GREYC
E-payment & Biometrics

Influence de la qualité des données biométriques

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Plan

1. Introduction
2. Framework de validation des métriques
3. Evaluation de la qualité des empreintes digitales
4. Conclusion

Introduction

Introduction

Quality of biometric data vs performance

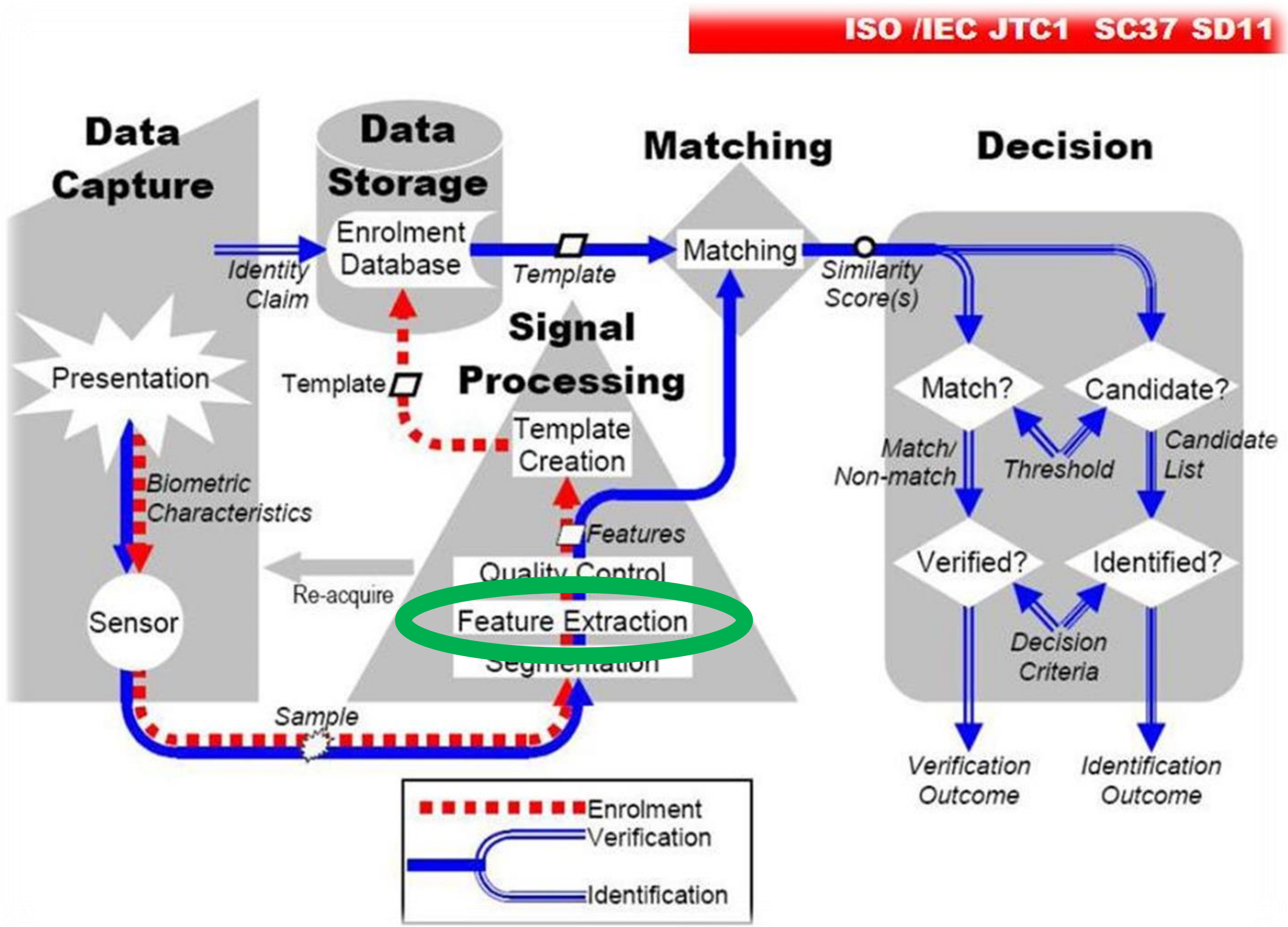
- Variability of the acquisition context

- Variability of the quality of biometric data

178 associations

31 associations

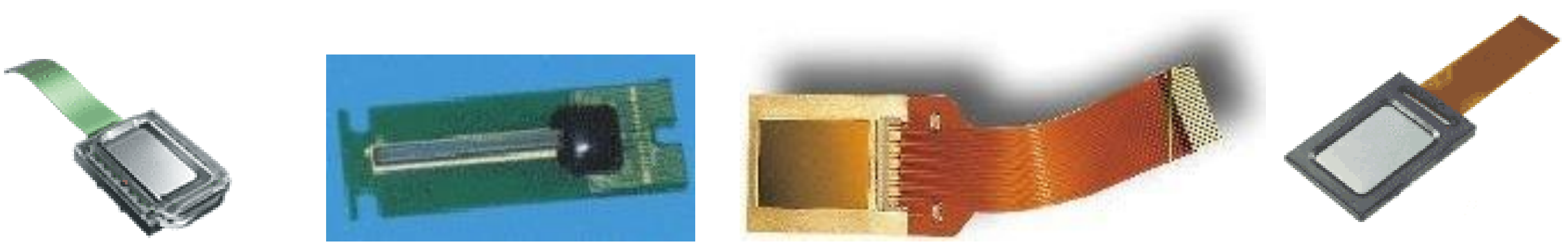
Introduction



Introduction

Benefits of evaluating the quality of biometric data

- Improving performance with a better enrollment
- New capture during verification if quality is insufficient
- Quality can be used as a soft biometric information
- Comparison of biometric sensors

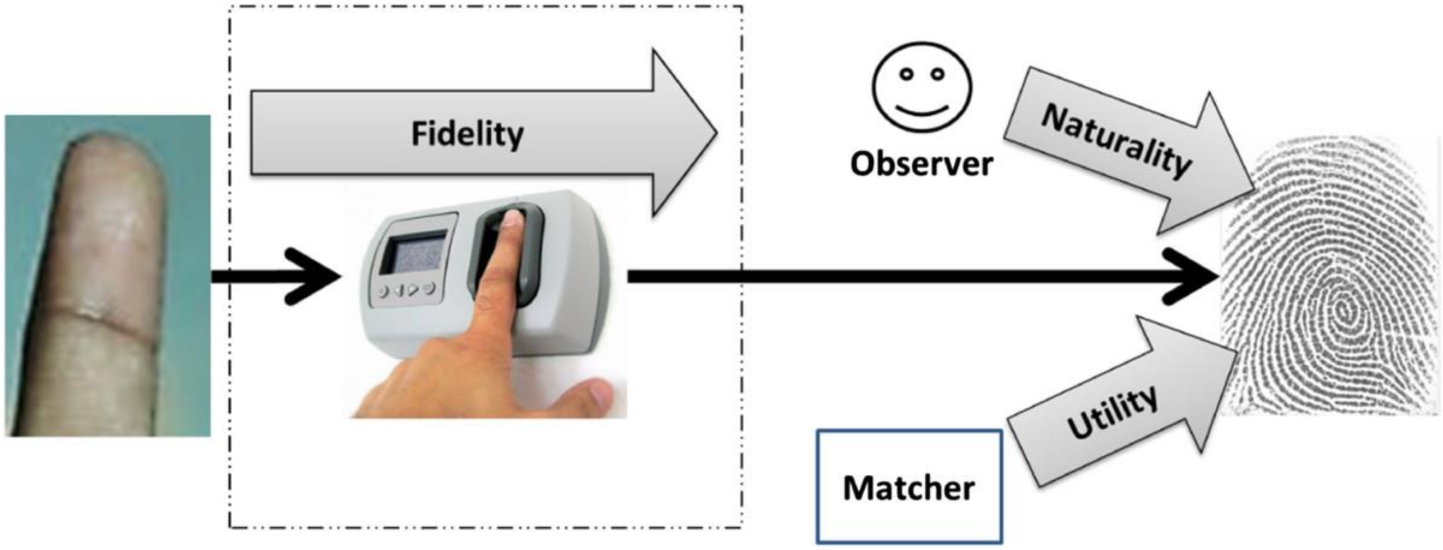


Different types of fingerprint sensors

Introduction

Aspects of quality assessment

- **Naturalness**: Does it look like a fingerprint?
- **Fidelity**: How the sample represents the acquired fingerprint?
- **Utility**: Which performance can I expect with this sample?



Samarth Bharadwaj, Mayank Vatsa, Richa Singh, "Biometric quality: a review of fingerprint, iris, and face", EURASIP Journal on Image and Video Processing:34, 2014

Introduction

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Quality assessment of biometric data

Table 1

Different interpretations of quality in biometrics from literature

Reference	Modality	Interpretation of quality in biometrics
Chen et al.[3]	Fingerprint	A global measure of the strength of ridges
Grother and Tabassi[4]	Fingerprint	Suitability for automatic matching
Youmaran and Adler[5]	Face	The decrease in uncertainty of identity due to a given sample
Kryszczuk et al.[6]	Face	Conditionally relevant class predictors
Beveridge et al.[7]	Face	A measurable and actionable predictor of performance
ISO/IEC standards[13]	Face	Biometric data that adheres to best capture practices
Kalka et al.[8]	Iris	The measurement of various degradations known to affect iris recognition
Kumar and Zhang[9]	Knuckles	Confidence of generating reliable matching scores from the user templates
Poh and Kittler[10]	General framework	Degree of *extractability* of recognition features
BioAPI[14]	General framework	Biometric data that provides good performance for the intended purpose

Samarth Bharadwaj, Mayank Vatsa and Richa Singh, "Biometric quality: a review of fingerprint, iris, and face", EURASIP Journal on Image and Video Processing:34, DOI: 10.1186/1687-5281-2014-34, Springer, 2014.

Introduction

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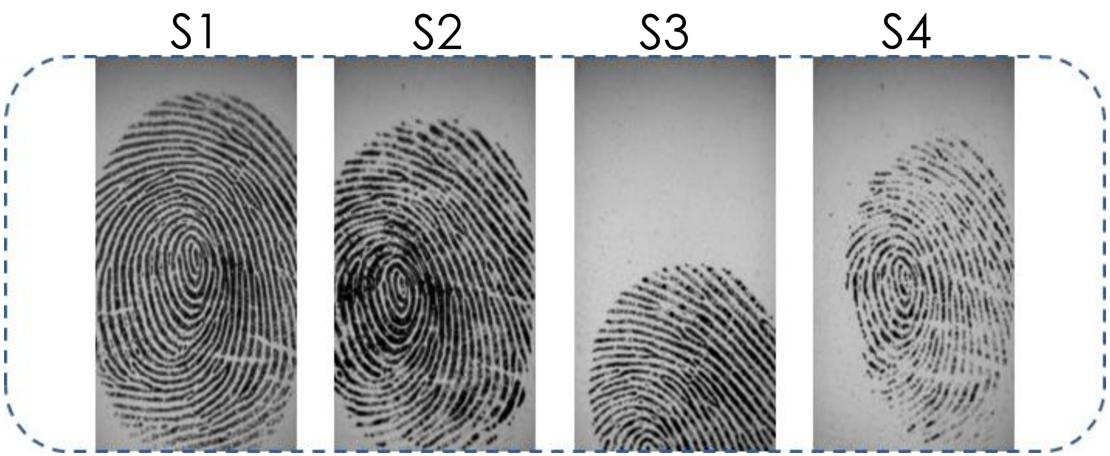
Which metric is more reliable?



Sample	S1	S2	S3	S4
Metric 1	66	63	41	40
Metric 2	1	2	2	2

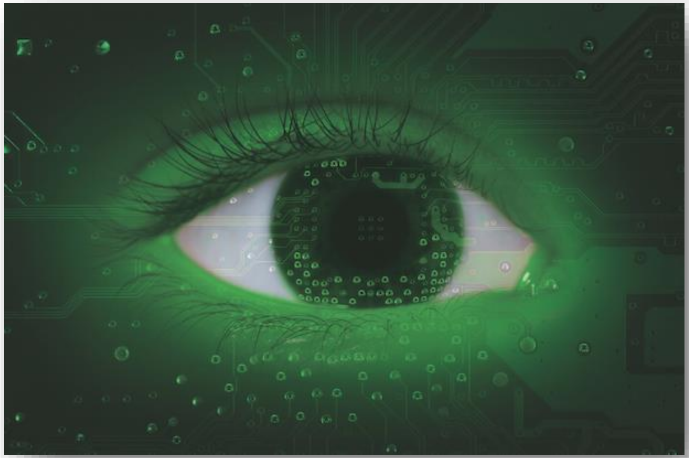
Validation of a quality metric is required.

Framework de validation des métriques

Validation

What to achieve for a validation framework ?

- **Generality:** can be used for any biometric modality;
- **Biometric test:** overall error rate to be considered;
- **Reliability:** computation of statistical measures;
- **Usability**: should be objective, reliable and reproducible.



Validation

Related works

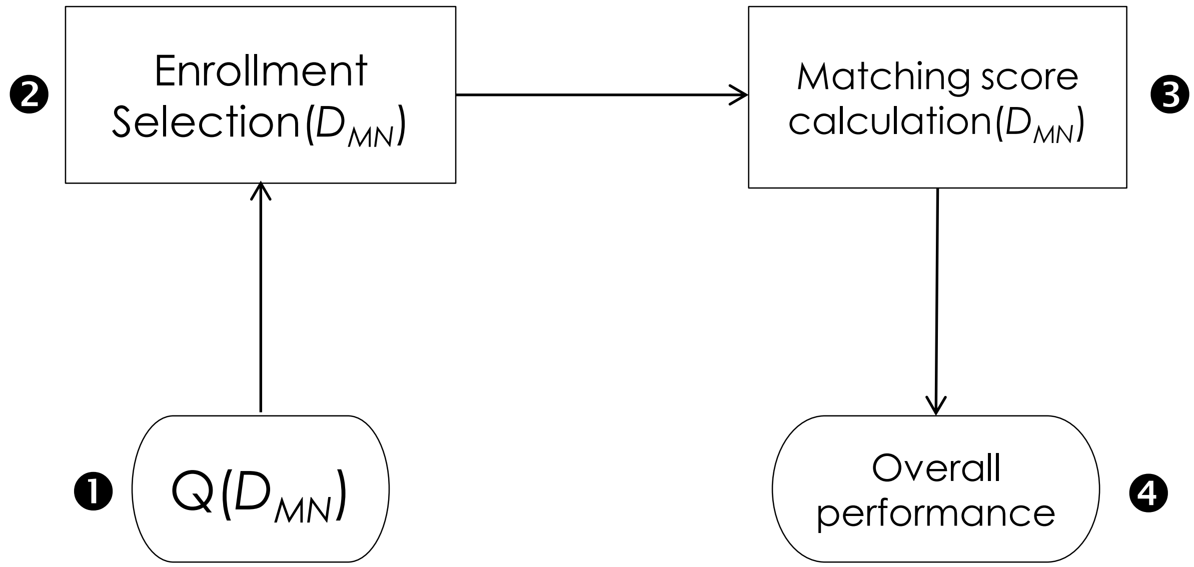
- **Fitting of a reference or subjective results (Bolle 1999)**
  Problem: Not completely reliable, objective and not repeatable.

- **Genuine matching error (Grother 2007)**
  Shortage: only genuine matching is considered.

- **Overall error rate based on sorting samples (Chen 2005)**
  Shortage: it is complex to deal with the matching scores of samples.

Validation

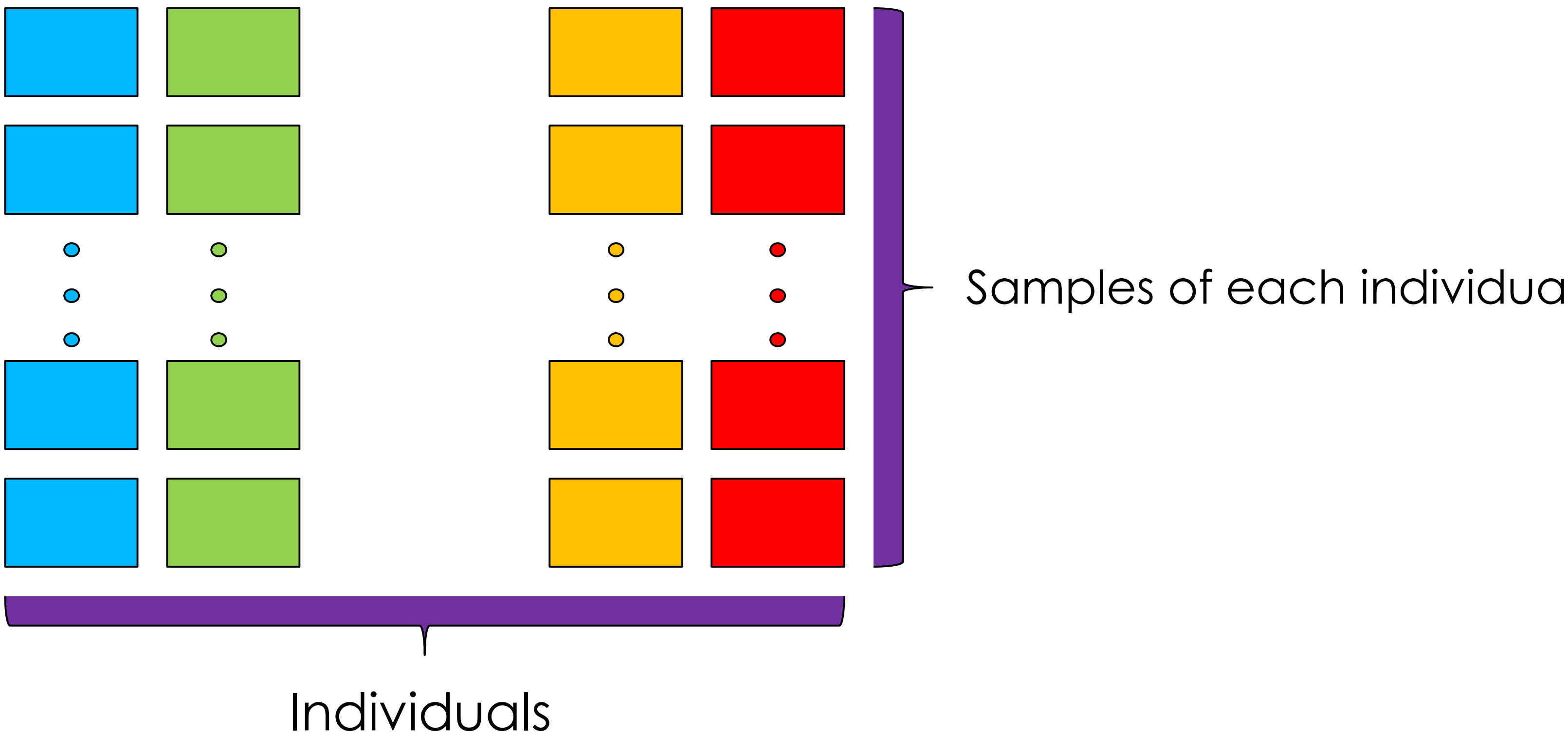
Enrollment Selection:
How a quality metric can help to choose the best sample as reference?



The overall performance can be: global Equal Error Rate (EER), Area Under Curve (AUC), *etc*.

Validation

Impact of quality during enrollment (1/3)



Z. Yao, C. Charrier, C. Rosenberger, "Utility validation of a new fingerprint quality metric". In International Biometric Performance Testing Conference (IBPC), Gaithersburg, USA, Apr. 2014.

Validation

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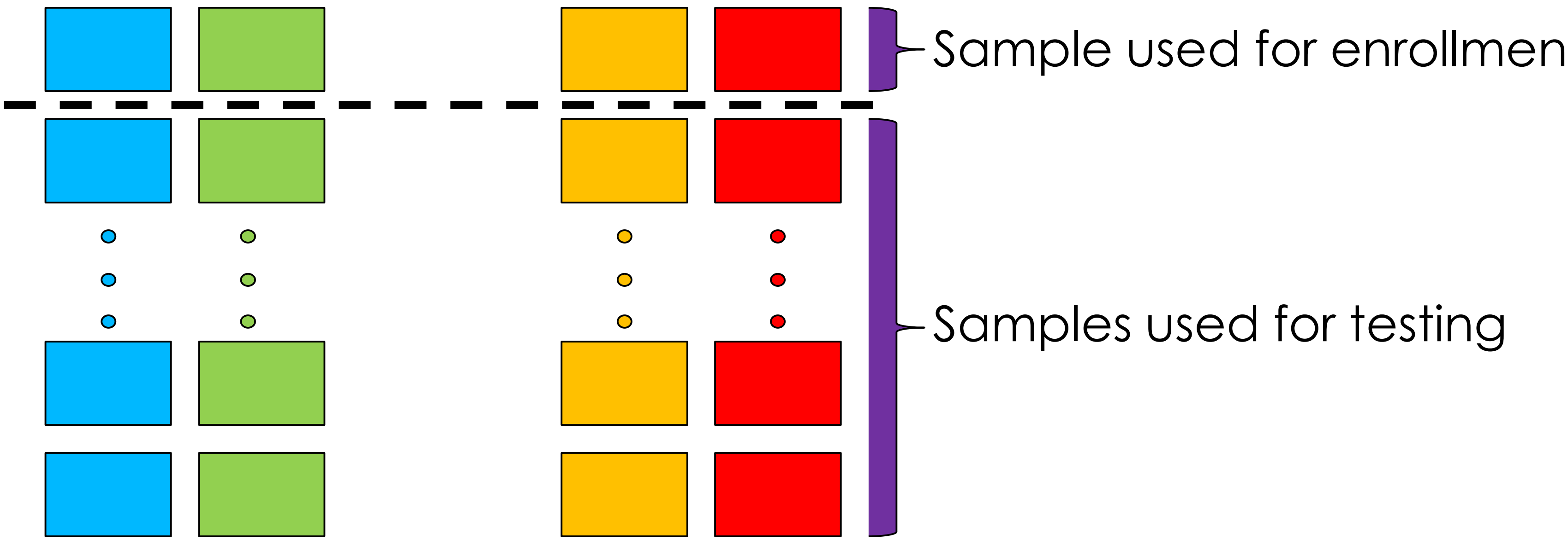
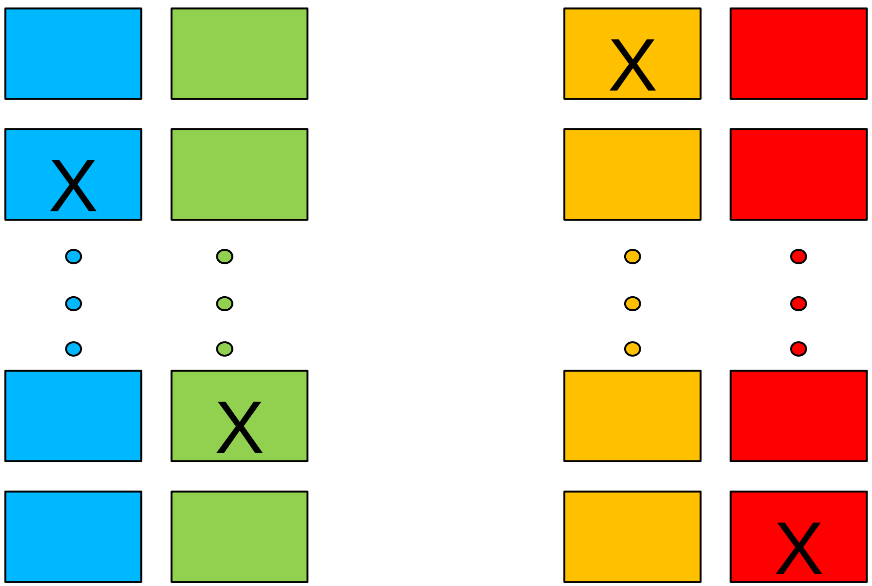
Impact of quality during enrollment (2/3)



Enrollment without quality checking

Validation

Impact of quality during enrollment (3/3)



X Sample used for enrollment

Other samples used for testing

Enrollment with quality checking

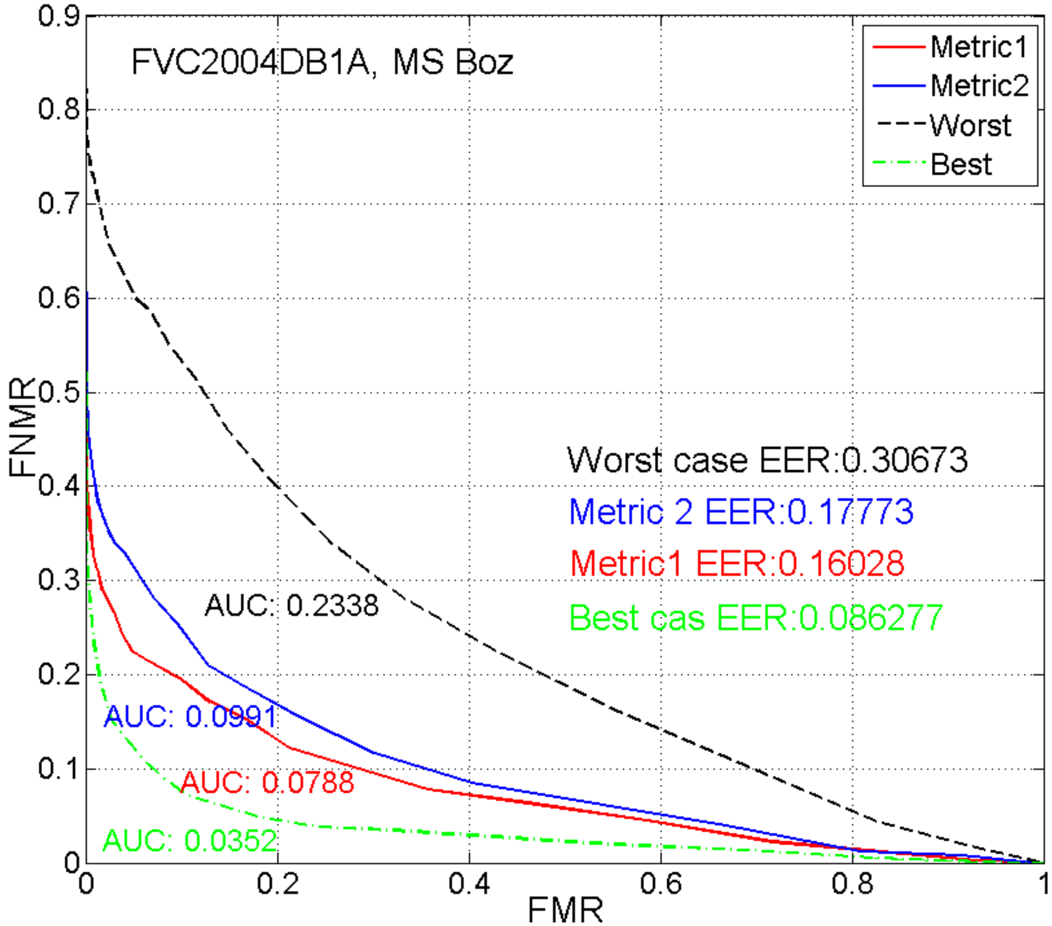
Best: choosing the sample minimizing errors

Worst: choosing the sample maximizing errors

Quality metric: choice driven by quality value

Validation

Comparison of quality metrics



A graphical illustration

Validation

An illustration on fingerprint recognition

Selection without quality checking

FAR = 0.41%

FRR = 17.36%

NFIQ template selection

FAR = 0.05%

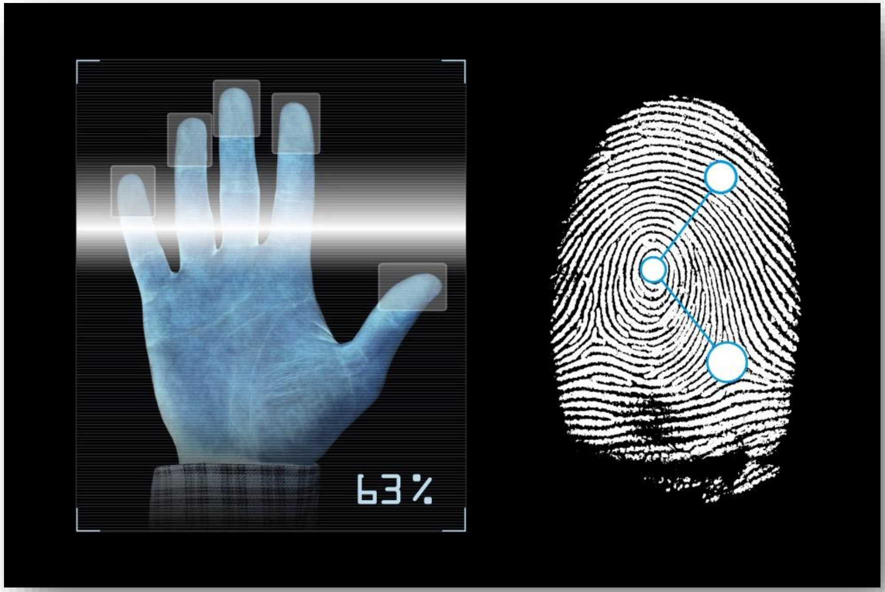
FRR = 14.36%

GREYC Q metric template selection

FAR = 0.003%

FRR = 4.75%

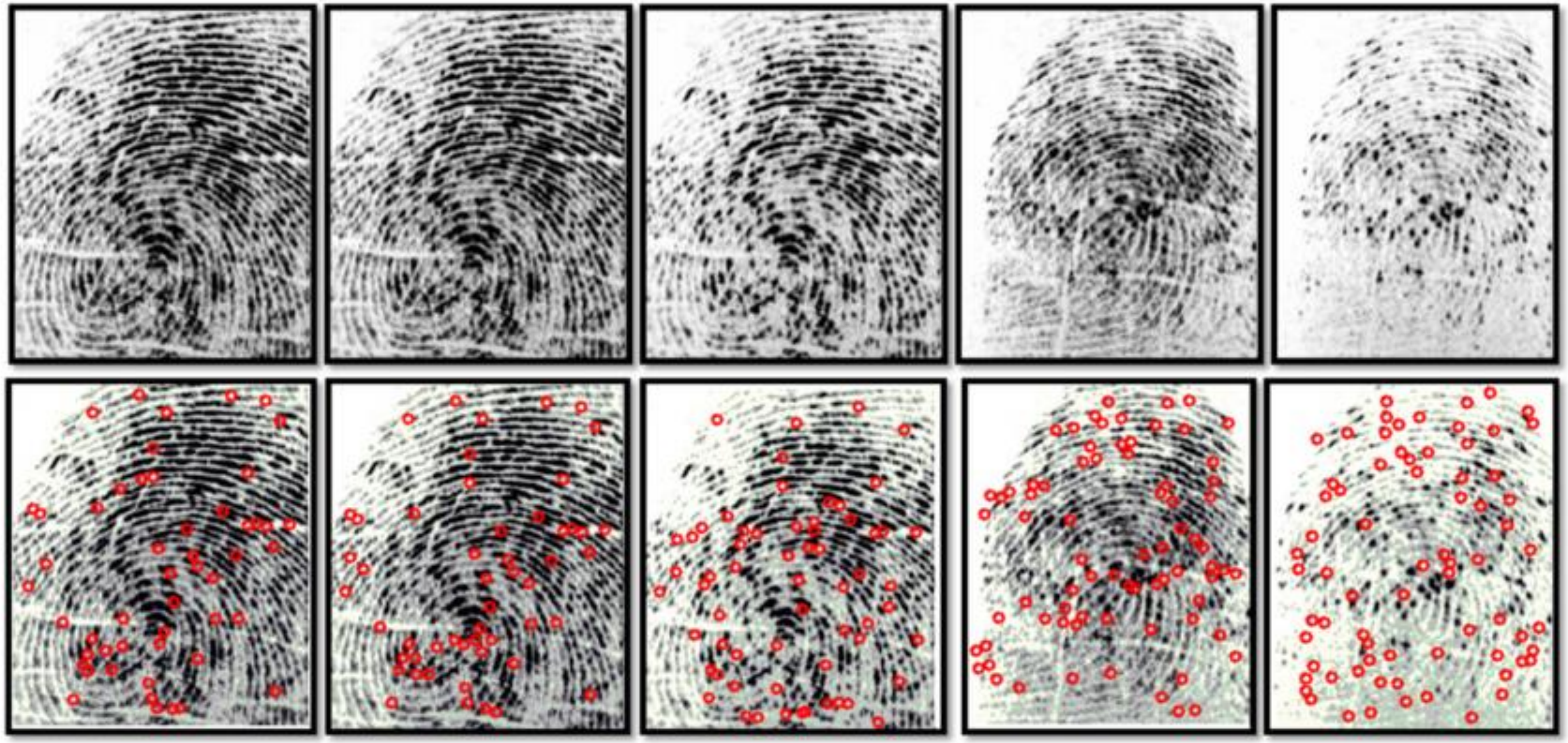
Fingerprint Quality Assessment



State of the art

Fingerprint quality assessment

Poor quality fingerprint images lead to spurious minutiae



State of the art

Fingerprint quality assessment

- Chen et al. 2004: Grey level distributions of segmented ridges
- Vatsa et al. 2008: Combined response from RDWT for dominant edge information
- Chen et al. 2005: In a ring-shaped region of the spectrum
- NFIQ1.0 2005: Amplitude, frequency, and variance of sinusoid to model valid ridges
- Fronthaler et al. 2006: Encode orientation with parabolic symmetry features
- NFIQ2.0 2016: combination of various features such as Gabor features

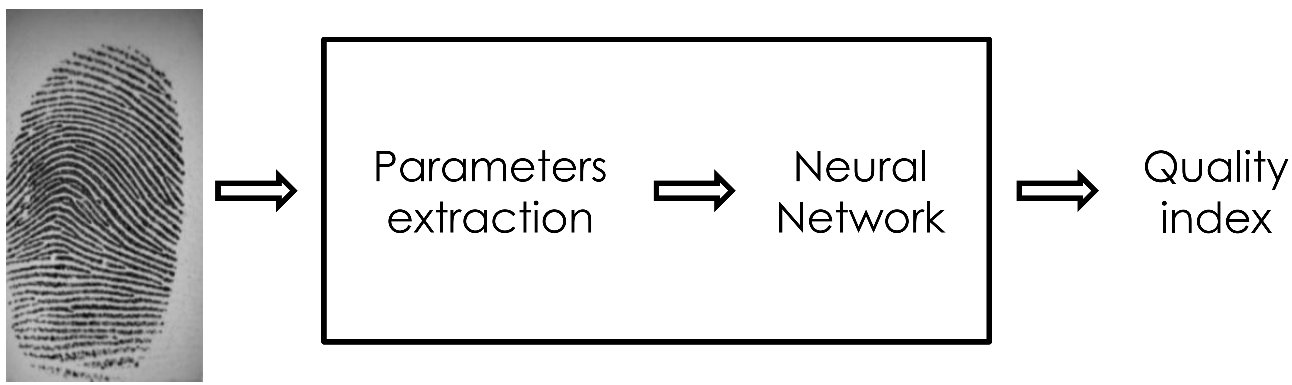
State of the art

NFIQ1.0 metric:

Quality metric for fingerprints

Returns a value between 1 and 5

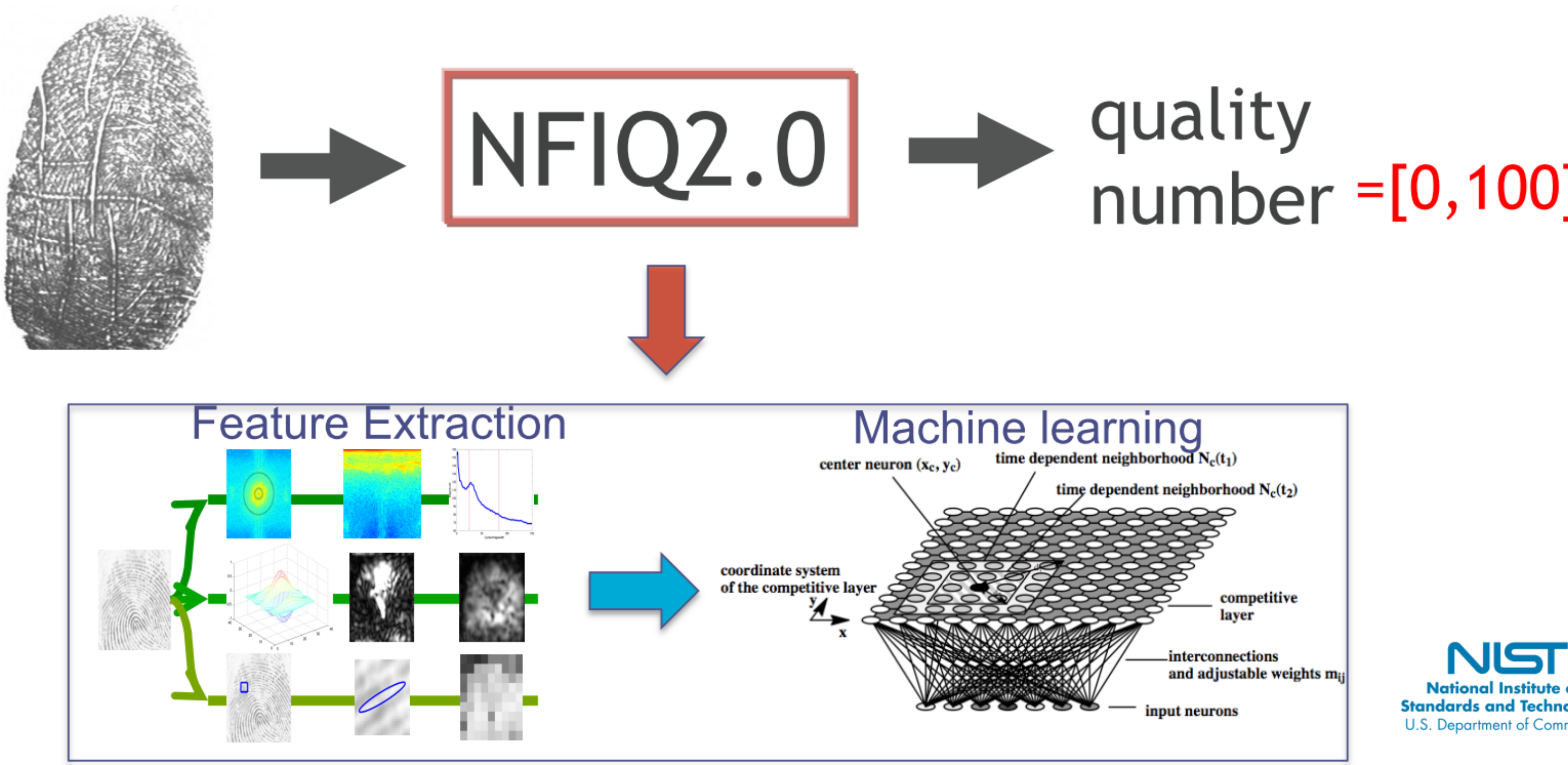
- 1 means a good quality fingerprint
- 5 means a poor quality fingerprint



E. Tabassi and C.L. Wilson. A novel approach to fingerprint image quality. *International Conference on Image Processing (ICIP)*, p. 37-40, 2005.

State of the art

NFIQ2.0 metric:



E. Tabassi et al., "The push towards zero error biometrics", NIST International conference of Biometric Performance, 2016

State of the art

NFIQ 1.0

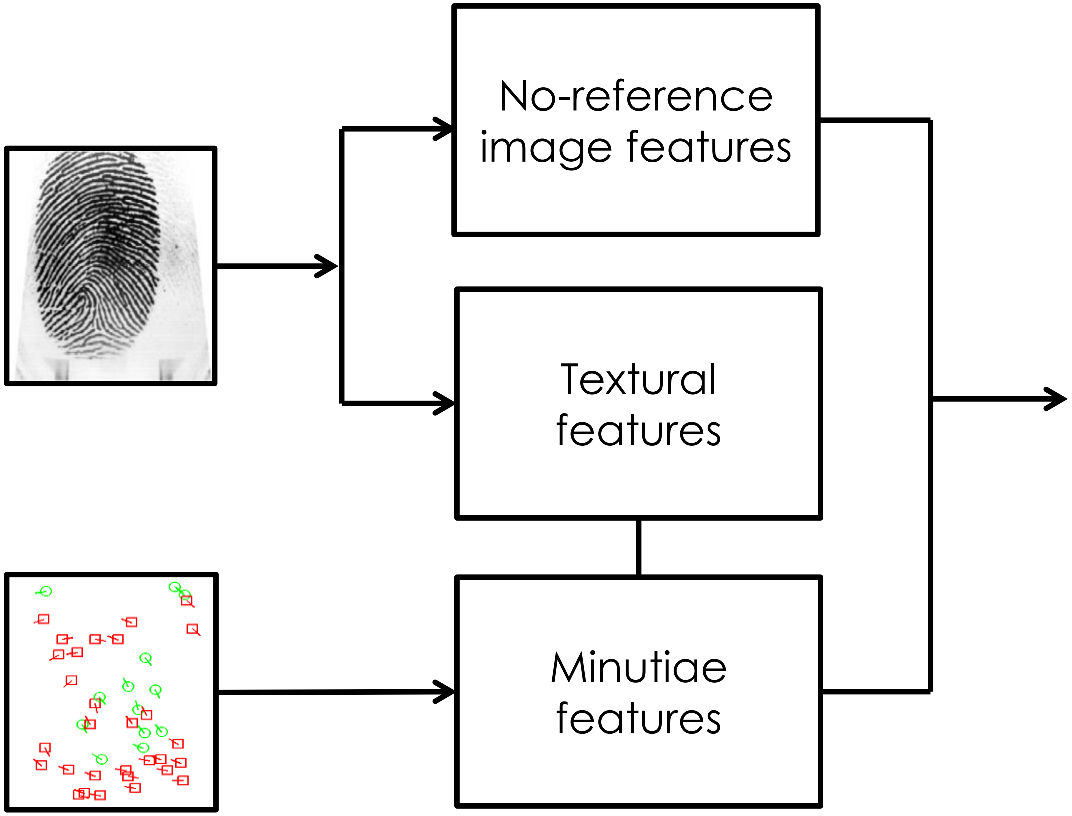
- 5 levels.
  - 1(highest) to 5(lowest)
- 11 features
- Comparison scores of 3 algorithms used for training
- 3400 training images
- Neural network
- ~300 msec per image

NFIQ 2.0

- 100 levels
  - 0(lowest) to 100(highest)
- 14 (69) features
- Comparison scores of 7 algorithms used for training
- ~5000 training images
- Random forest
- ~ 120 msec per image
- Actionable quality
  - Flags for blank image, low contrast
- Design for NFIQ Mobile

E. Tabassi et al. “The push towards zero error biometrics”, NIST International conference of Biometric Peformance, 2016

GREYC QMF metric



$$QMF = \frac{1}{A} \sum_{i=1}^{N} a_i . C_i$$

M. El Abed, A. Ninassi, C. Charrier and C. Rosenberger, "Fingerprint Quality Assessment Using a No-Reference Image Quality Metric", EUSIPCO conference, 2013

GREYC QMF metric

Different types of image quality metrics

- Quality metrics using a reference (FR)
- Quality metrics with reduced reference (RR)
- Quality metrics without any reference (NR)

NR-IQA BLIINDS-2 index

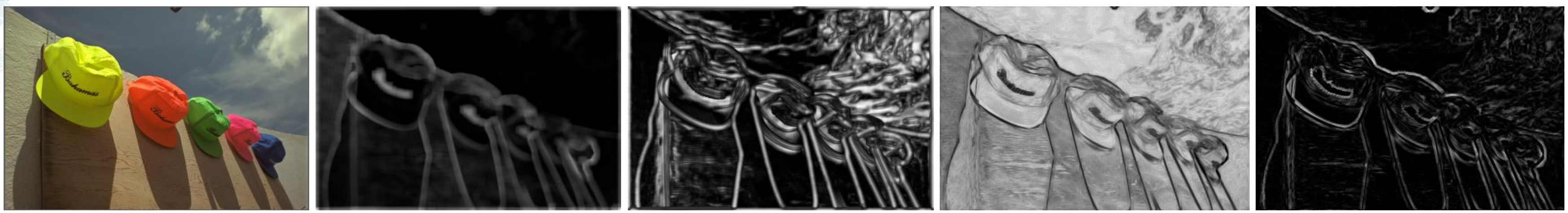
- Quality metric without any reference
- Based on the computation of 4 degradation factors in the DCT domain at different spatial resolutions

M. Saad, A. C. Bovik, and C. Charrier. A DCT Statistics-Based Blind Image Quality Index. *IEEE Signal Processing Letters*, p. 583-586, 2010.

GREYC QMF metric

- ❑ Contrast distortion (v_1)
- ❑ Structure distortion (v_2)
- ❑ Orientation anisotropy (v_3 & v_4)

Multi-scale approach ⟹ **BLIINDS2**



v1 v2 v3 v4

v1 v2 v3 v4

GREYC QMF metric

Some examples

- Alteration by adding some noise

BLIINDS : 13,8 | 9,1 | 7,4 | 6,6

- Alteration by resolution

BLIINDS : 13,8 | 13,8 | 13,7 | 12,6

GREYC QMF metric

Experimental protocol

- Fingerprint FVC2002 DB2 database (800 images)
- Three types of alterations (blurring, Gaussian noise and resolution) and three levels for each type of alteration
- Verification system based on SIFT matching

Some fingerprint examples from FVC2002 DB2.

U. Park, S. Pankanti, A. K. Jain, Fingerprint Verification Using SIFT Features, *SPIE Defense and Security Symposium*, Florida, p. 1-9, 2008.

GREYC QMF metric

Simulating alterations on FVC2002

3000 altered fingerprints by different artifacts: Gaussian noise (600), contrast (500), luminance (600), median blurring (20), rotation (360), scratches (200), occlusion (720).

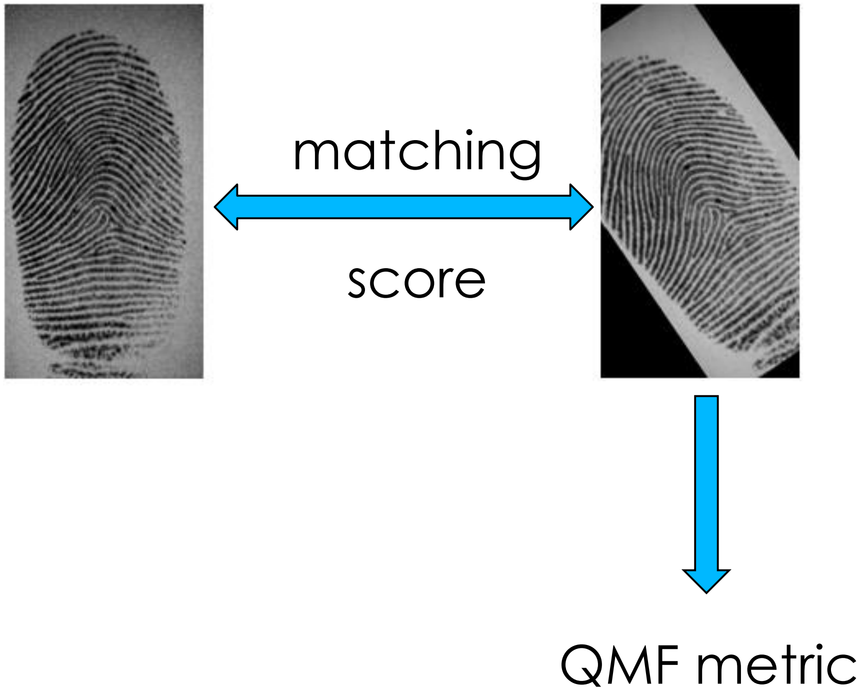
GREYC QMF metric

Comparison of the matching score and the QMF metric

One fingerprint for each user as reference

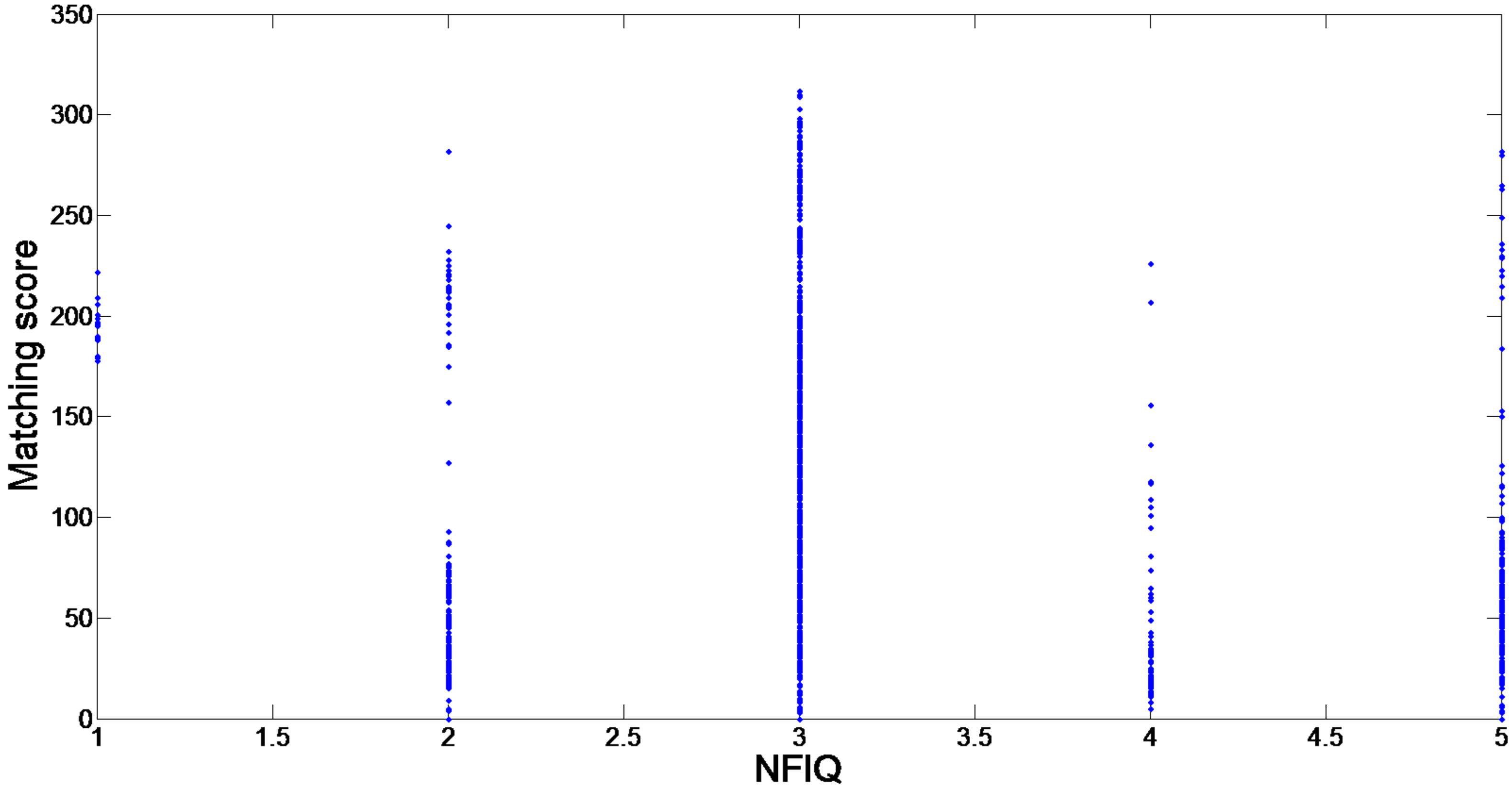
Matching score between the reference and altered ones

Comparison between the matching score and the QMF metric



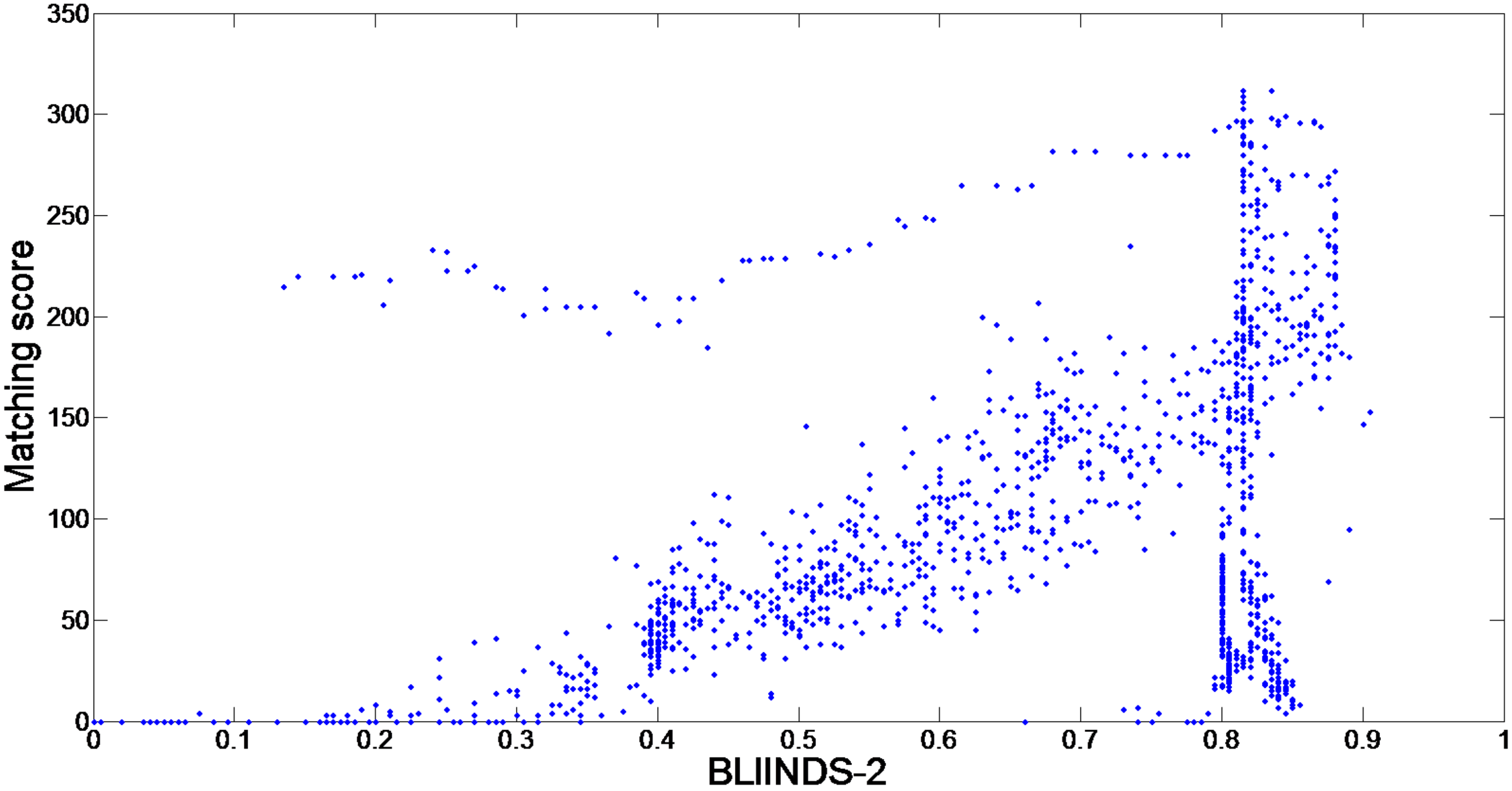
GREYC QMF metric

NFIQ metric: correlation 0.204



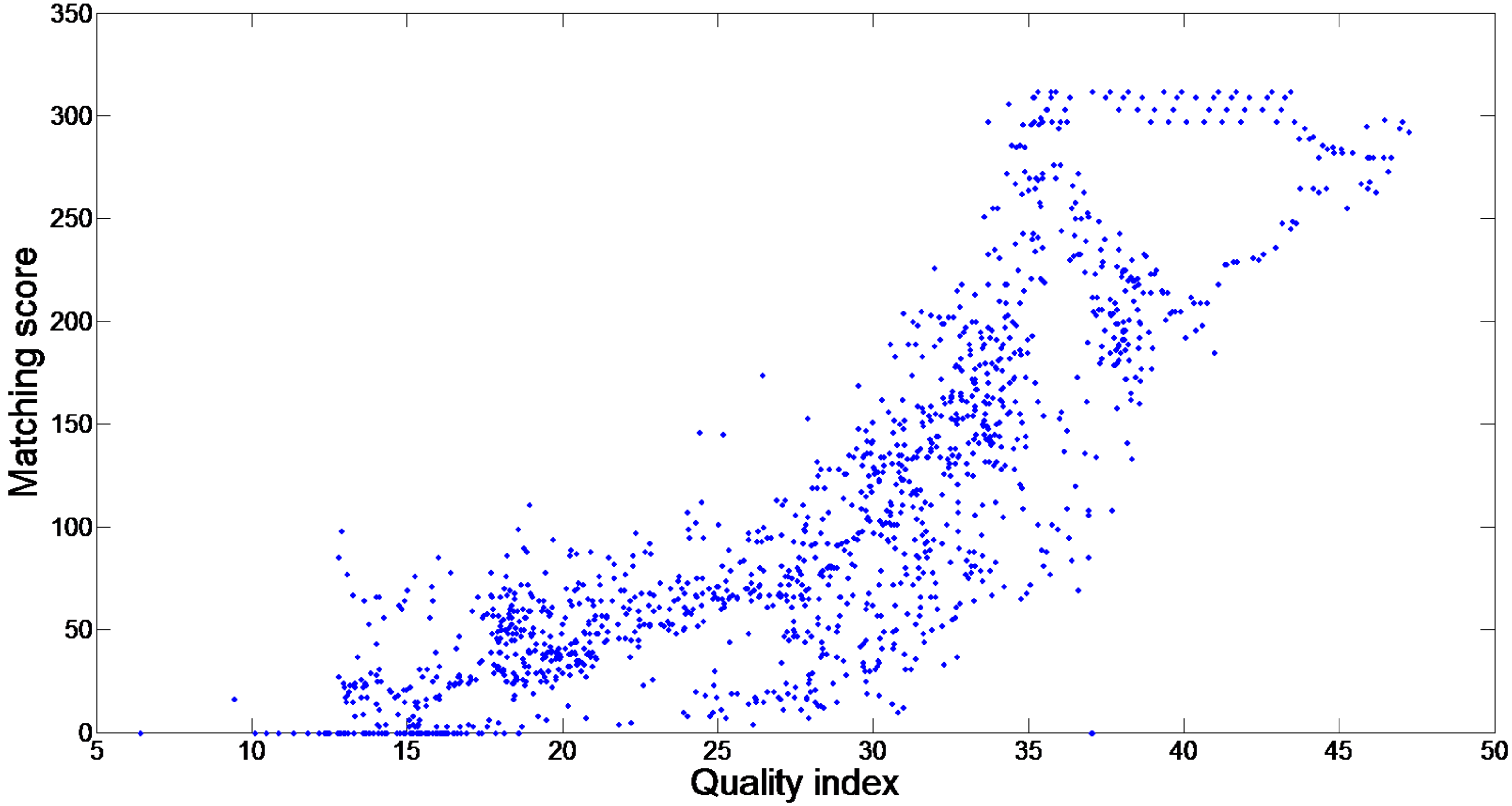
GREYC QMF metric

BLIINDS 2 metric: correlation 0.654



GREYC QMF metric

QMF metric: correlation 0.854



GREYC QMF metric

Validation with the Enrollment Selection method

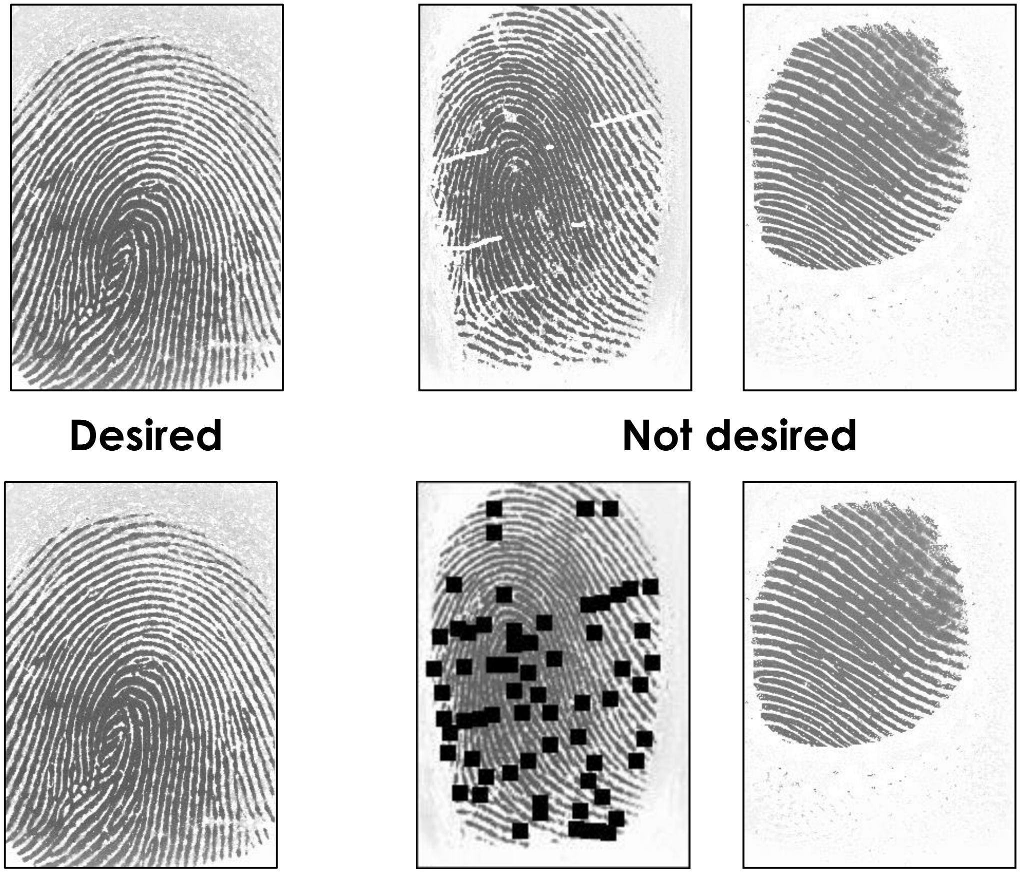
Comparison with NFIQ on 5 fingerprint databases

DB / Metric	00DB2	02DB2	04DB1	04DB2	04DB3
NFIQ	0.22%	0.11%	2.66%	3.86%	1.89%
QMF	0.40%	0.30%	1.73%	3.94%	1.66%

- Similar results with NFIQ on three databases
- Good improvement on two datasets

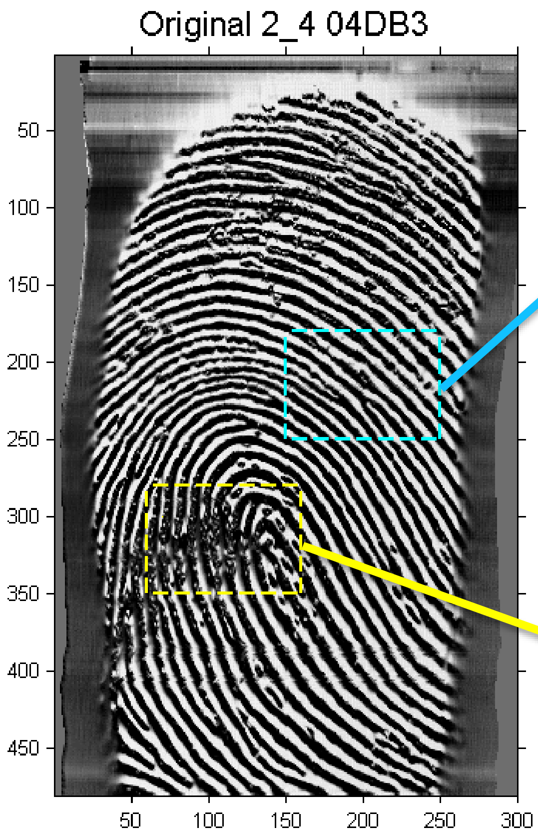
GREYC MSEG metric

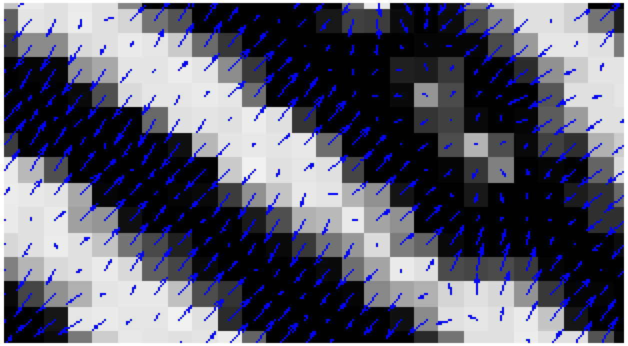
Considering the number of pixels of good quality



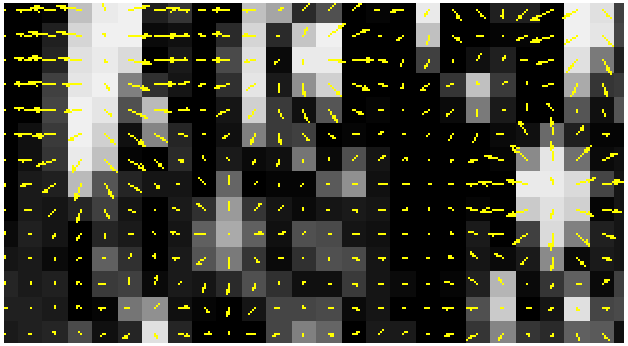
GREYC MSEG metric

Variation of pixels affects local gradients





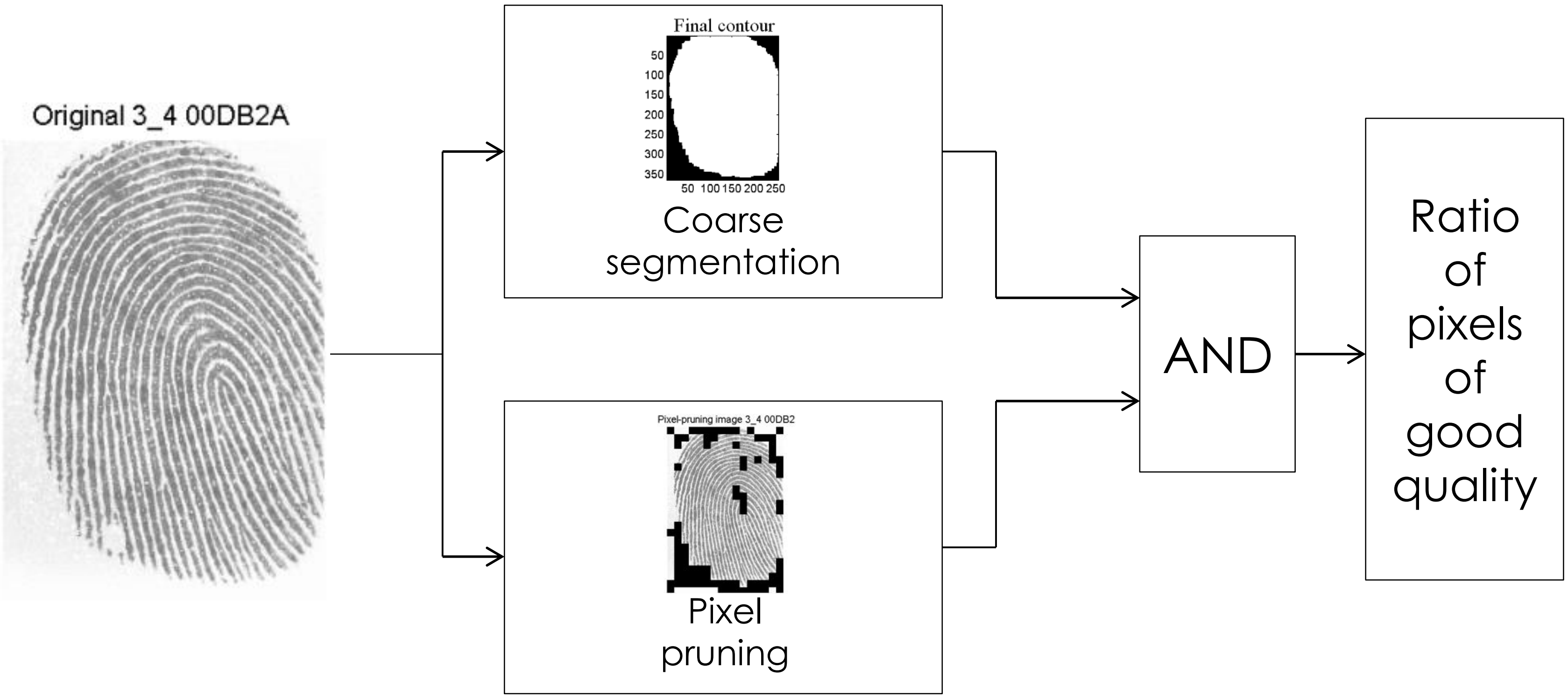
Gradients descent against ridge.



no uniform gradients

GREYC MSEG metric

General principle



Quality is represented by fusing two region masks.

GREYC MSEG metric

Validation with the Enrollment Selection method

Comparison with NFIQ on 5 fingerprint databases

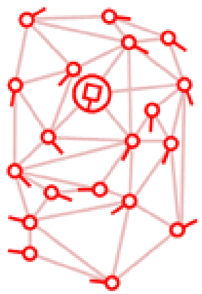
DB / Metric	00DB2	02DB2	04DB1	04DB2	04DB3
NFIQ	0.22%	0.11%	2.66%	3.86%	1.89%
MSEG	0.10%	0.20%	1.93%	3.24%	1.51%

- Good improvement of most datasets

Z. Yao, J-M Le Bars, C. Charrier, C. Rosenberger. Fingerprint Quality Assessment With Multiple Segmentation. In 2015 International Conference on Cyberworlds (CW) IEEE. Scotland, Sweden. Oct. 7, 2015.

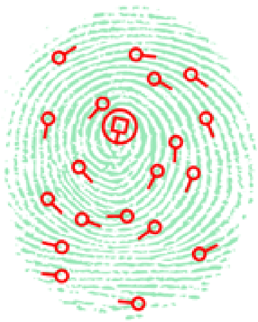
GREYC MQF metric

What about minutiae template quality?



Minutiae map

Biometric card

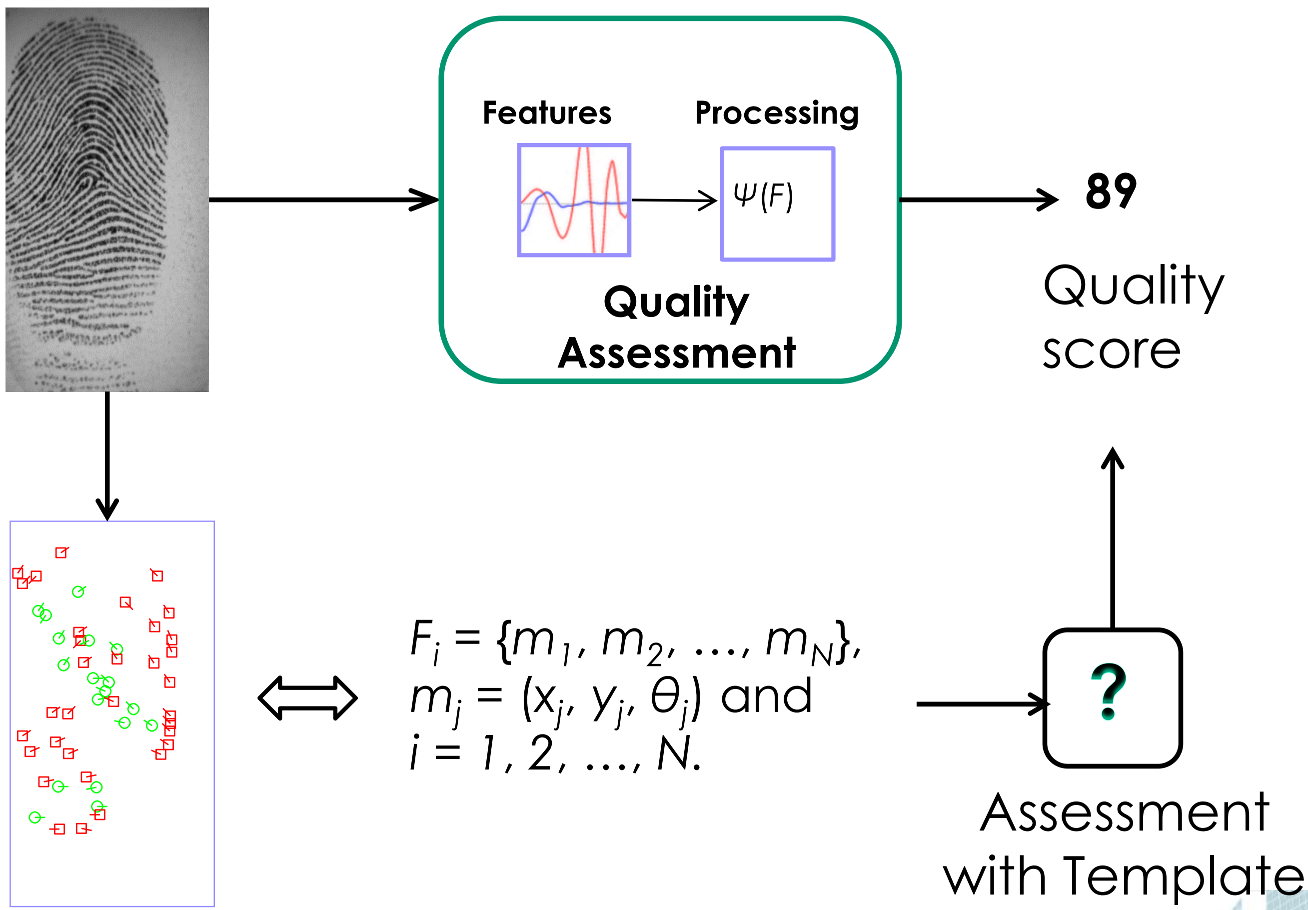


Fingerprint

On-card comparison

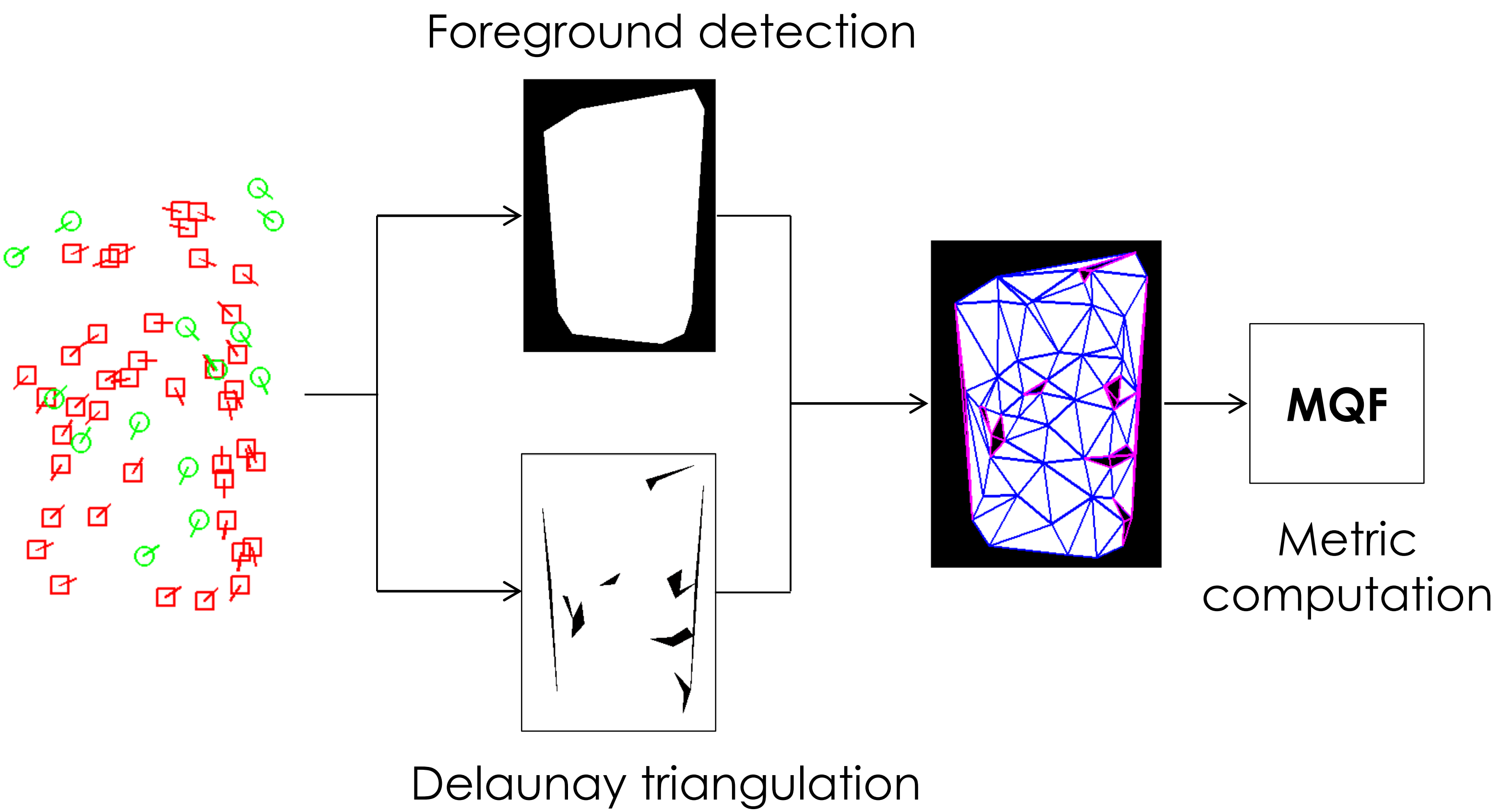
GREYC MQF metric

General principle



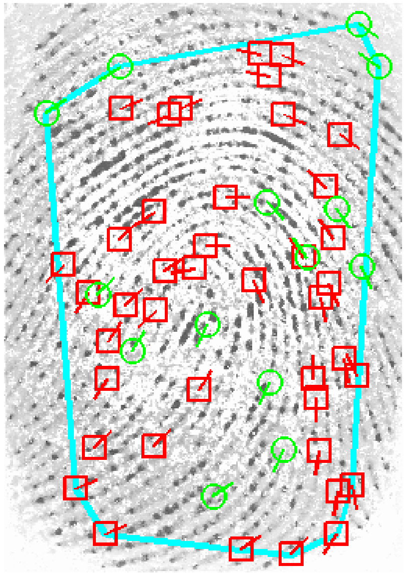
GREYC MQF metric

General principle:



GREYC MQF metric

Foreground detection



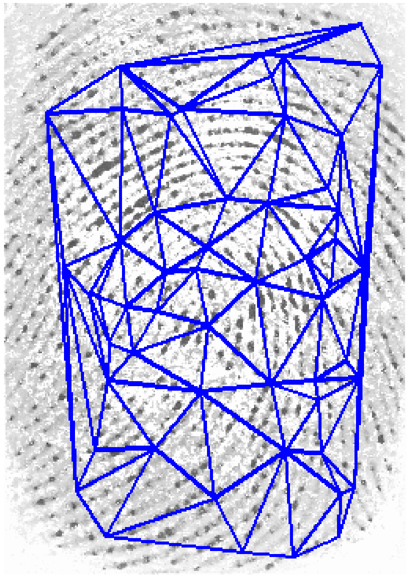
Minutiae are located in a part of foreground.

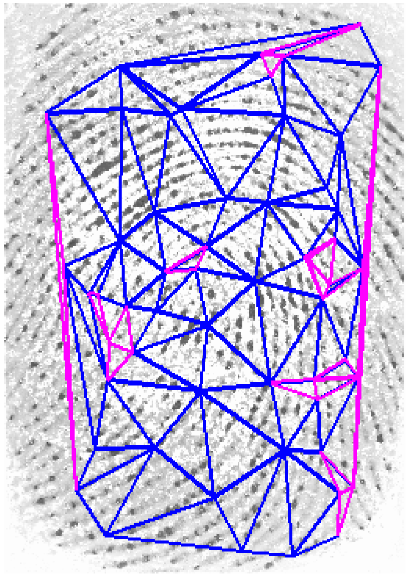
This region is can be modeled by the convex-hull.

GREYC MQF metric

Delaunay triangulation

Spurious points lead to unreasonable triangles:





The minutiae map is modeled by Delaunay triangulation.

GREYC MQF metric

Algorithm Computation of the quality score MQF

Input:

Minutiae Template F_i.

Output:

Quality index MQF

1: Calculate the area of the convex hull C_i, denoted as A_i;

2: Calculate perimeter and area for each triangle T_k, denoted as P_k and S_k;

3: $A_{Y_p} = area(Search(P_k < Y_p))$;

4: $A_{Y_a} = area(Search(S_k < Y_a))$;

5: $A_{Y_{pa}} = area(Search(P_k < Y_p \,\&\, S_k < Y_a))$;

6: $A_{Y_r} = area(Search(P_k / S_k) > Y_r)$;

7: $S_{area} = (A_i - A_{Y_p} - A_{Y_a} - A_{Y_r} - A_{Y_{pa}})$;

8: **return** S_{area};

GREYC MQF metric

Validation with the Enrollment Selection method

Comparison with NFIQ on 5 fingerprint databases

Metric \ DB	00DB2	02DB2	04DB1	04DB2	04DB3
NFIQ	0.22%	0.11%	2.66%	3.86%	1.89%
MQF	0.76%	1.12%	1.74%	3.43%	1.51%

- Good results compared to NFIQ
- Quality assessment without the fingerprint image
- Only metric for minutiae templates

Z. Yao, J.-M. LeBars, C. Charrier, and C. Rosenberger. Quality assessment of fingerprints with minutiae delaunay triangulation. In ICISSP - 1st International Conference on Information Systems Security and Privacy. INSTICC, Feb. 2015.

Conclusion and perspectives

Conclusion

Quality of biometric data

Very important for research and industrial applications

Most works focus on fingerprints

Still a lot to do

Contributions

Jean-Marie Lebars (Permanent - GREYC)

Christophe Charrier (Permanent - GREYC)

Zhigang Yao (PhD - GREYC)

Mohamad El Abed (PhD – GREYC)

Thème spécifique

Biométrie

2 conférenciers invités :

Alan C. Bovik (Univ. Texas at Austin)

Christoph Busch (Darmstadt Univ)

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