

# Benchmarking Quality-dependent and Cost-sensitive Multimodal Biometric Fusion Algorithms



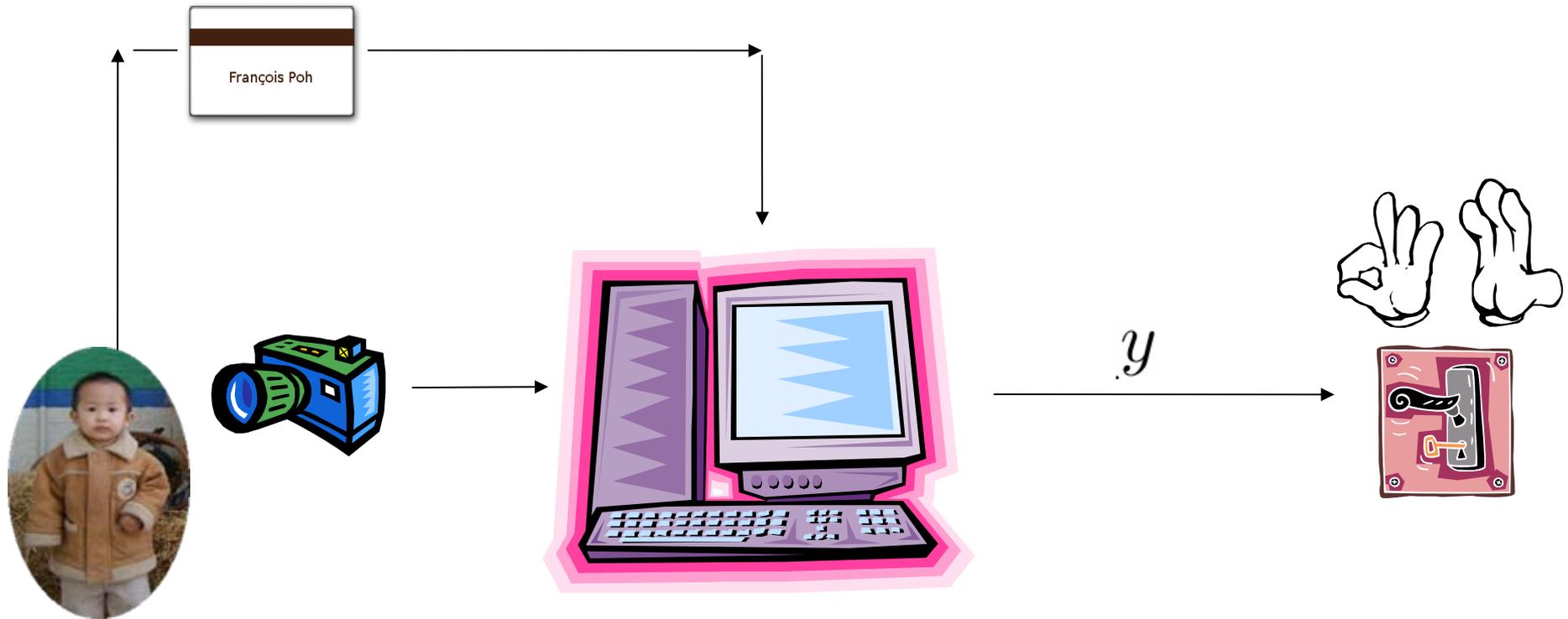
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CVSSP



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# Biometric Authentication: The Access Control Scenario



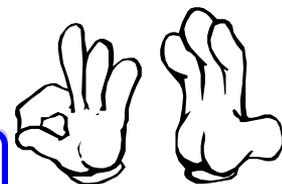
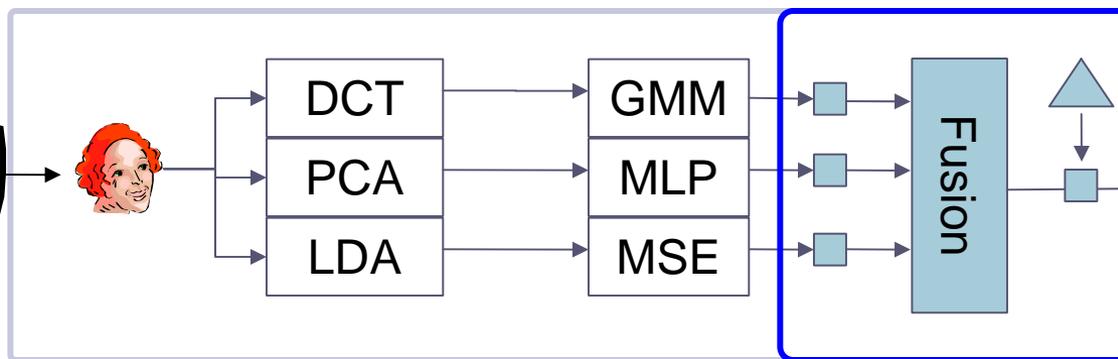
500 users

$$\text{decision}(\mathbf{x}) = \begin{cases} \text{accept} & \text{if } f(\mathbf{x}) > \Delta \\ \text{reject} & \text{otherwise} \end{cases}$$

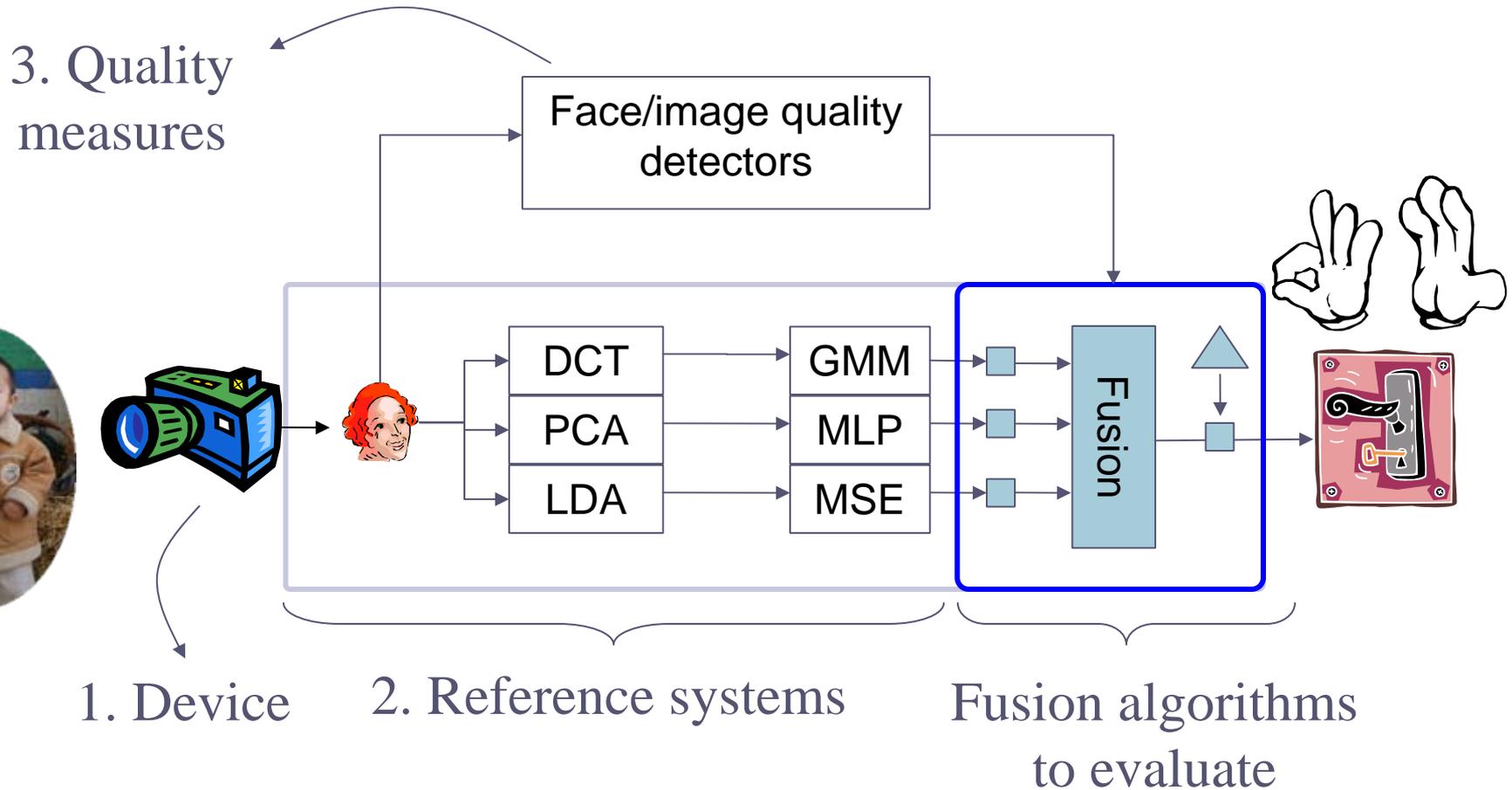
# Motivations

- ☞ How well can a multimodal biometric system cope with **missing information**?
- ☞ How well can *automatically derived* **quality measures** improve the fusion system performance?
- ☞ How well can a multimodal system perform given **restricted computation** and in the presence of hardware/software **failures**?
  - Failure to enrol and failure to match
- ☞ What if the device used during authentication is different from that used during enrollment? [**device mismatch**]
- ☞ Principally interested in performance improvement due to the use of quality measures in fusion
  - w.r.t the baseline system
  - w.r.t. a fusion system without given any quality measure
- ☞ Not particularly concerned with state-of-the-art performance
  - Simulate failures by masking the data!

# Conventional Fusion Algorithms



# Quality-dependent Fusion Algorithms



# Score/Quality Measures Generation Principles

- ☛ Use **baseline** systems
  - standard algorithms
  - LDA for face, NIST's fingerprint matcher, Daugman's algo. for iris
- ☛ **Fully automatic** segmentation and matching
  - If a system cannot process a query, e.g., due to failure to segment or failure to match, output a dummy match score '-999'
- ☛ Automatically computed quality measures
  - If a quality detector fails, output a dummy '-999' instead
- ☛ Consequence: Algorithms have to deal with missing observations/values

# Capturing Devices

CAPTURING DEVICE	MODALITY	SAMPLE IMAGES
<b>WACOM INTUOS 3 A6 Tablet + Inking Pen</b> 	<b>SIGNATURE</b>	
<b>Phillips SPC 900NC web camera +</b> 	<b>AUDIO+VIDEO</b>	 
<b>Thermal sensor (acquired by sweeping)</b> 	<b>FINGERPRINT</b>	
<b>Optical sensor</b> 	<b>FINGERPRINT</b>	
<b>LG3000 iris capturing system</b> 	<b>IRIS</b>	
<b>CANON EOS 30D Digital Camera</b> 	<b>FACE + HAND</b> <i>HIGH QUALITY</i>	 

Legend:



Used in the evaluation

Biosecure project

# Face Quality Measures

## Face

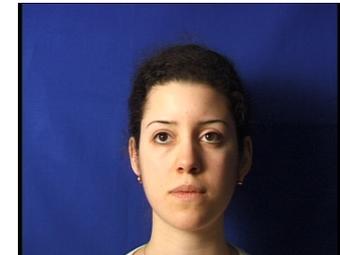
- Frontal quality
- Illumination
- Rotation
- Reflection
- Spatial resolution (between eyes)
- Color bit per pixel
- Focus
- Brightness
- Background informity
- Glasses

Well  
illuminated



Glass=89%  
Illum.=100%

Side  
illuminated



Glass=15%  
Illum=56%

Quality measures for iris

Quality measures for fingerprint

# Low vs High Quality Face Images



webcam



Digital camera

Note: quality (e.g., image resolution), depends on the device and its operational settings (e.g., white balance adjustment).

Intra-site diversity

Cross-site diversity

# Examples of Segmented Face Images



Face detection may fail, but the matching will proceed anyway!

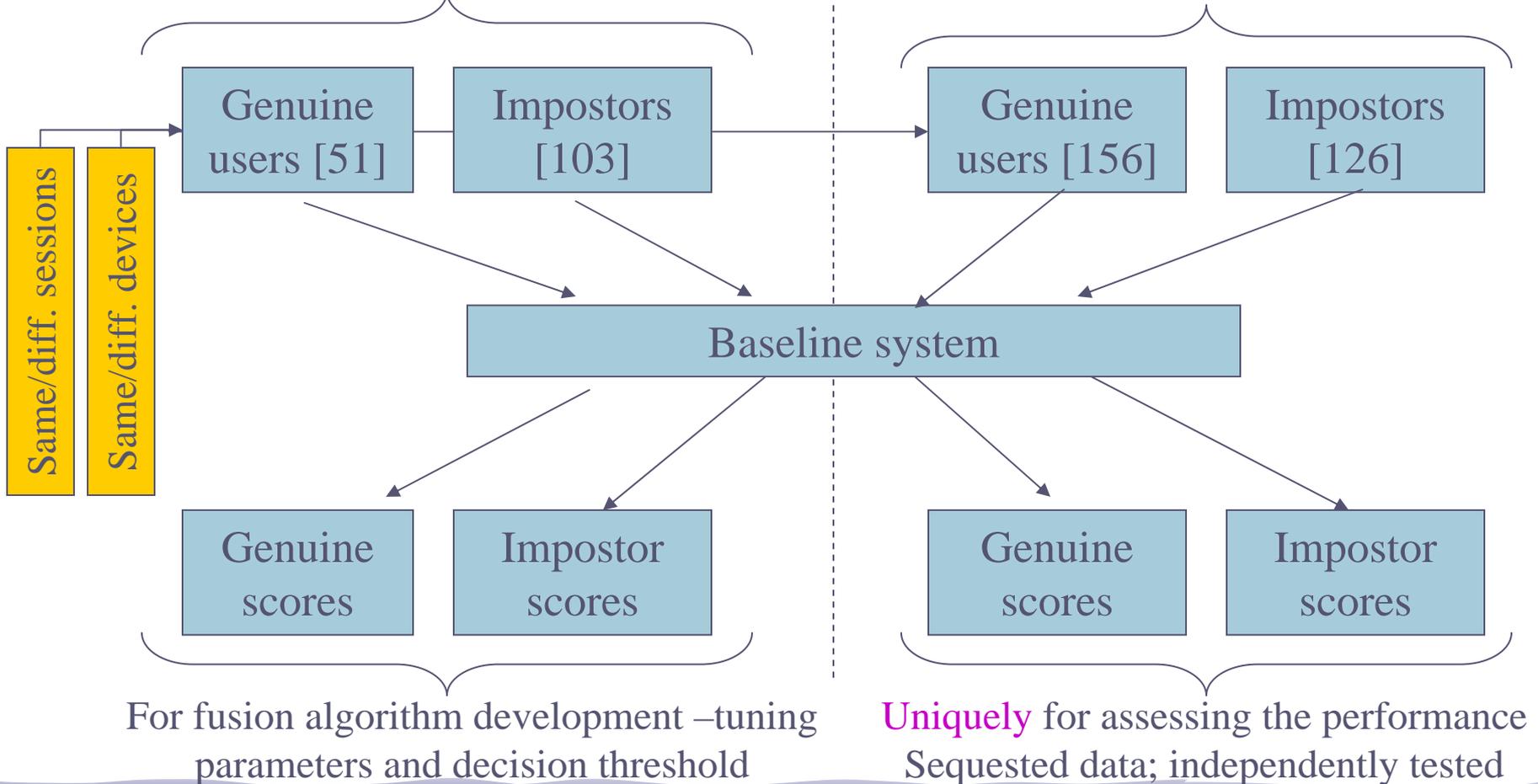
Examples of bad iris segmentation

# Experimental Protocol

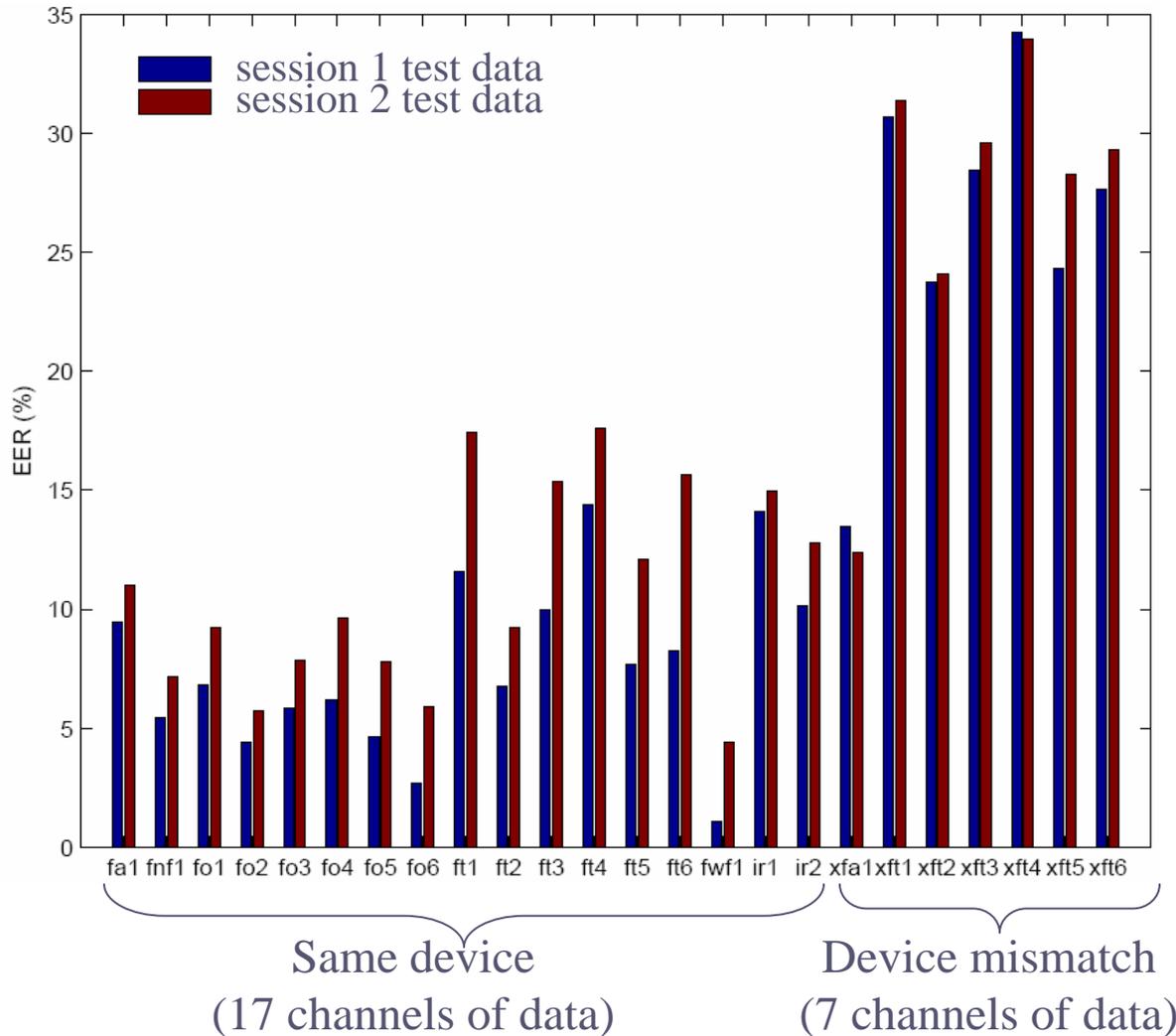
Two non-overlapping partition of users

Development set

Evaluation set (sequested)



# Preliminary Performance Analysis



Fa: face (webcam)

Fnf: face (digital; no flash)

Fwf: face (digital; with flash)

Fo: fingerprint (optical)

Ft: fingerprint (thermal)

xFa: mismatch (query is Fa;  
template is Fnf)

xFt: mismatch (query is Ft;  
template is Fo)

☛ Intra session performance is consistently optimistically biased compared to the inter-session one

☛ Device mismatch can degrade the performance

# Evaluation Results

7 teams, 22 fusion algorithms, 2 evaluation protocols, 6 months

Examples of algorithms submitted:

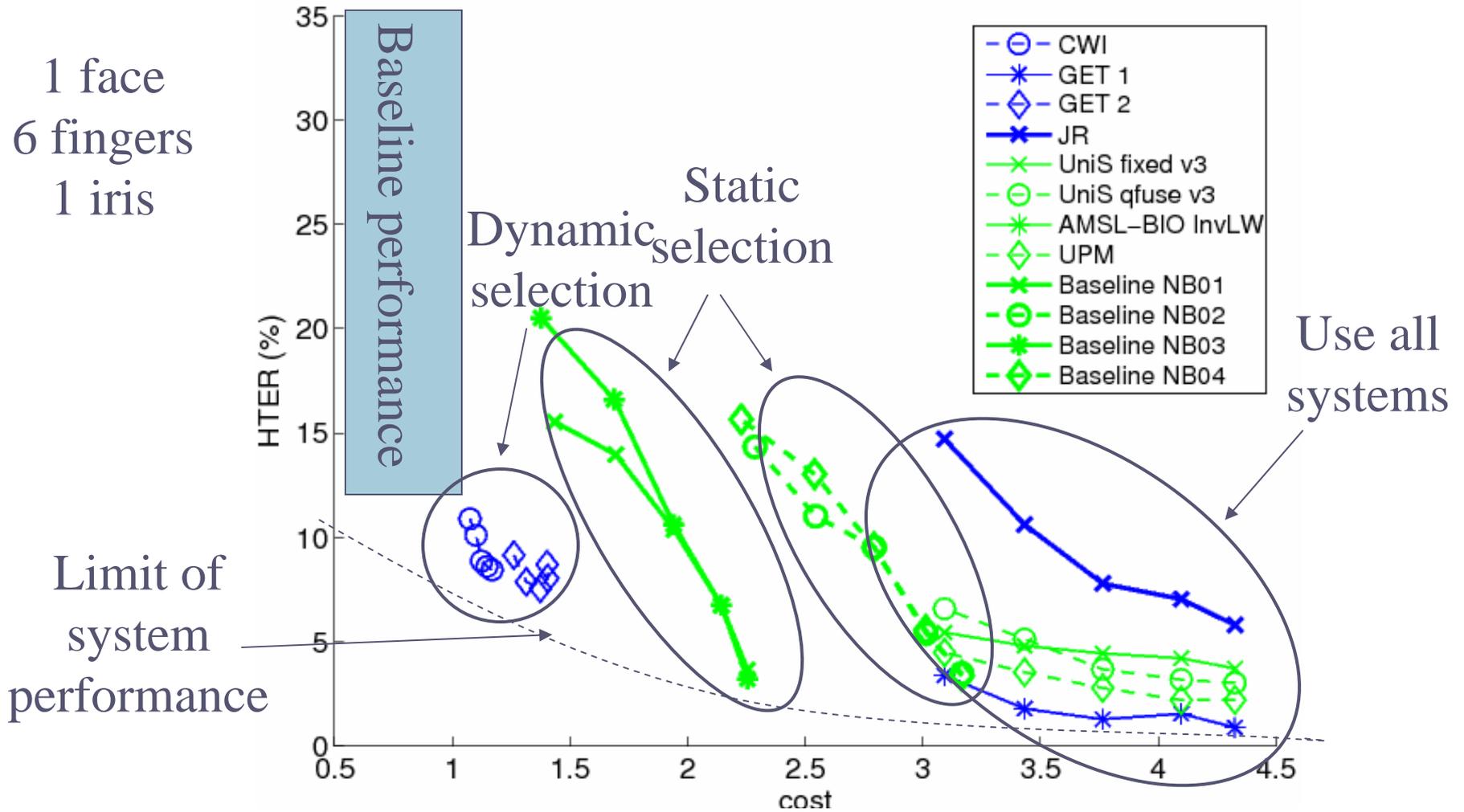
Naive bayes, Bayes classifier with GMM density estimator and mixture of factor analyzers, logistic regression, fixed rule, device-specific fusion, linear classifier (with error-dependent weights), SVM, bayesian network, Dempster fusion rule

Short name

- ☞ Tobias Scheidat (**AMSL-BIO**, U. of Magdeburg)
- ☞ Lorene Allano, Institut National des Télécommunications (**GET-INT**), France.
- ☞ Fernando Alonso, Universidad Autonoma de Madrid, (**UPM**), Spain
- ☞ O Fatukasi and N. Poh, U. of Surrey (**UniS**), UK.
- ☞ Harald Ganster, Joanneum Research (**JR**), Austria
- ☞ Albert Salah and Onkar Ambekar, Centrum voor Wiskunde en Informatica (**CWI**), the Netherlands
- ☞ John Baker, Johns Hopkins University Applied Physics Laboratory (**JHUAPL**), USA

# Cost-sensitive evaluation

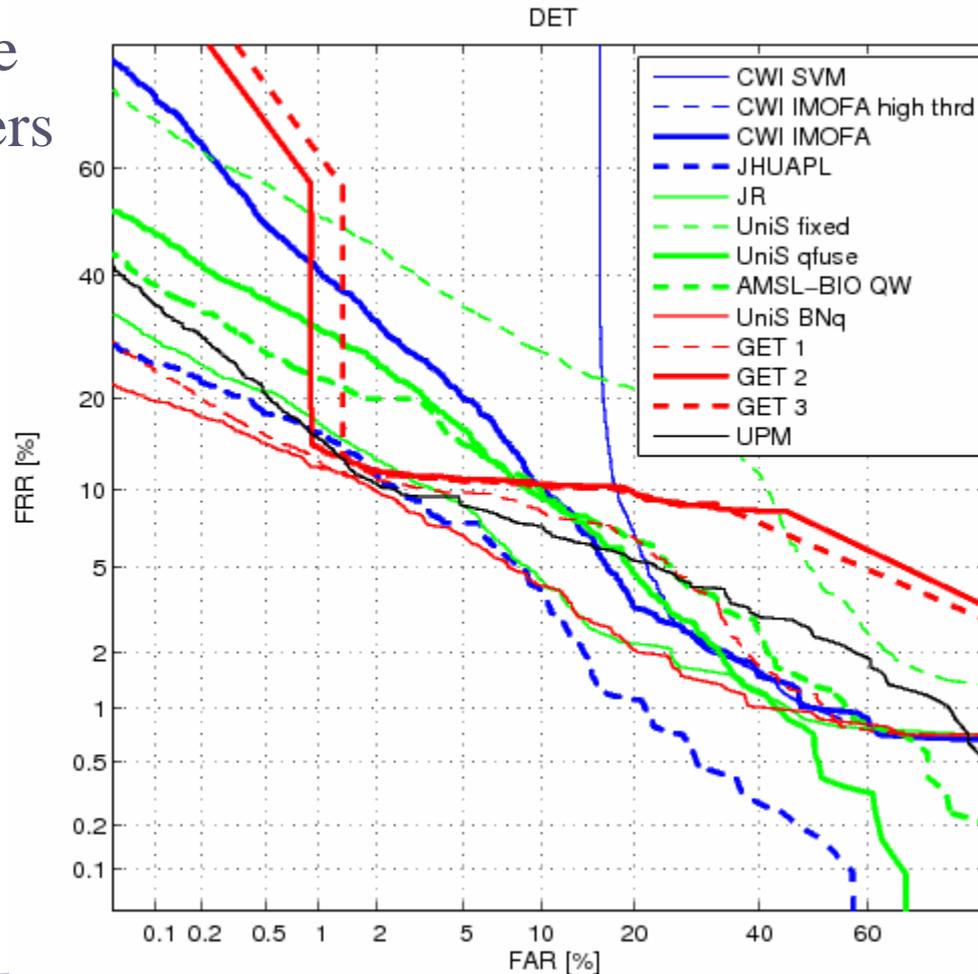
1 face  
6 fingers  
1 iris



More systems → more costly but also higher robustness to hardware/software failure

# Quality-based Evaluation

1 face  
3 fingers



Template: good quality  
Query data: same or  
different device

All systems degrade  
with missing data (not  
shown here)

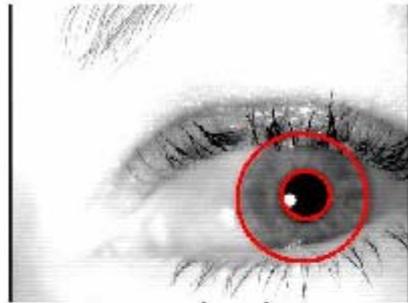
Top 3 systems make  
use of quality  
information – first  
identify device, then  
pick the right fusion



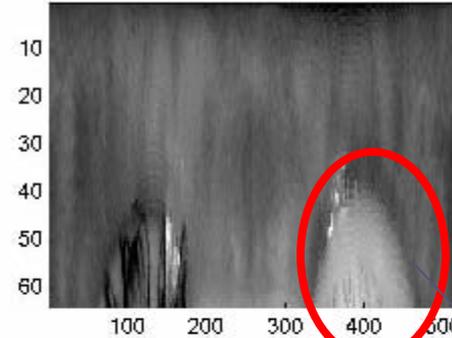
Q&A

Thank you!

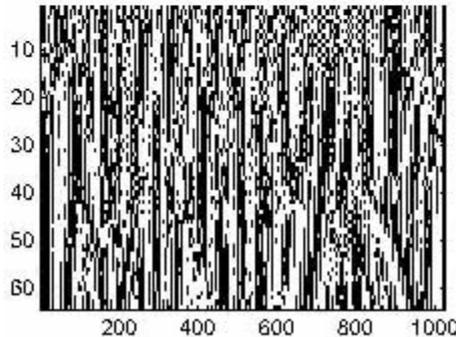
# Minimally Optimized Eye-lid and Eyelashes Segmentation



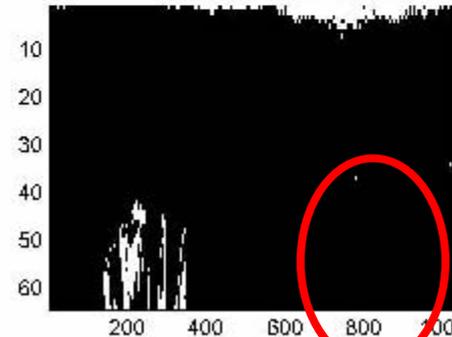
Segmented iris



Wrapped iris image



Iris code



Iris mask

Eye-lid  
included in  
matching

Ideally, two thresholds are needed for the mask:  
to remove eye-lids and eyelashes

The threshold for eyelashes are not optimal too (not shown here)

# Intra-site Diversity



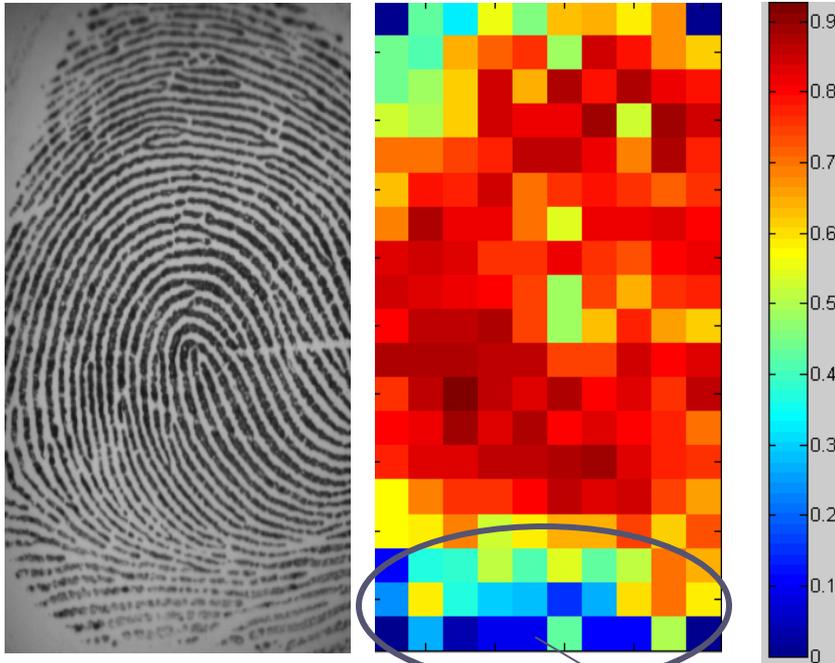
Each row represents data collected at a site

# Cross -site Diversity



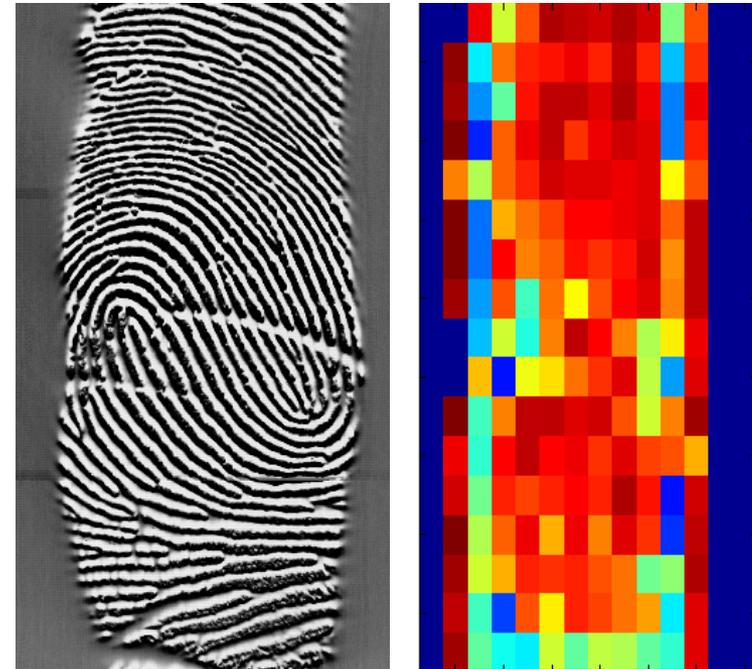
# Fingerprint Quality Measure

Optical sensor (impression)



Low quality region (low contrast)

Thermal sensor (sliding)



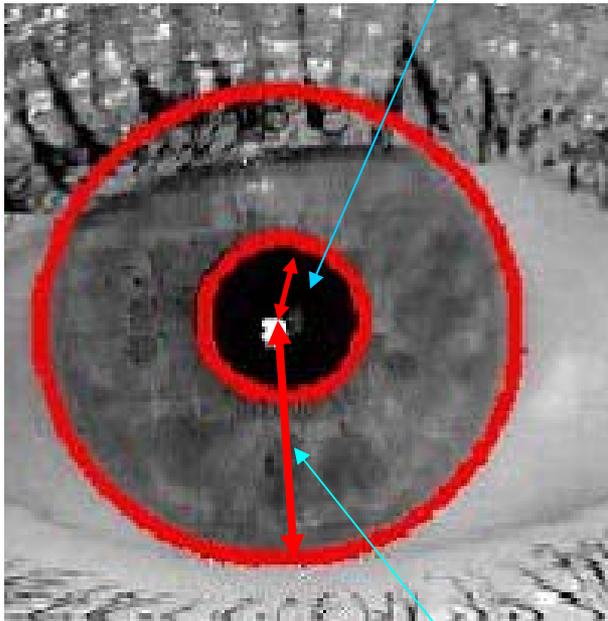
image

Quality map

The global quality is the average of local quality measures

# Iris Quality Measures

Pupil diameter,  $d_P$



$Q_1 =$  Average texture gradient  
(similar to fingerprint quality  
map)

$$Q_2 = d_I - d_P$$

$Q_3 =$  Proportion of  
masked use for  
matching

Iris diameter,  $d_I$

# Badly Segmented Iris Images



Good  
segmentation

Bad segmentation

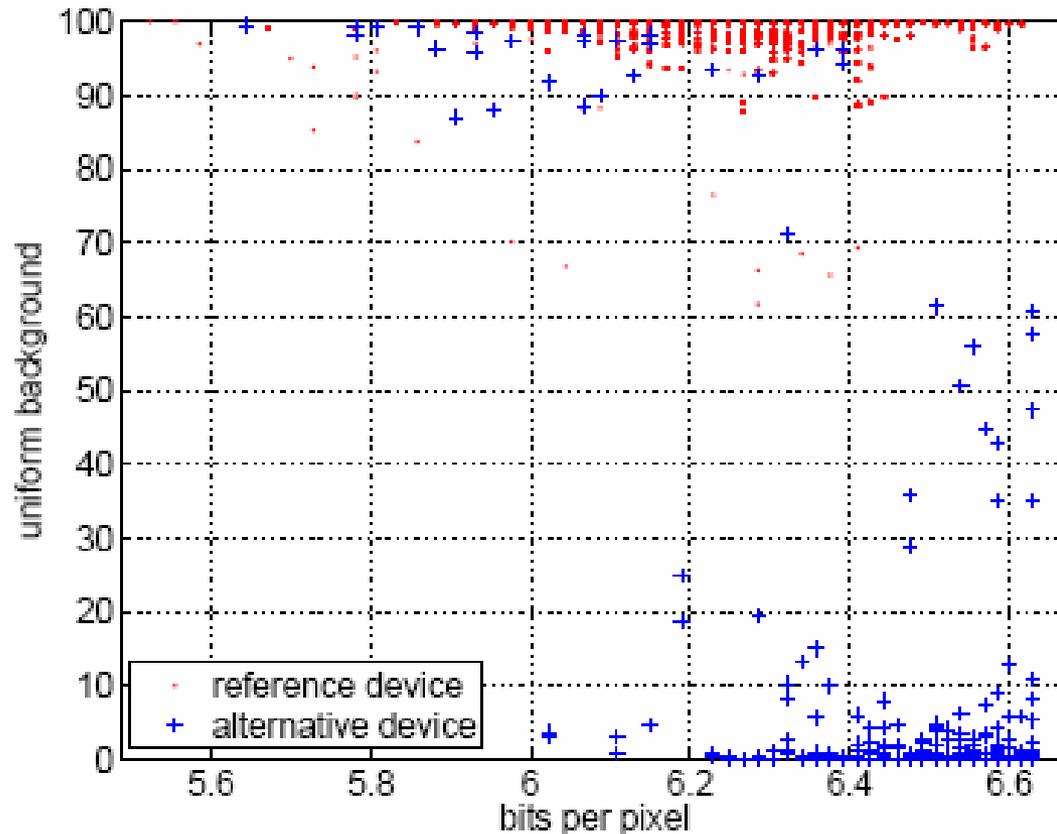
# Devices and Modalities

Label	template ID {n}	Modality	Sensor	Remarks
fa	1	Still Face	web cam	Frontal face images (low resolution)
fnf	1	Still Face	CANON	Frontal face images without flash (high resolution)
fwf	1	Still Face	CANON	Frontal face images with flash (high resolution)
ir	1-2	Iris image	LG	1 is left eye; 2 is right eye
fo	1-6	Fingerprint	Optical	1/4 is right/left thumb; 2/5 is right/left index; 3/6 is right/left middle finger
ft	1-6	Fingerprint	Thermal	1/4 is right/left thumb; 2/5 is right/left index; 3/6 is right/left middle finger

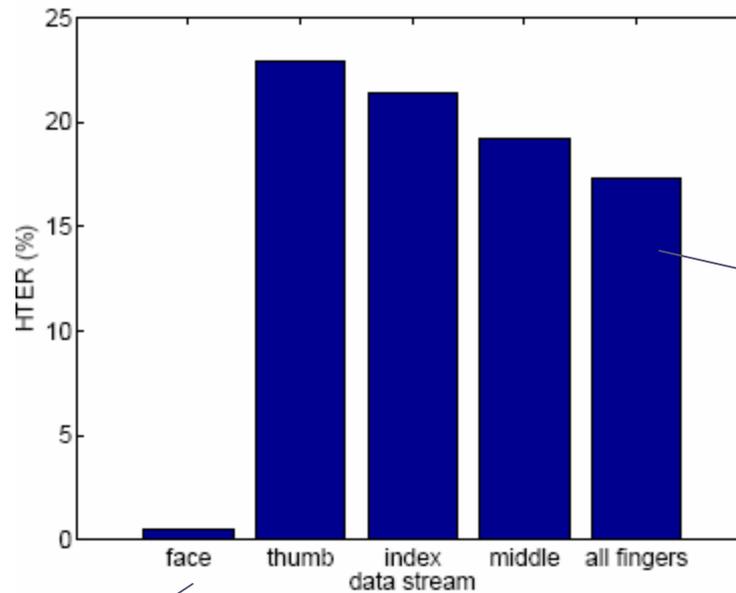
# Reference Systems and Quality Measures

Modality	Reference systems	Quality measures
Still Face	Omniperception's Affinity SDK face detector; LDA-based face verifier	face detection reliability, brightness, contrast, focus, bits per pixel, spatial resolution (between eyes), illumination, degree of uniform background, background brightness, reflection, glasses, rotation in plane, rotation in depth and degree of frontal face (from Omniperception's Affinity SDK)
Fingerprint	NIST Fingerprint system	texture richness [5] (based on local gradient)
Iris	A variant of Libor Masek's iris system	texture richness [6], difference between iris and pupil diameters and proportion of iris used for matching

# Example of Quality Measures to Distinguish Two Devices



# Ability of Quality Measures to Distinguish Devices (fingerprint)



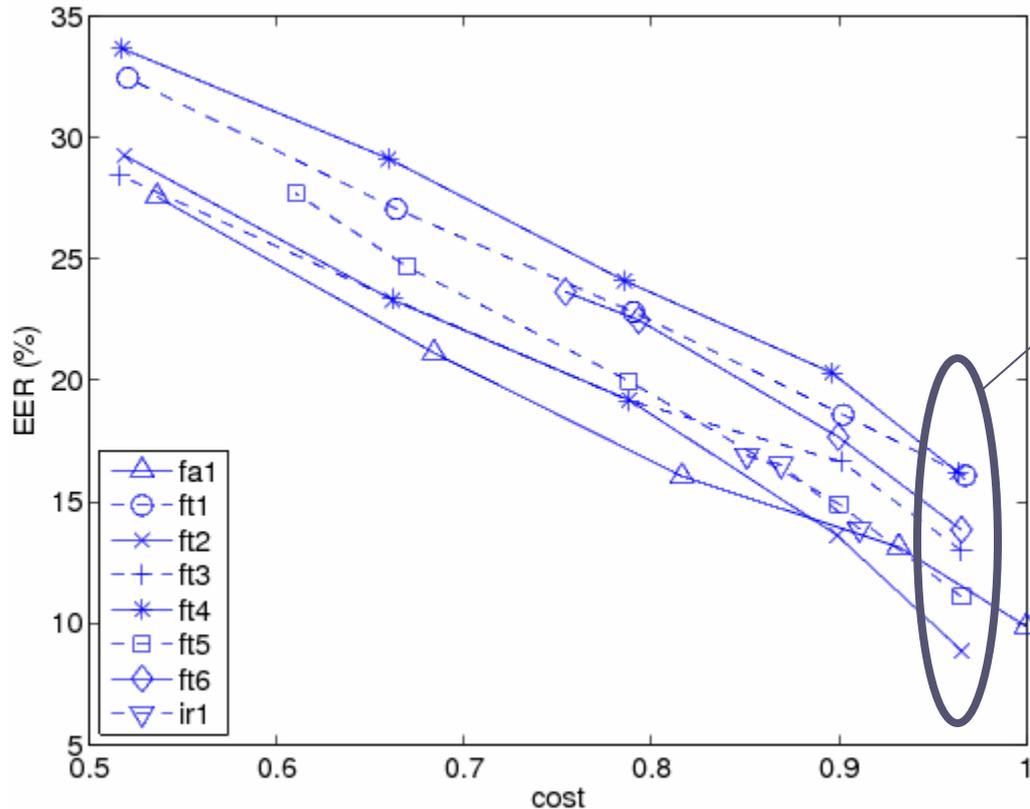
Decide the device after observing three fingerprints

Face quality measures used are 5,6,8

# Some Observations

- ☛ Quality measures can be used to estimate the identity of the device
- ☛ Quality measures are device-dependent

# Baseline Performance



The fingerprint data always contains missing data due to failure to process or to match queries

Note: If all the data in a channel is used, the average cost per access is simply 1.