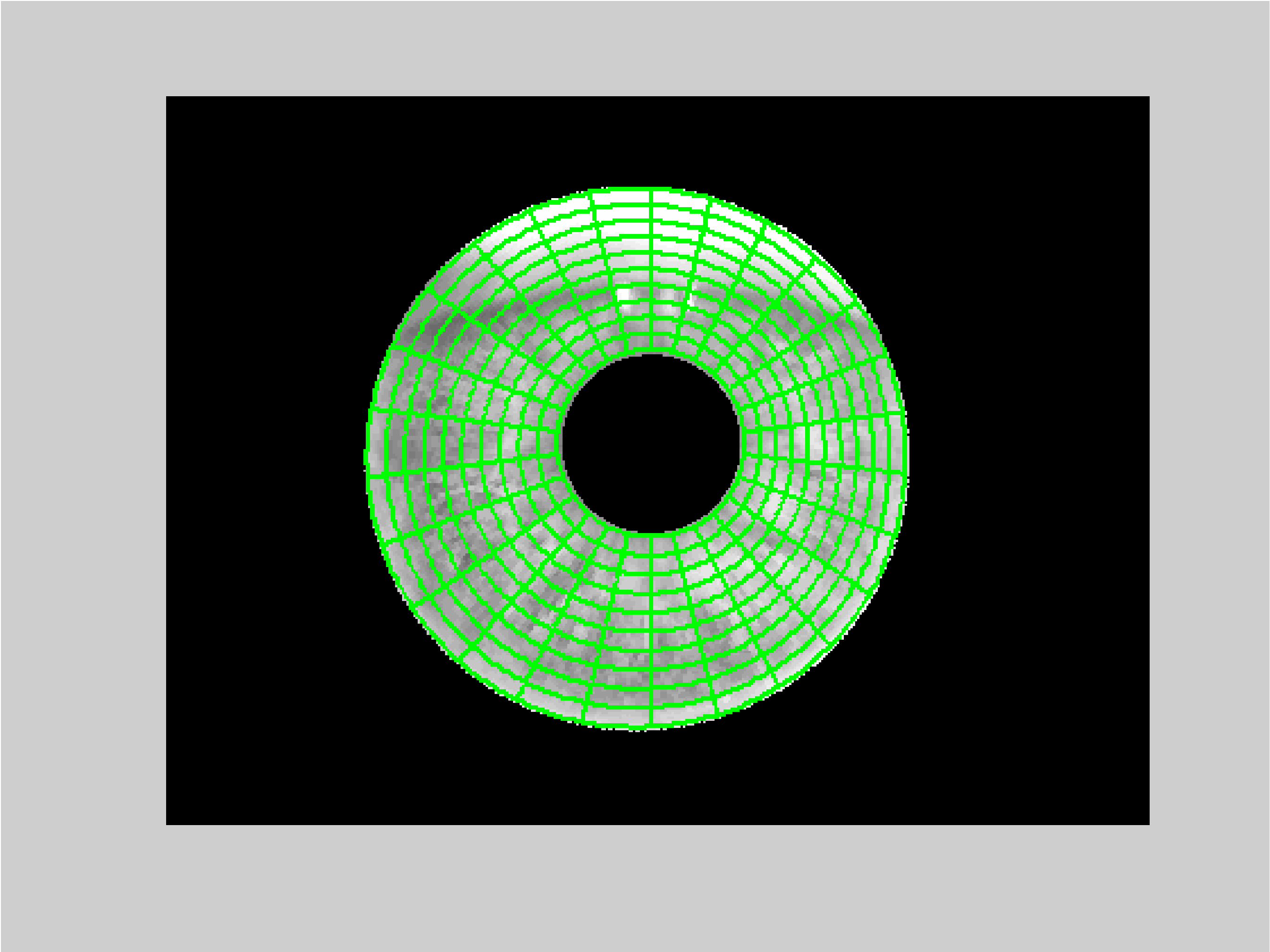


Other Fast Segmentation Examples (from CASIA)



Iris Polar Mapping

Video : Illustration of the mapping into normalized polar coordinates



Common Algorithm: Gabor Wavelets

John Daugman[1] proposed Gabor wavelet feature extraction.

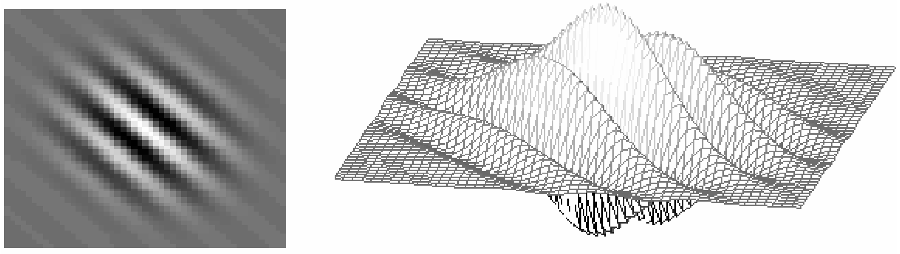
Gabor wavelets have the form:

$$\psi(x, y) = \exp\left[-\frac{x^2}{2\sigma_x^2} - \frac{y^2}{2\sigma_y^2} - j\omega y \right]$$

- Complex exponential with a Gaussian envelope
- Localized in both space and frequency
- Projections of different Gabor wavelets of different orientations and scale are performed on different parts of the Iris image

Gabor wavelet (real part)

Left: 2D, Right: 3D



1 J.G. Daugman, "High Confidence Visual Recognition of Persons by a Test of Statistical Independence," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 11, pp. 1148-61, Nov. 1993. h

Implementation

Daugman’s method (original 2048 bits)

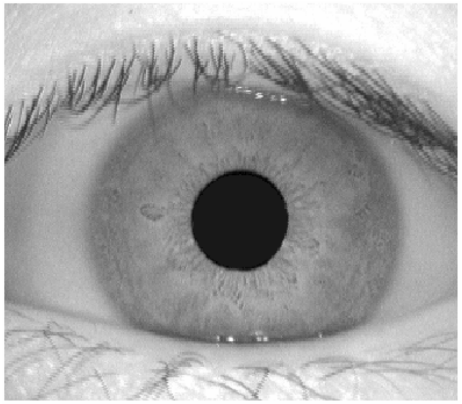
Result : 15,696 bit code for each iris pattern
(our implementation)

Shifts : store multiple codes at 10 shifts (3 pixels apart)

Why Is Shift Invariance Important?

Rotation

Shift (in polar coordinates)



Gabor wavelet codes: shifting changes the iris projection onto the wavelet family, altering the bit code

PCA/ICA: even small shifts completely change the subspace representation

As a result, these methods must try to patch the problem with multiple templates of shifted images.

Further Experiments: CMU Iris Database

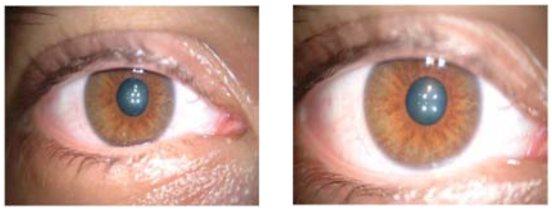
We collected an iris image database for testing recognition algorithms.

Sample images

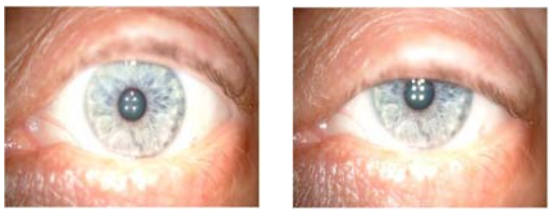
- 101 different iris classes
- Every class contains approx. 24 images from same eye, collected on 2 different days
- Collected at high resolution under *visible illumination*

Further Experiments: CMU Iris Database

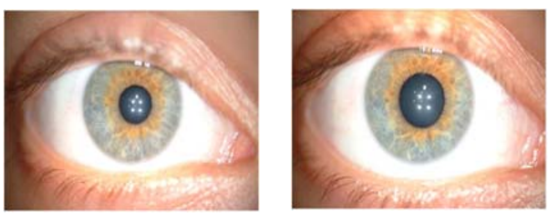
Typical within-class variations:



Scale change – caused by changes in head position and camera zoom



Eyelid occlusion – subjects relax their eyelids to varying degrees during image capture



Pupil dilation – pupil contraction and dilation is an involuntary response

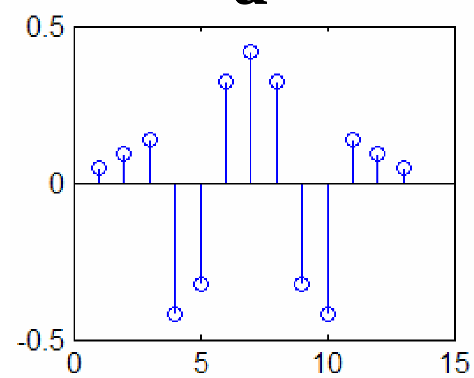
Other difficulties

- inconsistent camera focus
- eyelash obstruction
- head / eye rotation
- saturation due to reflected flash

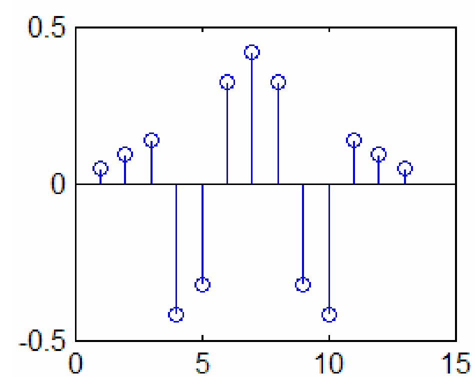
Pattern Matching

- How to match two patterns?
- How do you locate where the pattern is in a long sequence of patterns?
- Are these two patterns the same?
- How to compute a match metric?

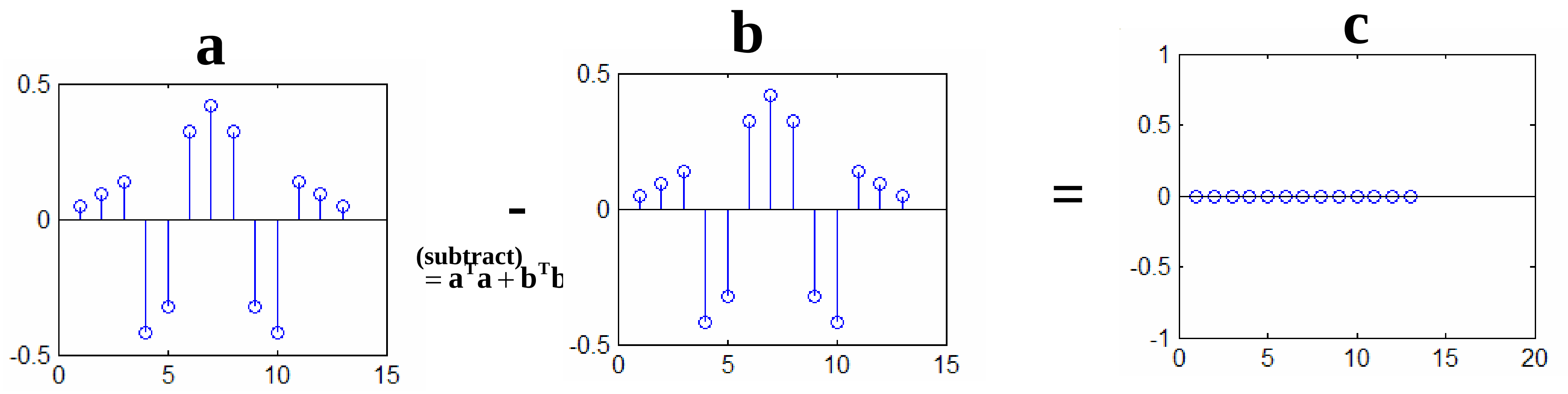
a



b



Pattern Matching



Lets define mean squared error, i.e.

$$e = \left\| \mathbf{a} - \mathbf{b} \right\|^2 = (\mathbf{a} - \mathbf{b})^T (\mathbf{a} - \mathbf{b}) = \mathbf{a}^T \mathbf{a} + \mathbf{b}^T \mathbf{b} - 2\mathbf{a}^T \mathbf{b}$$

$$\mathbf{a}^T \mathbf{a} = \sum_{i=1}^{N} a(i)^2 = energy\_of\_a$$

$$\mathbf{a}^T \mathbf{b} = \sum_{i=1}^{N} \mathbf{a}(i)\mathbf{b}(i) = correlation\_term$$

$$\mathbf{b}^T \mathbf{b} = \sum_{i=1}^{N} \mathbf{b}(i)^2 = energy\_of\_\mathbf{b}$$

Pattern Matching

$$e = \|\mathbf{a} - \mathbf{b}\|^2 = (\mathbf{a} - \mathbf{b})^{\mathrm{T}}(\mathbf{a} - \mathbf{b}) = \mathbf{a}^{\mathrm{T}}\mathbf{a} + \mathbf{b}^{\mathrm{T}}\mathbf{b} - 2\mathbf{a}^{\mathrm{T}}\mathbf{b}$$

$$\mathbf{a}^{\mathrm{T}}\mathbf{a} = \sum_{i=1}^{N} a(i)^2 = energy\_of\_a$$

$$\mathbf{a}^{\mathrm{T}}\mathbf{b} = \sum_{i=1}^{N} \mathbf{a}(i)\mathbf{b}(i) = correlation\_term$$

$$\mathbf{b}^{\mathrm{T}}\mathbf{b} = \sum_{i=1}^{N} \mathbf{b}(i)^2 = energy\_of\_\mathbf{b}$$

- Assume we normalize energy of a and b to 1 i.e. $a^T a = b^T b = 1$
- Then to minimize error, we seek to maximize the correlation term.

- So performing correlation, the maximum correlation point is the location where the two pattern match best.

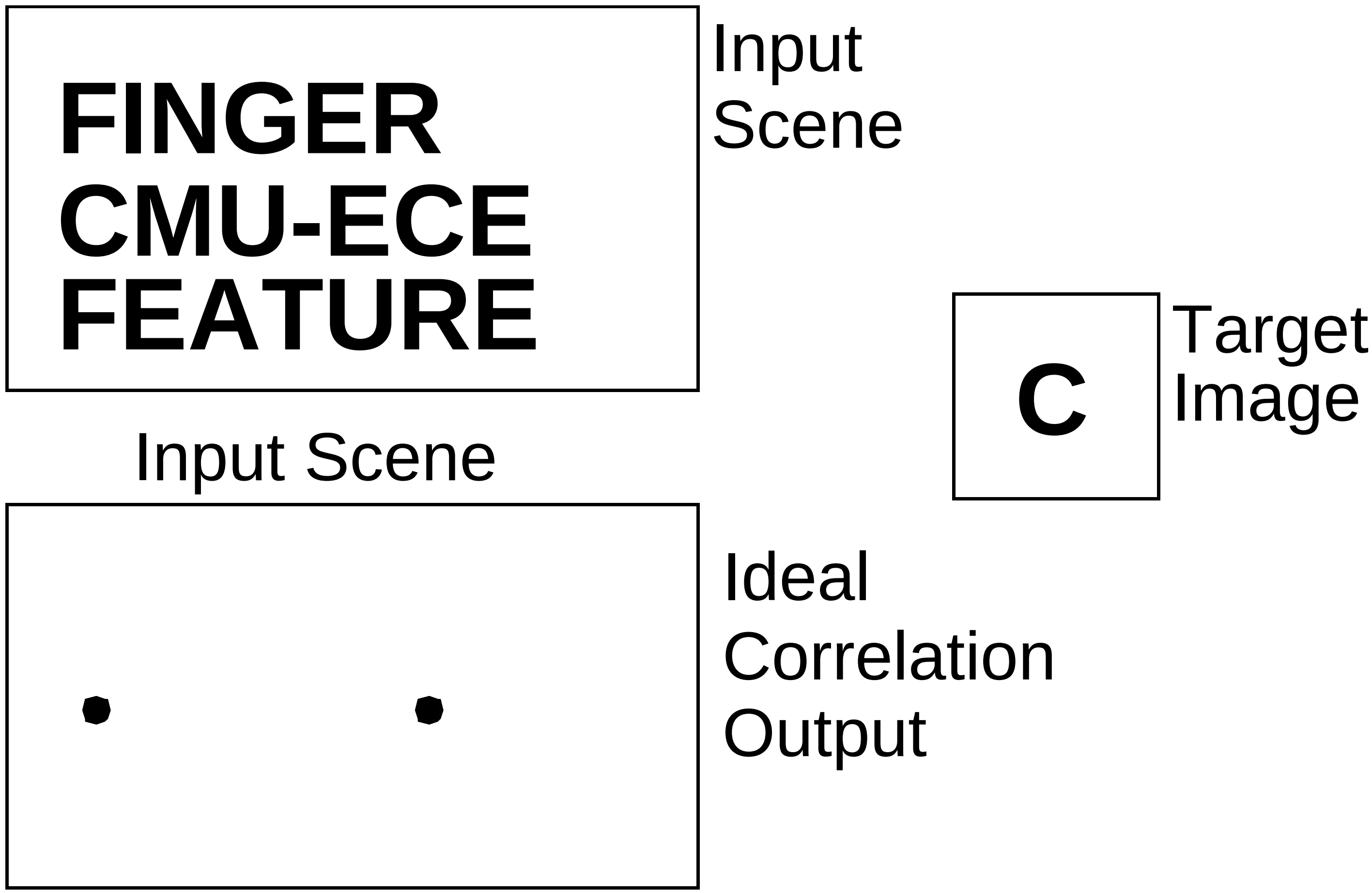
Correlation Pattern Recognition

- r(x) test pattern
- s(x) reference pattern

$$-1 \leq \frac{\mathbf{a}^{\mathrm{T}}\mathbf{b}}{\sqrt{(\mathbf{a}^{\mathrm{T}}\mathbf{a})(\mathbf{b}^{\mathrm{T}}\mathbf{b})}} \leq 1$$

- Normalized correlation between a(x) and b(x) gives 1 if they match perfectly (i.e. only if a(x) = b(x)) and close to 0 if they don't match.
- Problem: Reference patterns rarely have same appearance
- Solution: Find the pattern that is consistent (i.e., yields large correlation) among the observed variations.

Object Recognition using correlation



Goal: Locate all occurrences of a target in the input scene

Why correlation filters?

- Built-in Shift-Invariance: shift in the input image leads to a corresponding shift in the output peak. Classification result remains unchanged.
- Matched filters are just replicas of the object that we are trying to find. Problem is we need as many matched filters as the different appearances that object can look under different conditions. (i.e. a matched filter for every pose, illumination and expression variation).
- Using Matched filters is computationally and memory very expensive.
- We can synthesize distortion tolerant filters that can recognize more than one view of an object.
- We can build different types of distortion-tolerance in each filter (e.g. scale, rotation, illumination etc).
- We will show advanced correlation filters exhibit graceful degredation with input image distortions.

How to do Correlations Efficiently?

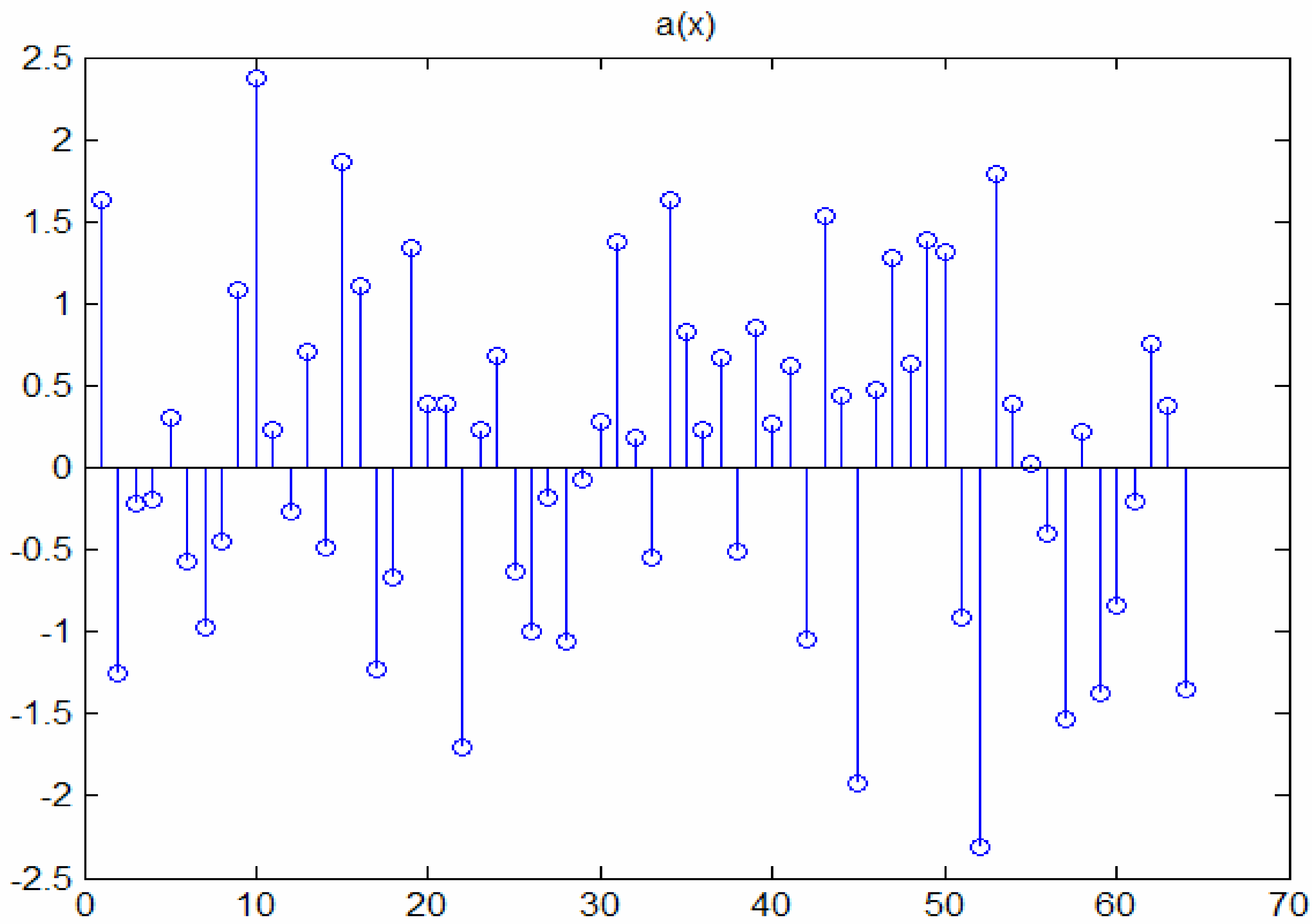
- Use Fast Fourier Transforms…
- How? Fourier Transform property tells us:
  - Convolution Theorem:
    - Convolution of two functions a(x) and b(x) in the spatial domain is equivalently computed in the Fourier domain by multiplying the FT{a(x)} with the FT{b(x)}.
    - i.e. in matlab this would be
      - Convolution=IFFT (FFT(a) .* FFT(b)) (assuming 1 D)
  - Correlation Theorem:
    - Similar to convolution except the correlation of functions a(x) and b(x) in the spatial domain is equivalently computed in the Fourier domain by multiplying FT{a(x)} with conjugate of FT{b(x)}.
      - Correlation=IFFT (FFT(a) .* conj(FFT(b)))

So Correlation in Fourier domain is…..

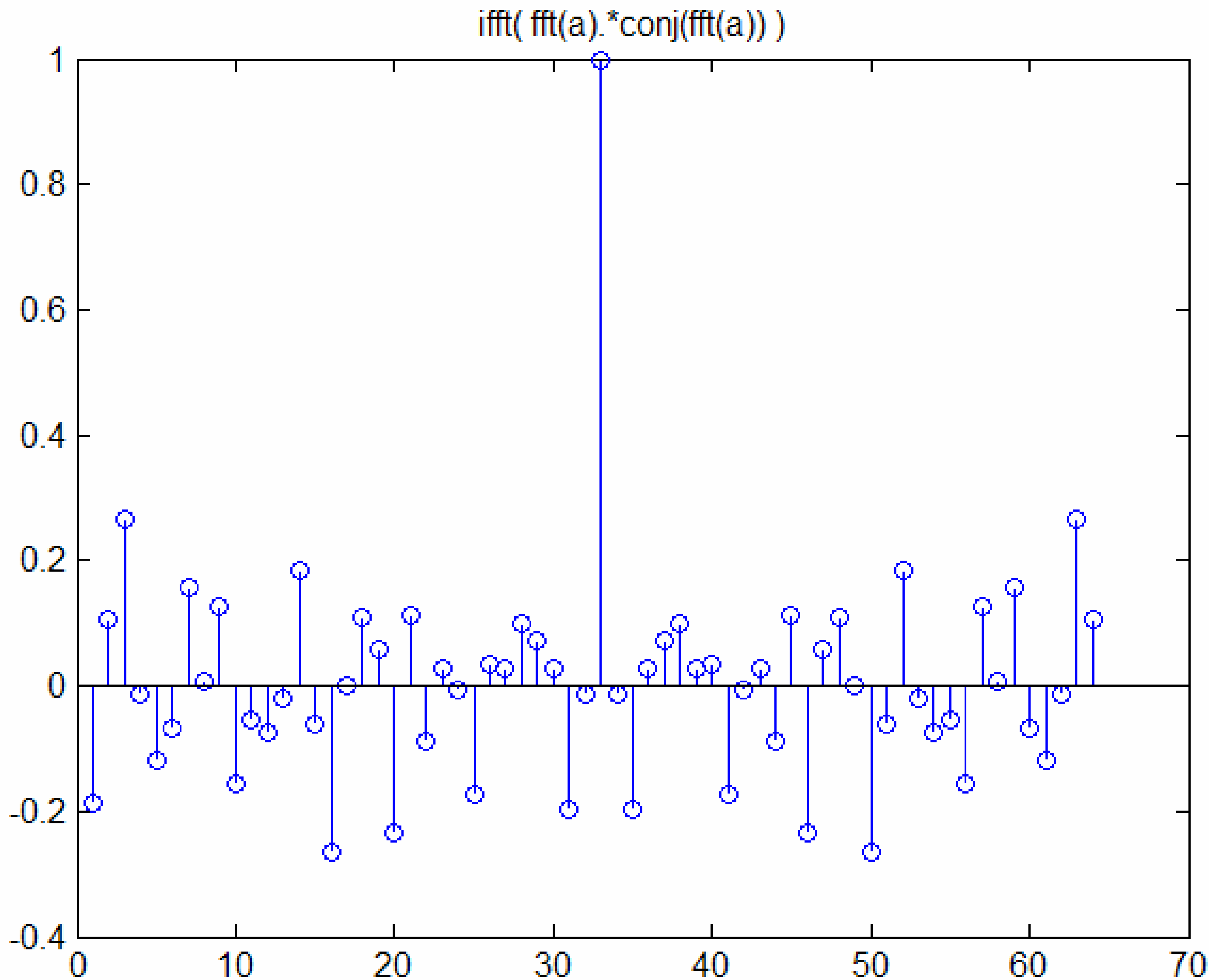
- Is just like convolution except we convolve the test signal t(x) with a time-reversed signal h(x).
- Taking the conjugate in the Fourier domain time-reverses the signal in the time domain.

- Since convolution automatically time-reverses h(x) also..(there is a double time reversal, which cancels out, meaning that you end up computing inner-products with the reference signal and the test signal in the Fourier domain.

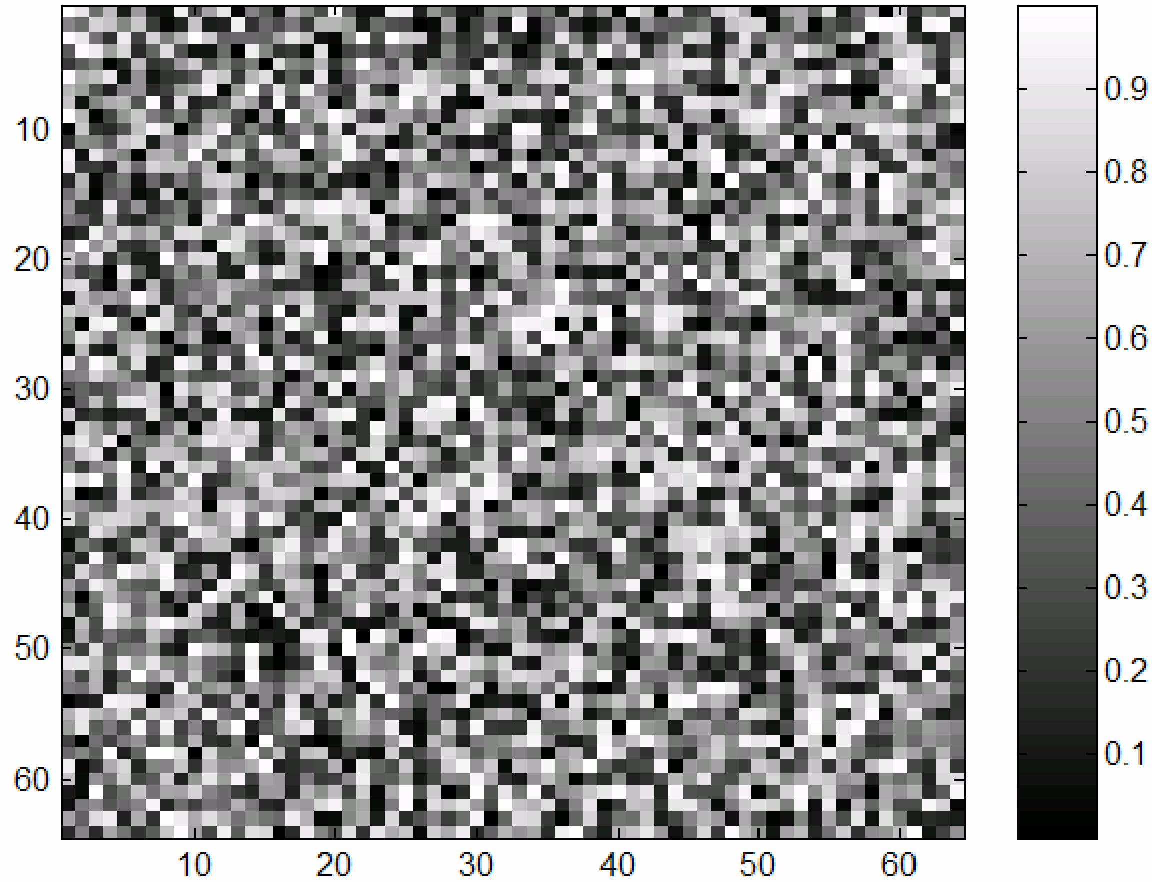
Lets start with a random sample signal a(x)



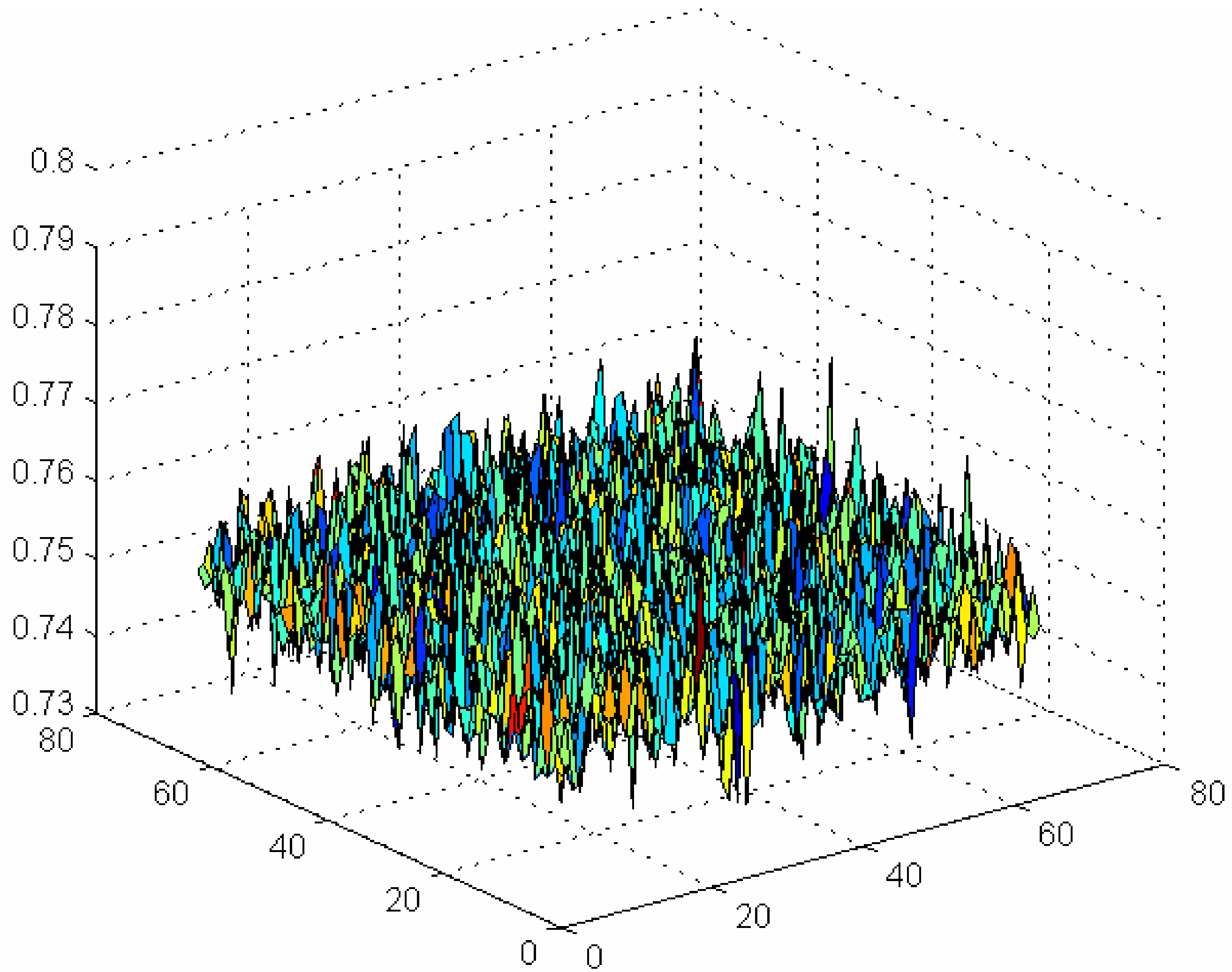
Here is the result of correlating a(x) with a(x)



2D random image s(x,y)

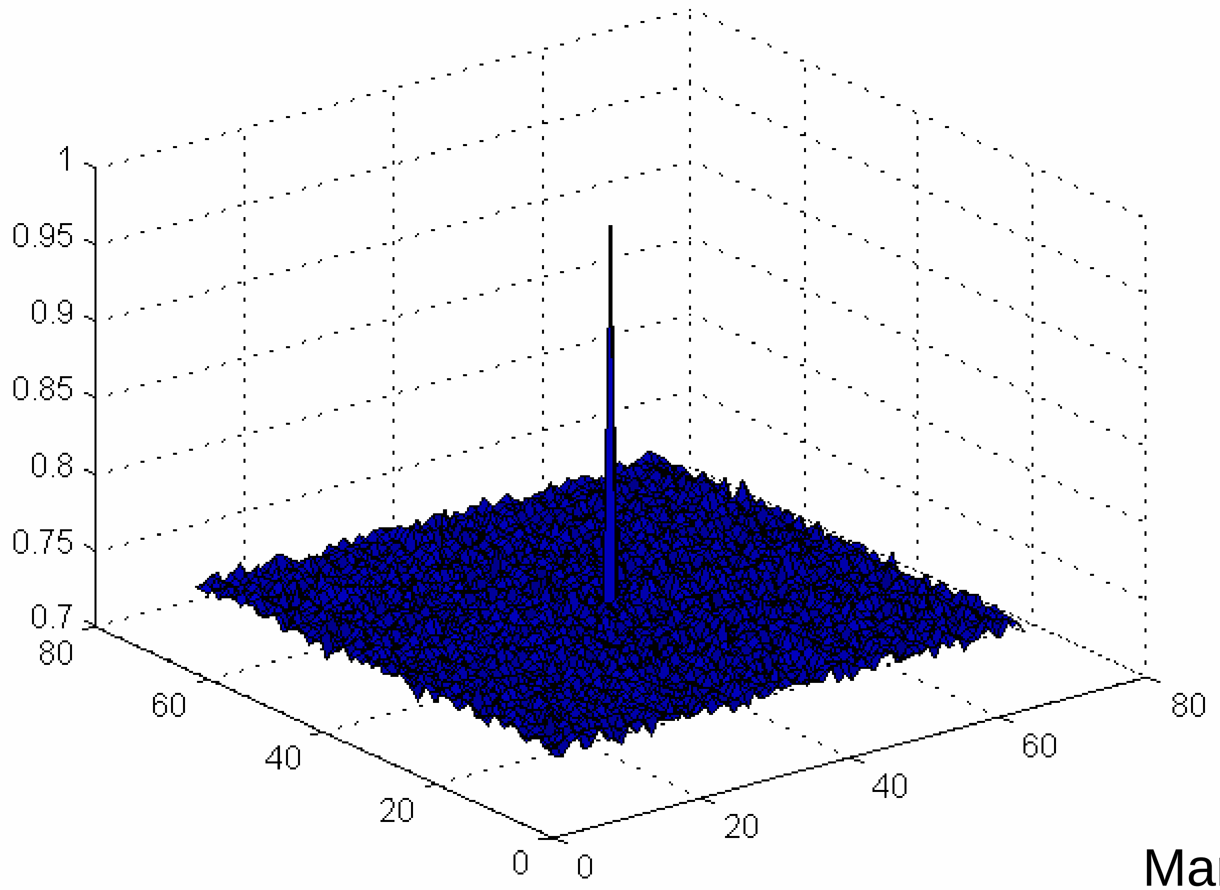


Convolution of s(x,y) with s(x,y)



Correlation of s(x,y) with s(x,y) (auto-correlation)

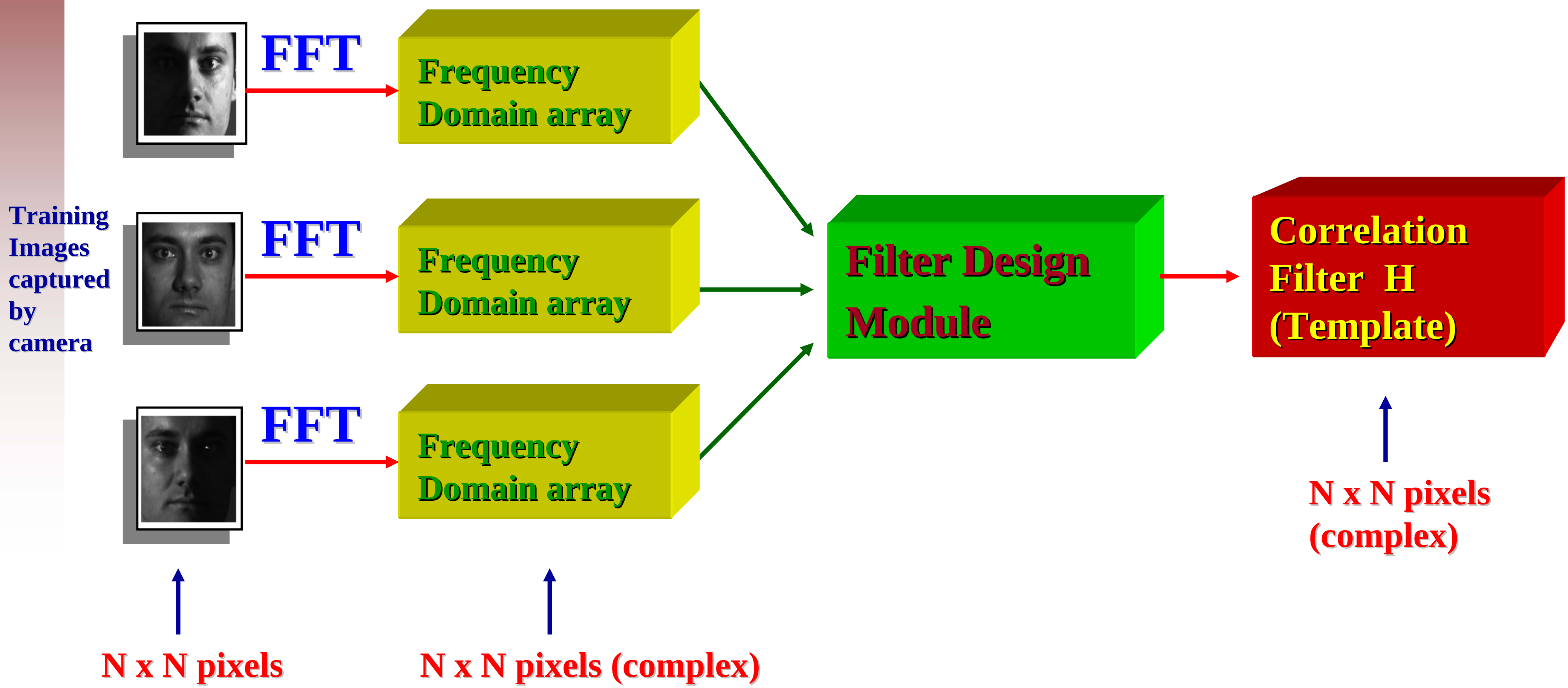
- Notice nice peak..with height of 1 at the location where the images perfectly align. The peak height indicates confidence of match. Because s(x,y) is random signal, no other shifts of the signal match and there is only a single peak appearing exactly where the two signals are aligned.



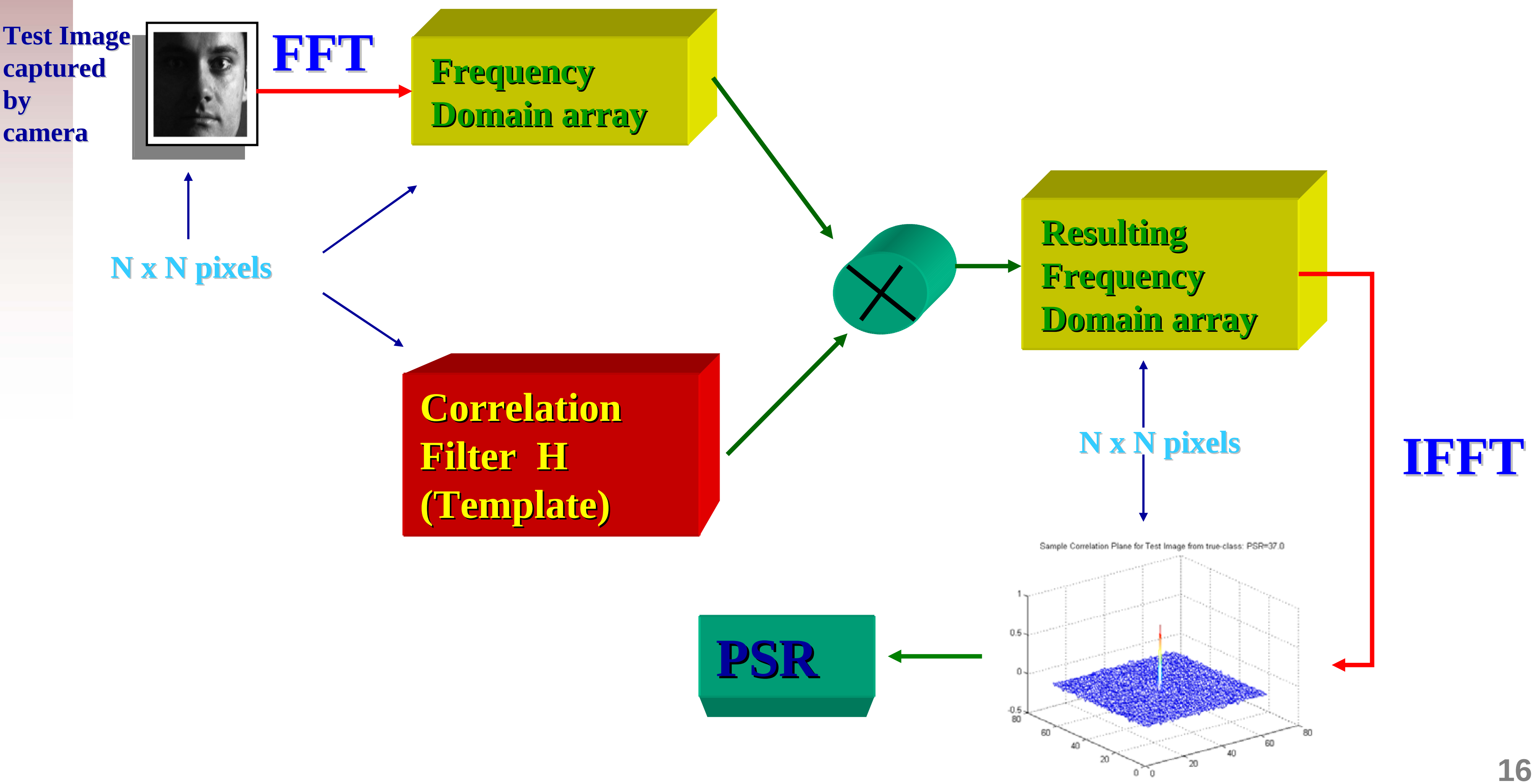
Matched Filter

- Matched Filter is simply the reference image that you want to match in the scene.
- Matched Filter is optimal for detecting the known reference signal in additive white Gaussian noise (AWGN) – it has maximum Signal-to-Noise Ratio.
- OK...but what are the short-comings of Matched Filters?
  - Matched Filters only match with the reference signal, and even slight distortions will not produce a match.
  - Thus you need as many matched filters as number of training images (N).
  - Not feasible from a computational viewpoint as you will need to perform N correlations and store all N filters.

Typical Enrollment for Correlation Filters



Recognition stage

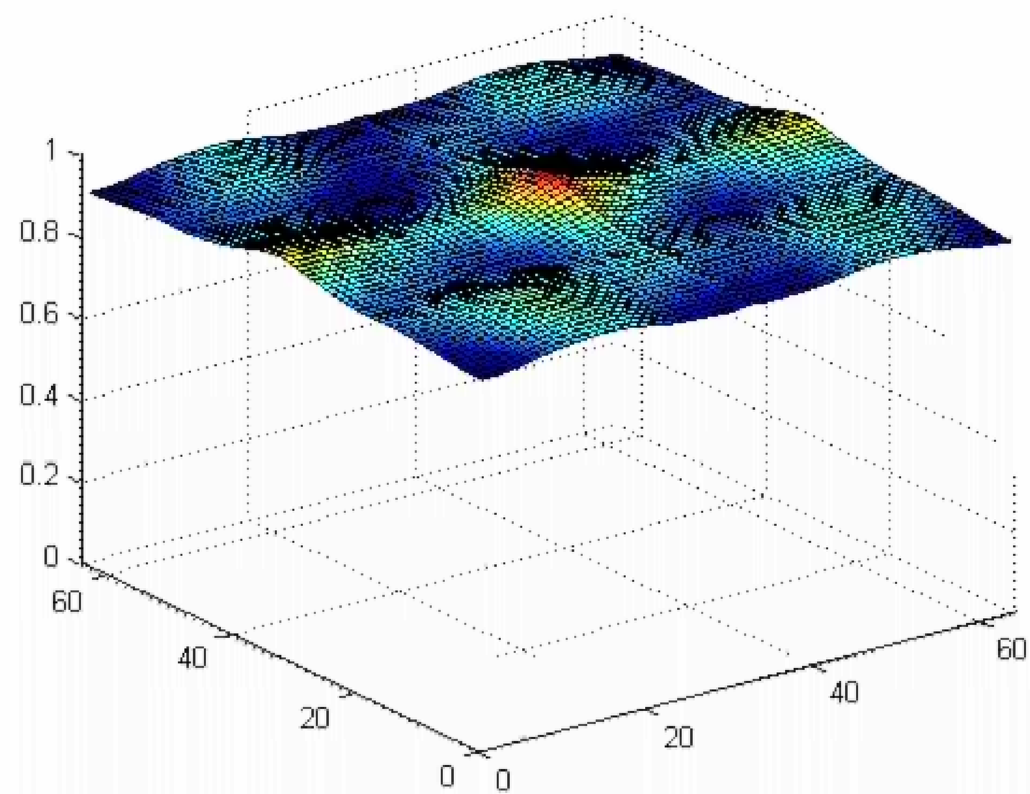


Minimum Average Correlation Energy (MACE) Filters

- MACE filter minimizes the average energy of the correlation outputs while maintaining the correlation value at the origin at a pre-specified level.
- Sidelobes are reduced greatly and discrimination performance is improved

MACE Filter produces a sharp peak at the origin

Correlation Plane



MACE Filter Formulation

- Minimizing spatial correlation energy can be done directly in the frequency domain by expressing the *i*th correlation plane (c_i) energy E_i as follows:

$$E_i = \tfrac{1}{d}\sum_{p=1}^{d} \left|c_i(p)\right|^2 = \tfrac{1}{d}\sum_{k=1}^{d} \left|H(k)\right|^2 \left|X_i(k)\right|^2 = \mathbf{h}^+ \mathbf{X}_i \mathbf{X}_i^* \mathbf{h} = \mathbf{h}^+ \mathbf{D}_i \mathbf{h}$$

Parseval's Theorem!

- The Average correlation plane energy for the N training images is given by E_{ave}

$$E_{ave} = \tfrac{1}{N}\sum_{i=1}^{N} E_i = \mathbf{h}^+ \left[\tfrac{1}{N}\sum_{i=1}^{N} \mathbf{X}_i \mathbf{X}_i^* \right] \mathbf{h} = \mathbf{h}^+ \mathbf{D} \mathbf{h}$$

MACE Filter Formulation (Cont'd.)

- The value at the origin of the correlation of the *i-th* training image is:

$$c_i(0) = \sum_{p=1}^{d} H(p)^* X_i(p) e^{j2\pi 0 p} = \sum_{p=1}^{d} H(p)^* X_i(p) = \mathbf{h}^+ \mathbf{x}_i$$

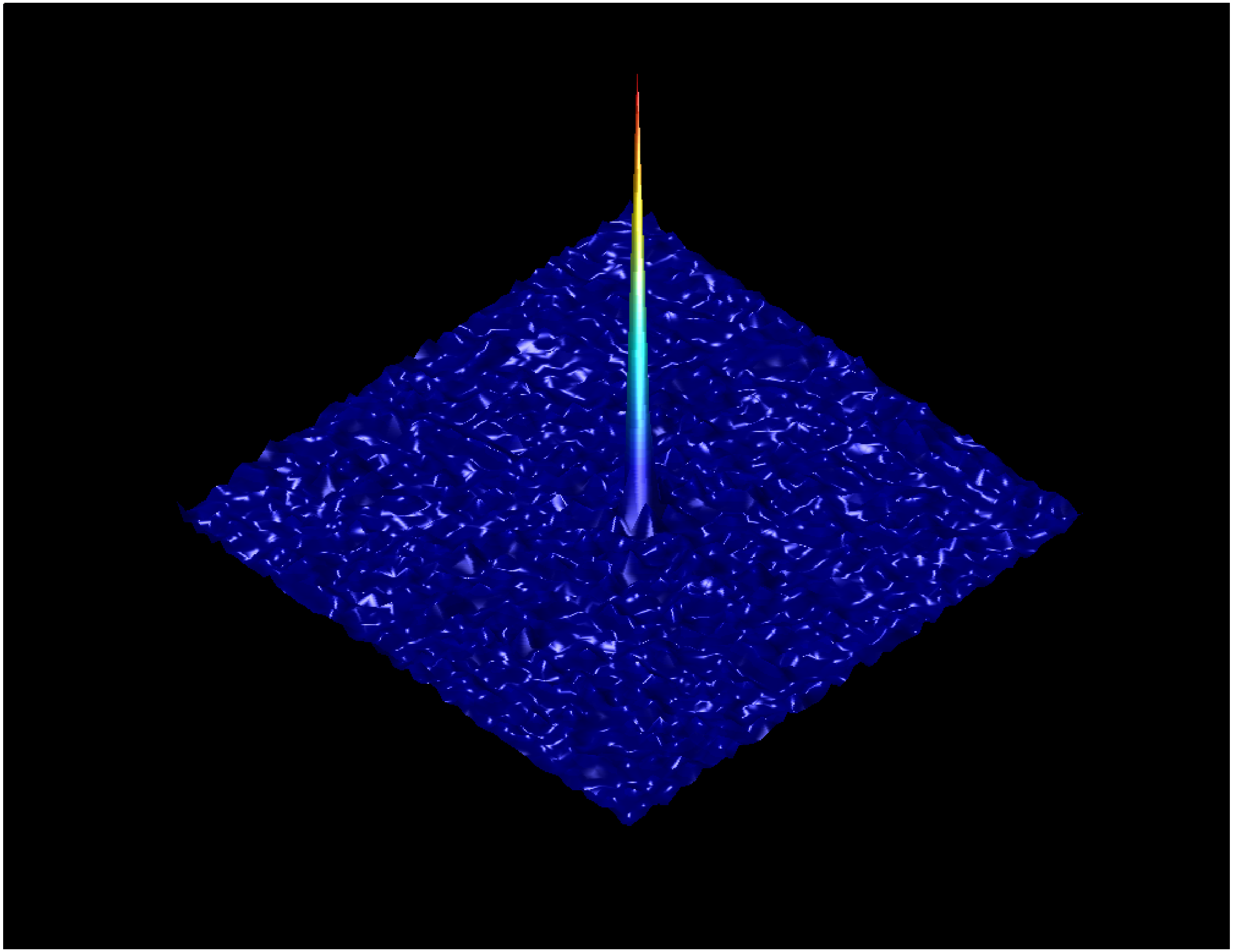
- Specify the correlation peak values for all the training image using column vector u

$$\mathbf{X}^+ \mathbf{h} = \mathbf{u}$$

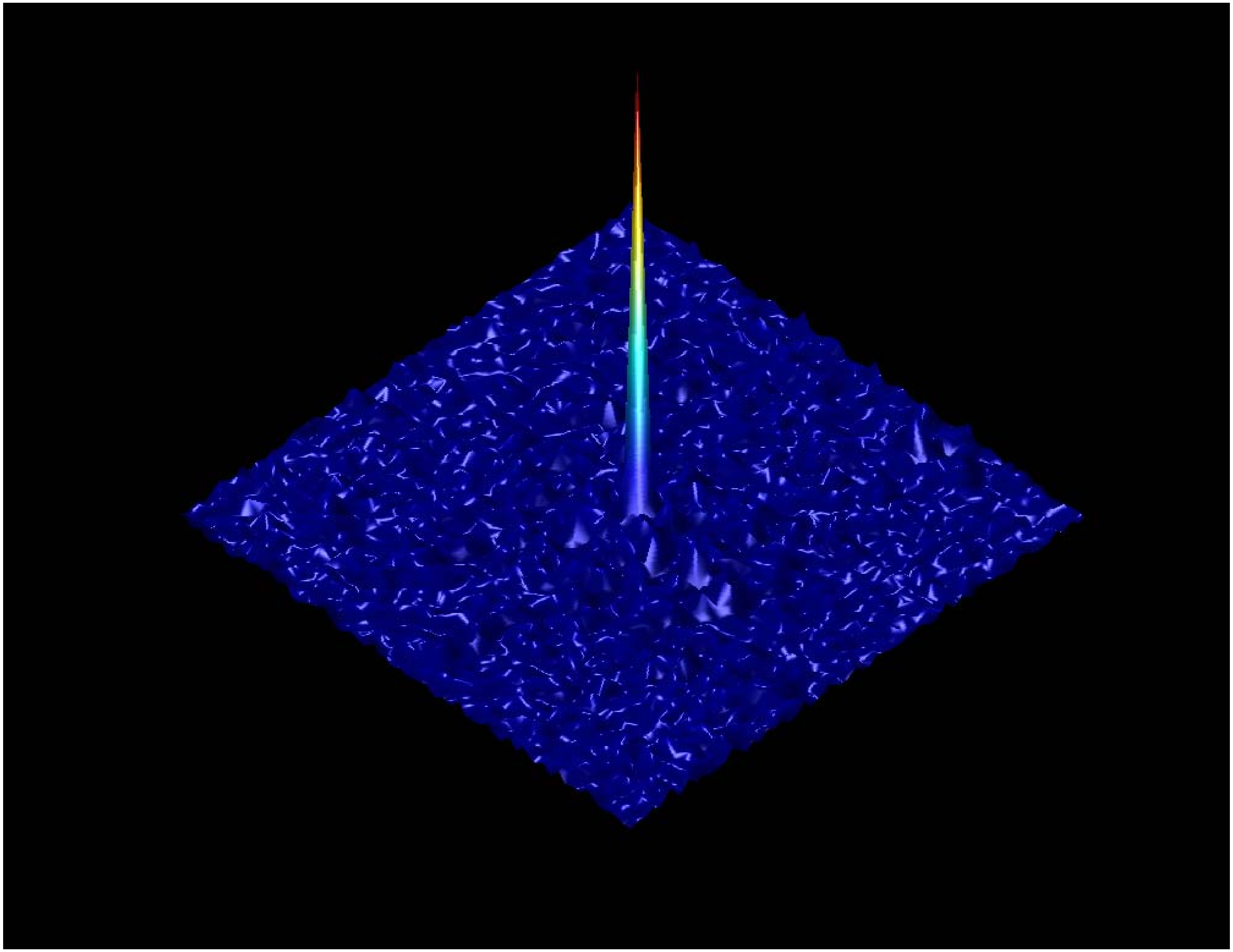
- Minimizing the average correlation energies h^+Dh subject to the constraints $X^+h=u$ leads to the MACE filter solution.

$$h_{MACE} = D^{-1} X (X^+ D^{-1} X)^{-1} u$$

Example Correlation Outputs from an Authentic



Example Correlation Outputs from an Impostor

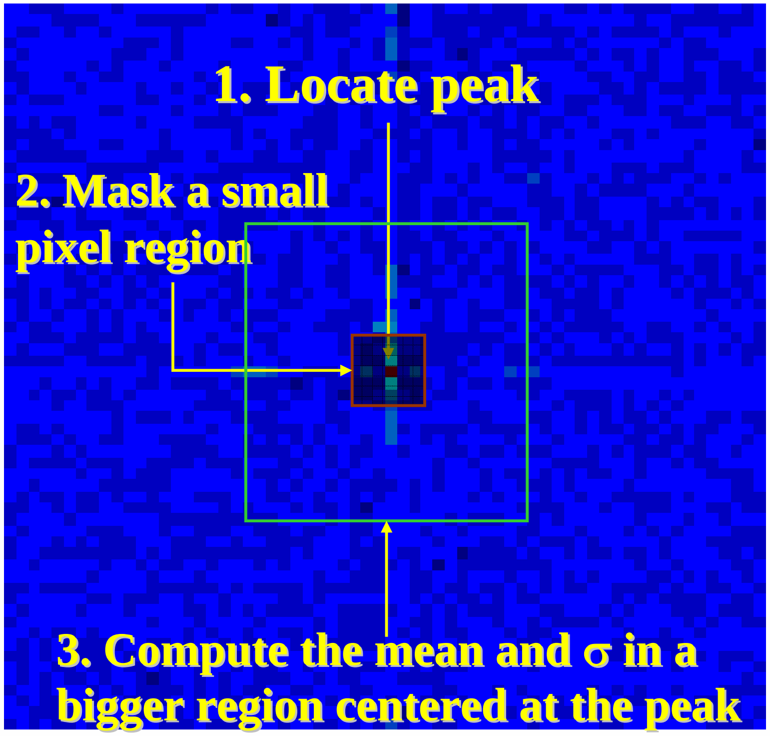


Different Figure of Merit (FOM)

- For Matched Filter we showed that the peak height is what was used for recognition.
- For MACE filters, the optimization is not only to keep the peak height at 1 but also to create sharp peaks.
- Thus it makes sense to use a metric that can measure whether we have achieved this optimization
- We need a metric that can measure the Peak sharpness! As images that resemble the training classes will produce a sharp peak whereas impostor classes will not produce sharp peaks as they were not optimized to do so!

Peak to Sidelobe Ratio (PSR)

- PSR invariant to constant illumination changes

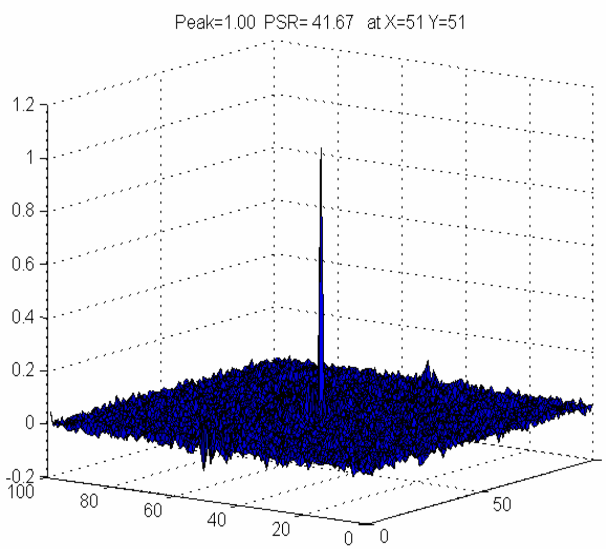


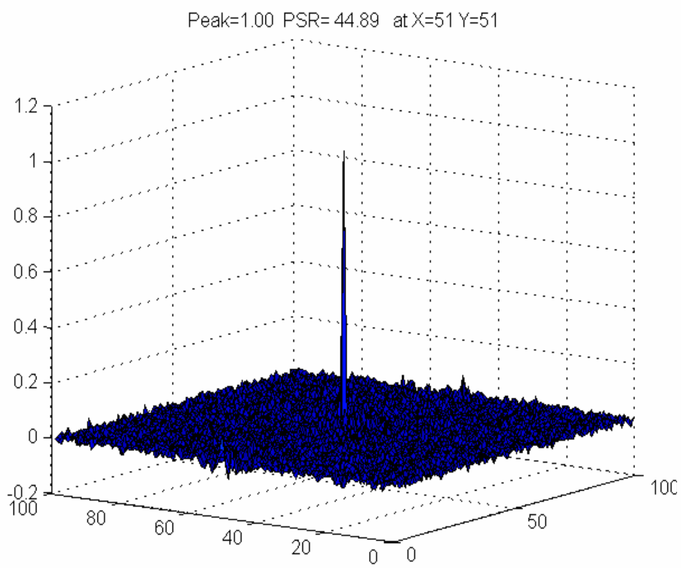
$$PSR = \frac{Peak - mean}{\sigma}$$

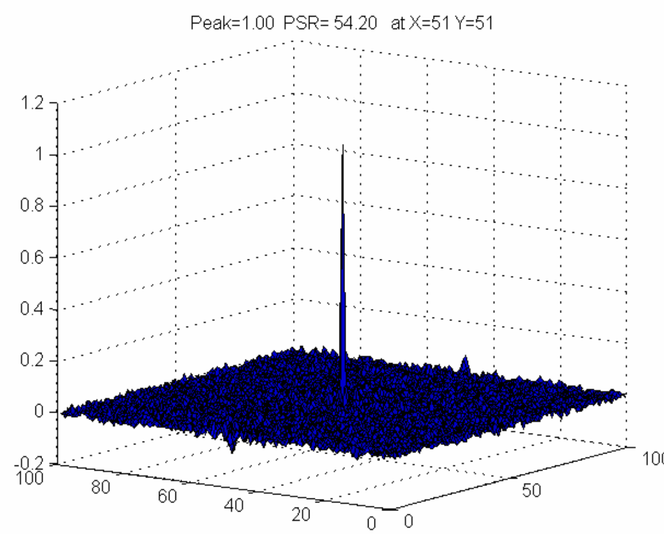
- Match declared when PSR is large, i.e., peak must not only be large, but sidelobes must be small.

Example Correlation Outputs

- Use these images for training (peak=1 for all correlation outputs)

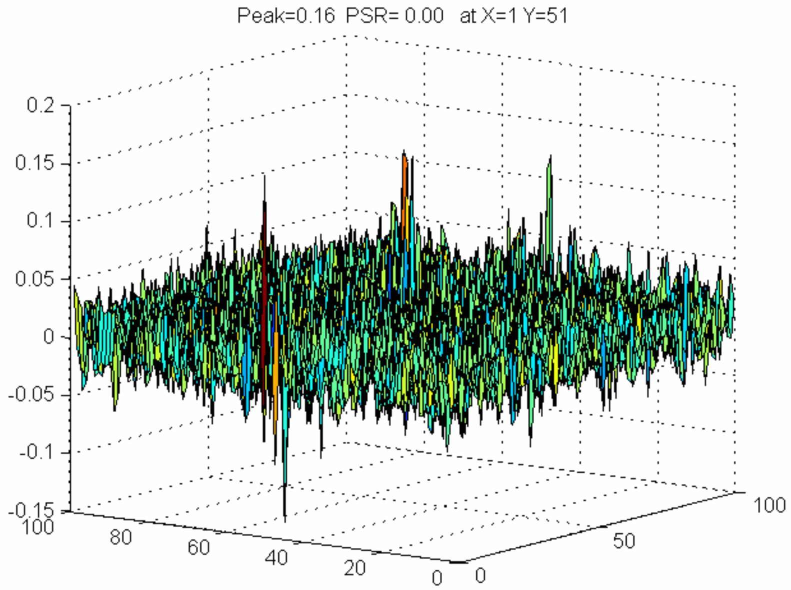


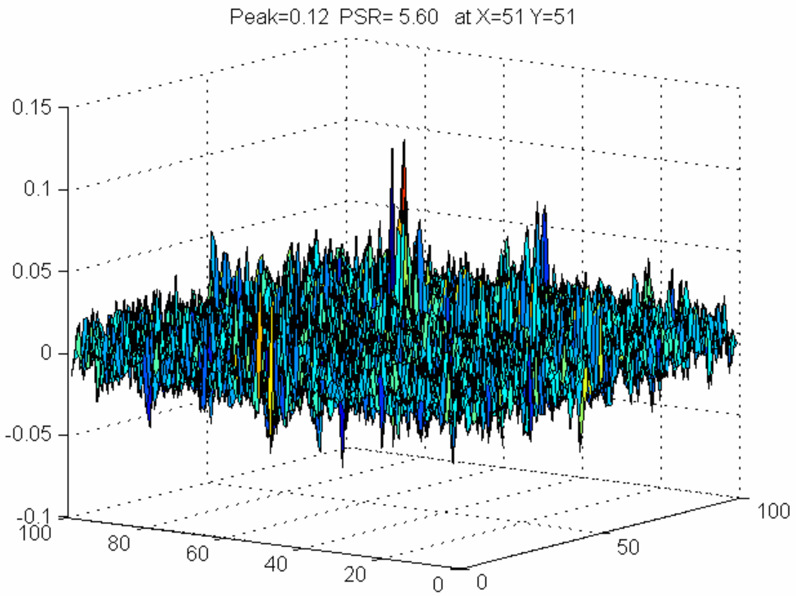




PSR: 41.6 44.8 54.2

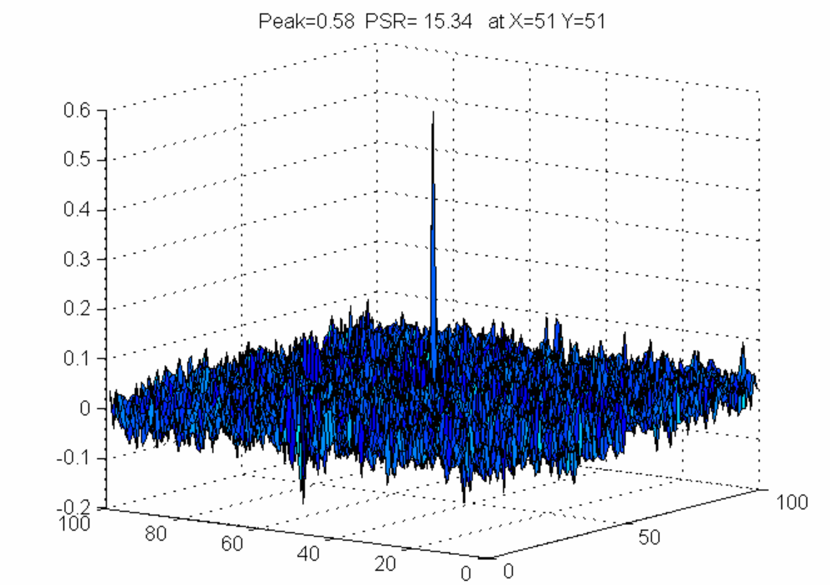
Example Correlation Output Impostors using MACE

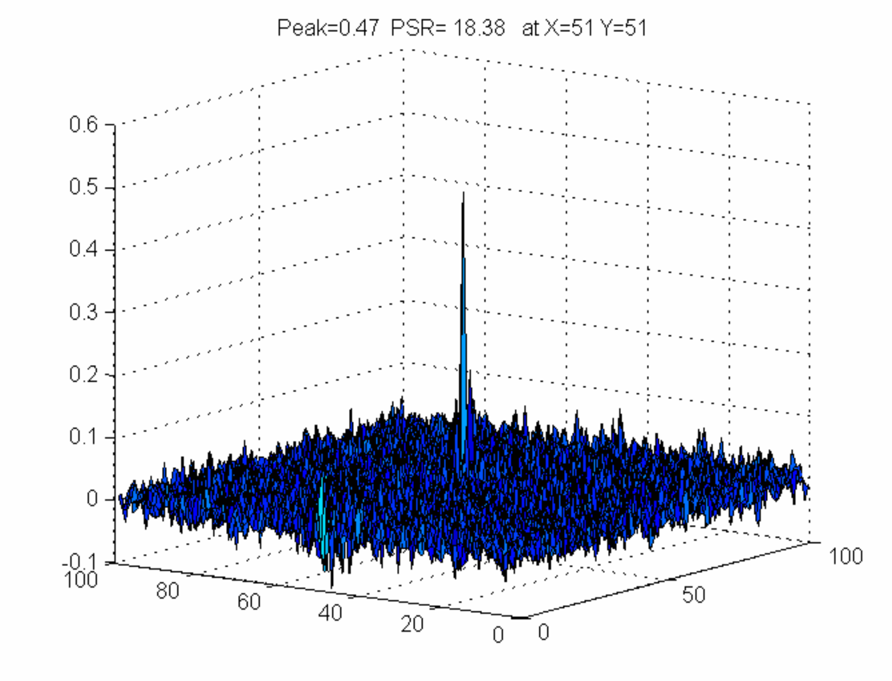




No discernible peaks (0.16 and 0.12 and PSR 5.6 for impostor class! Very good!

Example correlation output for authentic people (but slightly different illumination)





Marios Savvides

Facial Expression Database

- Facial Expression Database (AMP Lab, CMU)
  - 13 People
  - 75 images per person
  - Varying Expressions
  - 64x64 pixels
  - Constant illumination

- 1 filter per person made from 3 training images

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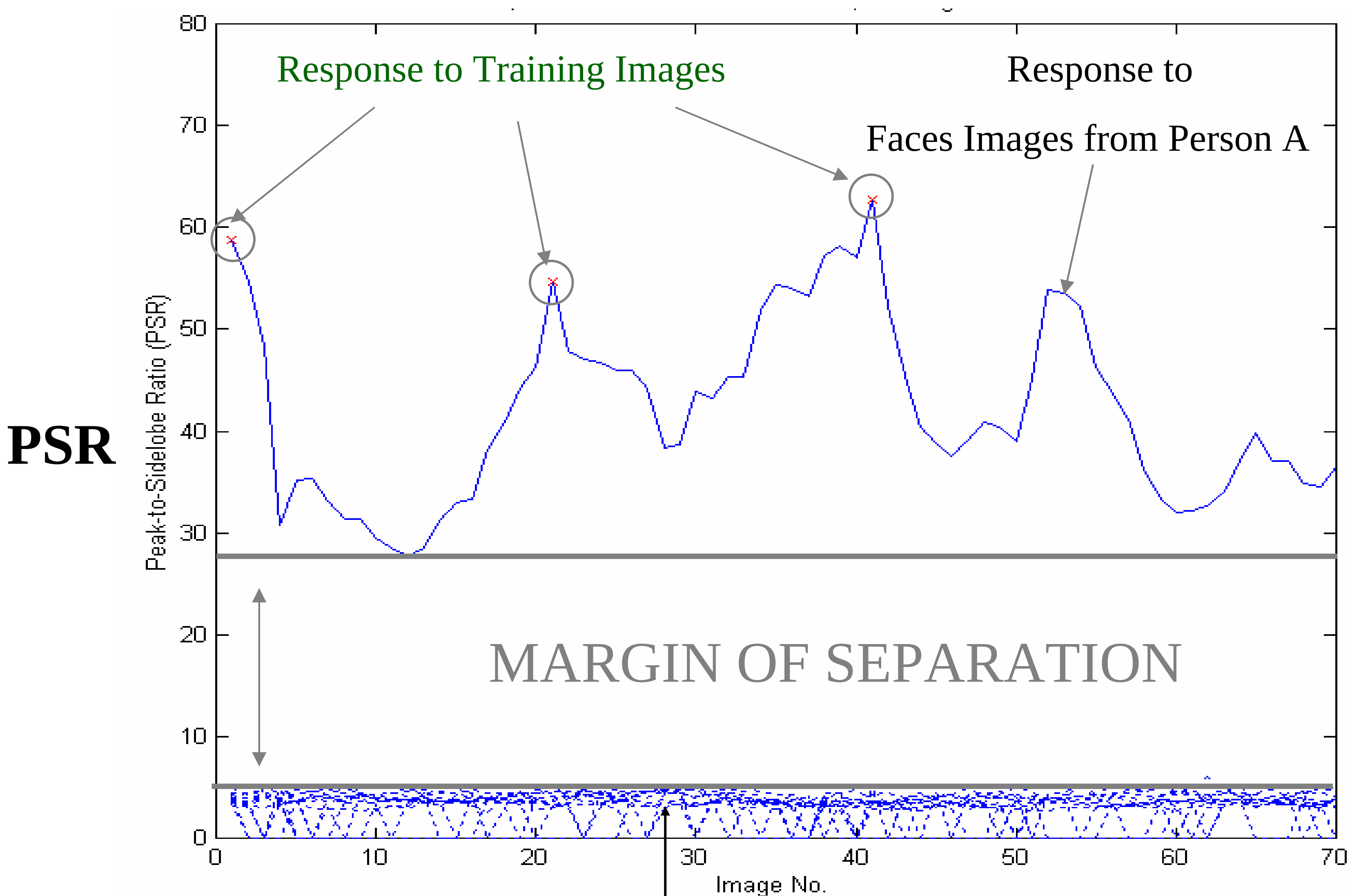
PSRs for the Filter Trained on 3 Images



Response to 75 face images of the other 12 people=900 PSRs

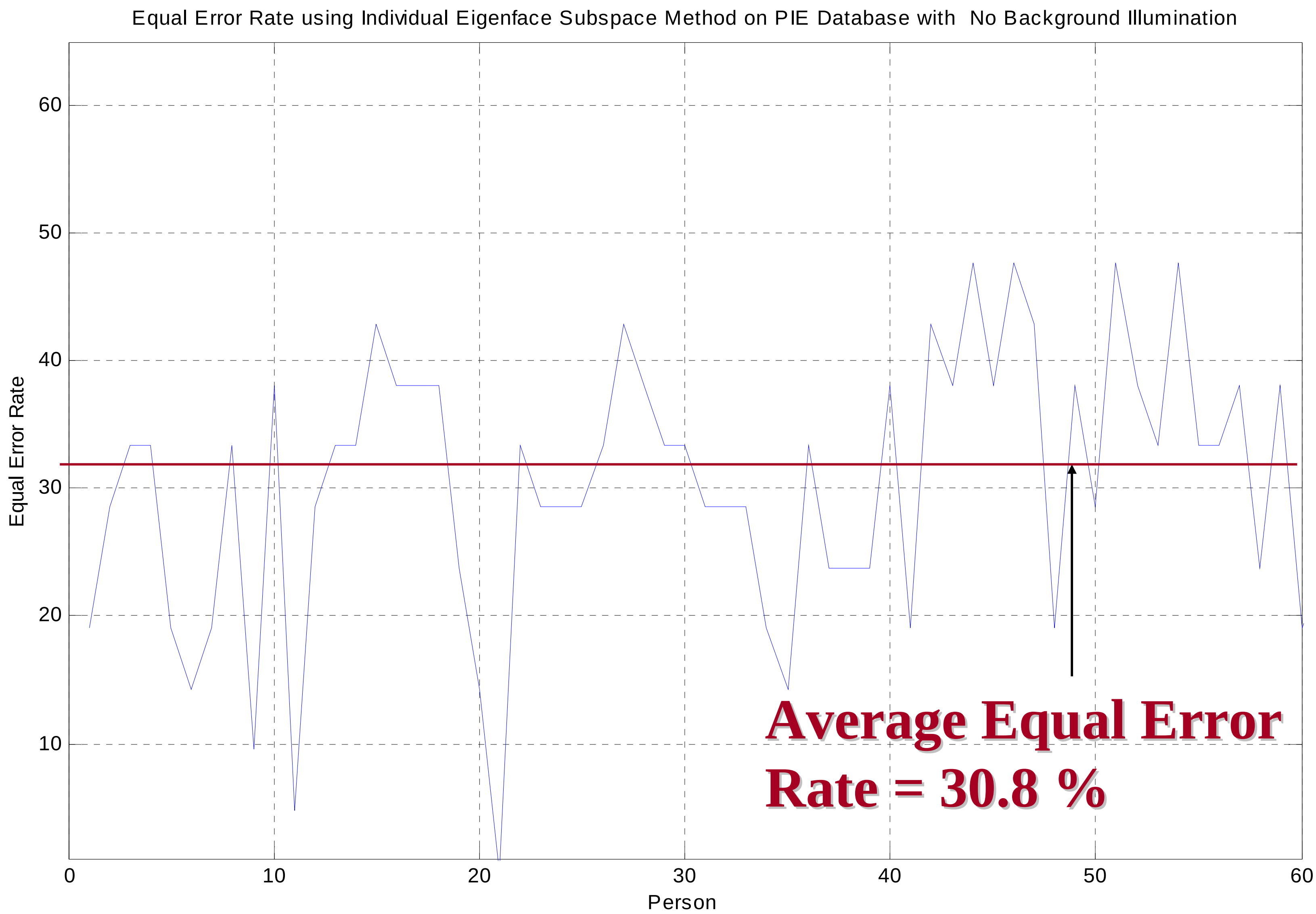
49 Faces from PIE Database illustrating the variations in illumination

Training Image selection

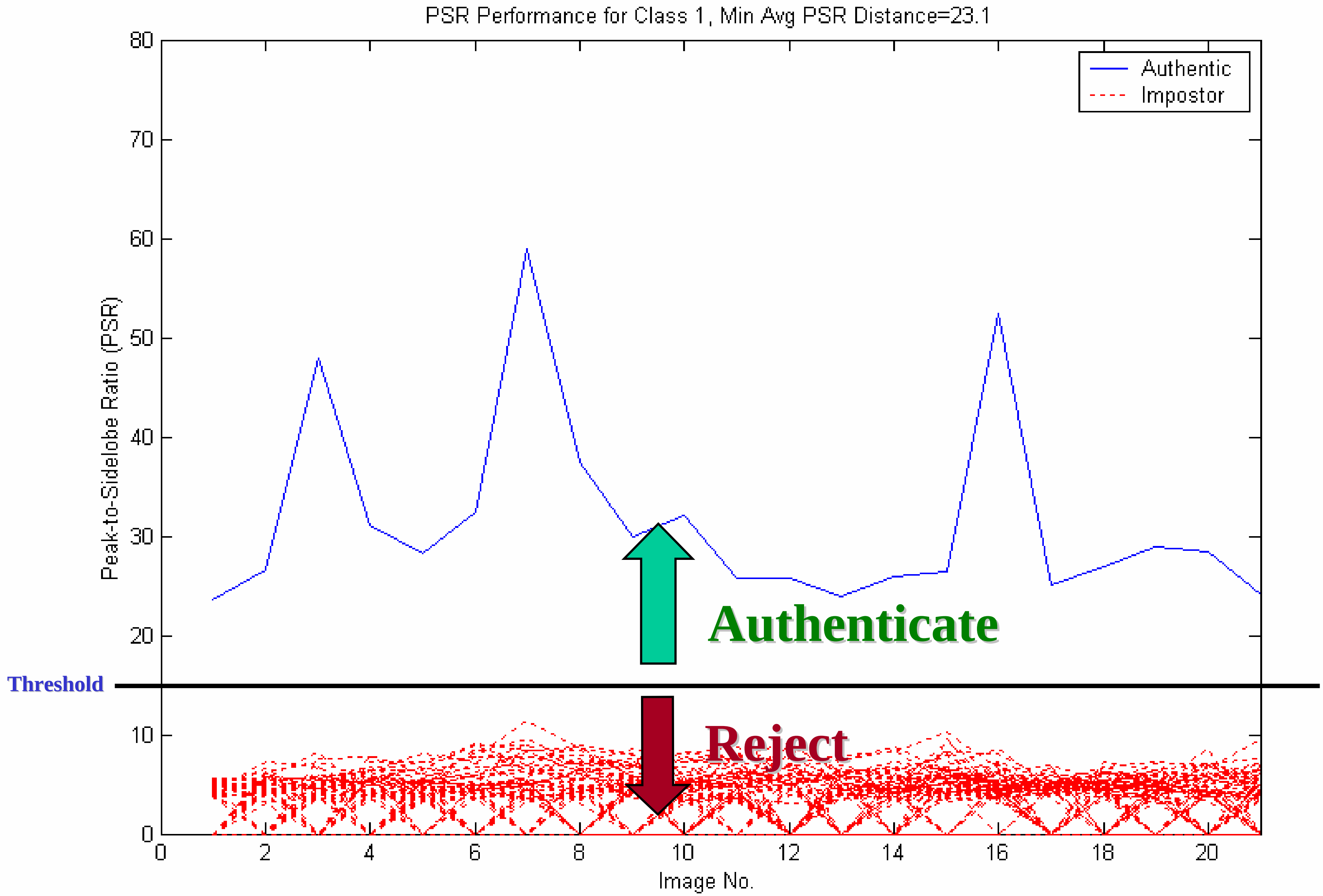
- We used *three* face images to synthesize a correlation filter
- The three selected training images consisted of 3 extreme cases (dark left half face, normal face illumination, dark right half face).

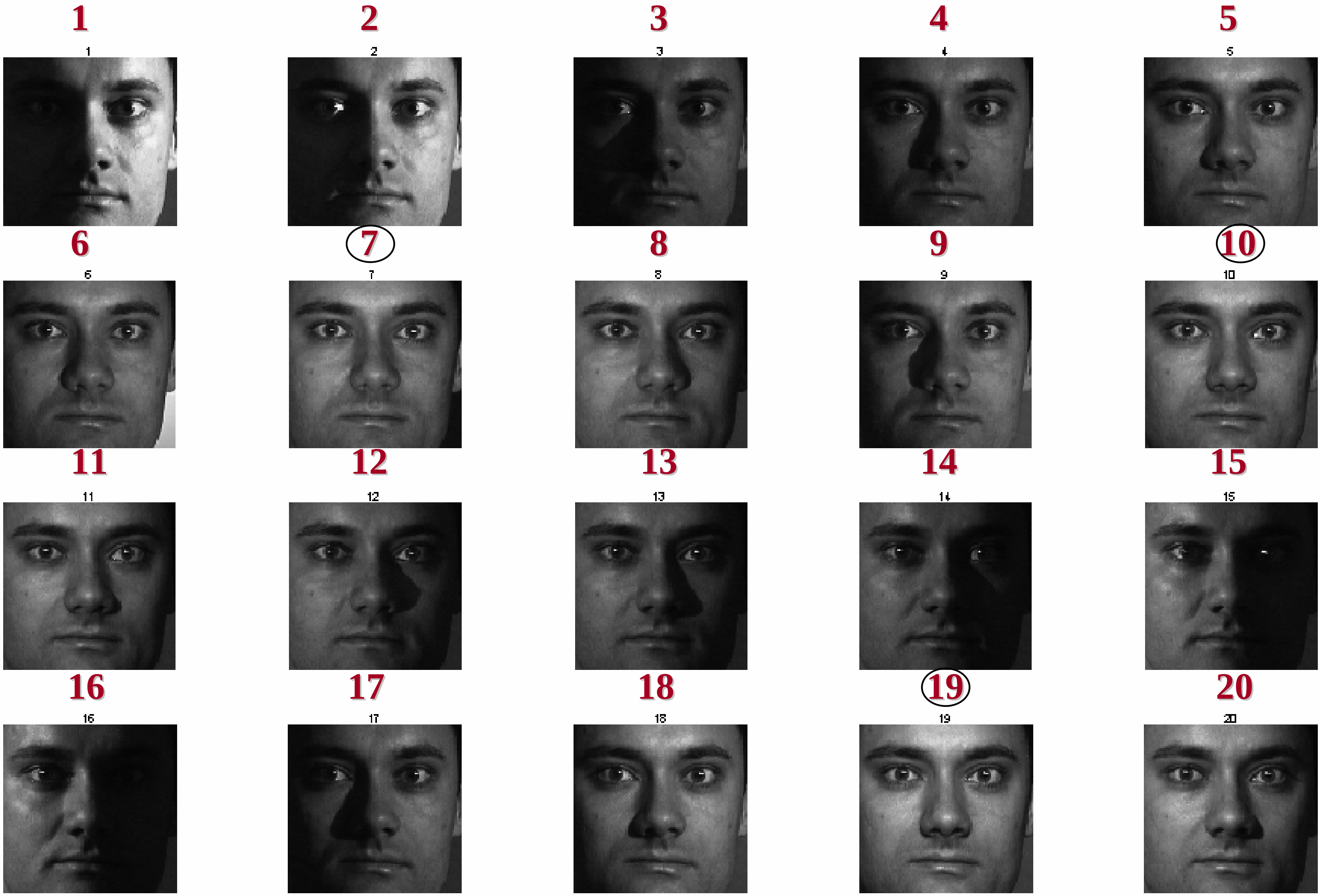


EER using IPCA with no Background illumination



EER using Filter with no Background illumination





21 different illuminations of a person's face in the database

Recognition Accuracy using Frontal Lighting Training Images

PIE dataset (face images captured with room lights off)										
Frontal Lighting	IPCA		3D Linear Subspace		Fisherfaces		MACE Filters		UMACE Filters	
Training Images	# Errors	%Rec Rate	# Errors	%Rec Rate	# Errors	%Rec Rate	# Errors	% Rec Rate	# Errors	% Rec Rate
5,6,7,8,9,10, 11,18,19,20	33	97.6%	31	97.3%	36	97.3%	0	100%	0	100%
5,6,7,8,9, 10	110	91.4%	40	97.1%	145	89.3%	1	99.9%	0	100%
5,7,9,10	337	72.4%	93	93.2%	390	71.4%	1	99.9%	3	99.7%
7,10,19	**872**	**36.1%**	**670**	**50.9%**	**365**	**73.3%**	**10**	**99.1%**	**10**	**99.1%**
8,9,10	300	78.0%	30	97.8%	244	82.1%	1	99.9%	1	99.9%
18,19,20	122	91.0%	22	98.4%	79	94.2%	2	99.9%	1	99.9%

Reduced Complexity Filters

- Reducing the computational and storage complexity of filters has many applications:
  - PDA's / Cellphone Biometric recognition
  - Ability to store Biometric templates on smart cards and other limited memory devices.
  - System-on-Chip implementations

- Idea is to reduce representation of filters to 4 phase levels.

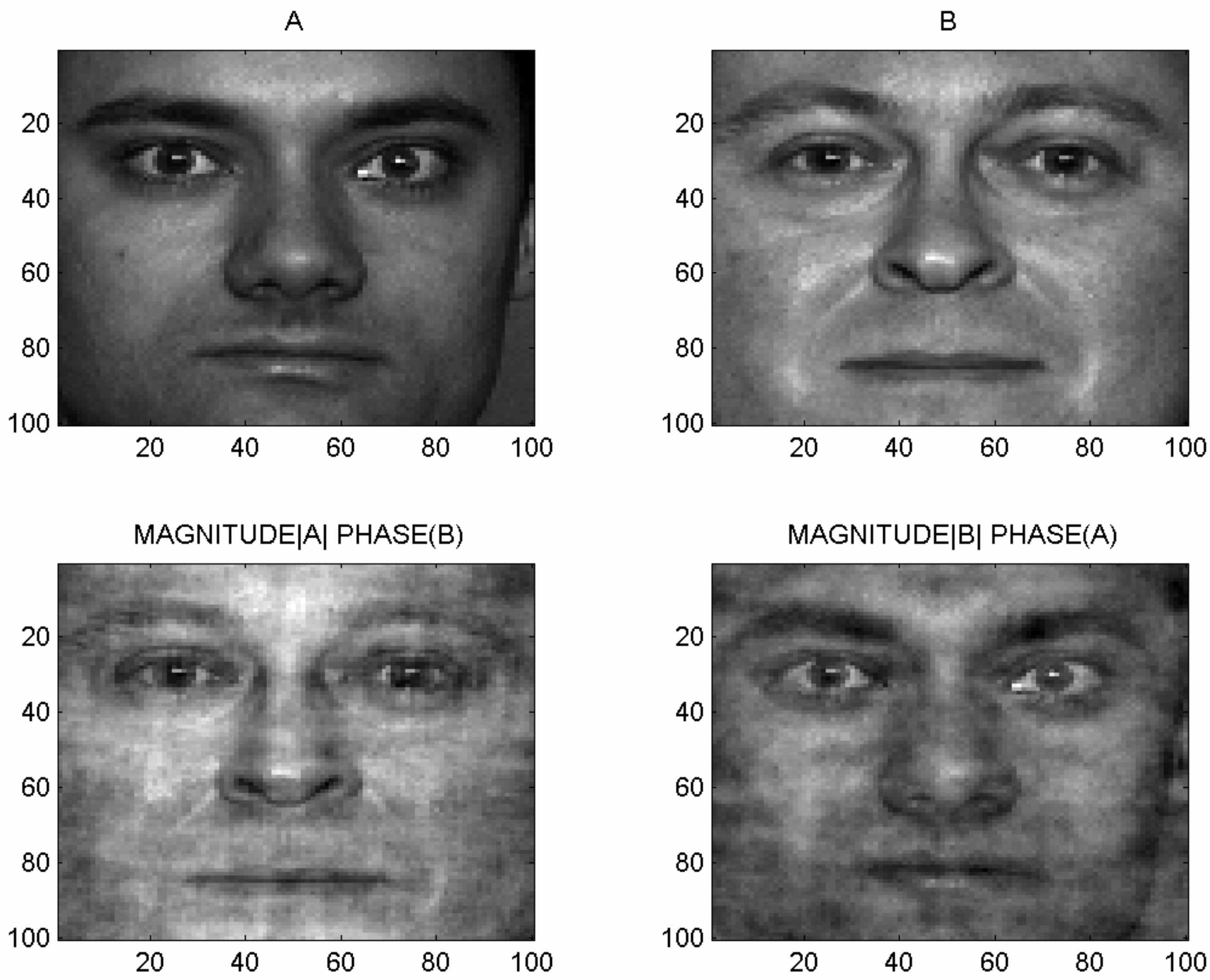
- We use phase since phase contains most of the information for reconstruction for images than magnitude.

- Ideal for Passport form-factor Biometric storage specifications. E.g. for face only 127bytes/templates are required.

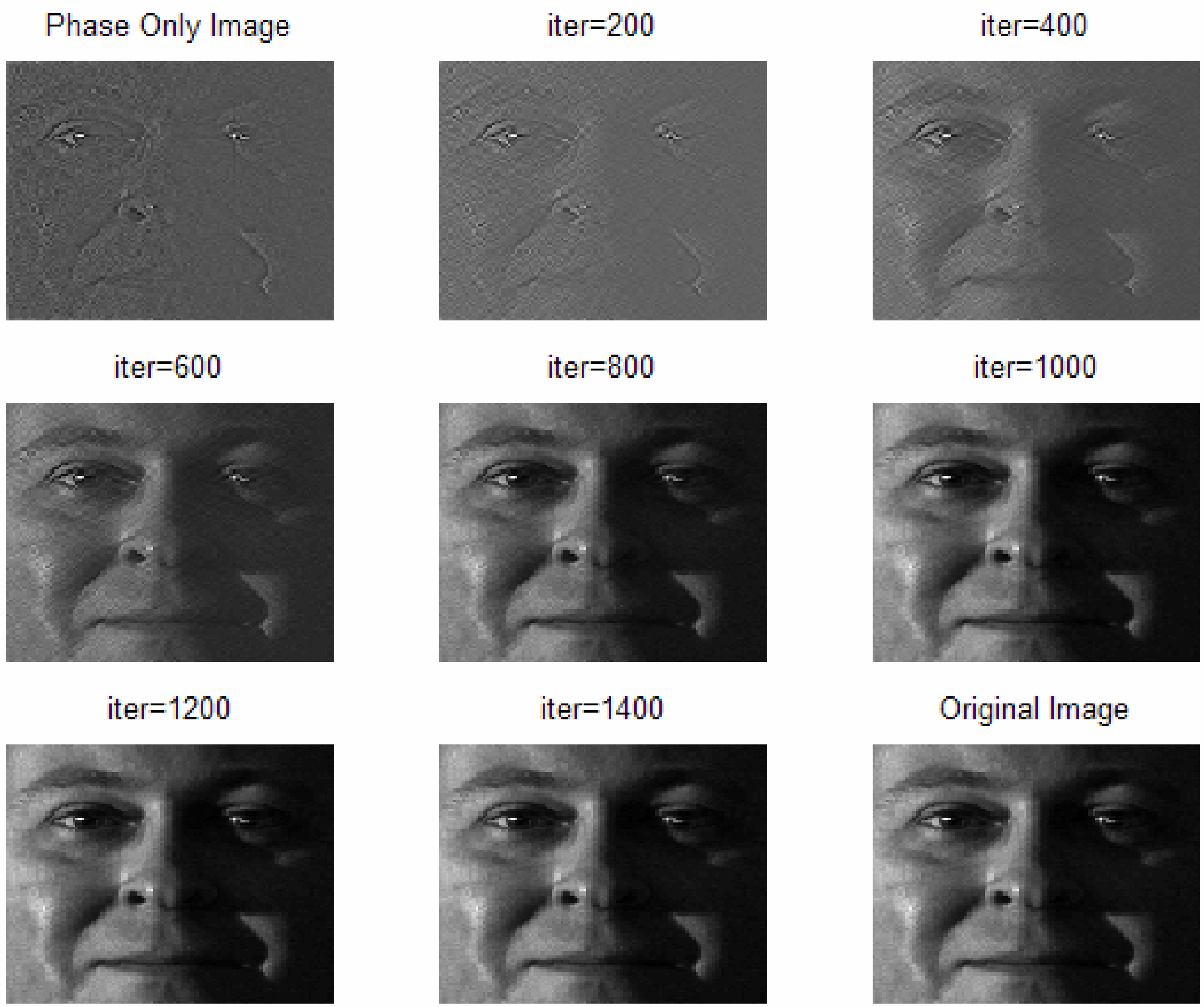
*M.Savvides and B.V.K. Vijaya Kumar, "Quad Phase Minimum Average Correlation Energy Filters for Reduced Memory Illumination Tolerant Face Authentication" pp. 19, Lecture Notes in Computer Science, Springer-Verlag Heidelberg, volume 2680 / 2003, January 2003

*** US Patent pending**

Phase retains most of the information for images

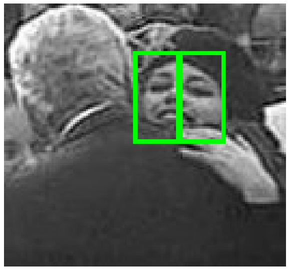


Iterative Reconstruction from Phase



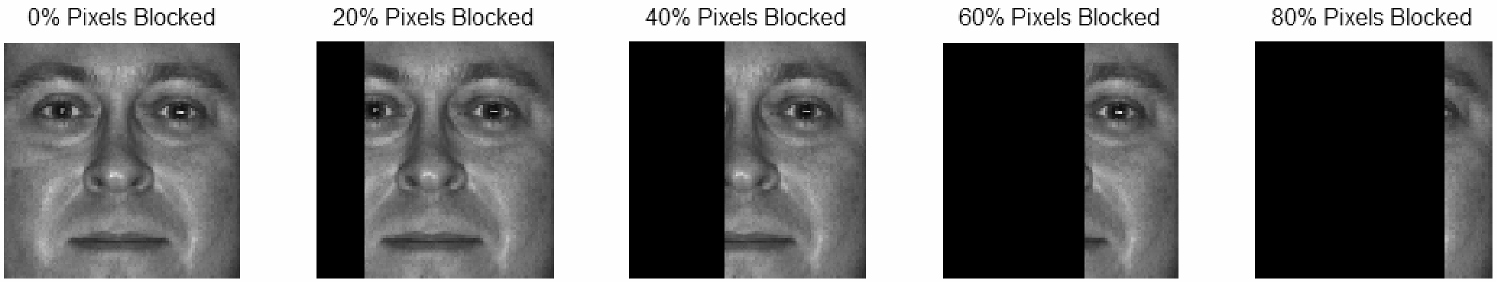
Face Identification from Partial Faces

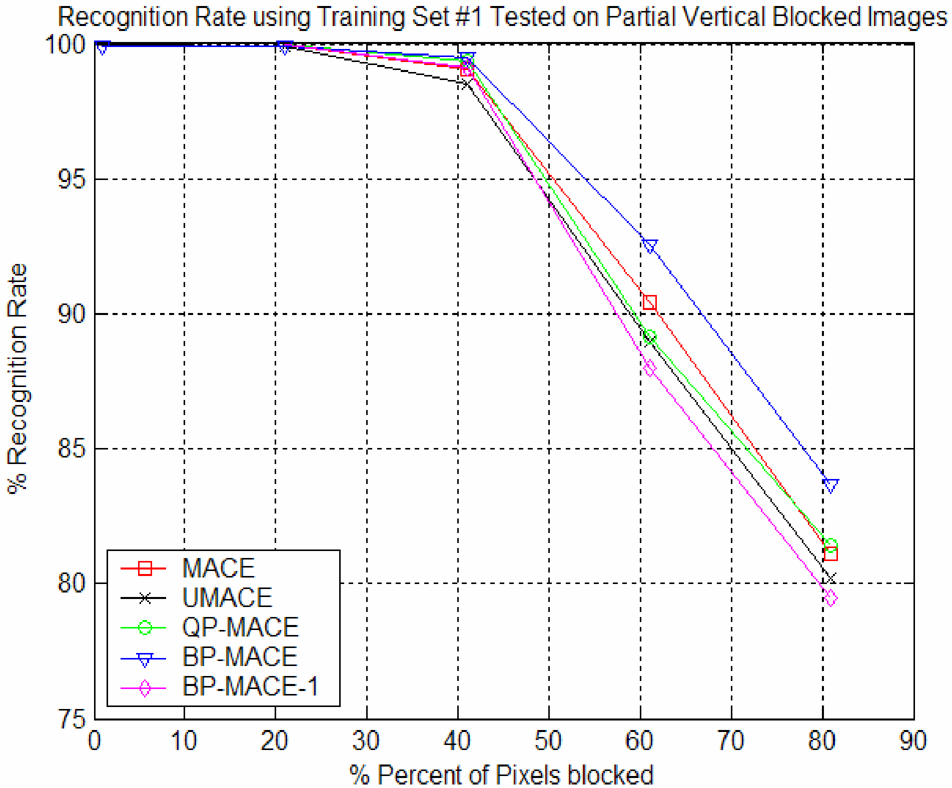
- We have shown that these correlation filters seem to be tolerant to illumination variations, even when half the face is completely black and still achieve excellent recognition rates.
- What about partial face recognition?
- In practice a face detector will detect and retrieve part of the face (another type of registration error). In many cases, occluded by another face or object. Other face recognition methods fail in this circumstance.

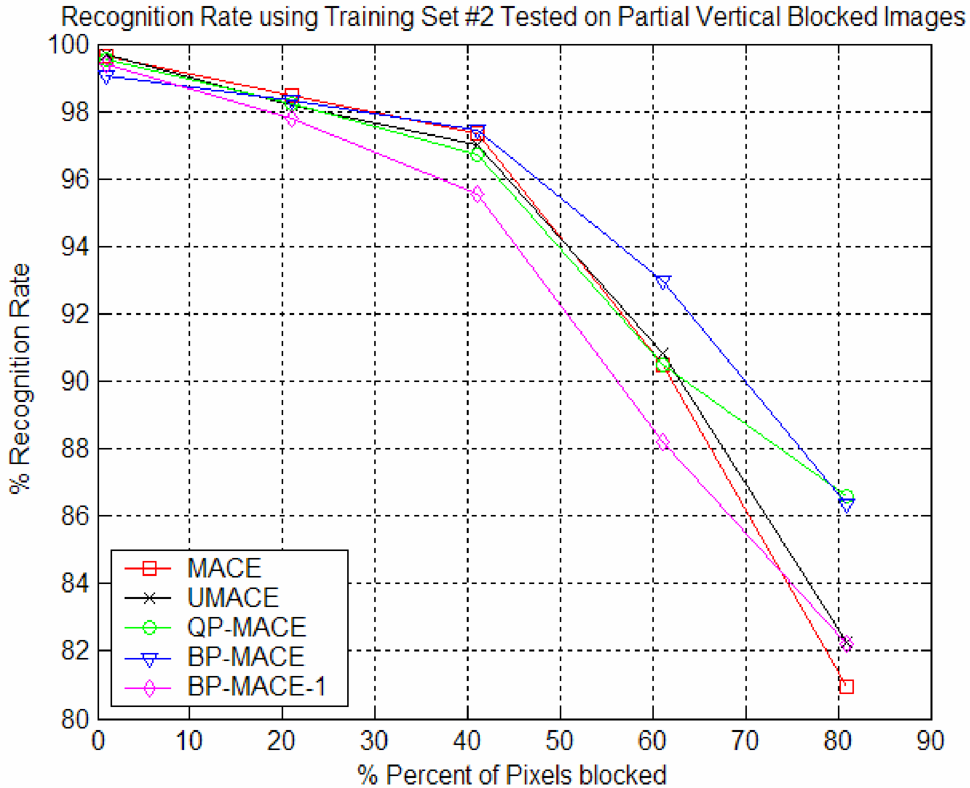


*M. Savvides, B.V.K. Vijaya Kumar and P.K. Khosla, "Robust, Shift-Invariant Biometric Identification from Partial Face Images", Defense & Security Symposium, special session on Biometric Technologies for Human Identification (OR51) 2004.

Vertical cropping of test face image pixels (correlation filters are trained on FULL size images)



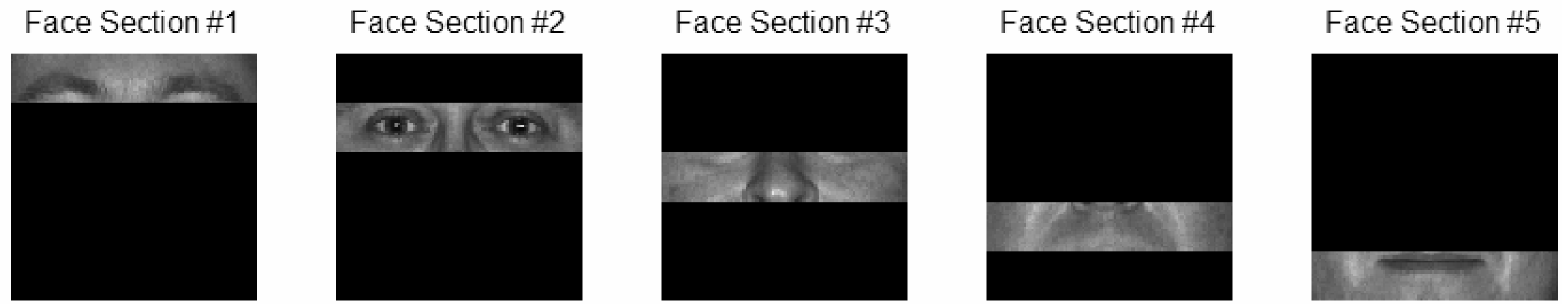


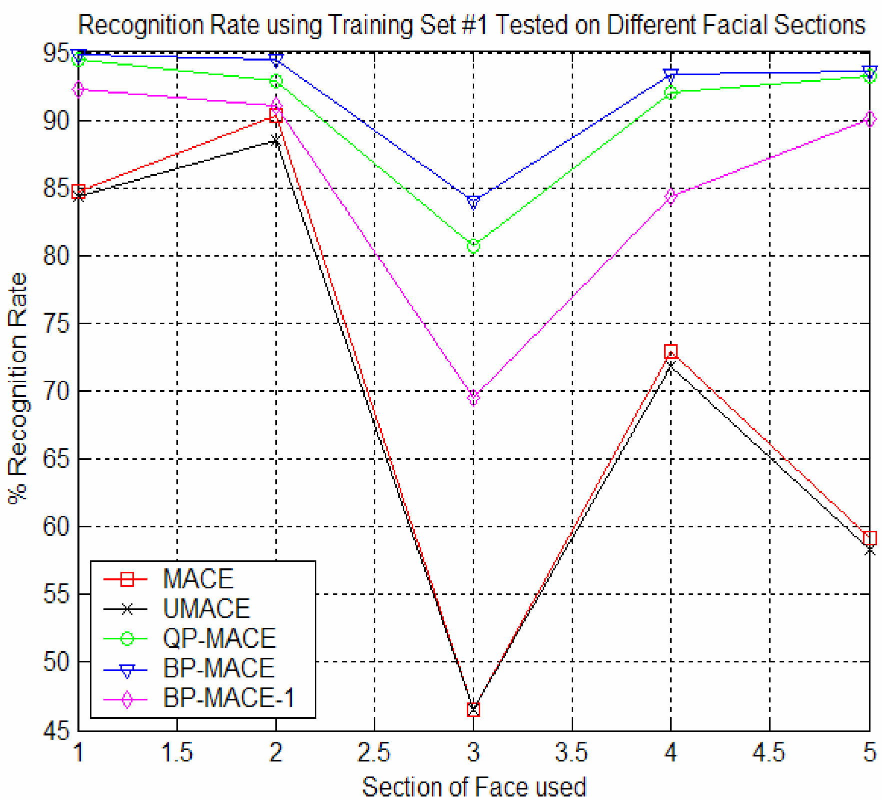


Using Training set #1 (3 extreme lighting images)

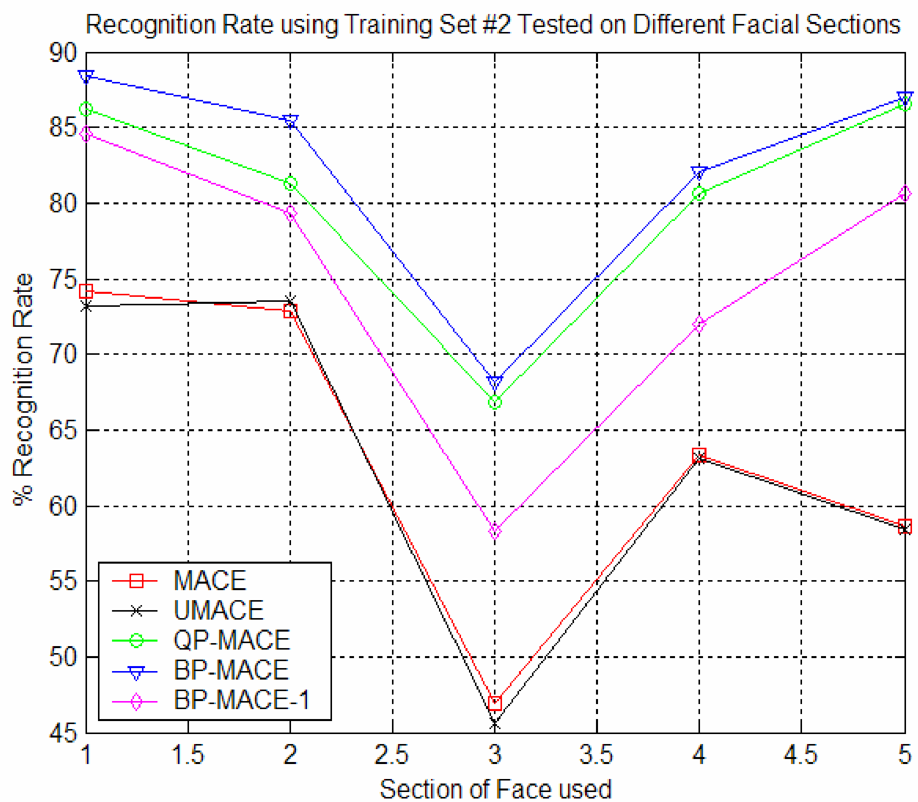
Using Training set #2 (3 frontal lighting images)

Recognition using selected face regions



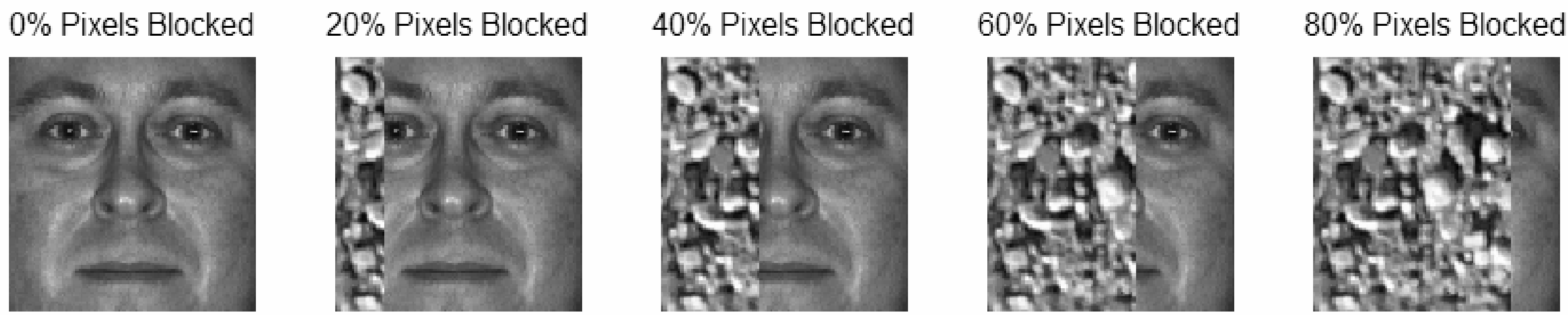


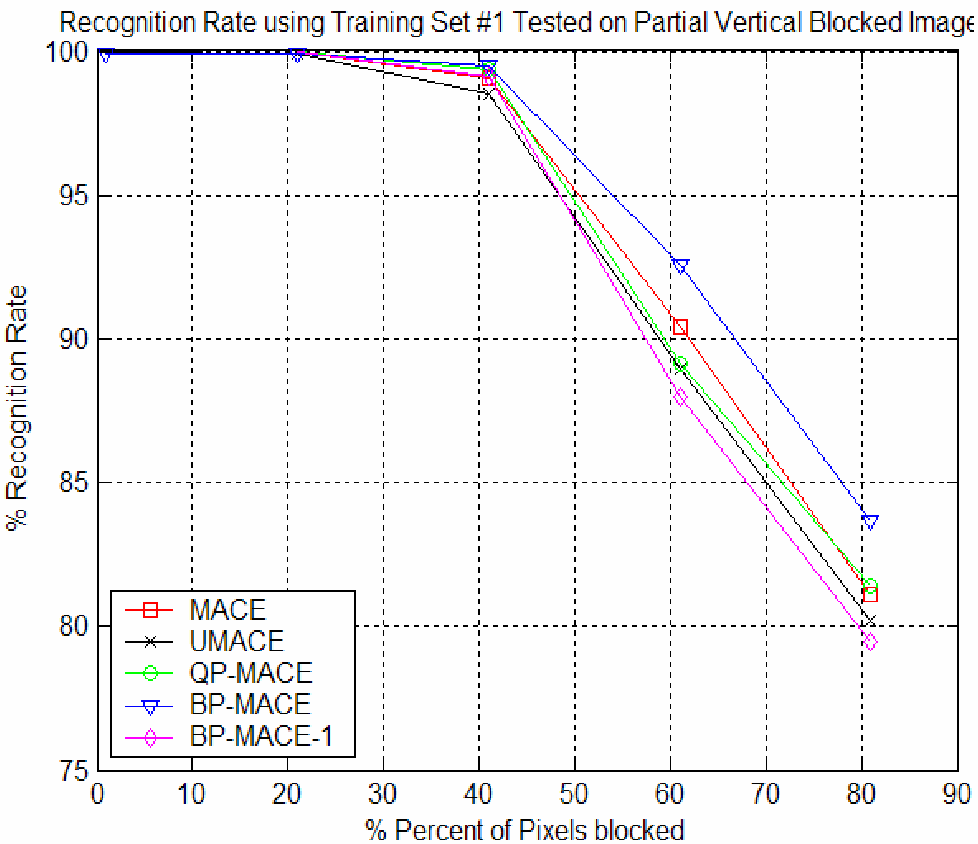
Using Training set #1 (3 extreme lighting images)



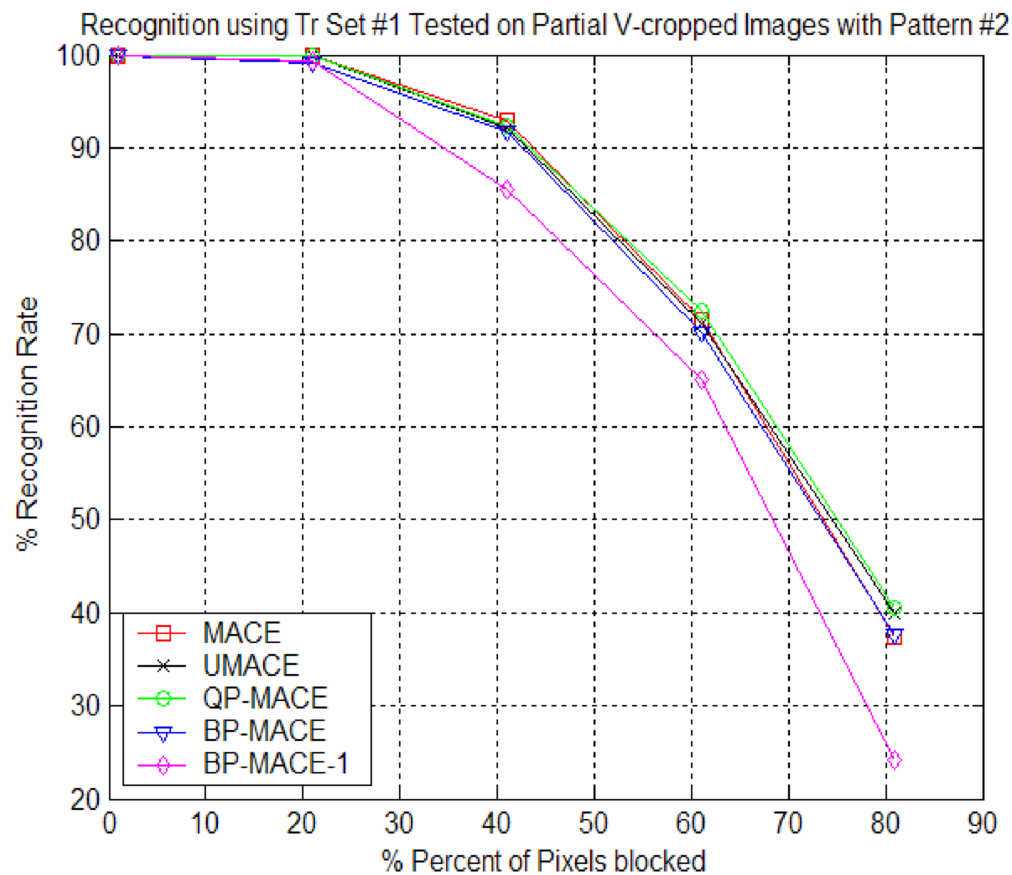
Using Training set #2 (3 frontal lighting images)

Vertical crop + texture #2





Zero intensity background



Textured background

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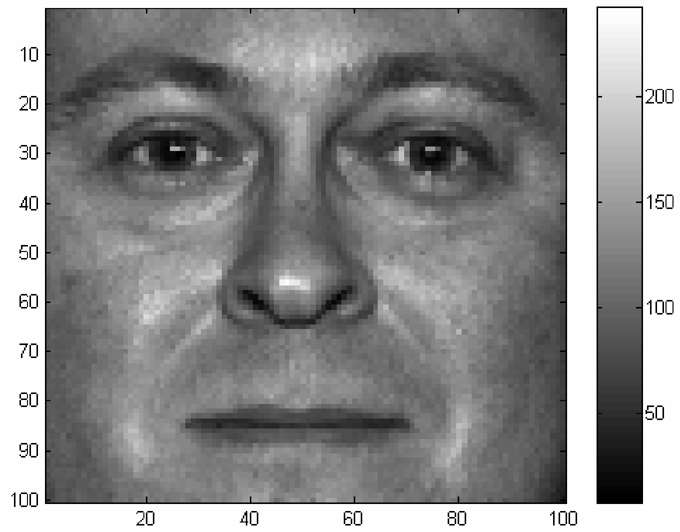
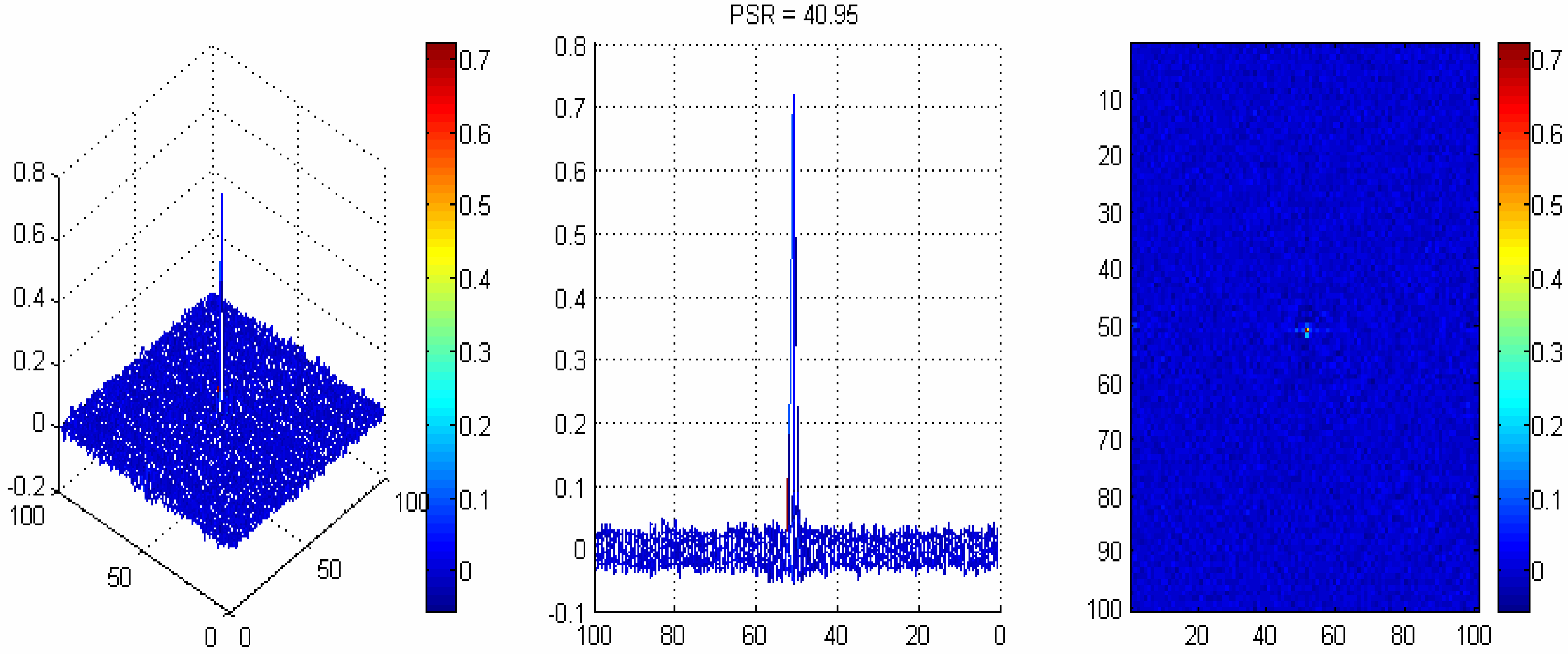
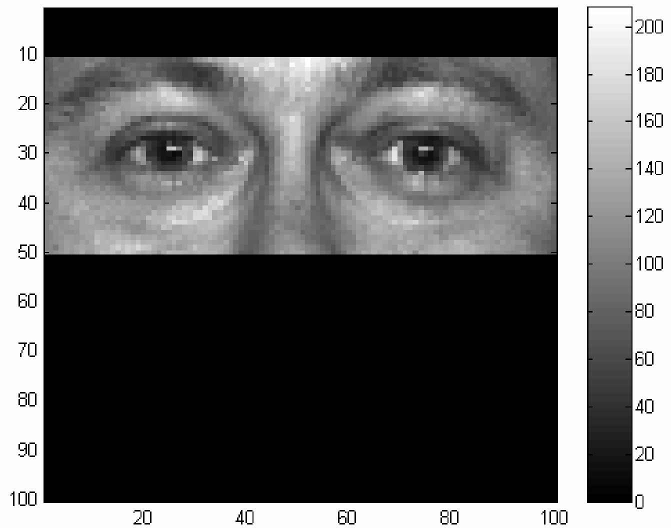
*M. Savvides, B.V.K. Vijaya Kumar and P.K. Khosla, "Robust, Shift-Invariant Biometric Identification from Partial Face Images", Defense & Security Symposium, special session on Biometric Technologies for Human Identification (OR51) 2004.



Train filter on illuminations 3,7,16.

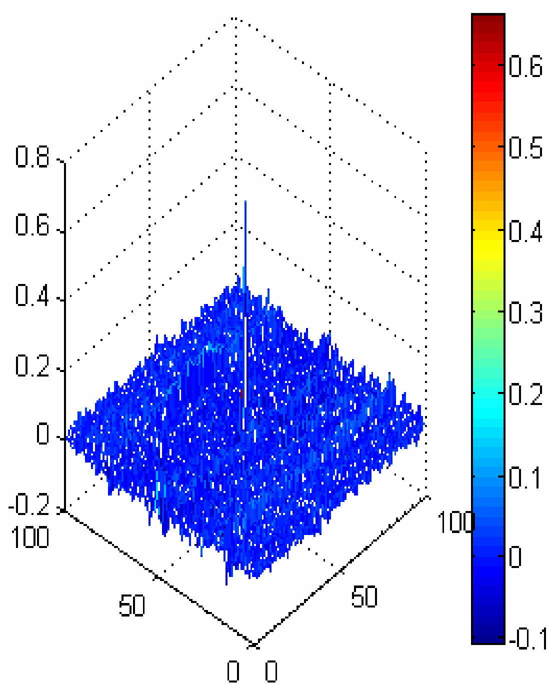
Test on 10.

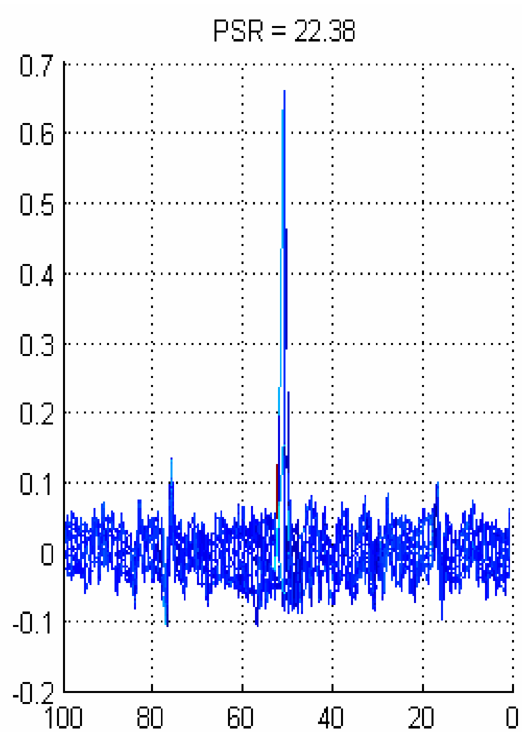


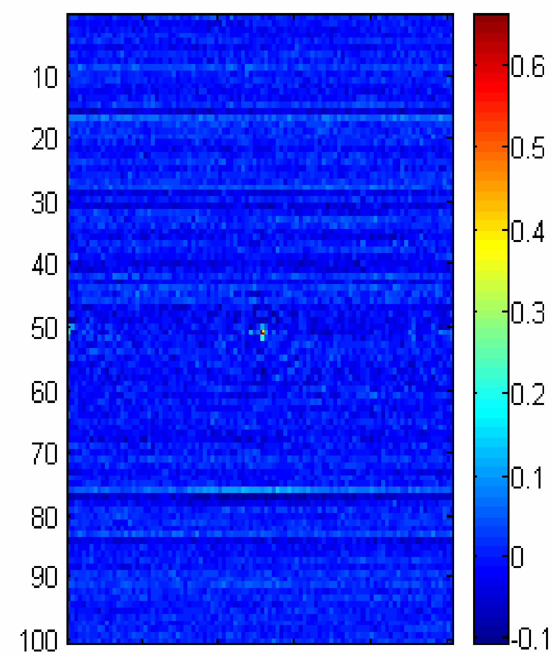


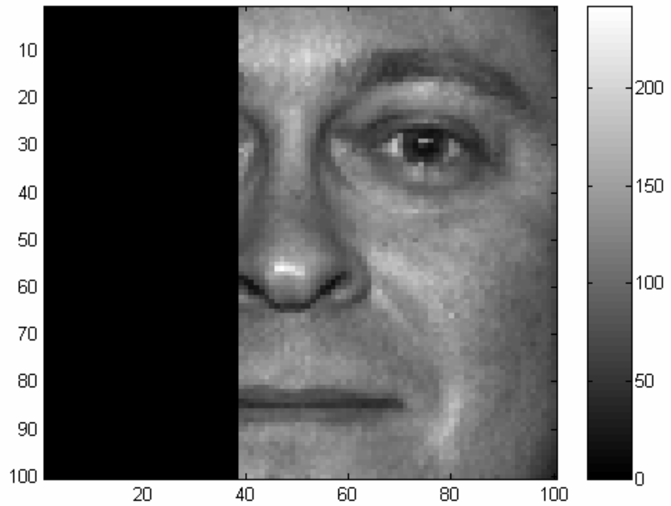
Using same Filter trained before,

Perform cross-correlation on cropped-face shown on left



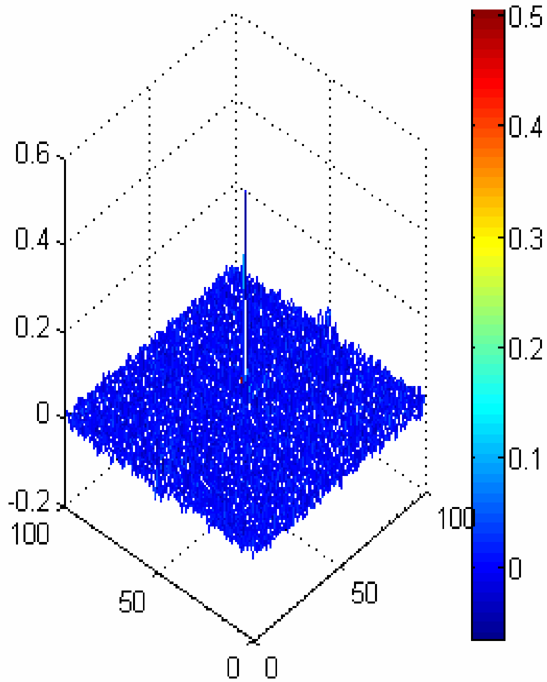


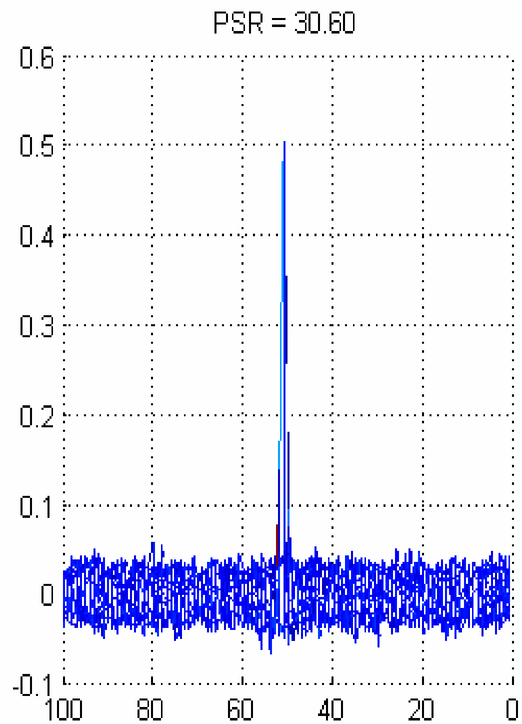


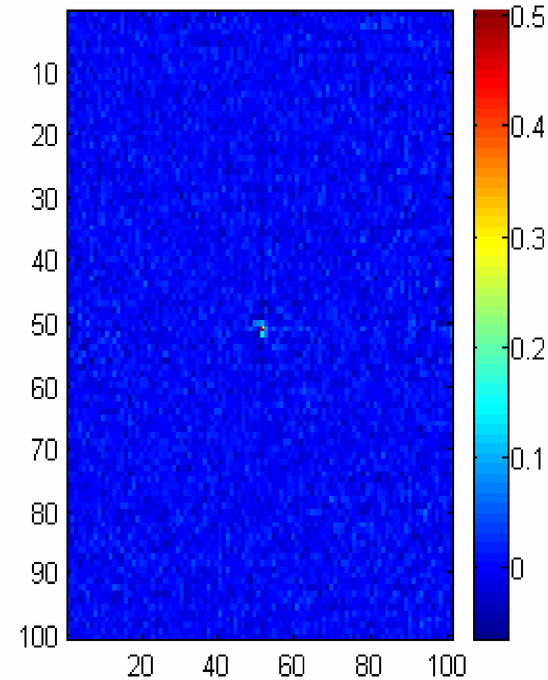


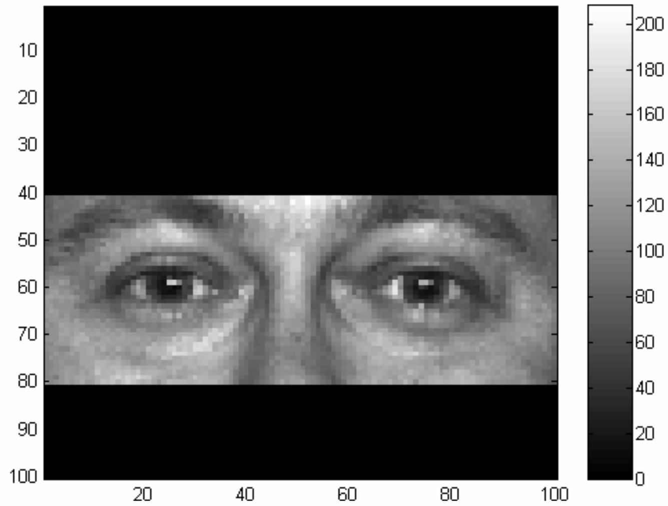
Using same Filter trained before,

Perform cross-correlation on cropped-face shown on left.

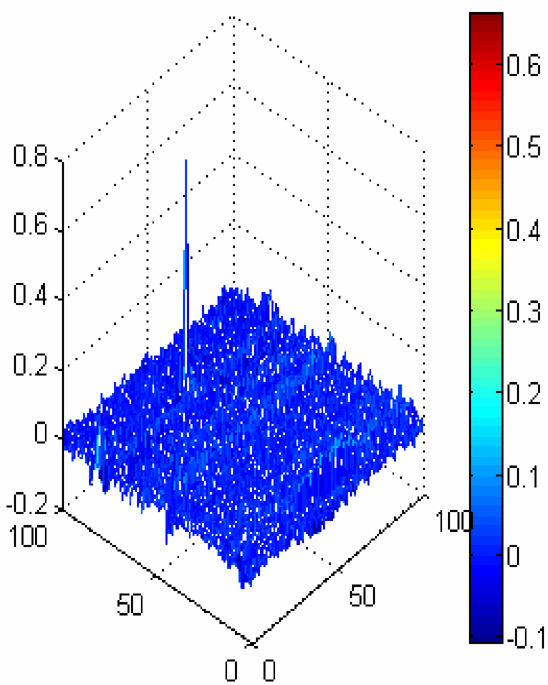


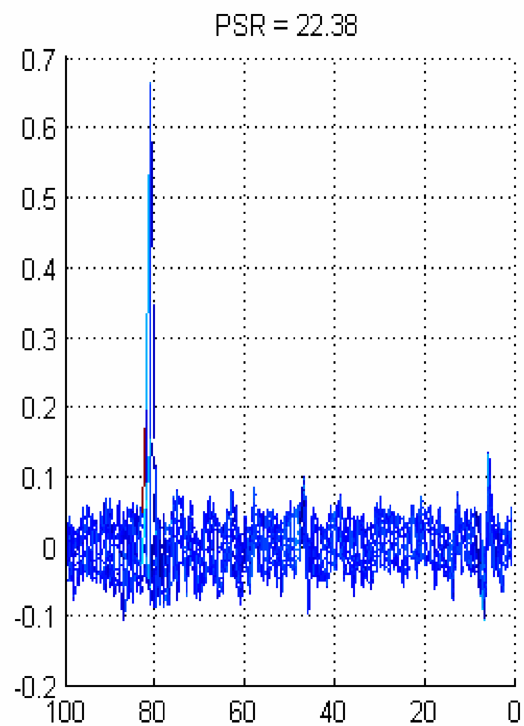


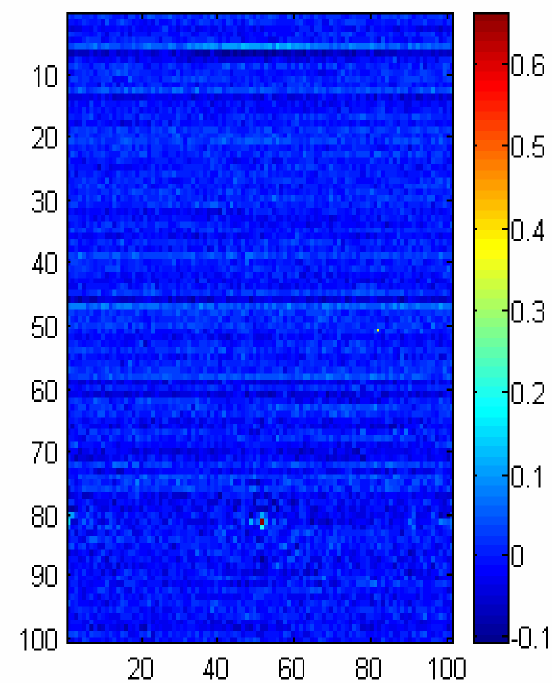




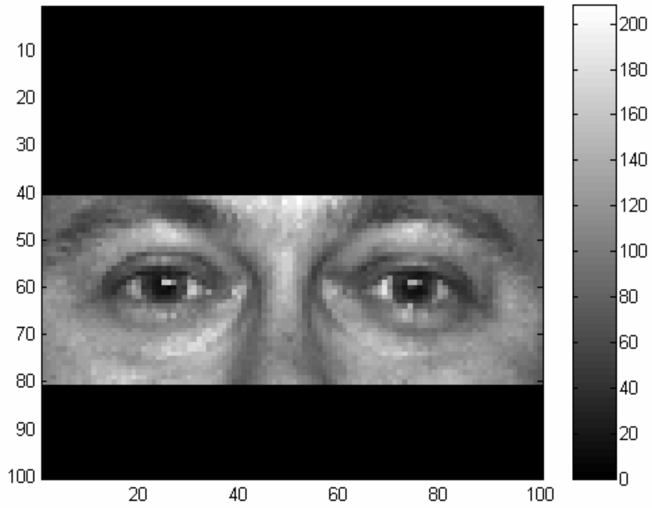
- **CORRELATION FILTERS ARE SHIFT-INVARIANT**
- **Correlation output is shifted down by the same amount of the shifted face image, PSR remains SAME!**





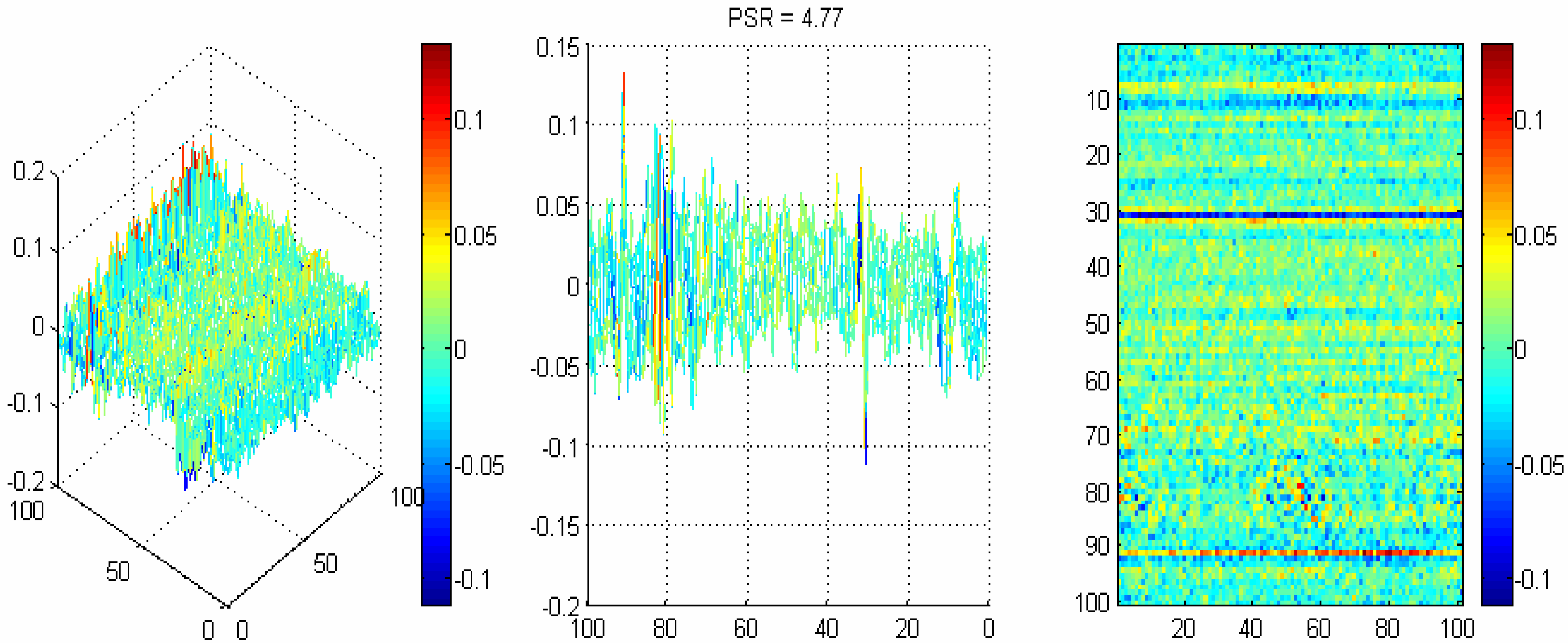


*M.Savvides and B.V.K. Vijaya Kumar, "Efficient Design of Advanced Correlation Filters for Robust Distortion-Tolerant Face Identification", IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS) 2003.



•**Using SOMEONE ELSE'S Filter,…. Perform cross-correlation on cropped-face shown on left.**

•**As expected very low PSR.**



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That's All Folks – Demo time

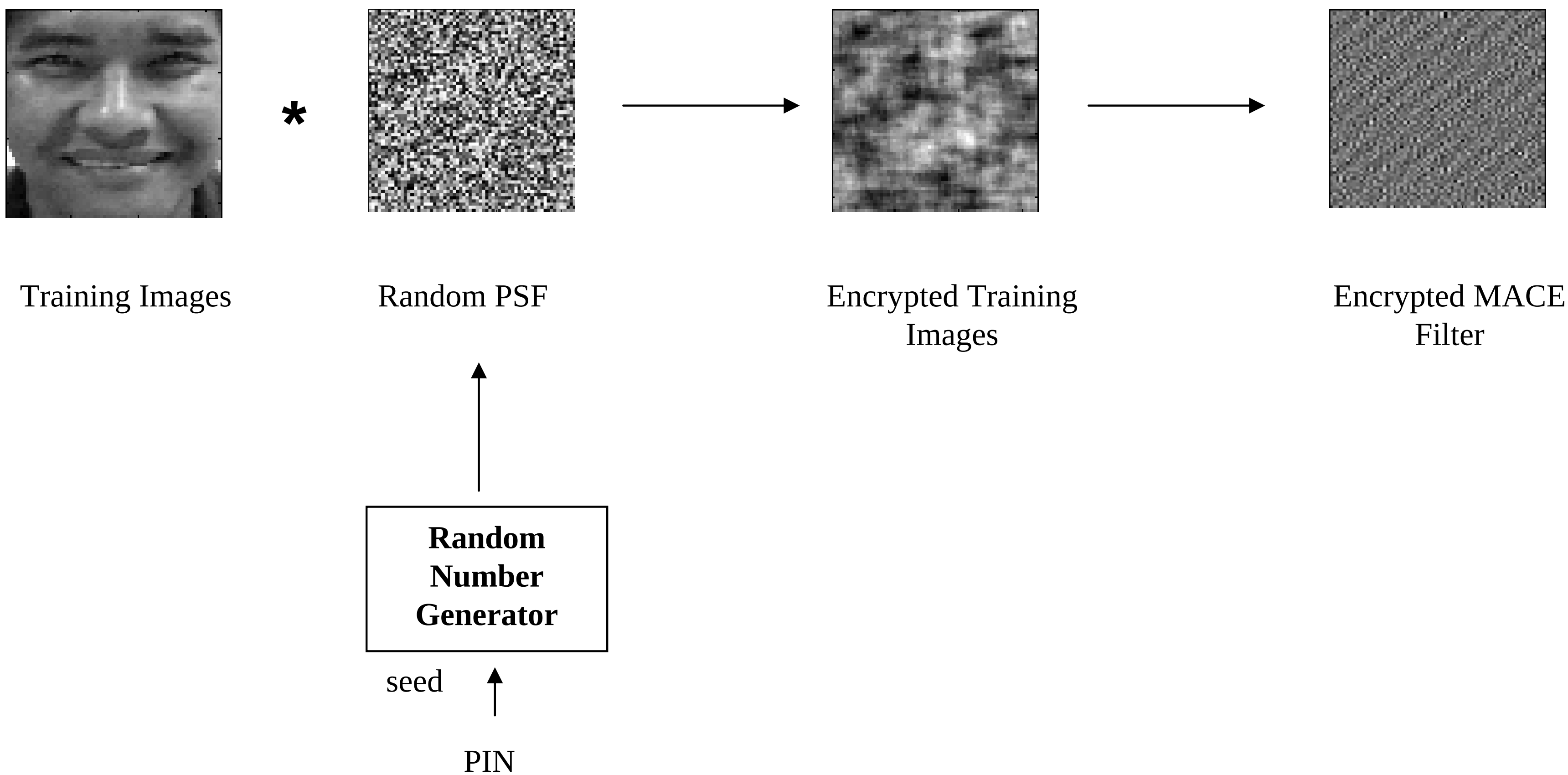
- Questions / Demo?

Cancellable Biometric Filters:-practical ways of deploying correlation filter biometrics

- A biometric filter (stored on a card) can be lost or stolen
  - Can we re-issue a different one (just as we re-issue a different credit card)?
  - There are only a limited set of biometric images per person (e.g., only one face)
  - We can use standard encryption methods to encrypt the biometrics and then decrypt them for use during the recognition stage, however there is a 'window' of opportunity where a hacker can obtain the decrypted biometric during the recognition stage.
  - We have figure out a way to encrypt them and 'work' or authenticate in the encrypted domain and NOT directly in the original biometric domain.

*M. Savvides, B.V.K. Vijaya Kumar and P.K. Khosla, "Authentication-Invariant Cancelable Biometric Filters for Illumination-Tolerant Face Verification", Defense & Security Symposium, special session on Biometric Technologies for Human Identification, 2004.

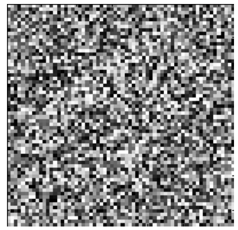
Enrollment Stage



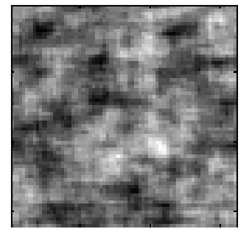
Authentication Stage

Test Image

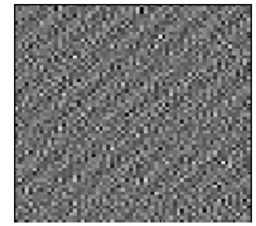
*



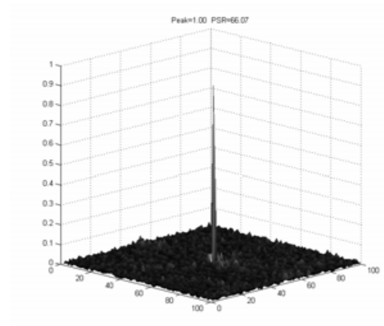
Random Convolution Kernel



Encrypted Test Image



Encrypted MACE Filter



PSR

Random Number Generator

seed

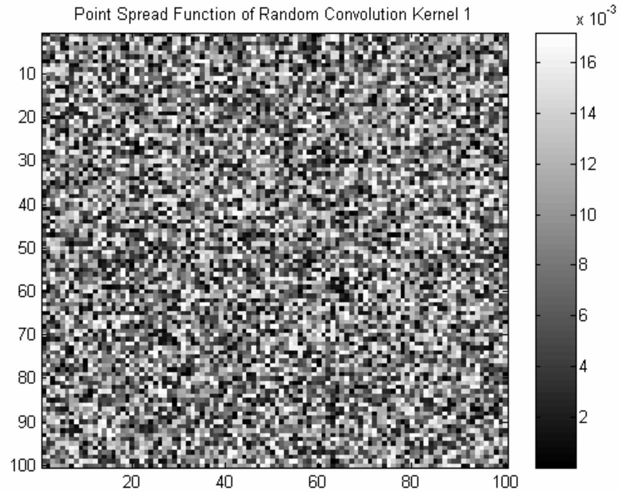
PIN
(can be obtained from another biometric e.g. fingerprint)

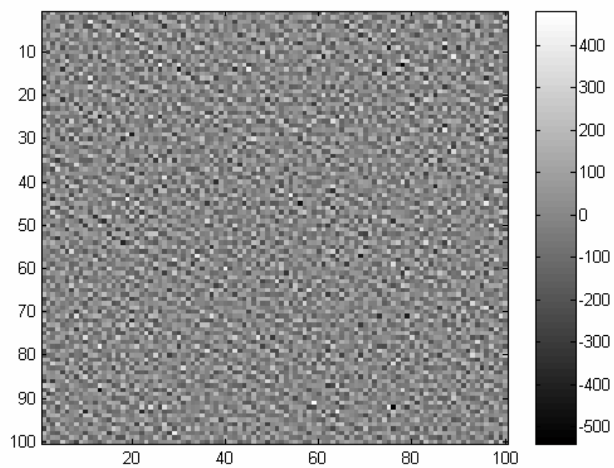
What about performance?

- We can show theoretically that performing this convolution pre-processing step does not affect resulting Peak-to-Sidelobe ratios.

- Thus, working in this encrypted domain does not change the verification performance

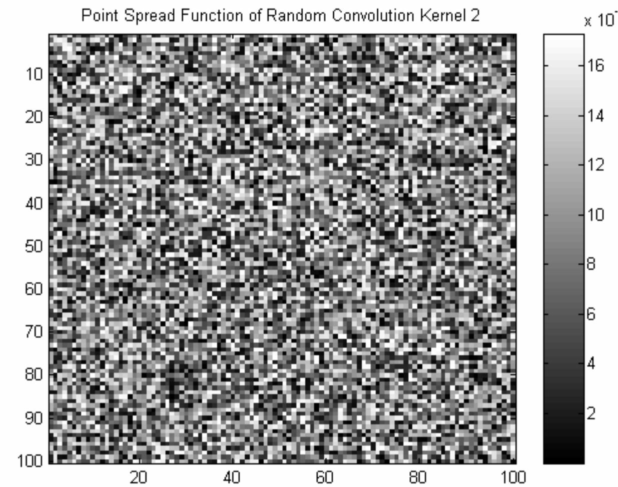
Random Convolution Kernel 1

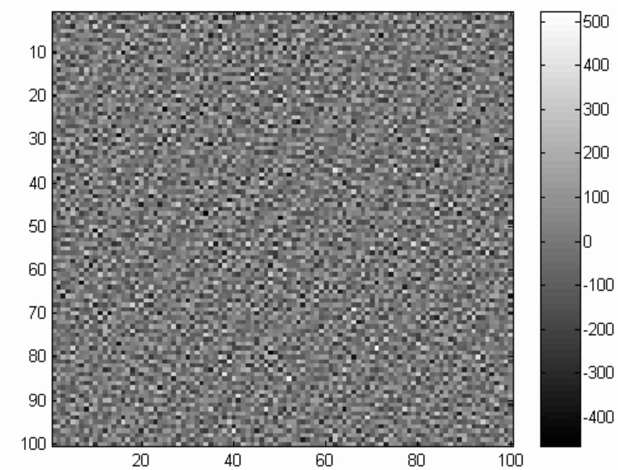




Encrypted MACE Filter 1

Random Convolution Kernel 2





Encrypted MACE Filter 2

Original Training Images

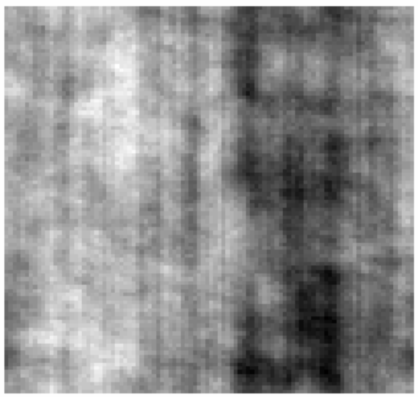
Original Training Image 1

Original Training Image 2

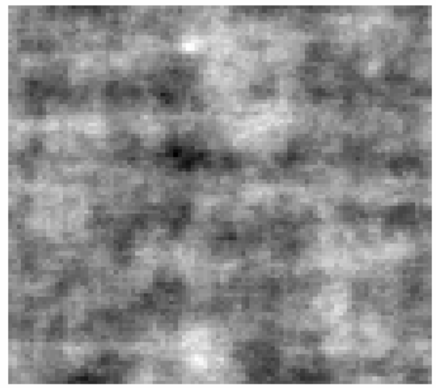
Original Training Image 3

Convolved with Random Convolution Kernel 1

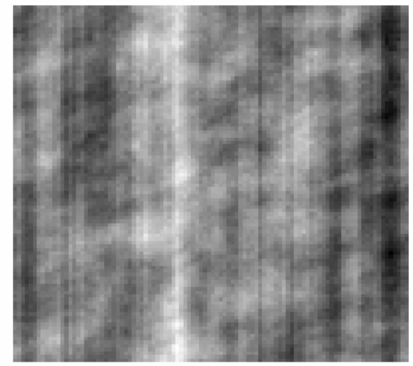
Point Spread Function 2, Training Image 1



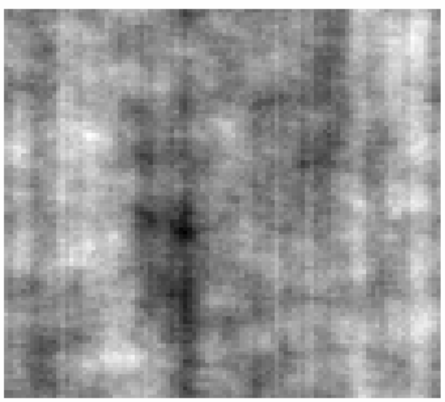
Point Spread Function 1, Training Image 2



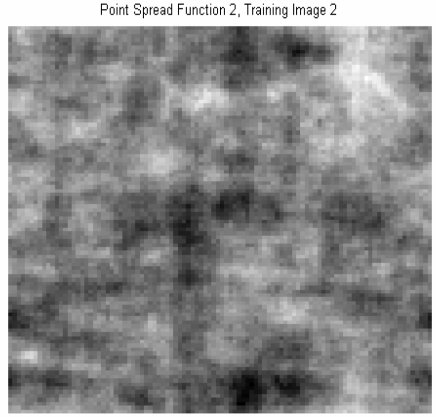
Point Spread Function 1, Training Image 3



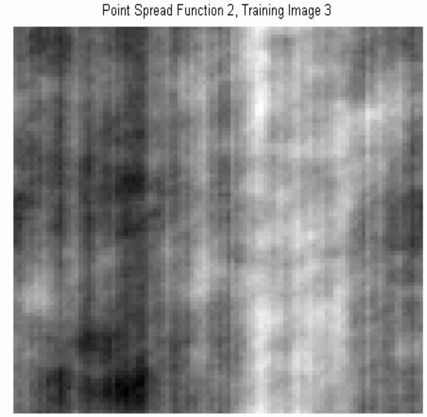
Convolved with Random Convolution Kernel 2

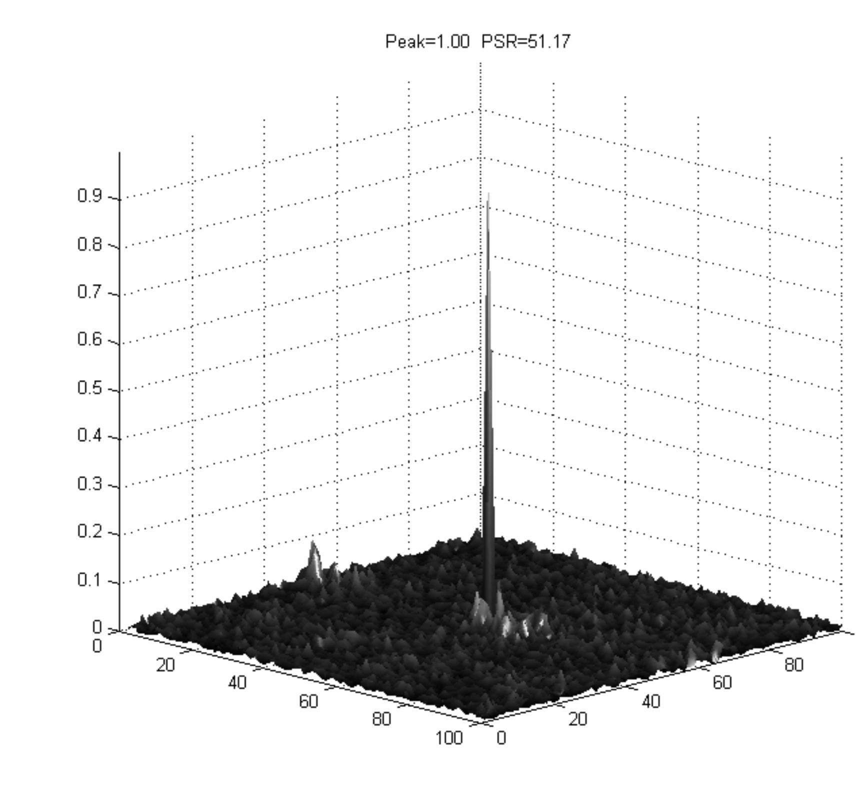


Point Spread Function 2, Training Image 2

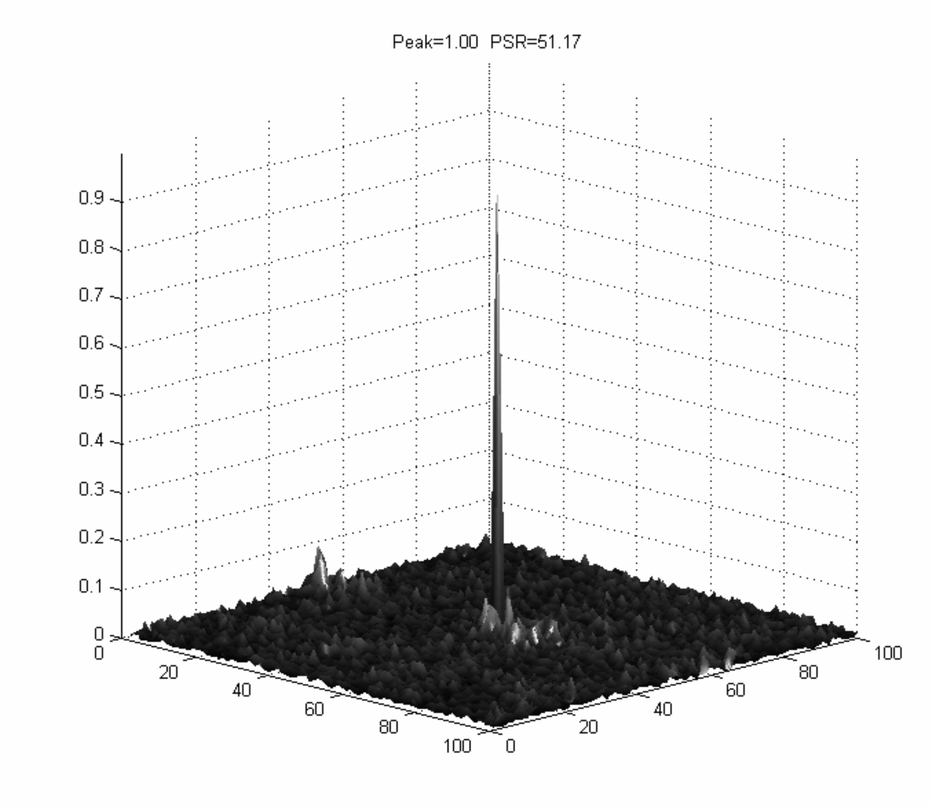


Point Spread Function 2, Training Image 3





Correlation Output from Encrypted MACE Filter 1



Correlation Output from Encrypted MACE Filter 2