



# Fingerprint Recognition

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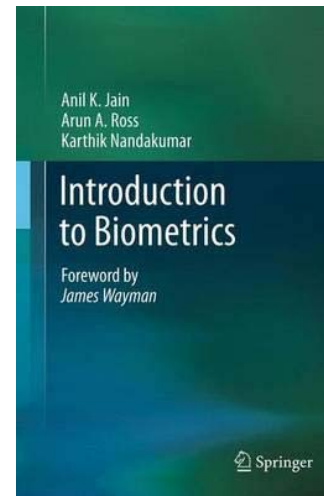
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# Outline

- Basics of fingerprint recognition
- Fingerprint orientation field estimation
- Detection and rectification of distorted fingerprint



## Reference:

- A. K. Jain, A. Ross, K. Nandakumar, Introduction to Biometrics, Springer, 2011.
- D. Maltoni, D. Maio, A. K. Jain, S. Prabhakar, Handbook of Fingerprint Recognition, Springer Verlag, 2009.

# Skin on the finger

finger



arm



- The skin on the finger contains friction ridges, has no hair, has no oil glands, and has lots of sweat pores.
- The pattern of ridges is **unique & persistent**, thus useful for person identification.
- Touching an object will leave **latent print** on it, thus useful for solving crime.

# Fingerprint recognition

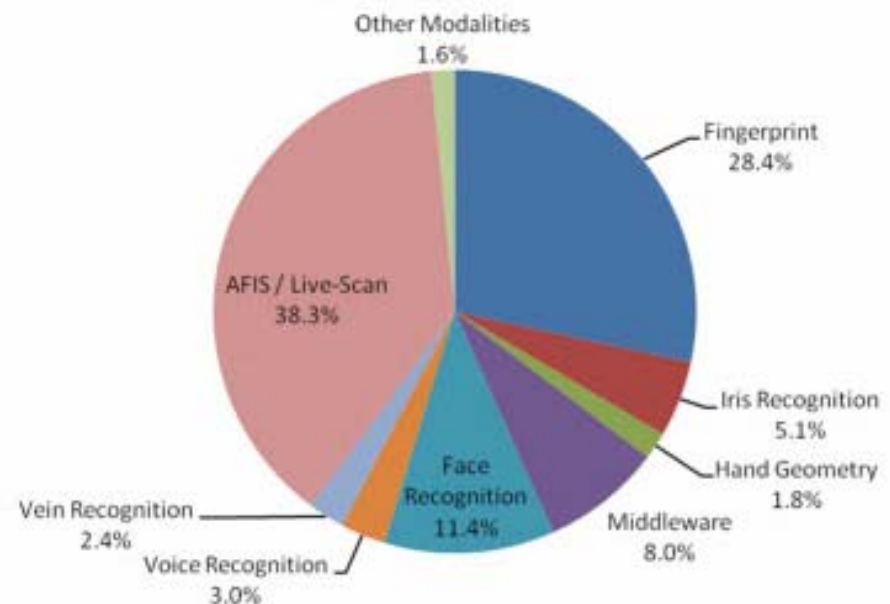
**Definition:** use technologies of sensor, image processing, and pattern recognition to automatically or semi-automatically determine if two fingerprints are matched or not.

# Fingerprint vs. other biometrics

- **Irreplaceable** role of latent prints in crime investigation
- High accuracy of 10-print identification
- Large existing databases with criminal history (FBI IAFIS **55M**)
- Large government systems (National ID, Border Control, Defense) should be **compatible** with law enforcement databases
- Easy to use, good performance/cost ratio, small size (for commercial use)

**Face:** large existing database, but not accurate for ident. in large population

**Iris:** accurate, but existing crime database does not have iris information



# 3 representative applications



FBI IAFIS  
Law enforcement  
1-to-N



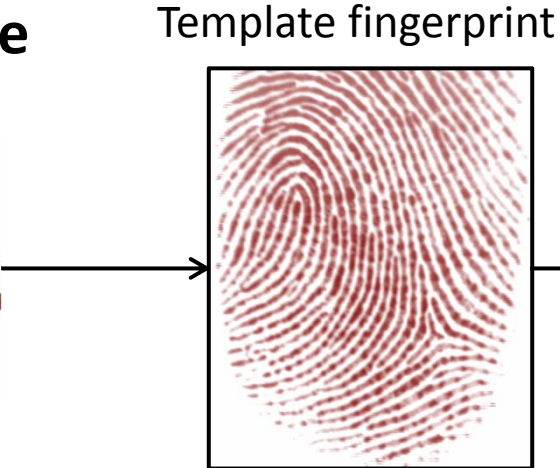
US-VISIT  
Border control  
1-to-N & 1-to-1



iPhone  
Access control  
1-to-1

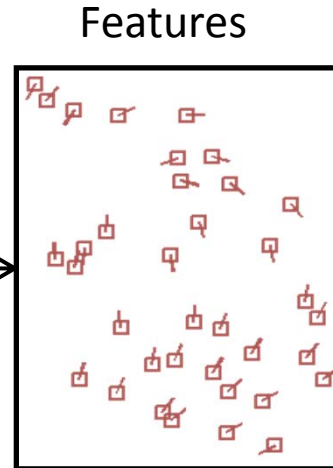
# Flowchart of fingerprint recognition

## Enrollment stage



Sensing

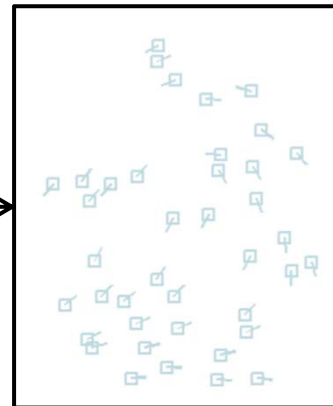
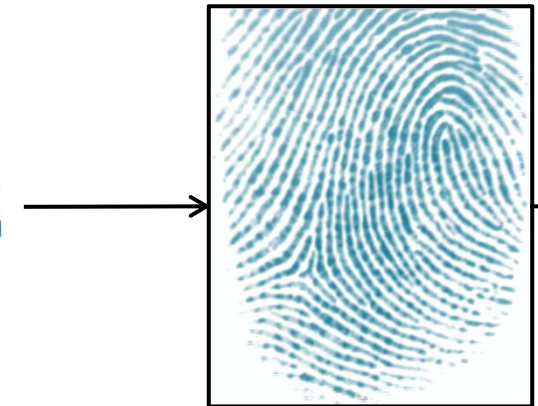
Feature extraction



Matching

score

## Verification stage



# Flowchart of fingerprint recognition

**Enrollment stage**



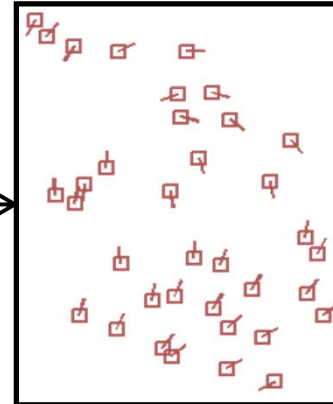
Template fingerprint



**Sensing**

**Feature extraction**

Features



**Matching**

score



Query fingerprint

**Feature extraction**



Features

**Matching**

score

**Verification stage**

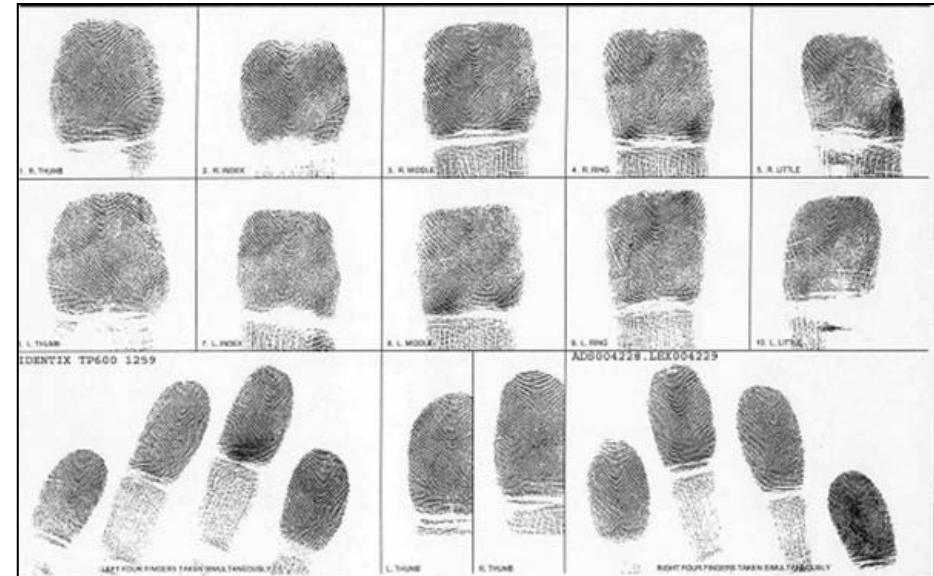


# Fingerprint sensing

- The process of capturing and digitizing the fingerprint of an individual.
- Digital images of the fingerprints can be acquired using
  - off-line method
  - on-line method

# Inking method

rolled fingerprints



plain fingerprints

- Rolled fingerprints are larger in size, but distortion is large due to rolling.
- Plain fingerprints are smaller in size, but distortion is smaller.
- Plain fingerprints are also used to ensure correct order of rolled fingerprints.
- Both rolled and plain fingerprints are captured in an attended mode, so quality is good and contain rich information.
- They are also called exemplar fingerprints.

# Recording latent prints

- Recording latent prints (latent development) requires diverse techniques, depending on residue type, surface type, age...
- Powder dusting is one of the oldest and most common techniques.



1. Dust by powder



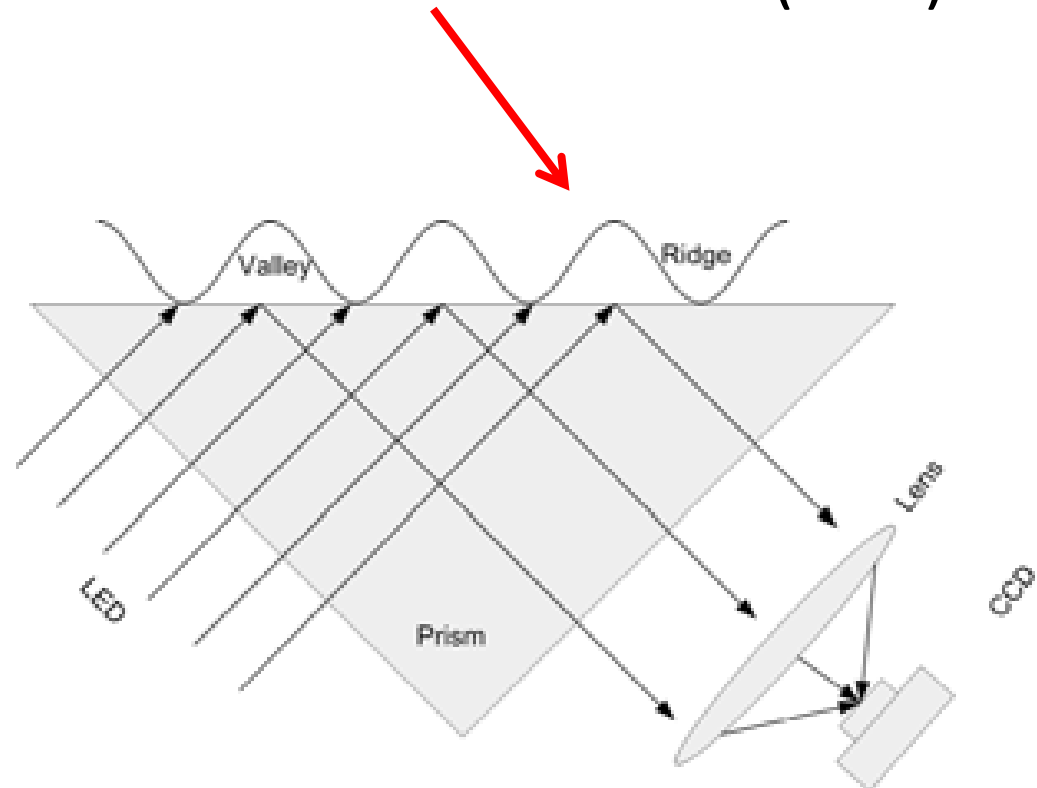
2. Take photograph



3. Lift by tape

# Online sensing techniques

- Many online fingerprint sensing techniques:
  - Optical Frustrated Total Internal Reflection (FTIR)
  - Capacitive
  - Ultrasound
  - Direct imaging



# Online sensing



Press the finger



Roll the finger



Sweep finger



Press the hand

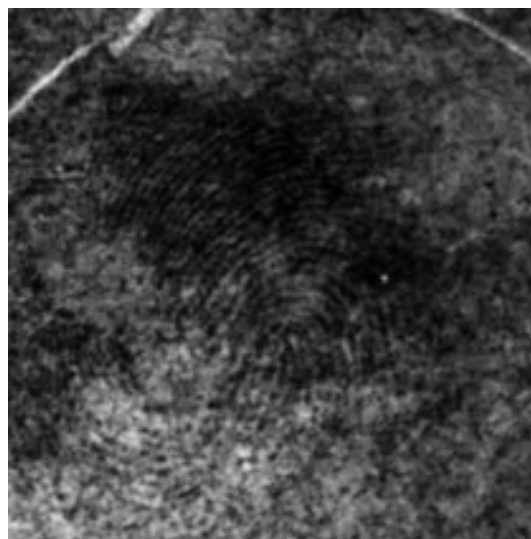


Sweep hand

# Images of different sensing methods



Inking



Latent



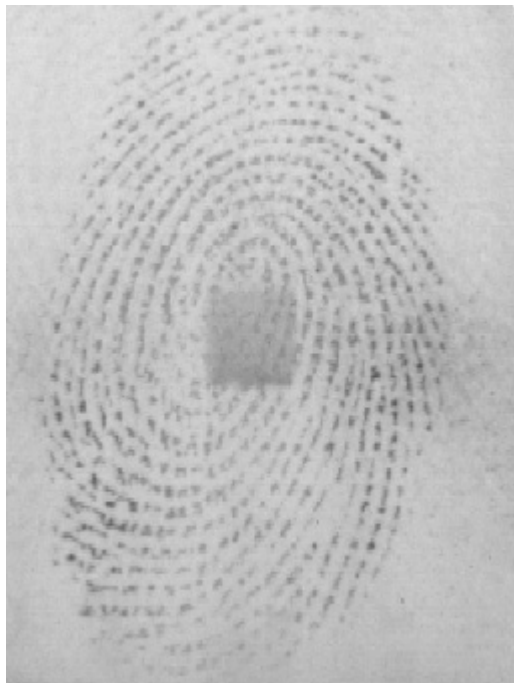
FTIR

Compared to inking and FTIR fingerprints, quality of latent fingerprint is much lower.

# Fingerprint Image Quality

- Fingerprint image quality has a large impact on the recognition performance.
- Influence factors:
  - Sensor: image resolution, sensing area
  - Finger: skin condition
  - Operation: direction and strength of pressing finger, pose of finger

# Non-ideal skin conditions



Dry



Wet



Creases



# Flowchart of fingerprint recognition

## Enrollment stage



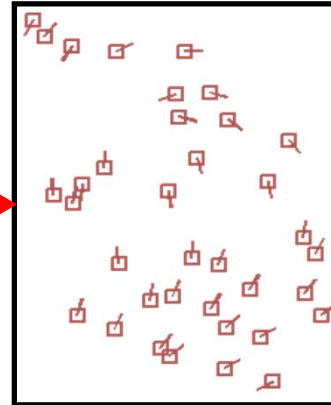
Template fingerprint



Sensing

Feature extraction

Features



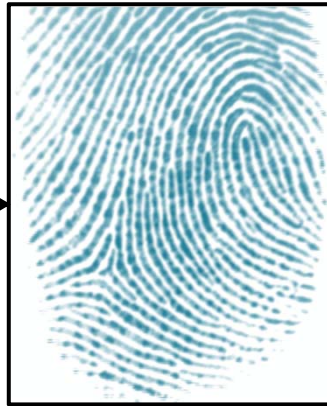
Matching

score

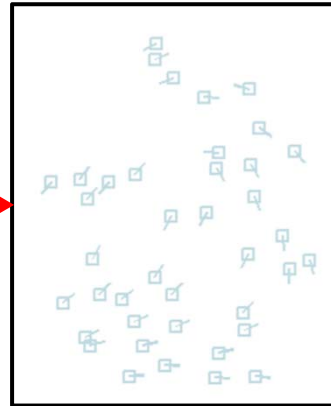
## Verification stage



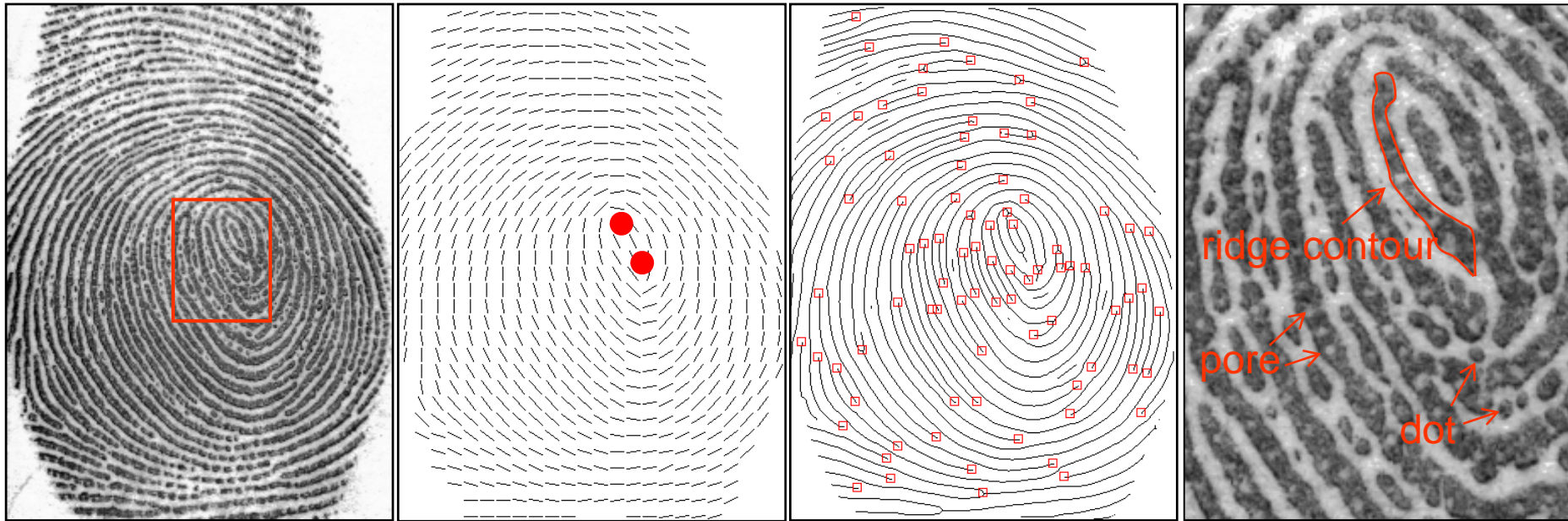
Query fingerprint



Features



# Fingerprint features



Fingerprint

Level 1

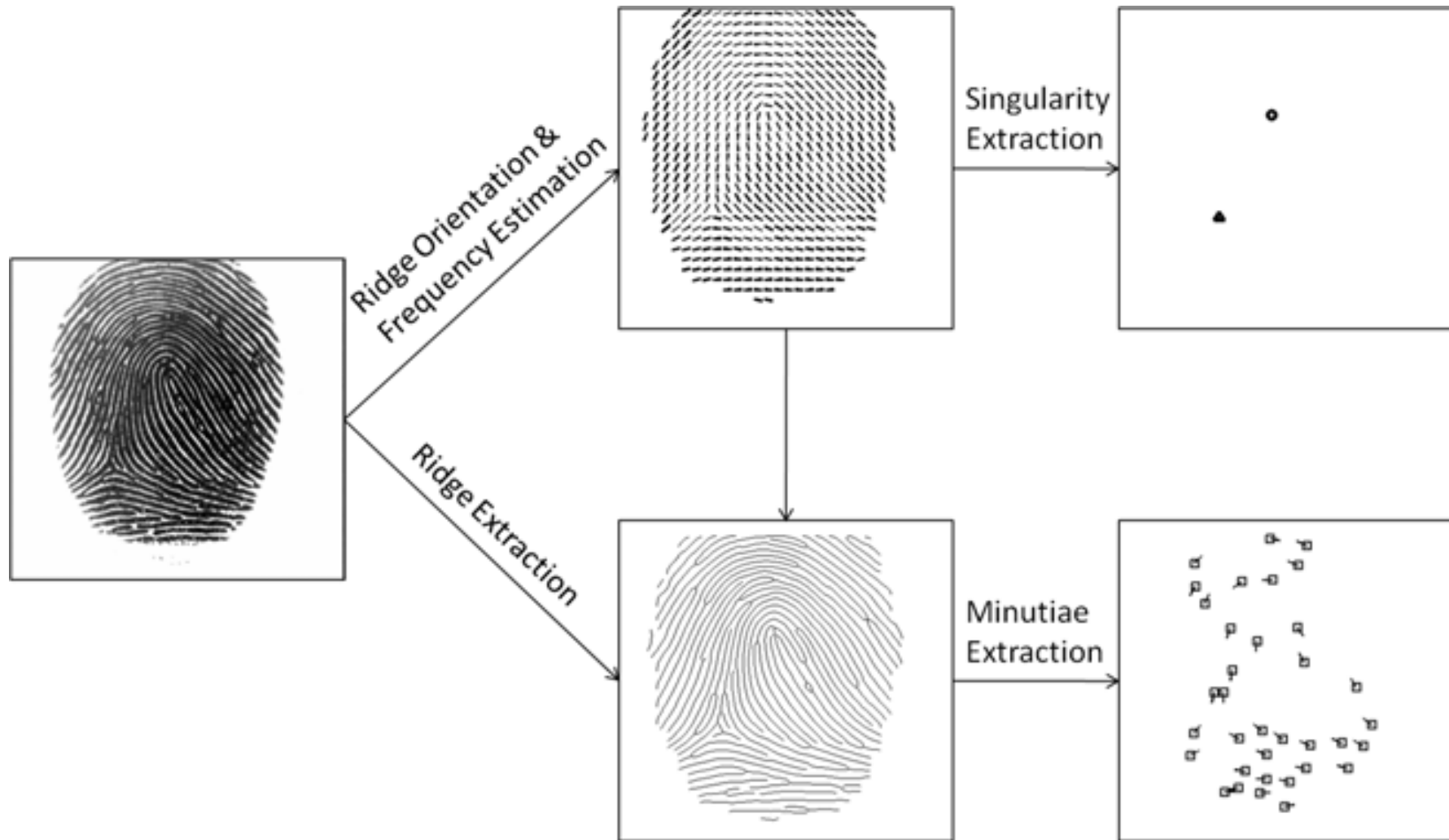
Level 2

Level 3

A fingerprint can be described at 3 levels from coarse to fine. Coarse level representation can be derived from finer level representations.

- Level 1: ridge orientation and frequency (singularity is a compact but lossy compression of ridge orientation field)
- Level 2: ridge skeletons (minutiae set is a compact but lossy compression of ridge skeletons)
- Level 3: outer and inner contours of ridges

# Feature extraction



Different feature extraction algorithms may have different flowcharts.

# Ridge orientation & frequency estimation

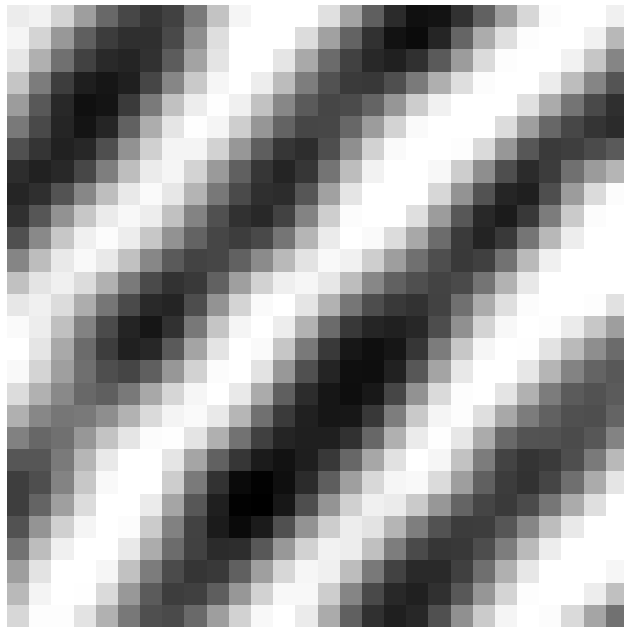
Ridge pattern in a local area of a fingerprint can be approximated by a cosine wave

$$w(x, y) = A \cos(2\pi f(x \cos \theta + y \sin \theta))$$

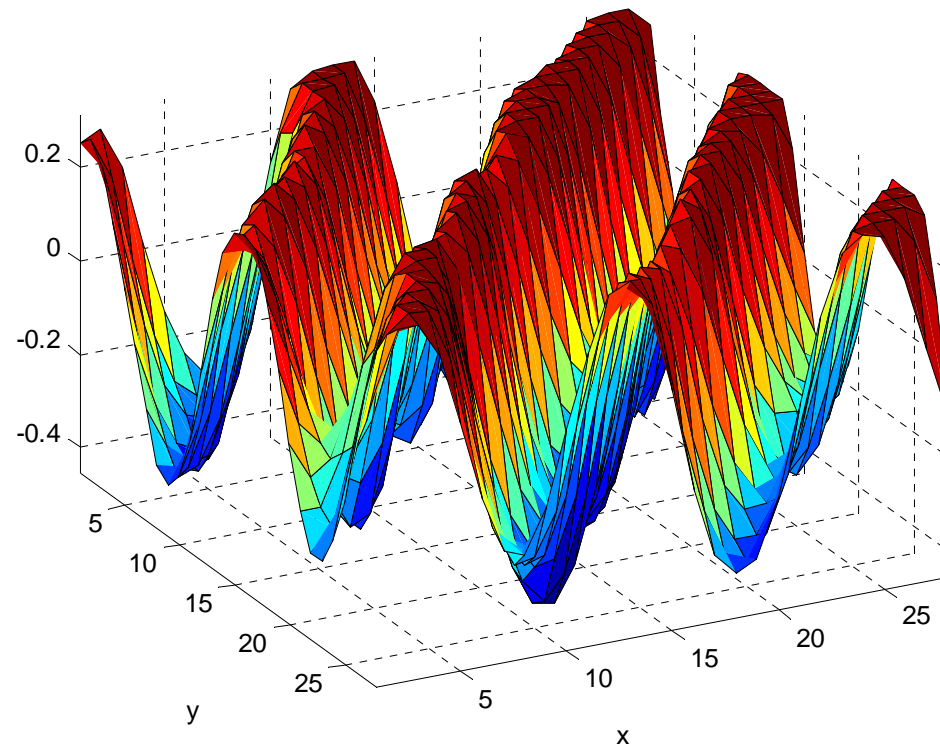
amplitude

frequency

orientation



Local fingerprint region



Shown as surface

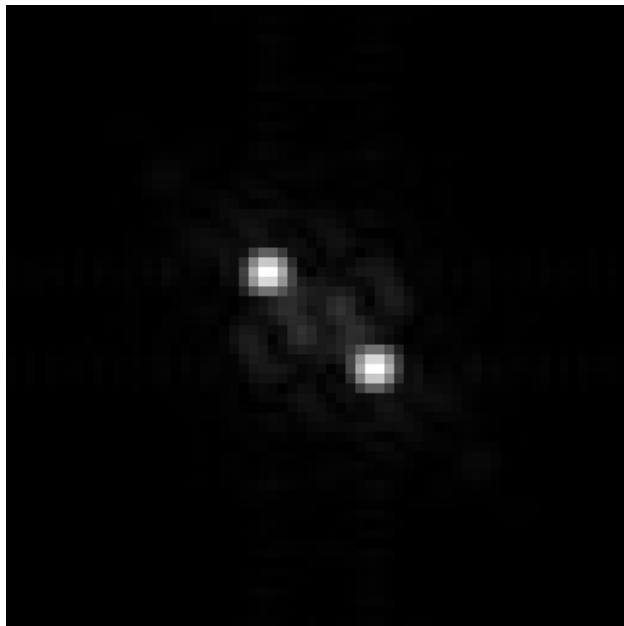
# Ridge orientation & frequency estimation

2D Fourier transform of cosine wave

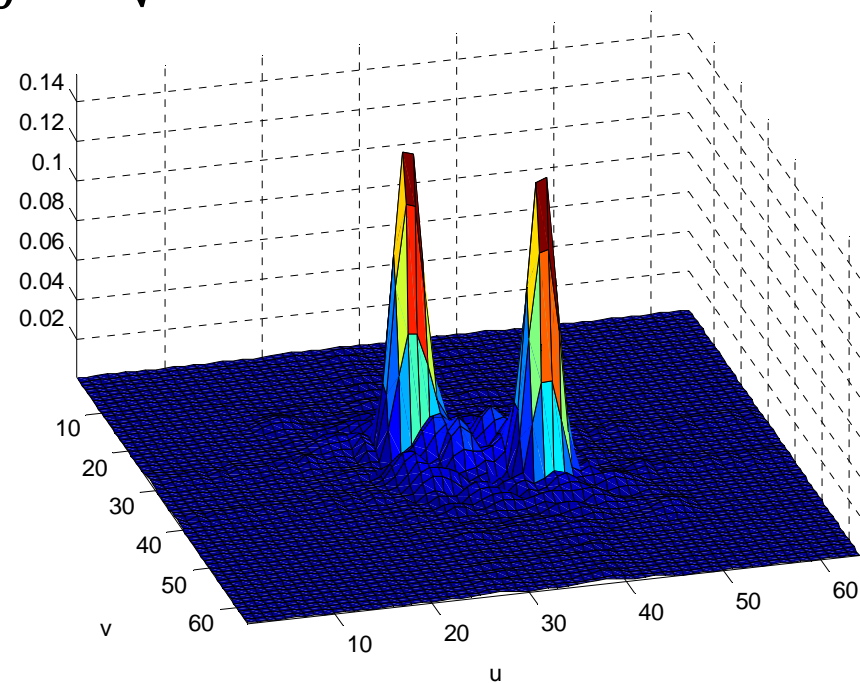
$$W(u, v) = \frac{A}{2} [\delta(u - f \cos \theta, v - f \sin \theta) + \delta(u + f \cos \theta, v + f \sin \theta)]$$

Let  $(\hat{u}, \hat{v})$  denote the location of the maximum magnitude, then

$$\hat{\theta} = \arctan\left(\frac{\hat{u}}{\hat{v}}\right), \hat{f} = \sqrt{\hat{u}^2 + \hat{v}^2}$$



Magnitude spectrum



Magnitude spectrum shown as surface

# Orientation field smoothing

- Orientation field using the above method is fragile to noise.
- Orientation field is particularly important for extracting minutiae. To deal with noise, we should smooth the orientation field.
- Special consideration on ridge orientation:
  - defined in the range  $[0, \pi)$
  - $\theta$  and  $(\theta + \pi)$  are the same orientation
  - the average value between  $\theta$  and  $(\theta + \pi)$  should be  $\theta$  rather than  $\frac{2\theta + \pi}{2}$

# Orientation field smoothing

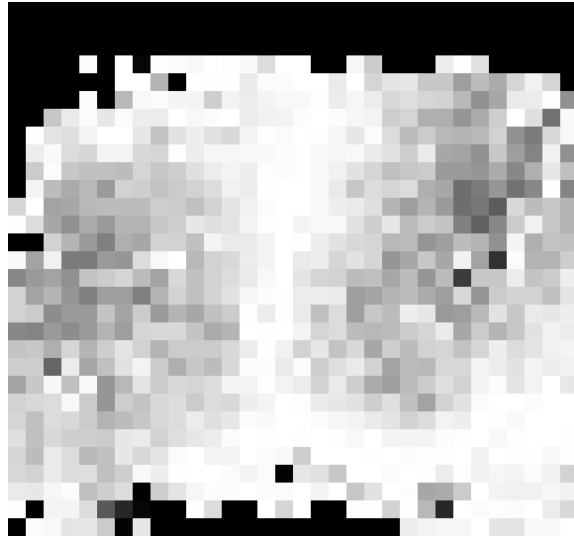
3 steps to smooth orientation field:

- Construct a vector field  $V = (V_x, V_y) = (\cos 2\theta, \sin 2\theta)$ ;
- Perform low pass filtering on the two components of the vector field separately to obtain the smoothed vector field  $V' = (V_x', V_y')$ ;
- Smoothed orientation field is given by  $\frac{1}{2} \arctan\left(\frac{V_x'}{V_y'}\right)$ .

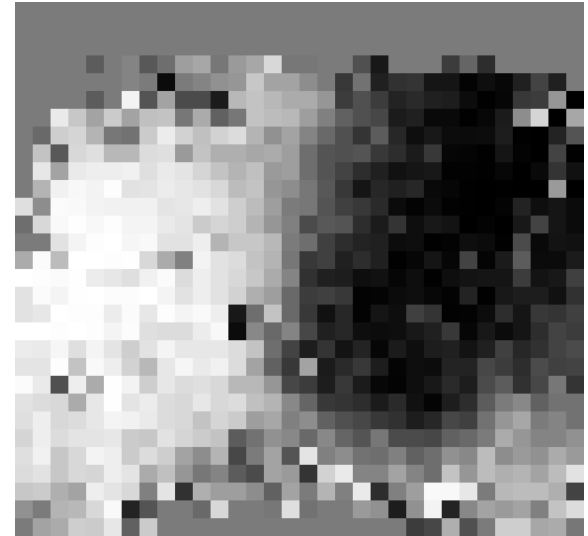
# Orientation field smoothing



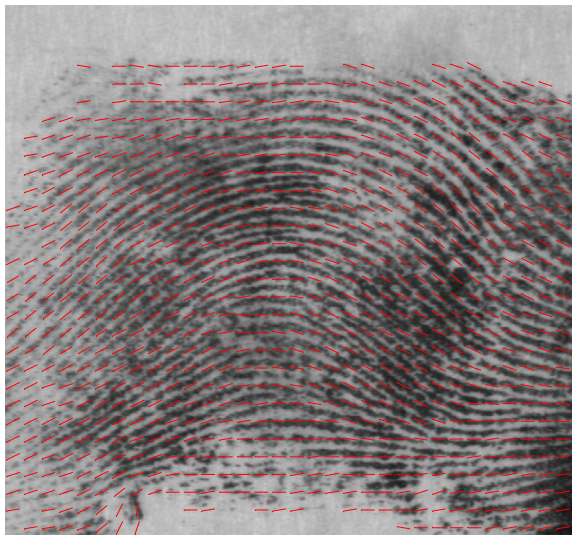
Initial OF,  $\theta$



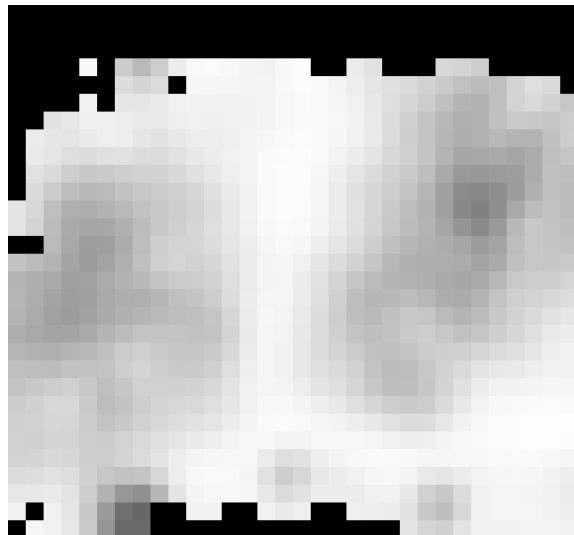
$V_x = \cos(2\theta)$



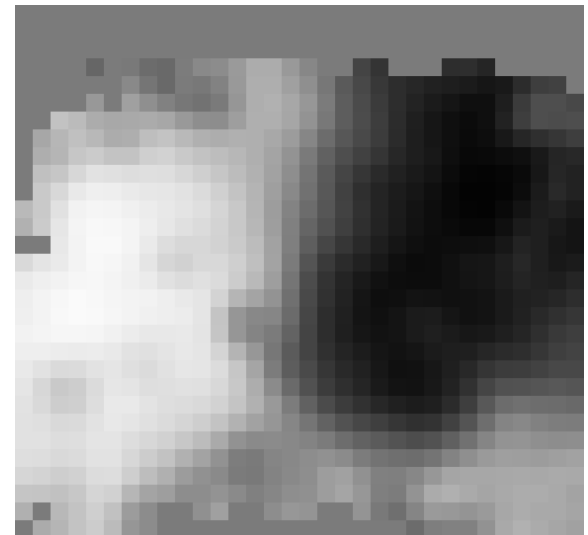
$V_y = \sin(2\theta)$



Smoothed OF,  $\theta'$



$V_x'$



$V_y'$



# Ridge extraction

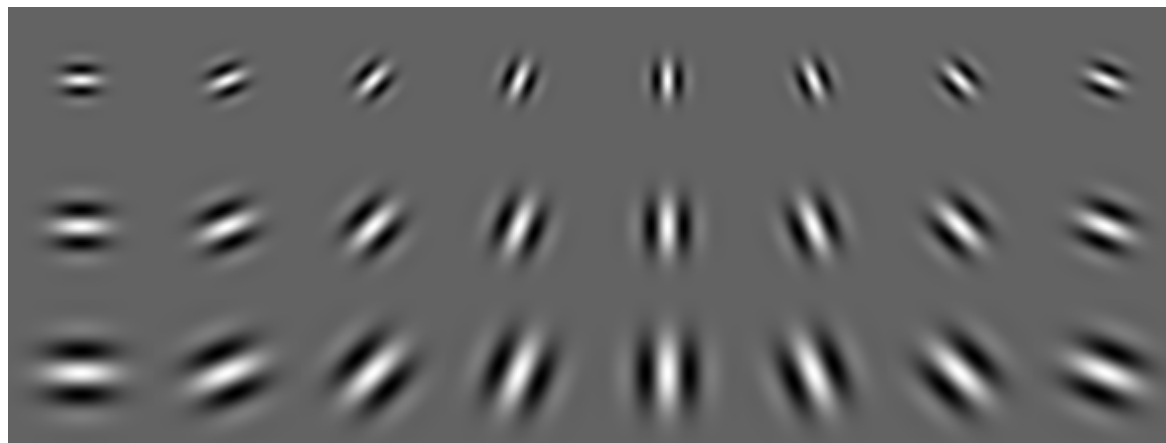
- A straightforward method is binarization.
- Problems:
  - Sweat pores on ridges are brighter than the surrounding pixels;
  - ridges can be broken due to cuts or creases;
  - adjacent ridges may appear to be joined due to wet skin or large pressure.
- Countermeasure: fingerprint enhancement.
- General purpose image enhancement is not effective for fingerprint.
- A successful fingerprint enhancement method is contextual filtering, such as Gabor filtering.

# 2D Gabor filters

2D Gabor wavelet:

$$G(x, y) = e^{-\pi[(x-x_0)^2/\alpha^2 + (y-y_0)^2/\beta^2]} e^{-2\pi i[u_0(x-x_0) + v_0(y-y_0)]}$$

where  $(x_0, y_0)$  denote the position in the image,  $(\alpha, \beta)$  denote the effective width and length, and  $(u_0, v_0)$  denote the wave direction with a spatial frequency  $\omega_0 = \sqrt{u_0^2 + v_0^2}$ .



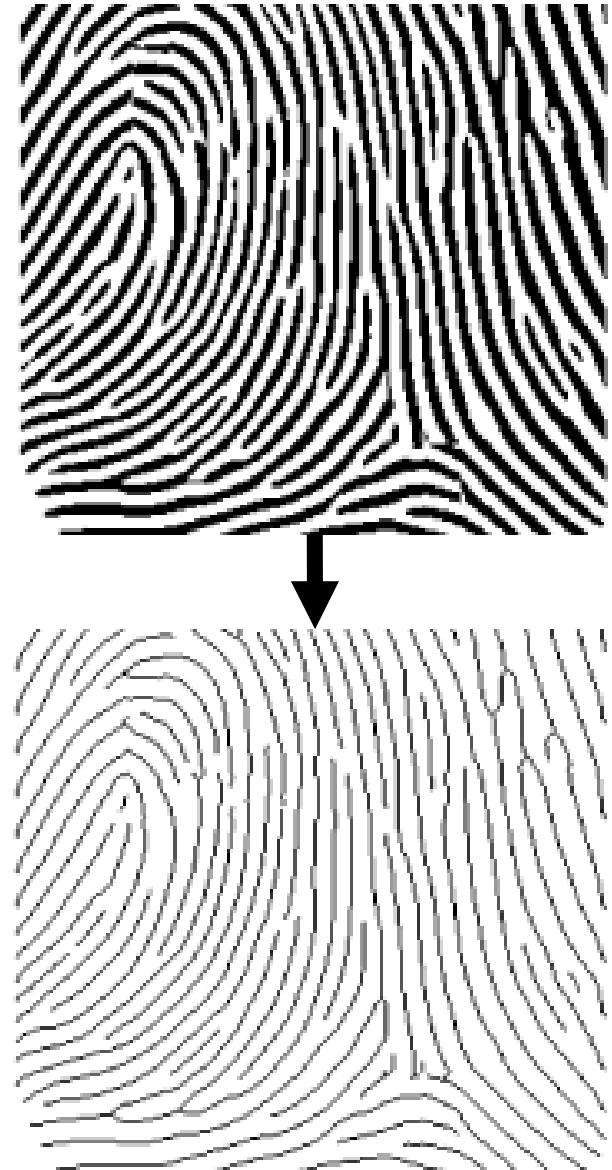
Real parts of Gabor filters (8 orientations and 3 scales)

# Effect of Gabor filtering



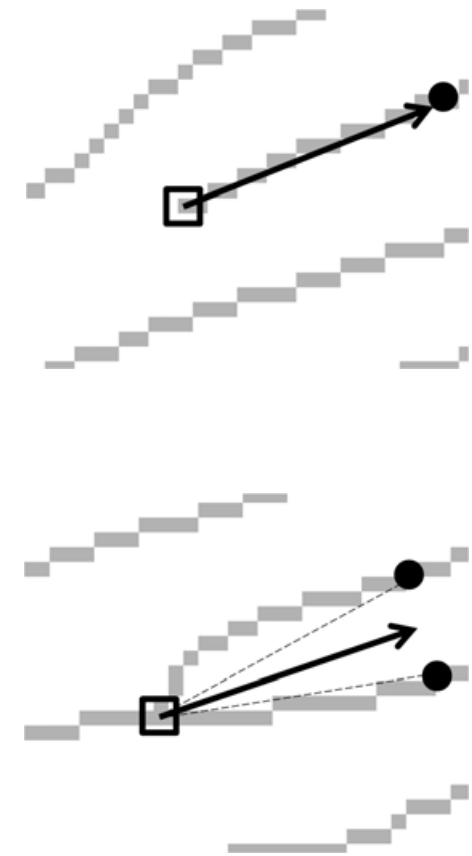
# Ridge extraction

- Enhanced image can be converted into a binary image by comparing to thresholds (e.g. local mean).
- A morphological operation, thinning, is used to obtain the skeleton image.
- Thinning is a common technique in image processing, which involves iteratively removing outer ridge pixels.



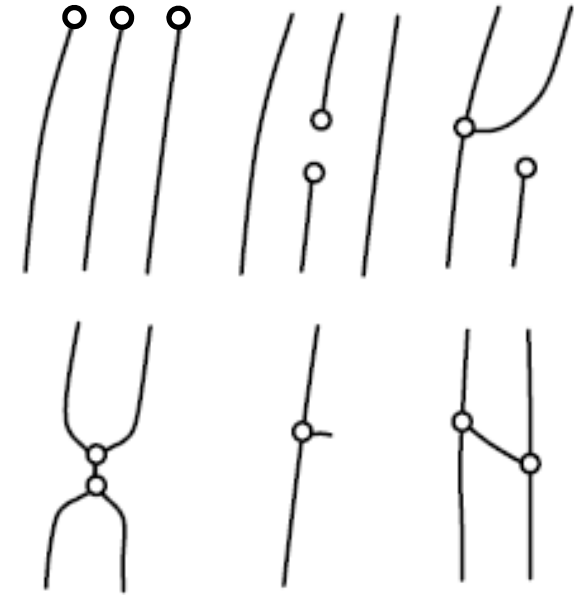
# Minutiae extraction

- Minutiae are special points on ridges:
  - ridge bifurcation (3 neighbors are black)
  - ridge ending (1 neighbor is black)
- Direction of a ridge ending:
  - Trace the associated ridge with a fixed distance (say 10 pixels) from  $x$  to  $a$ . The direction  $xa$  is the minutia direction.
- Direction of a bifurcation:
  - Trace the ridges to get three directions. The direction is the mean of the two smallest different directions.

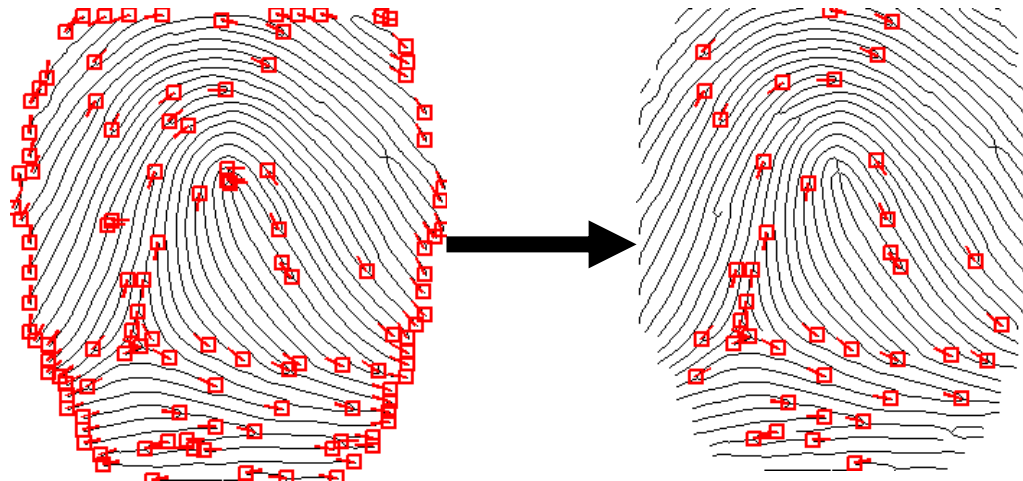


# Minutiae verification

- That method considers only  $3 \times 3$  window, producing false minutiae due to:
  - artifacts in image processing
  - noise in a fingerprint
- A minutia is classified as false if it meets any of the following conditions:
  - have no adjacent ridge on either side
  - be close in location and opposite in direction
  - too many minutiae in a small neighborhood

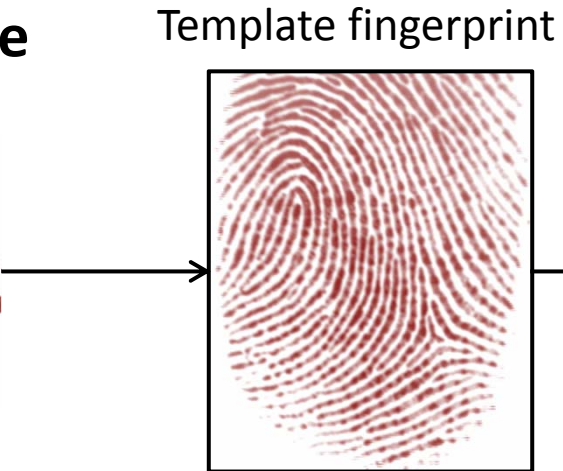


*Handbook of fingerprint recognition*



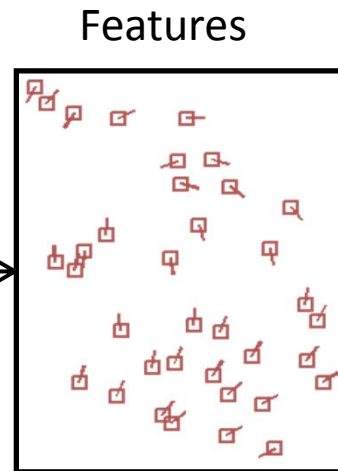
# Flowchart of fingerprint recognition

## Enrollment stage



Sensing

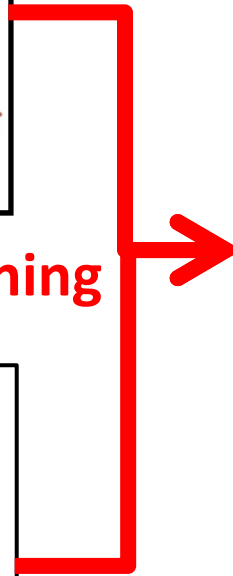
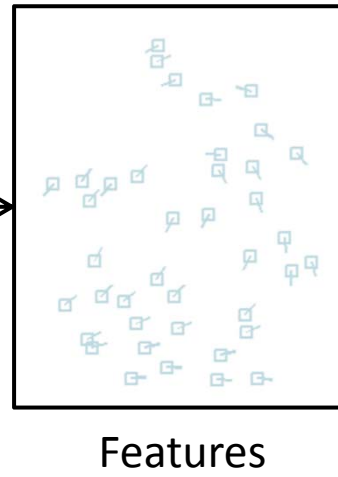
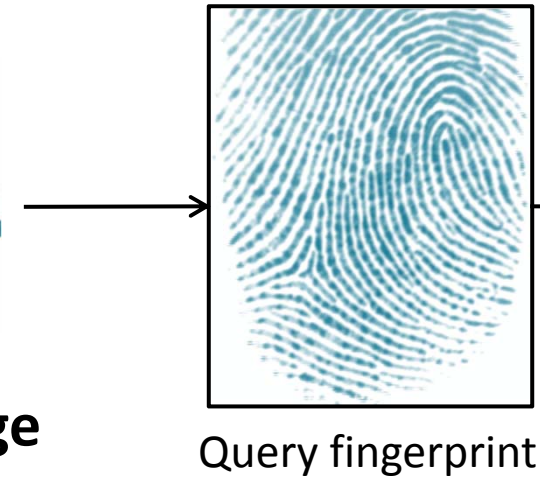
Feature extraction



Matching

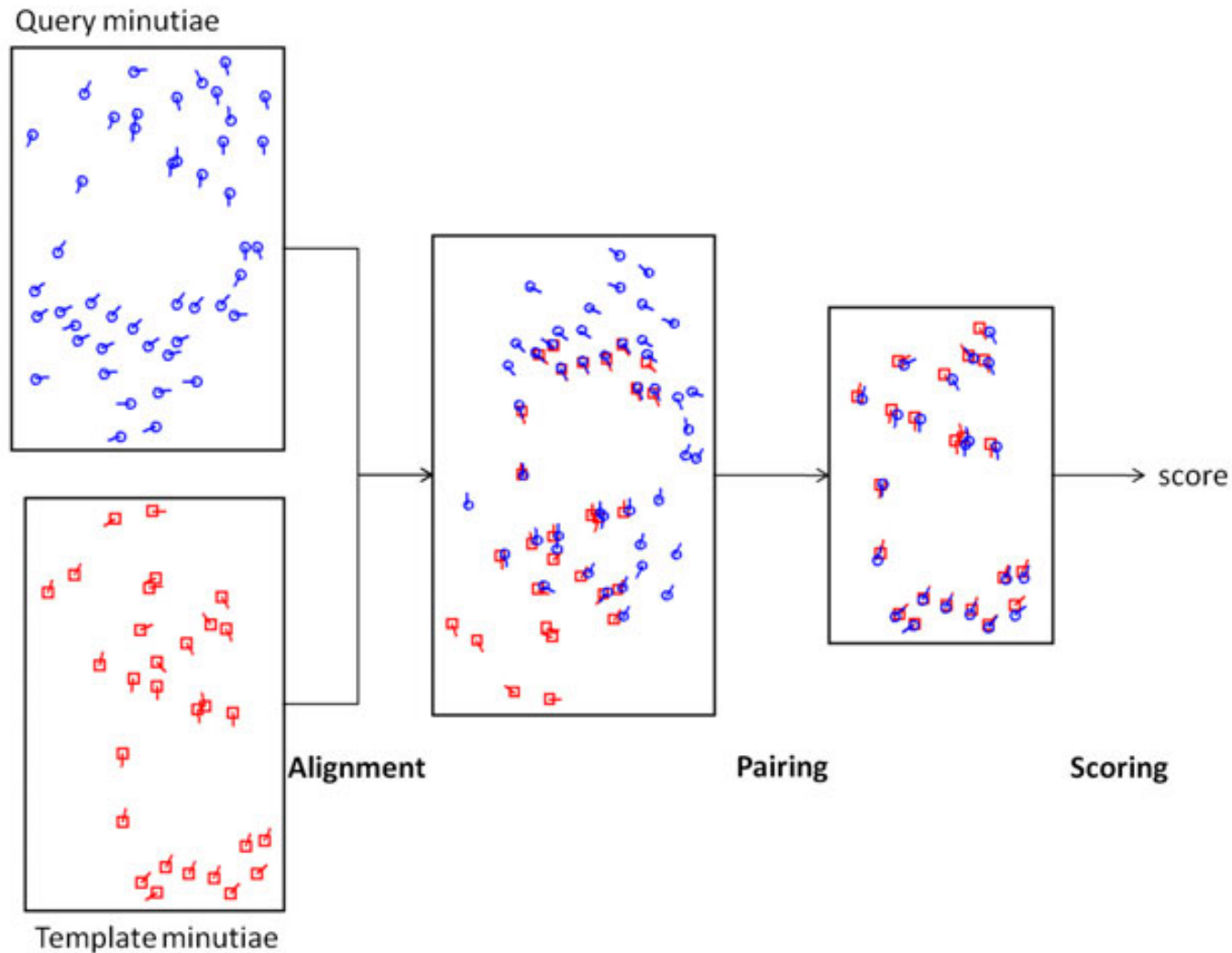
score

## Verification stage



# Minutiae matching

Almost all fingerprint matchers are based on minutiae matching.





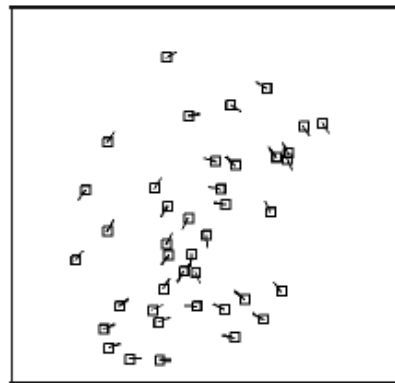
# Generalized Hough transform

GHT is a well known method for aligning two sets of minutiae:

- For every possible pair of minutiae, compute the transformation parameter and cast a vote in the parameter space.
- Find the peak in the parameter space.

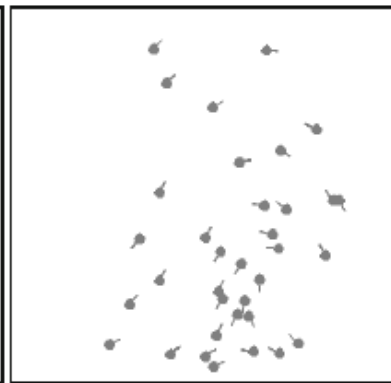
An example of GHT (assuming no rotation)

Minutia set 1



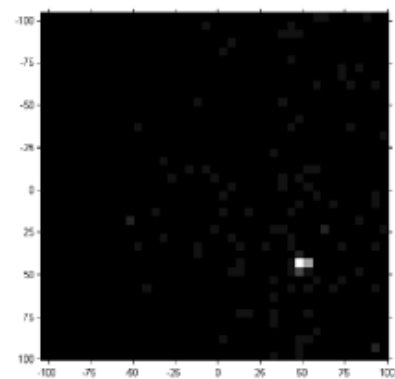
(a)

Minutia set 2



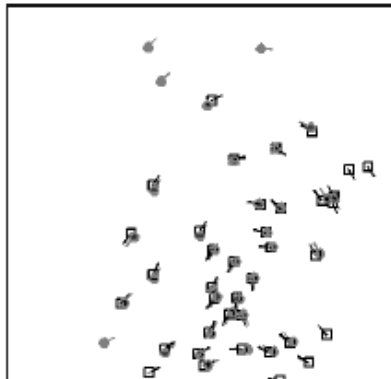
(b)

Accumulator array



(c)

Aligned two minutia sets



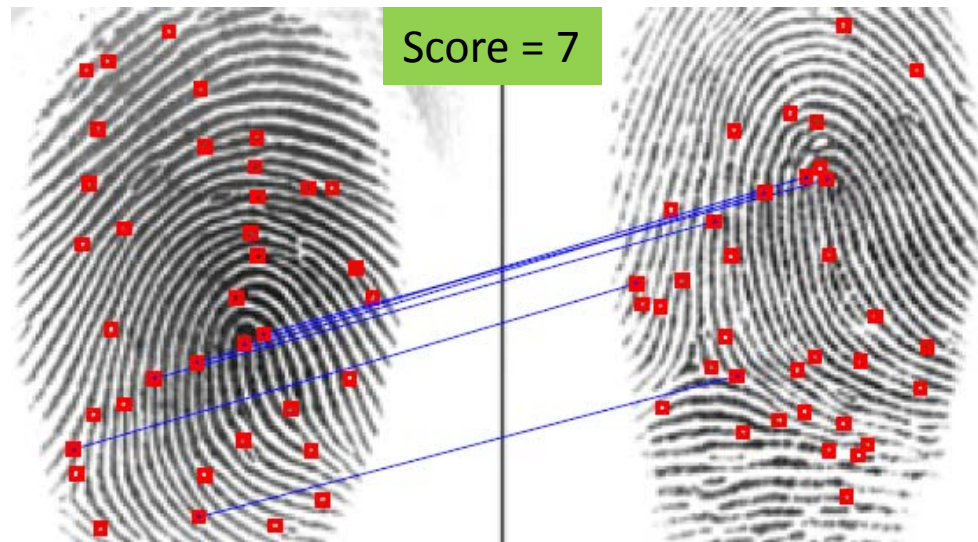
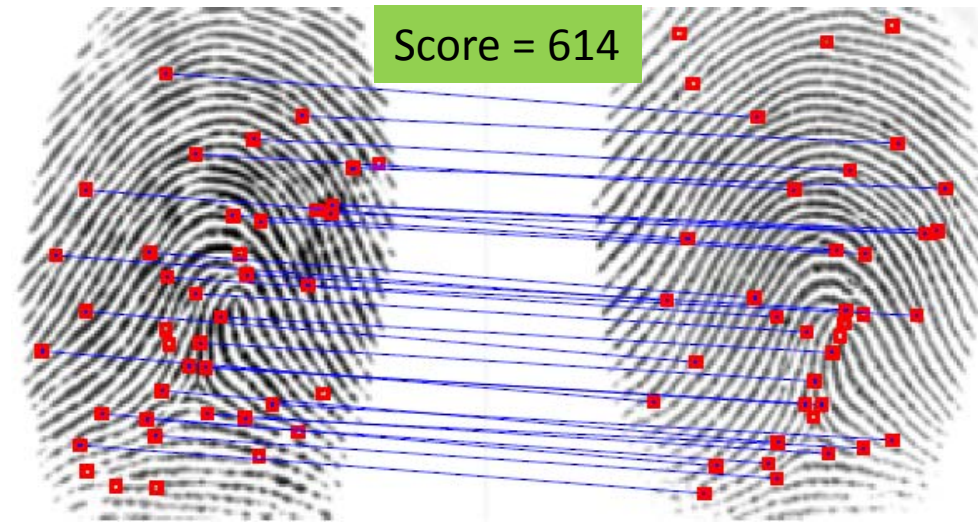
(d)

# Pairing minutiae

- When two minutiae sets are aligned, the corresponding minutiae are paired.
- A minutia  $a$  in  $T$  is paired with minutia  $b$  in  $Q$  iif
  - their distance is within predefined distance threshold;
  - the angle between their directions is within predefined angle threshold.

# Match score generation

- Matched minutiae and match scores of a genuine match and an imposter match using a commercial matcher, VeriFinger.
- The match scores are computed by some function of # matched minutiae, # missed minutiae, distortion, and some other features that are proprietary.



# Unsolved problems

- Recognition performance for low quality fingerprints is poor
- There are two types of low quality fingerprints:
  - Strong noise
  - Large skin distortion



# Outline

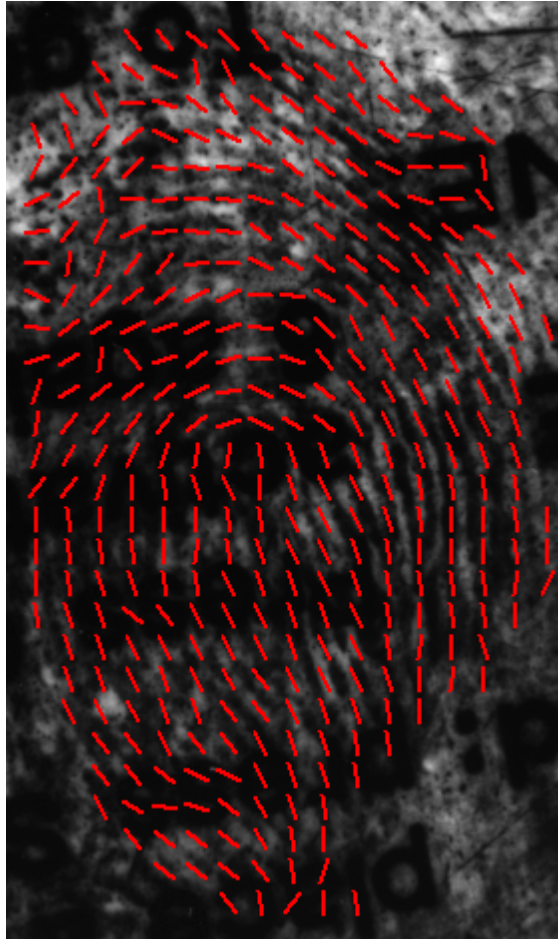
- Basics of fingerprint recognition
  - **Fingerprint orientation field estimation**
  - Detection and rectification of distorted fingerprint
- 
- J. Feng, J. Zhou, A. K. Jain, "Orientation field estimation for latent fingerprint enhancement", PAMI 2013.
  - X. Yang, J. Feng, J. Zhou, "Localized Dictionaries Based Orientation Field Estimation for Latent Fingerprints", PAMI 2014.

# Orientation field estimation

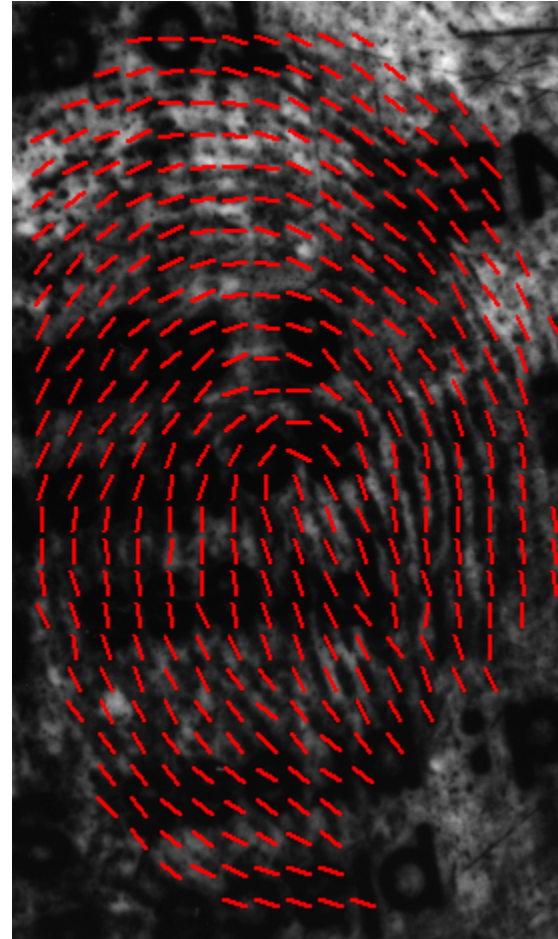
- OF estimation is **the most critical step** in fingerprint feature extraction; Extraction of ridge and minutiae depends on it.
- Most OF estimation algorithms have 2 steps:
  - Local estimation: gradient, DFT, ...
  - OF regularization: low pass filtering, global parametric model, ...
- For fingerprints captured by inking or livescan methods, these algorithms are reasonably good.

# OF estimation for latent

Gradient  
+FOMFE

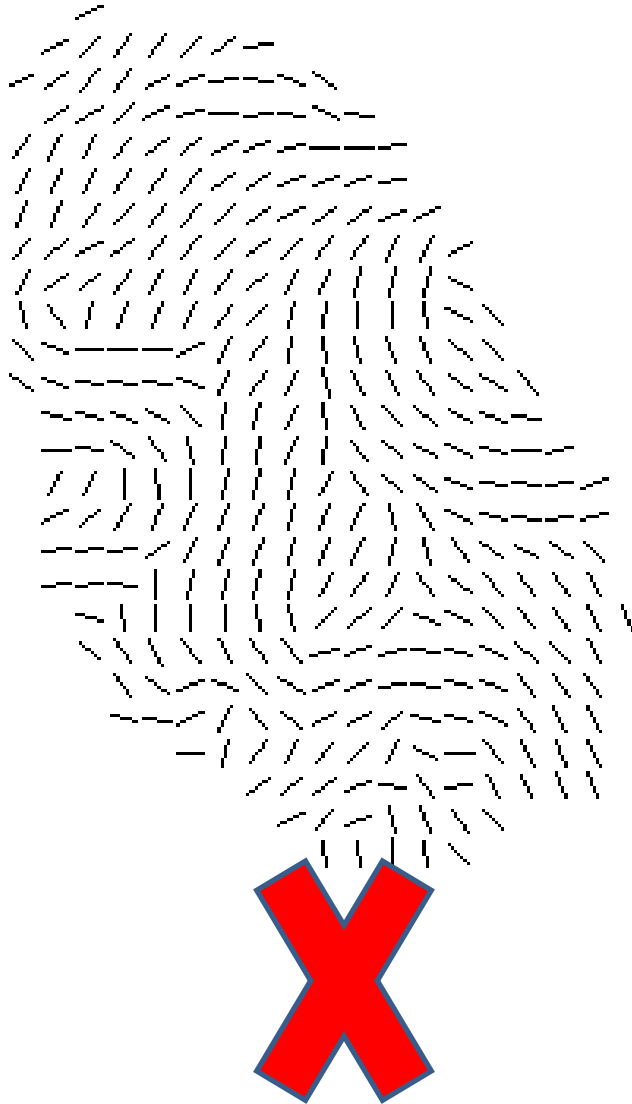


Manual



**Why human performs much better than the algorithm?**

# Is this OF correct?



Even without seeing the fingerprint, we are sure that this orientation field must be wrong.

Because we have prior knowledge on fingerprint.

Fingerprint experts are good at marking features in latents because they are very knowledgeable on FP.



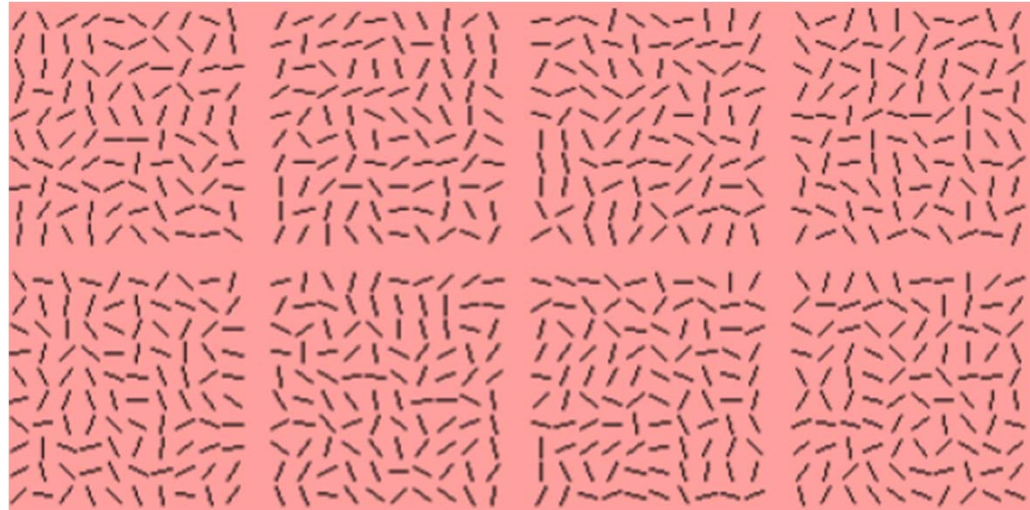
# Use prior knowledge

- We can develop a better OF estimation algorithm if prior knowledge of fingerprints can be used.
- How to represent, learn, and use prior knowledge?
- We do not know how prior knowledge on fingerprint OF is represented in the human (fingerprint examiners) brain.
- Inspired by spelling check technique, we represent prior knowledge using dictionary.

# Represent prior knowledge via dictionary

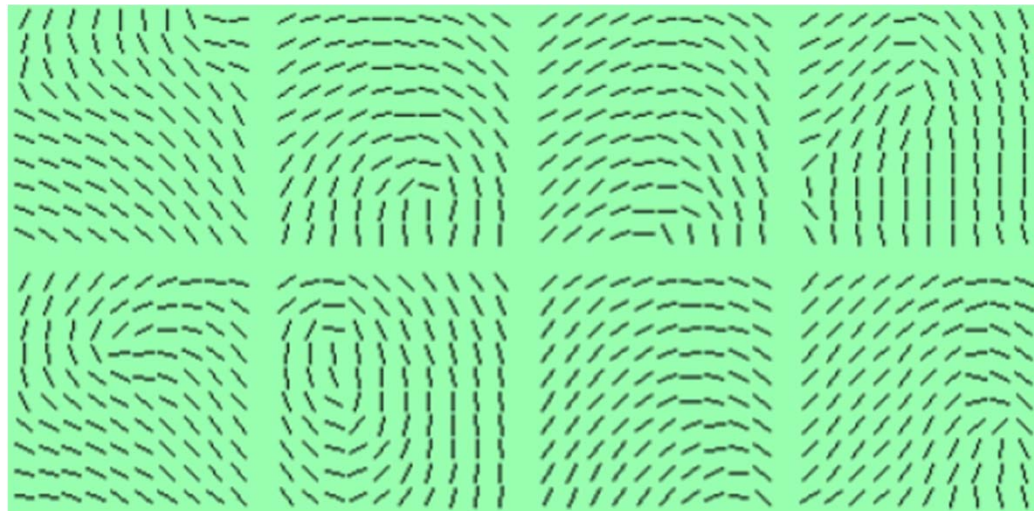
Invalid

zzzzzz  
abxxde  
lxlsoa  
dsfwws  
iuytrs  
yyuooj



Valid

work  
biometric  
topic  
talk  
add  
together

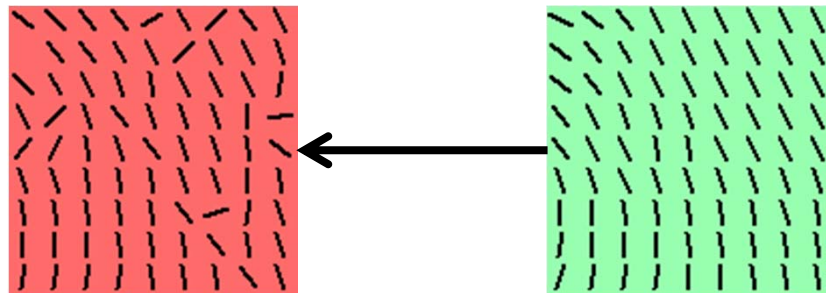
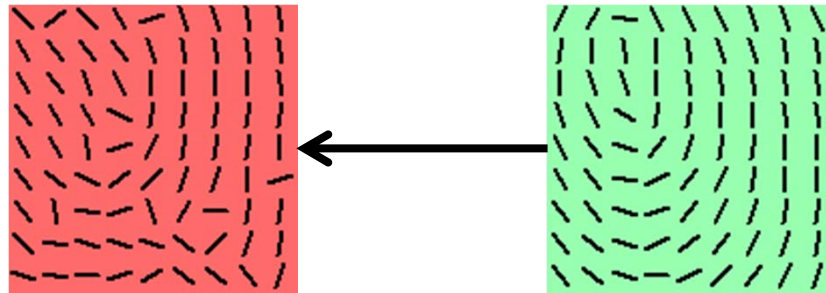


Words

Orientation patches

# Error correction via dictionary

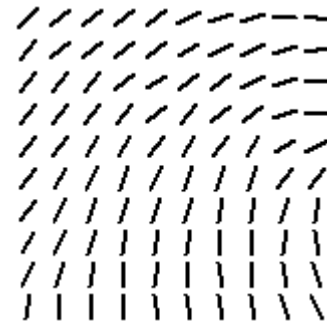
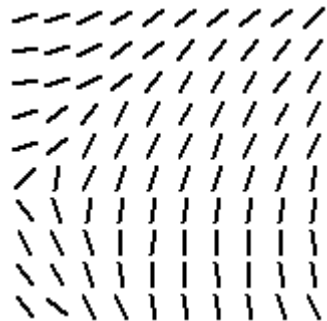
beaiteful ← beautiful  
charactorestic ← characteristic



# Ambiguity

frea

freak, free, flea, area?



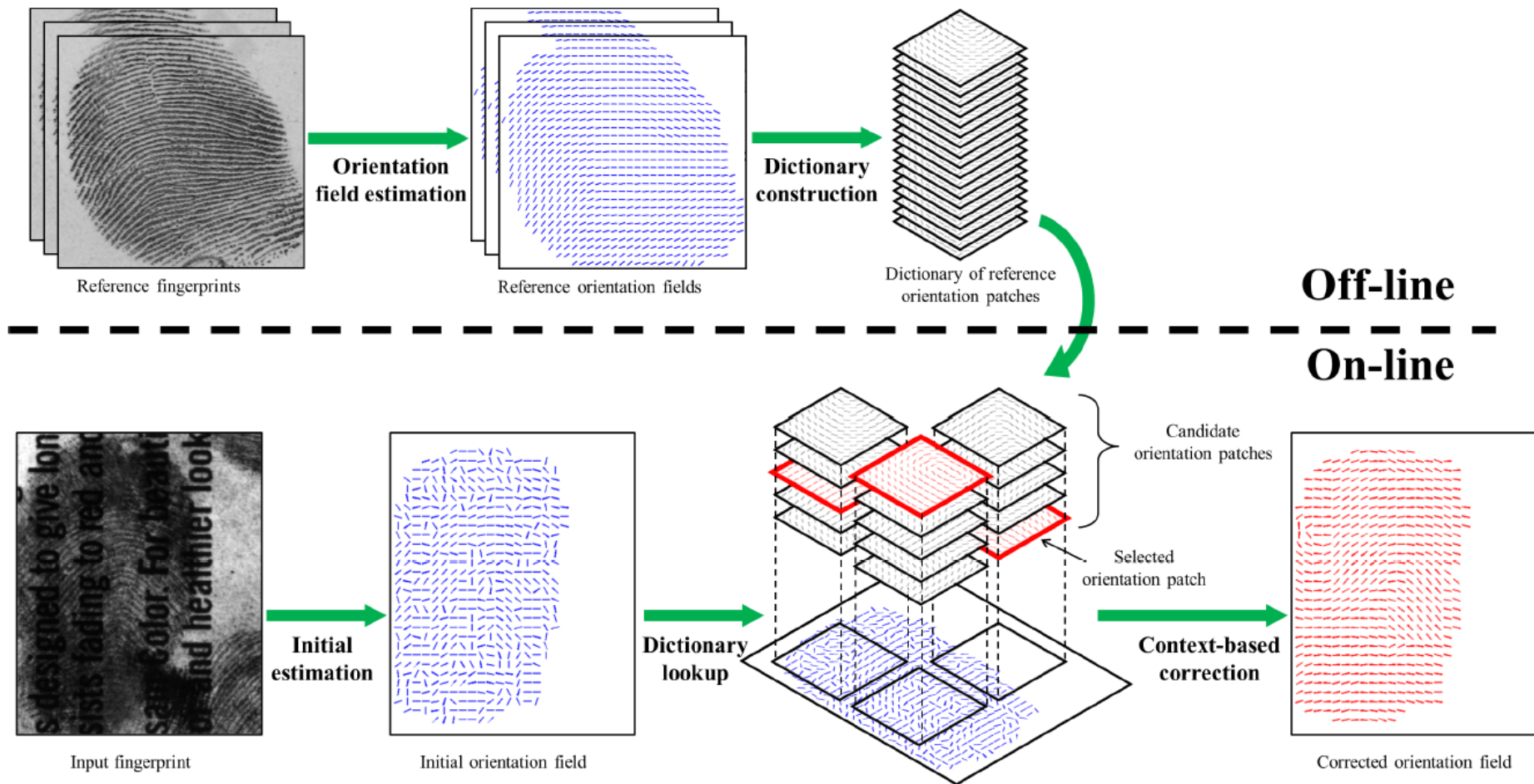
?

If we know the context, we can resolve the ambiguity.

There is no such thing  
as a frea lunch.

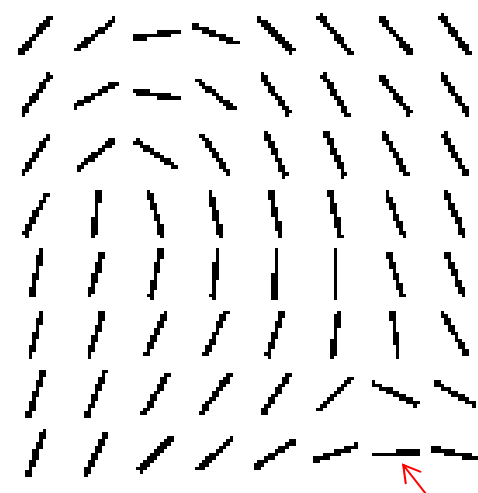
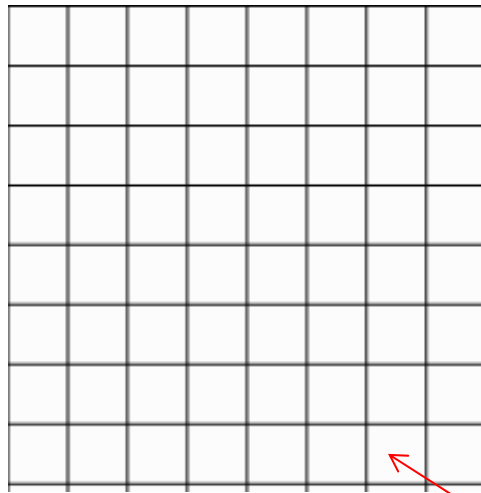
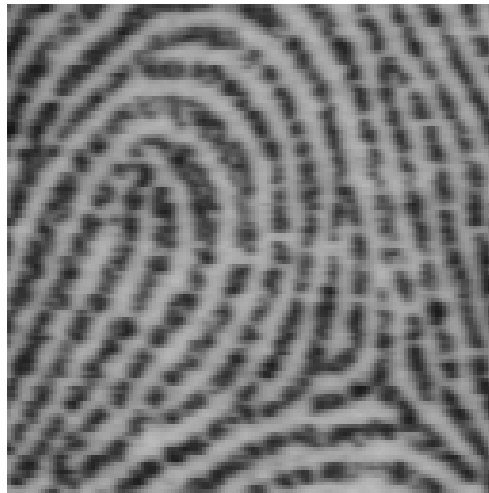
free

# Flowchart



J. Feng, J. Zhou, A. K. Jain, "Orientation field estimation for latent fingerprint enhancement", PAMI 2013.

# Dictionary of orientation patches



Block

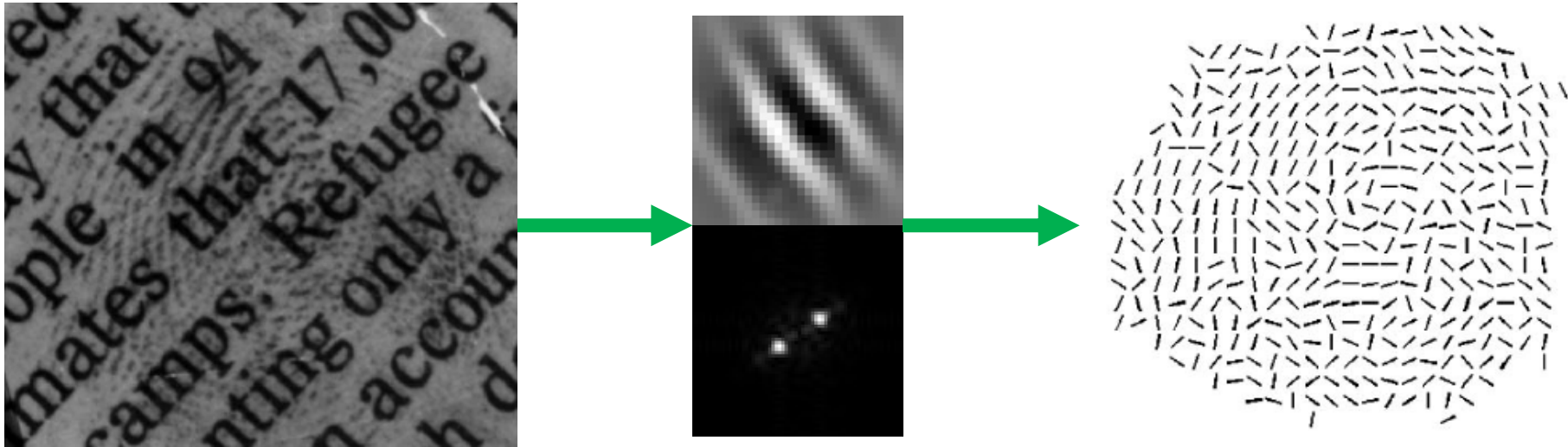
Orientation  
element

- The dictionary consists of a number of orientation patches of the same size.
- An orientation patch consists of  $8 \times 8$  orientation elements.
- An orientation element refers to the dominant orientation in a block of  $16 \times 16$  pixels.

# Dictionary learning

- We construct a dictionary of orientation patches from a set of high-quality fingerprints.
- The orientation fields are estimated using VeriFinger 6.2 SDK.
- High quality fingerprints and commercial algorithm are used to ensure that the dictionary does not contain invalid words.
- A number of orientation patches are obtained by sliding a window across each orientation field.
- Since direction of latent fingerprint is unknown, each orientation patch is rotated by different angles  $[-50, 50]$  to generate additional patches.

# Initial estimation



- Initial orientation field is obtained by local Fourier analysis.
- Although it is very noisy, smoothing should be avoided since correct orientation elements may even be degraded by strong noise in the neighborhood.
- Correcting OF is left to later stages



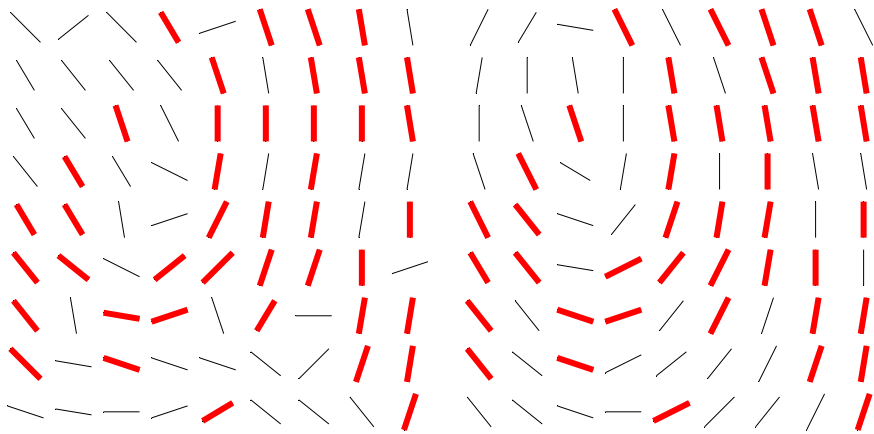
# Dictionary lookup: similarity measure

We need a similarity measure which is robust to severe noise.

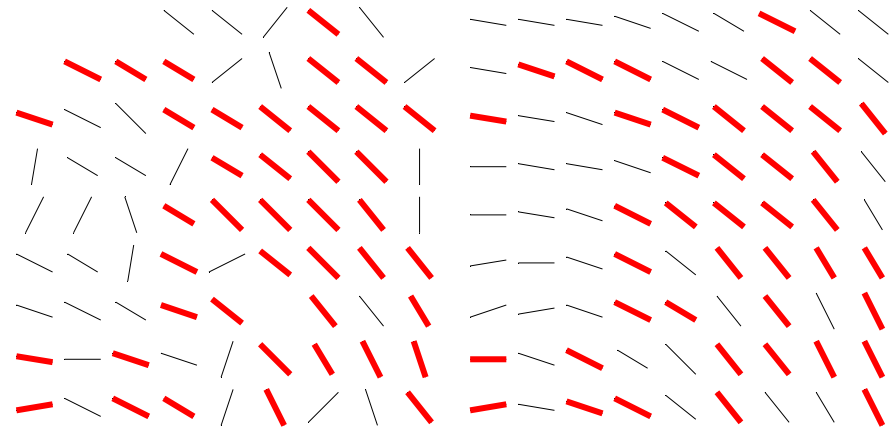
The similarity between two patches is defined as  $n_s/n_f$ .

$n_f$ : # orientation elements in the initial orientation patch.

$n_s$ : # orientation elements whose differences are less than a 10.

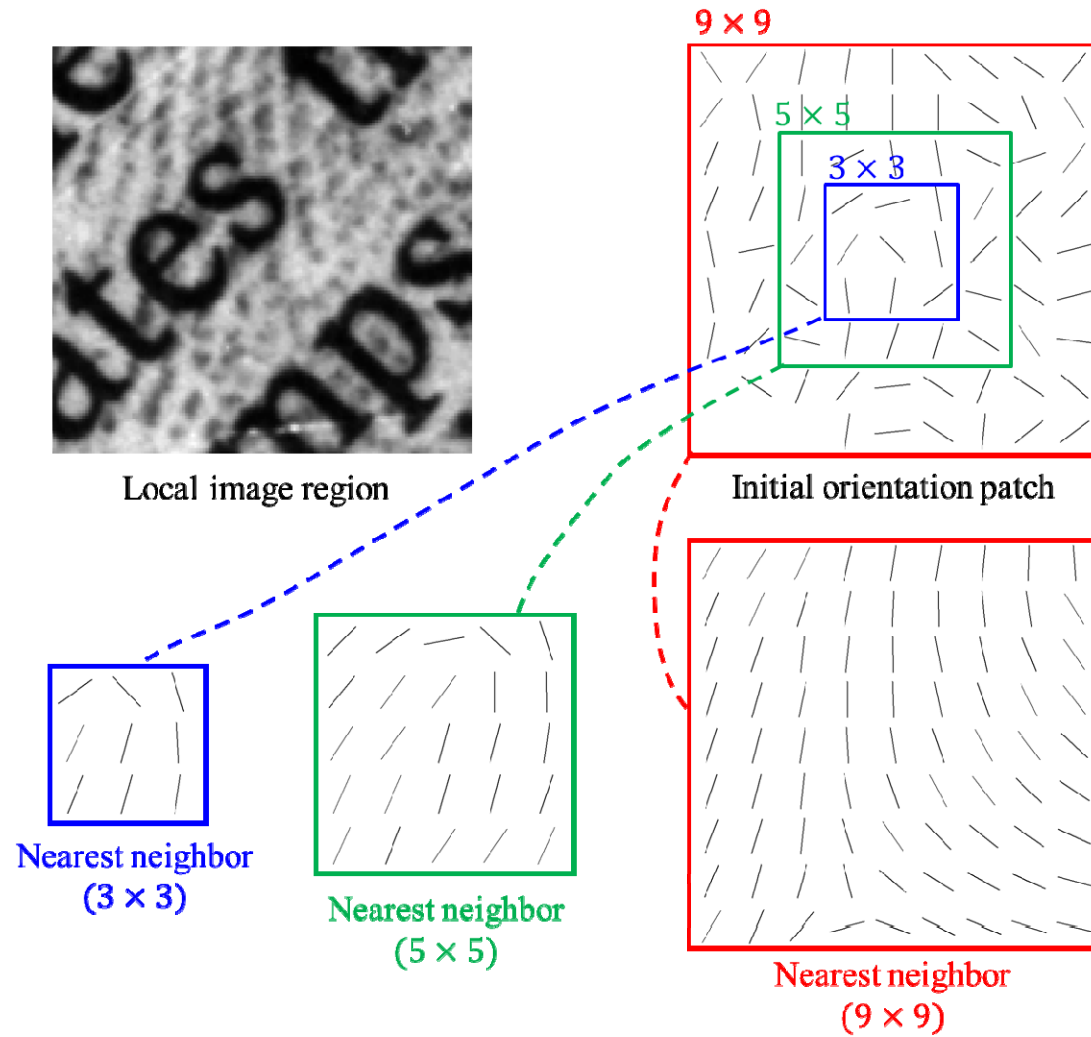


similarity: 42/81

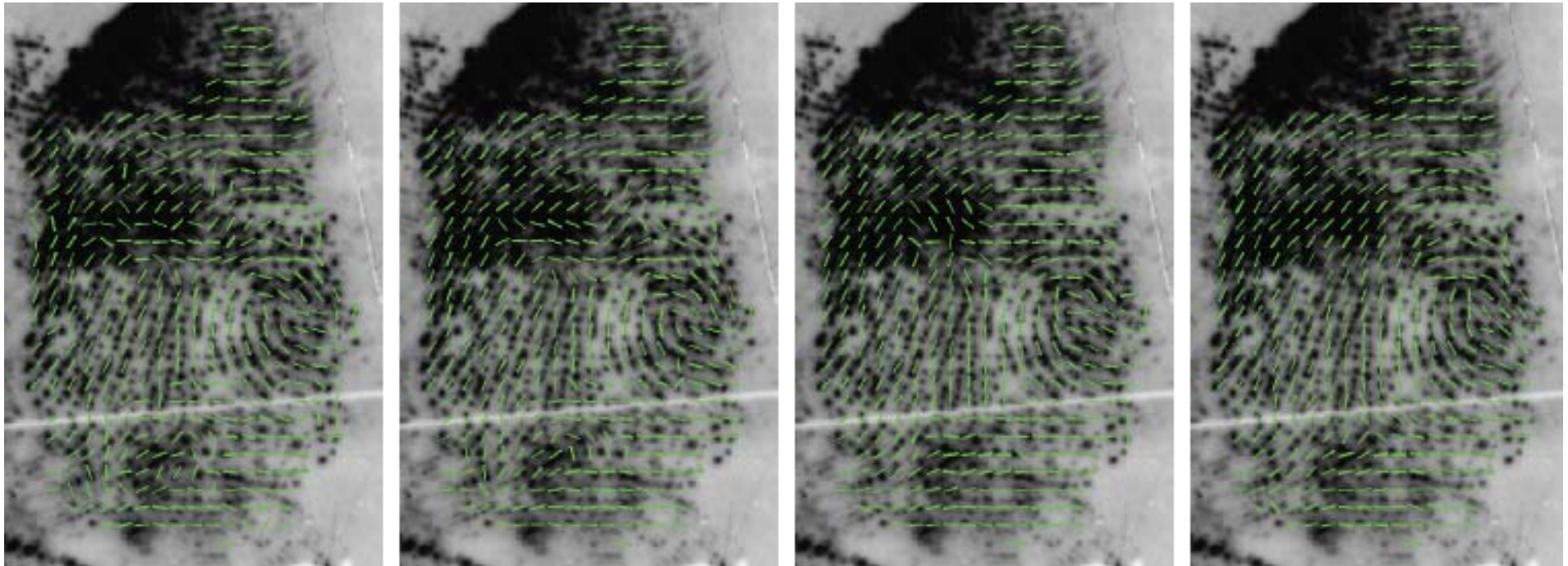


similarity: 42/75

# Dictionary lookup: patch size



# Dictionary lookup: patch size



$3 \times 3$

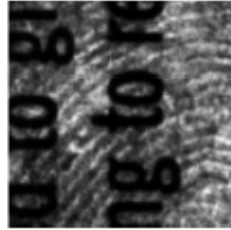
$5 \times 5$

$7 \times 7$

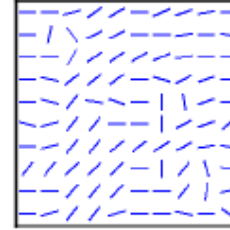
$9 \times 9$

- Performance of OF estimation using different patch sizes
- Larger patch size is more powerful in correcting error
- Note that context information is not used here

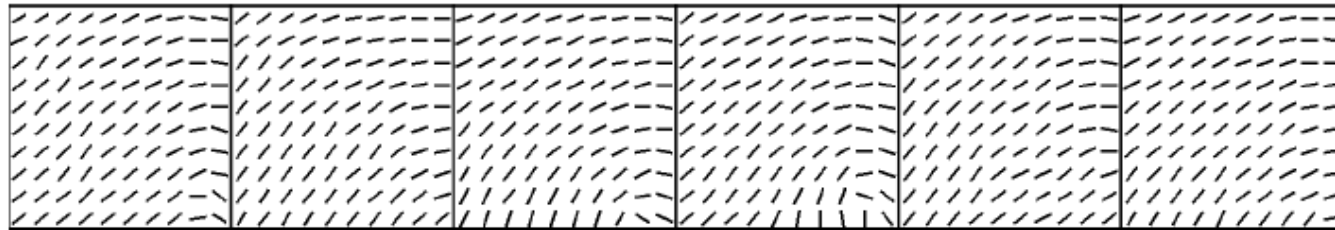
# Dictionary lookup: diversity



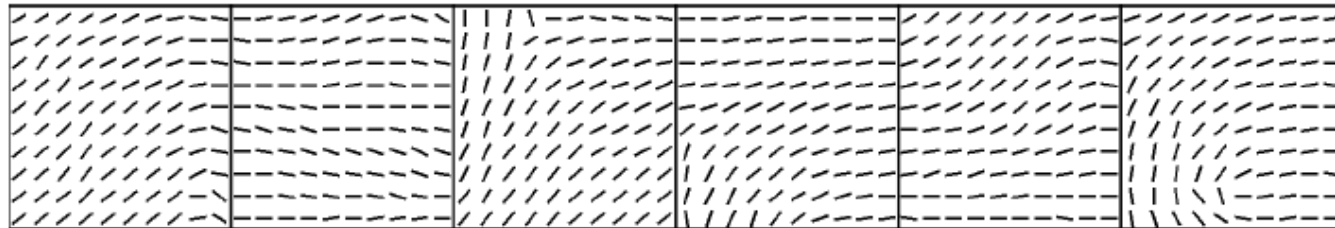
(a) Image patch



(b) Initial orientation patch



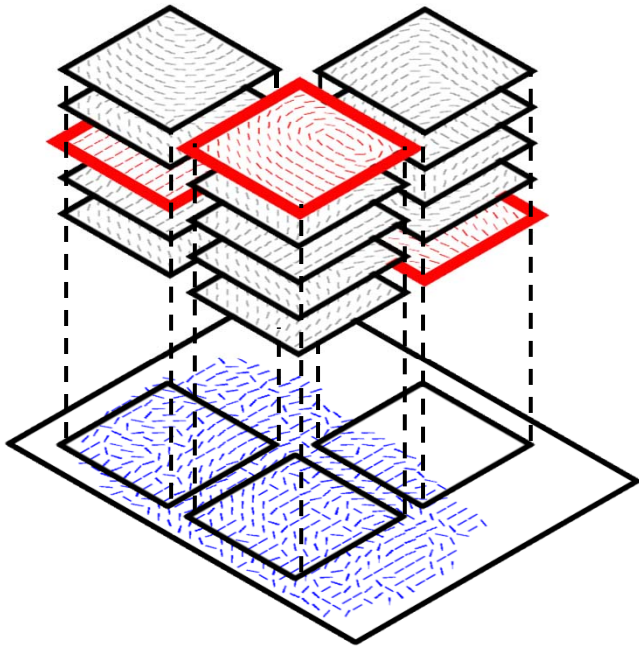
(c) Retrieved candidate patches without diversity rule



(d) Retrieved candidate patches with diversity rule

# Context-based correction: energy function

After dictionary lookup, we obtain a list of candidate orientation patches  $\{\Phi_{i,1}, \Phi_{i,2}, \dots, \Phi_{i,6}\}$  for an initial orientation patch  $\Theta_i$ . We search for a set of candidates (shown as red patches),  $\mathbf{r} = (r_1, r_2, \dots, r_{n_p})$ , which minimizes an energy function  $E(\mathbf{r})$ .



$$E(\mathbf{r}) = E_s(\mathbf{r}) + w_c E_c(\mathbf{r})$$

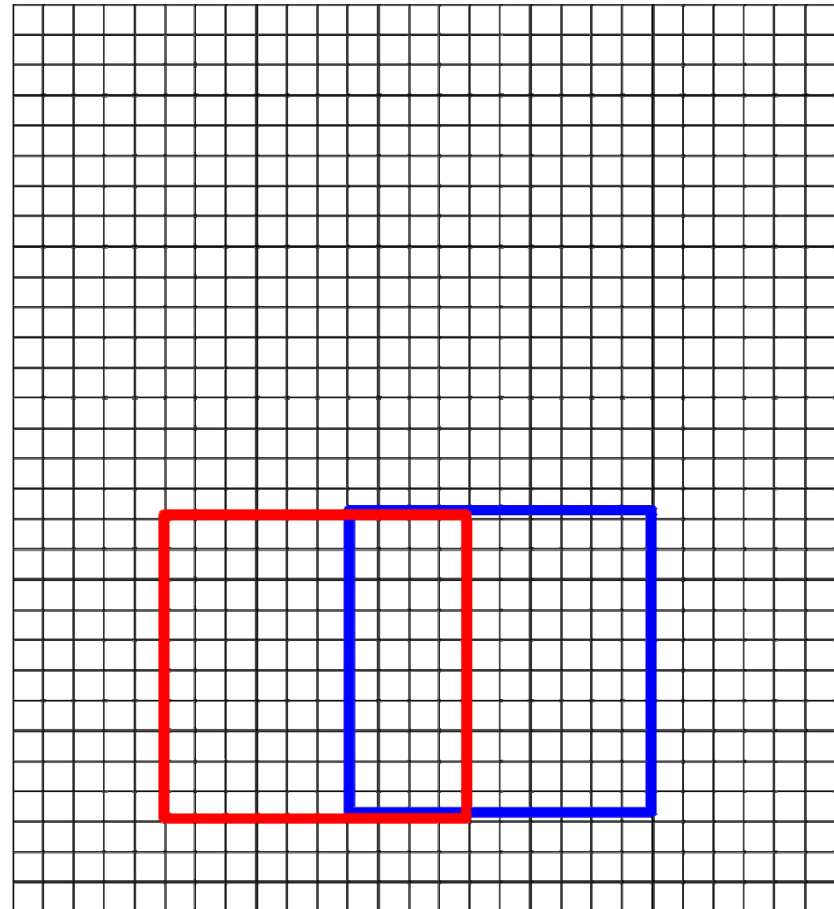
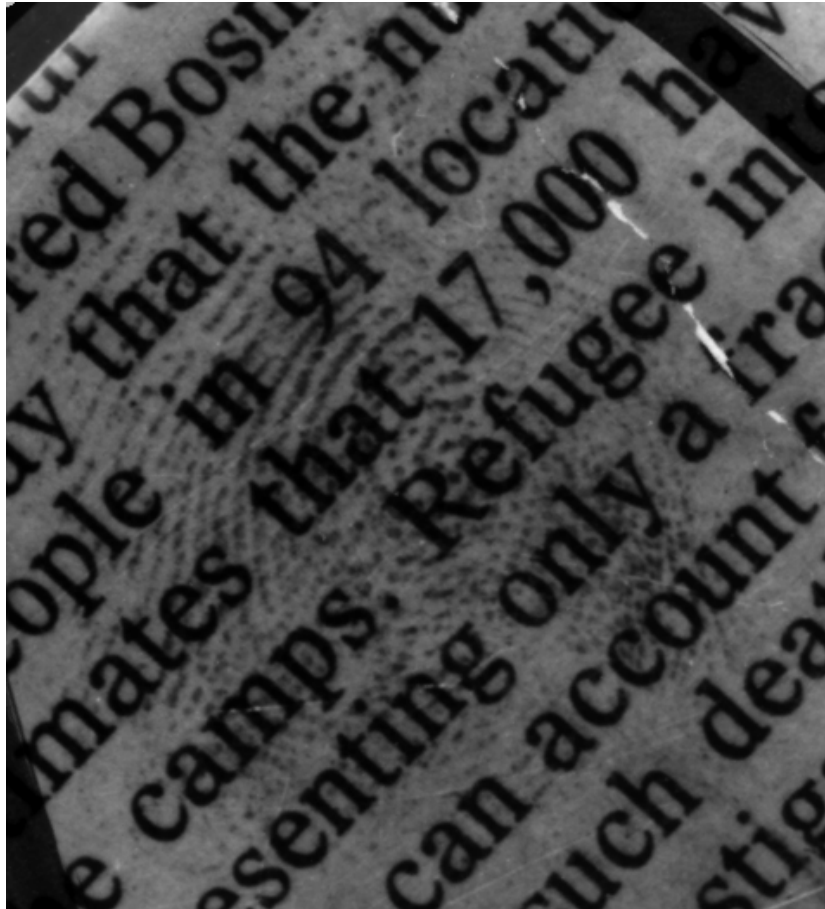
$$E_s(\mathbf{r}) = \sum_{i \in \mathcal{V}} (1 - S(\Theta_i, \Phi_{i,r_i}))$$

$$E_c(\mathbf{r}) = \sum_{(i,j) \in \mathcal{N}} (1 - C(\Phi_{i,r_i}, \Phi_{j,r_j}))$$

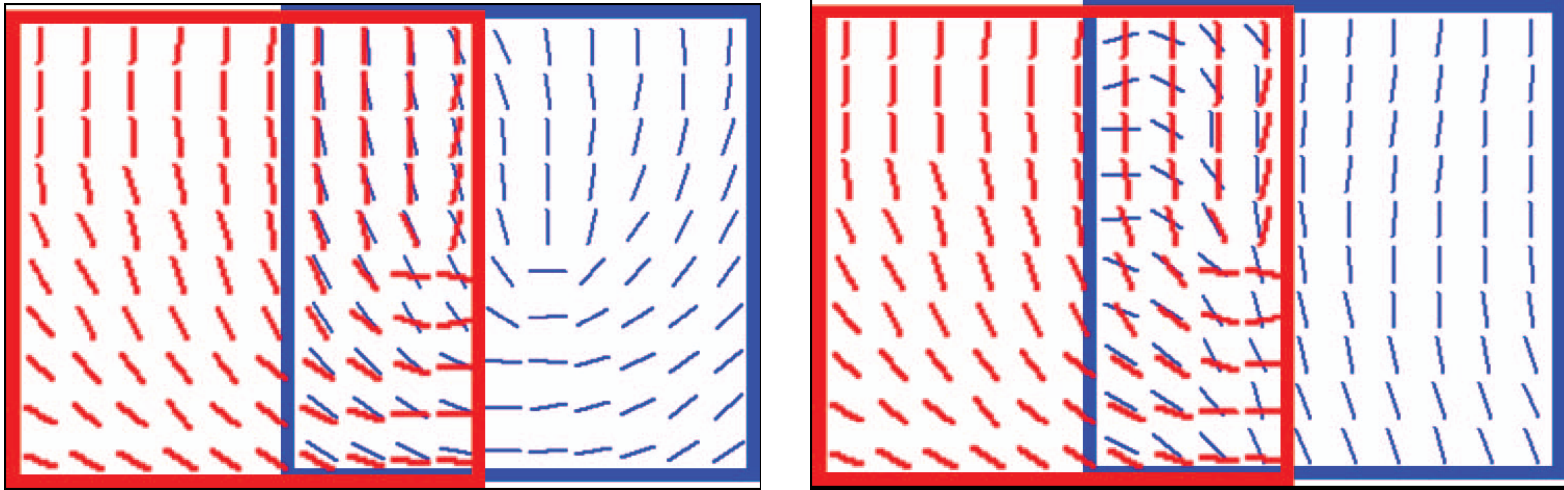
# Context-based correction: compatibility

Adjacent patches are overlapped.

Compatibility between two adjacent orientation patches is measured by the similarity of orientations in the overlapping blocks.

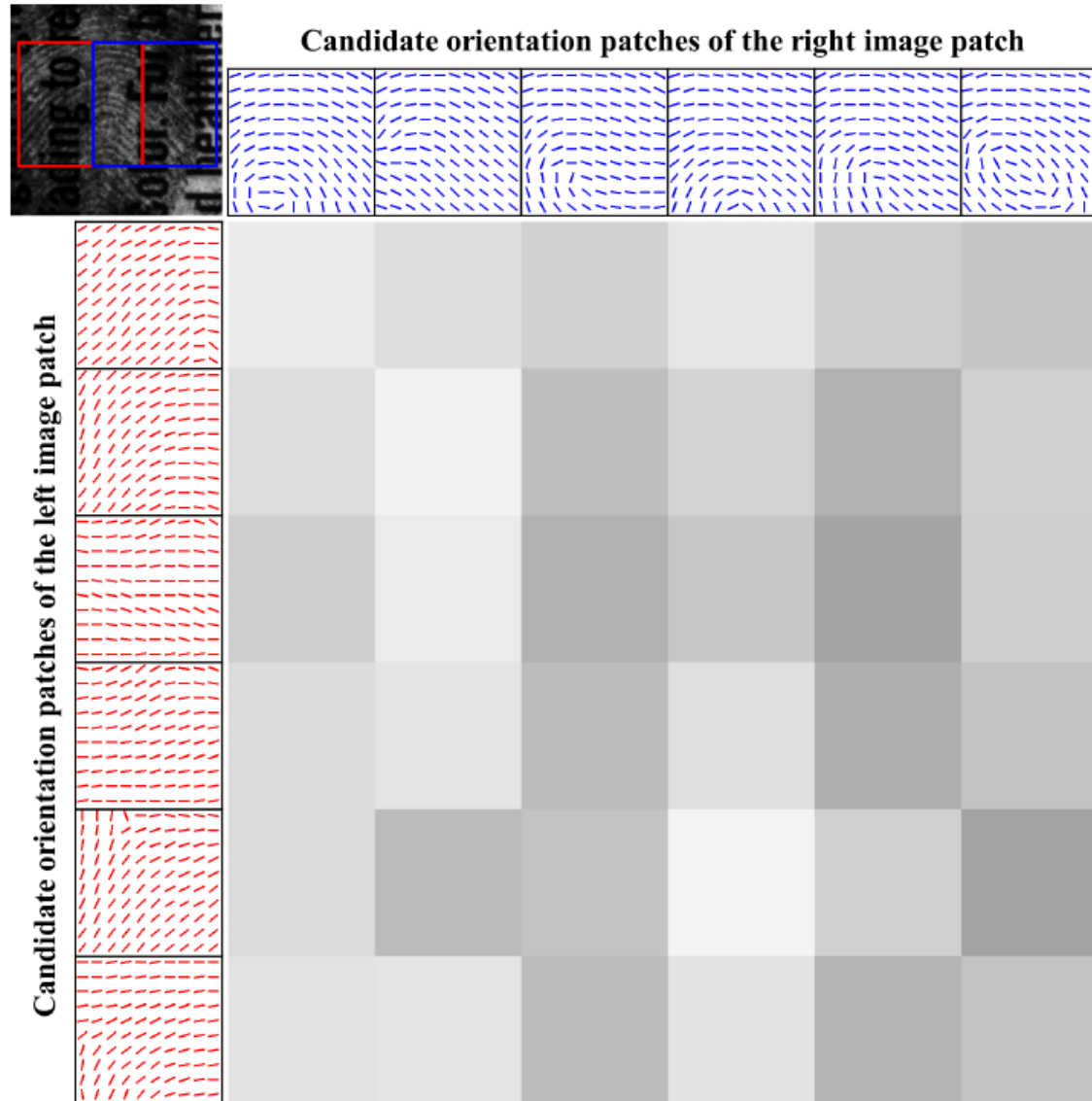


# Context-based correction: compatibility



The left one has a high compatibility value. The right one has a low compatibility value.

# Context-based correction: compatibility

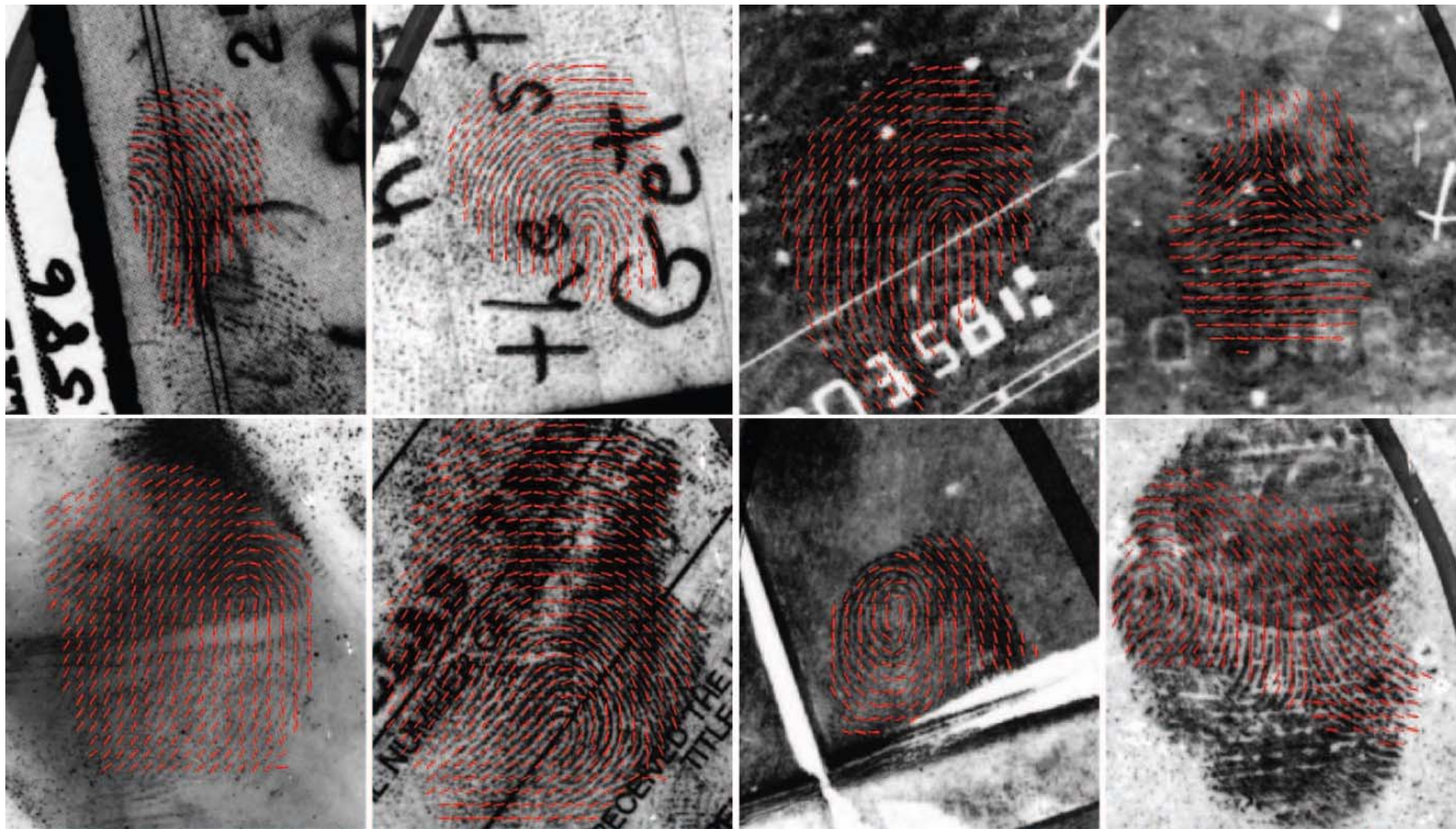




# Experiment

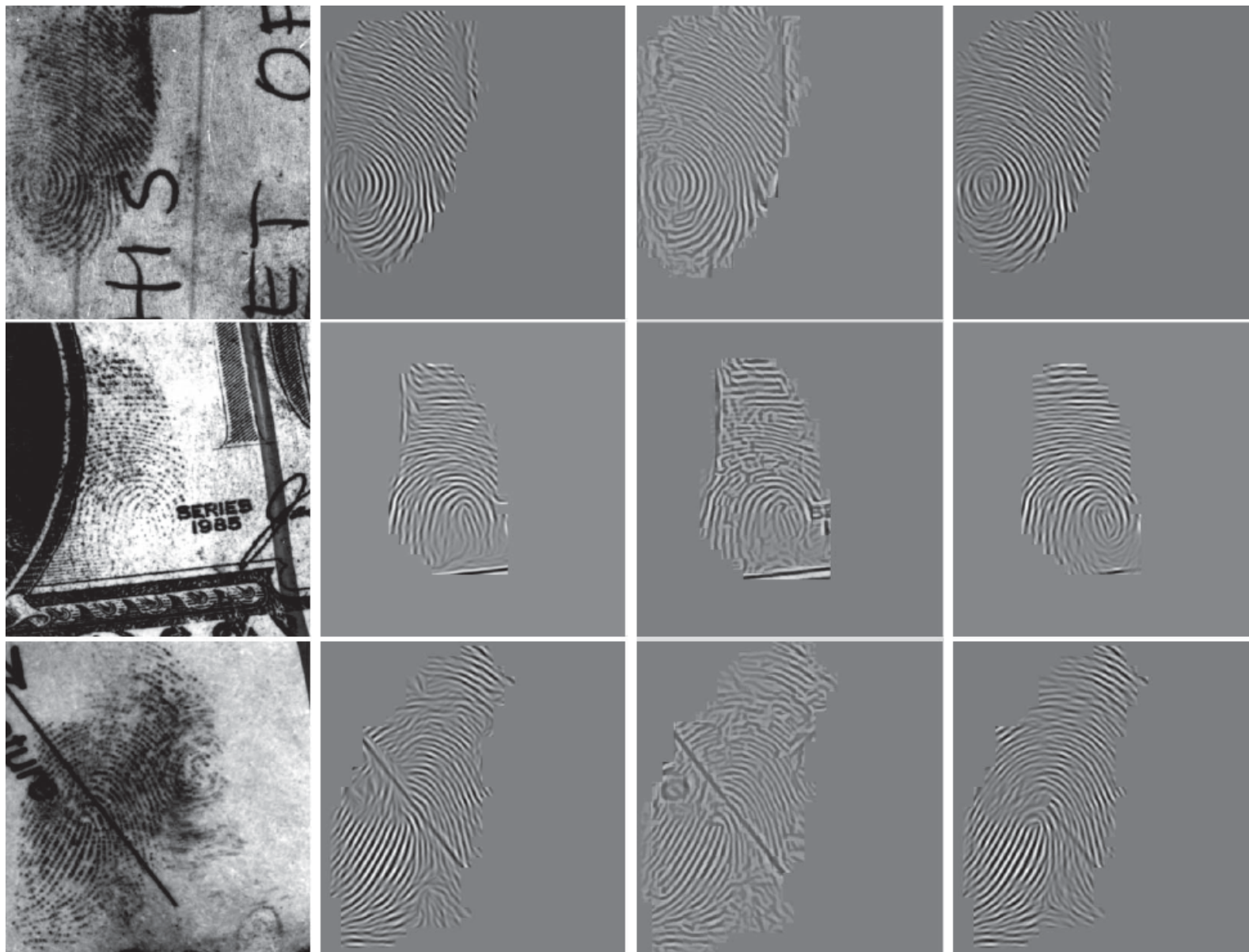
- Database:
  - NIST Special Database 27 contains 258 latent fingerprints and their corresponding rolled fingerprints.
  - To make matching problem more realistic and challenging, 27K rolled fingerprints in NIST SD14 were used as the background database.
- Two types of evaluation
  - Accuracy of orientation field estimation
  - Matching accuracy

# Results



Examples from NIST-27

# Comparison of OF algorithms



Gradient+FOMFE

STFT+smoothing

Dictionary

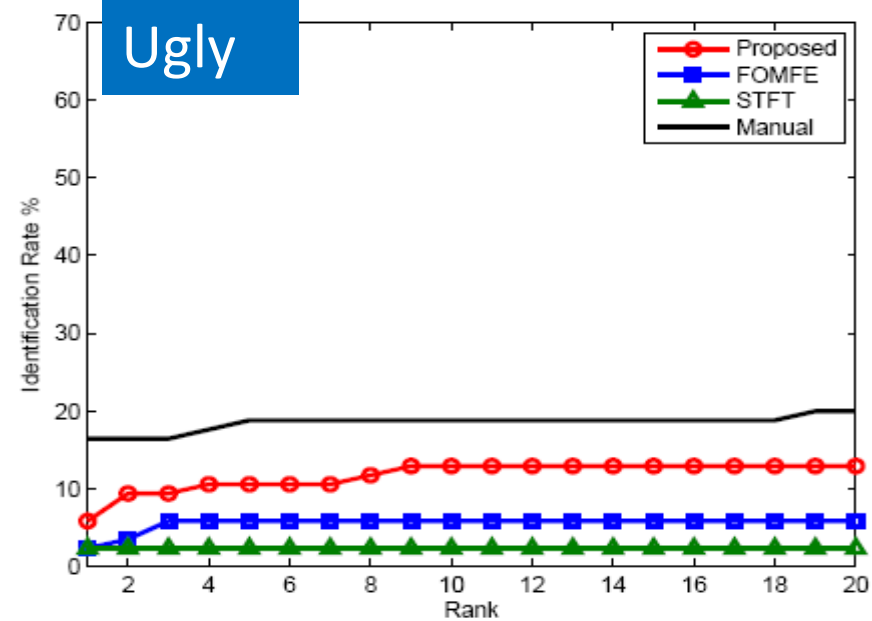
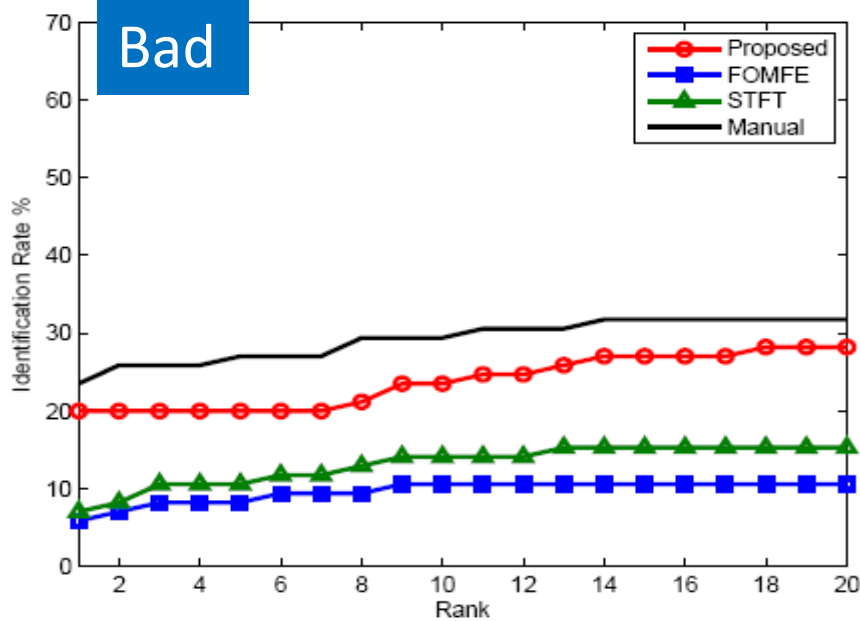
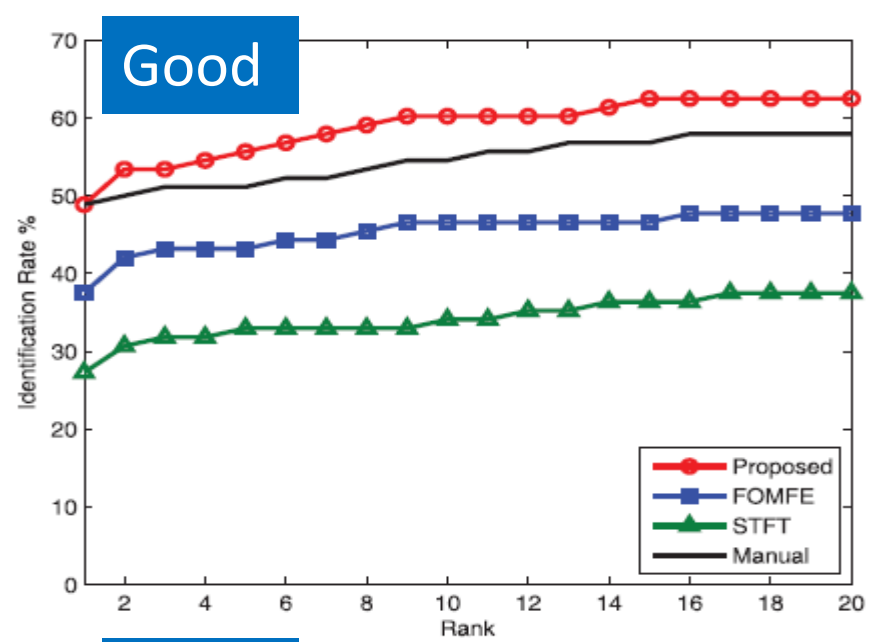
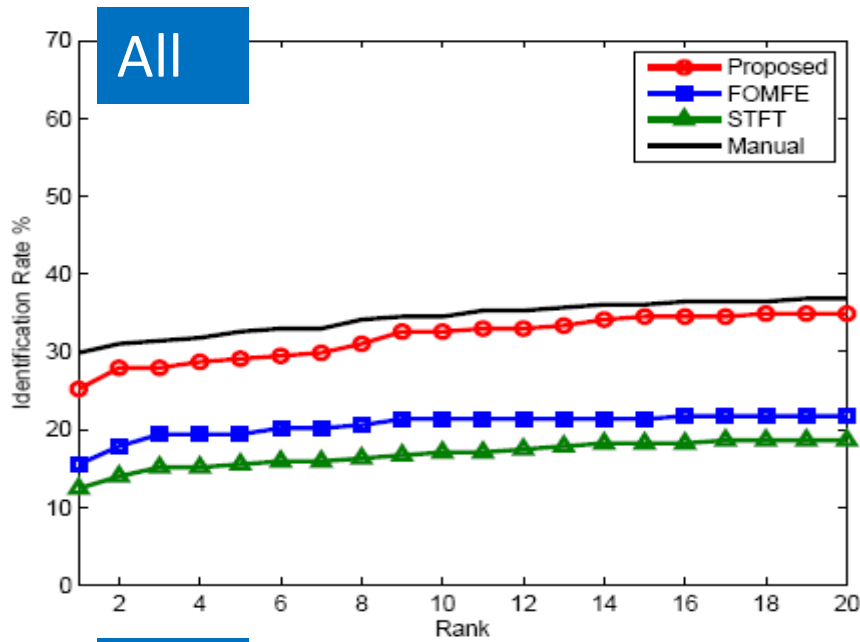
# Accuracy of OF estimation

- Data: whole NIST-27 and each of 3 subsets, good (88), bad (85), ugly (85)
- Measure: average Root Mean Square Deviation (RMSD) from the manually marked orientation fields

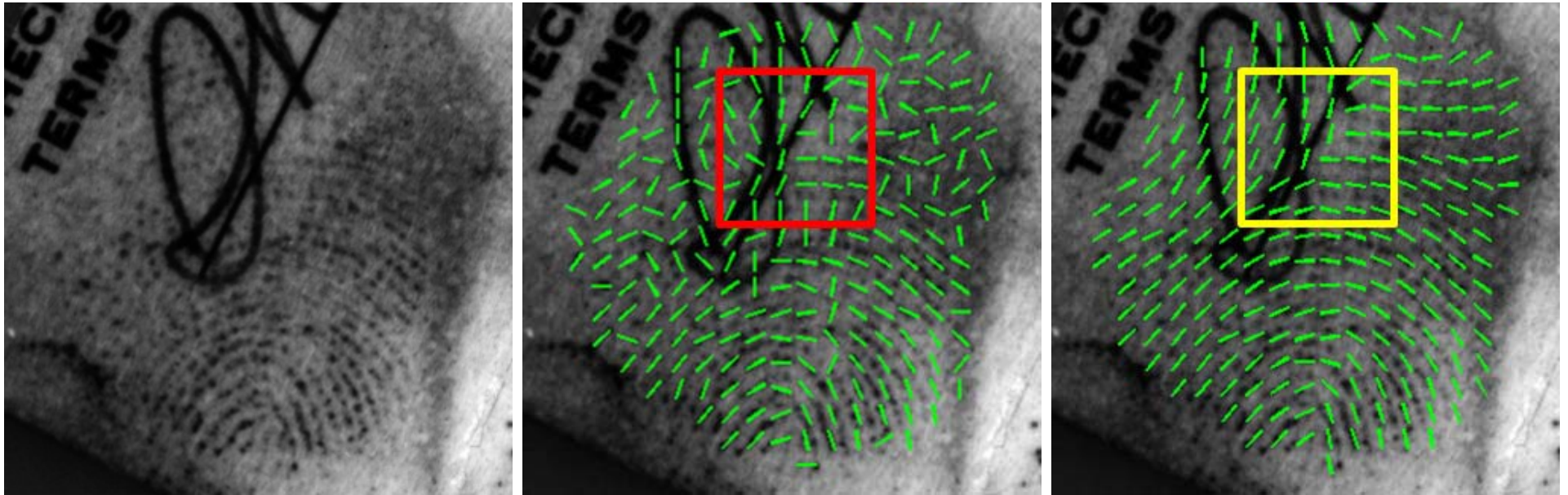
$$RMSD(\mathbf{D}, G) = \sqrt{\frac{\sum_{(i,j) \in F} d\phi(\theta_{i,j}, \theta_{i,j}^g)^2}{|F|}}$$

| <b>Algorithm</b> | <b>All</b> | <b>Good</b> | <b>Bad</b> | <b>Ugly</b> |
|------------------|------------|-------------|------------|-------------|
| Proposed         | 18.44      | 14.40       | 19.18      | 21.88       |
| FOMFE [25]       | 28.12      | 22.83       | 29.09      | 32.63       |
| STFT [11]        | 32.51      | 27.27       | 34.10      | 36.36       |

# Match accuracy on NIST-27



# Limitation of global dictionary



Orientation field by STFT

Orientation field by GlobalDict

The orientation field by STFT contains a lot of non-word errors as marked by the red box, while the orientation field by GlobalDict contains real word errors as marked by the yellow box.

We need stronger prior knowledge (location related).

# Prior knowledge



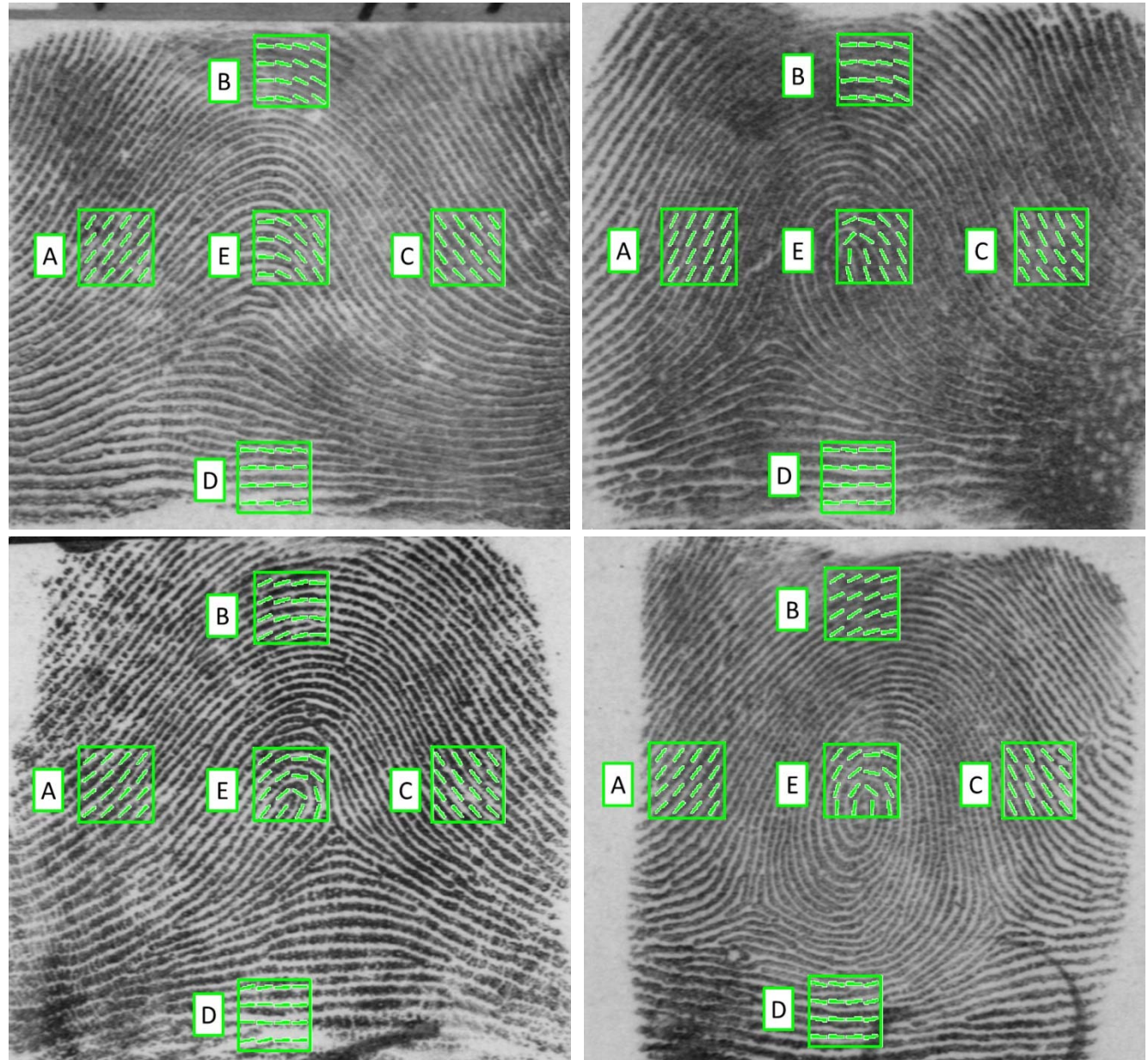
- Ridges on the fingertip always flow along the boundary
- Ridges on the finger joint always flow along the joint

# Prior knowledge

4 roughly aligned fingerprints (arch, right loop, left loop, whorl).

We observed:

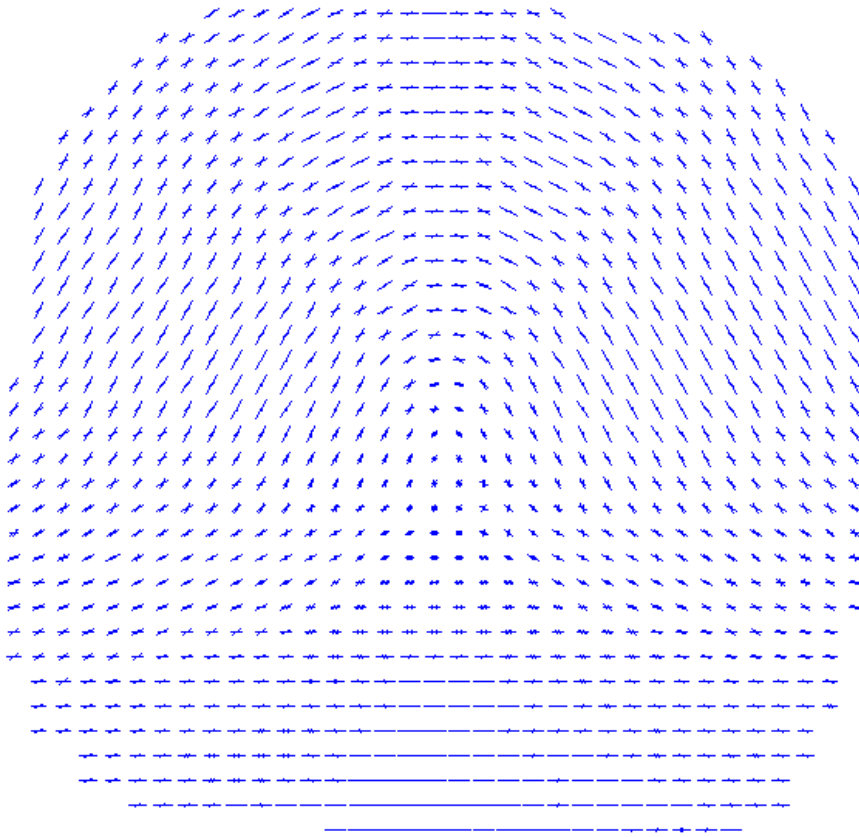
1. Orientation patches at the corresponding location in different fingerprints are similar;
2. Orientation patches at different locations are dissimilar.
3. Orientation patches in the center are more diverse



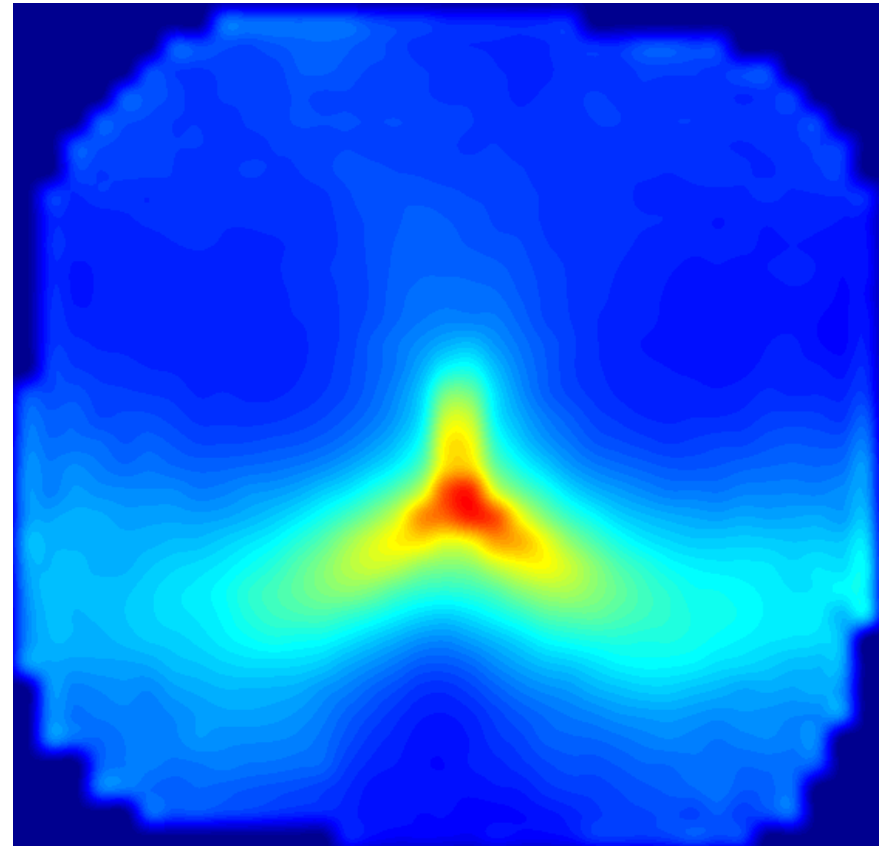


# Prior knowledge

The observations are also validated using statistics estimated from 398 registered orientation fields.



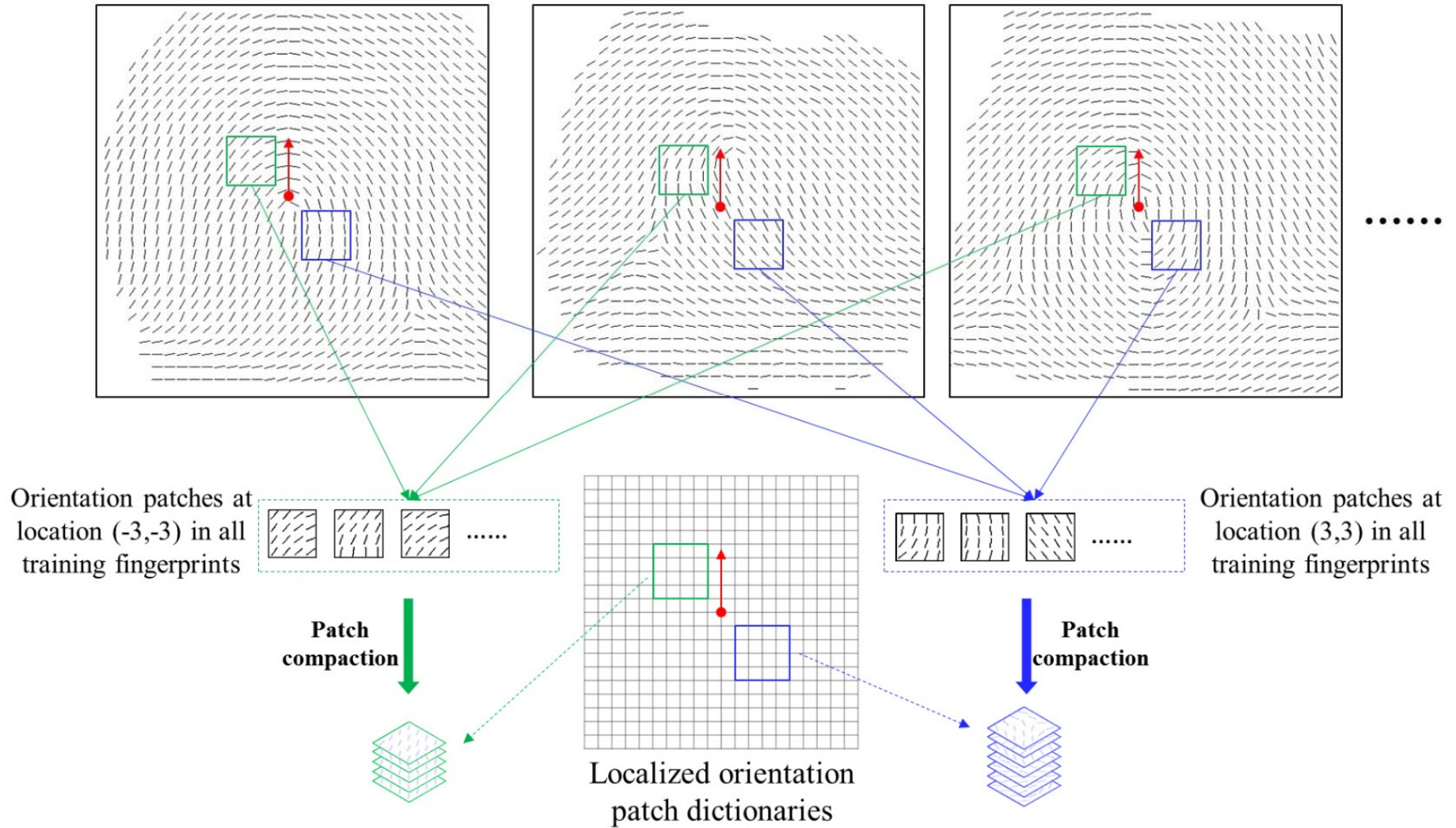
Histogram of orientations at each location



Variance of orientations at each location

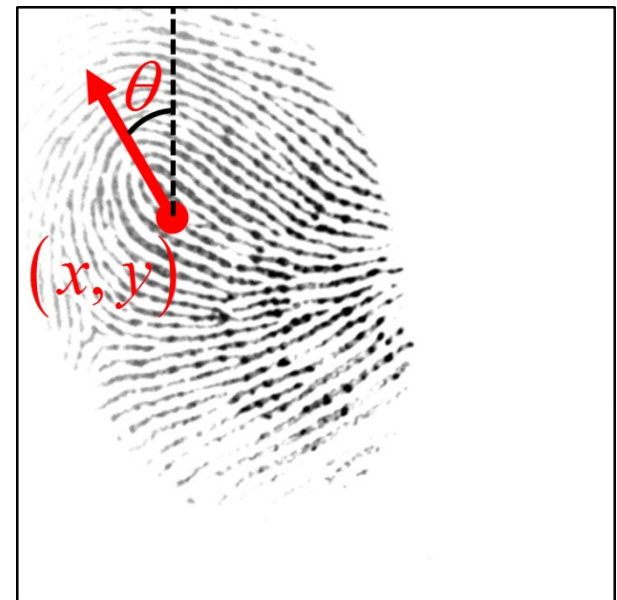
# Localized dictionaries

Registered Training Orientation Fields

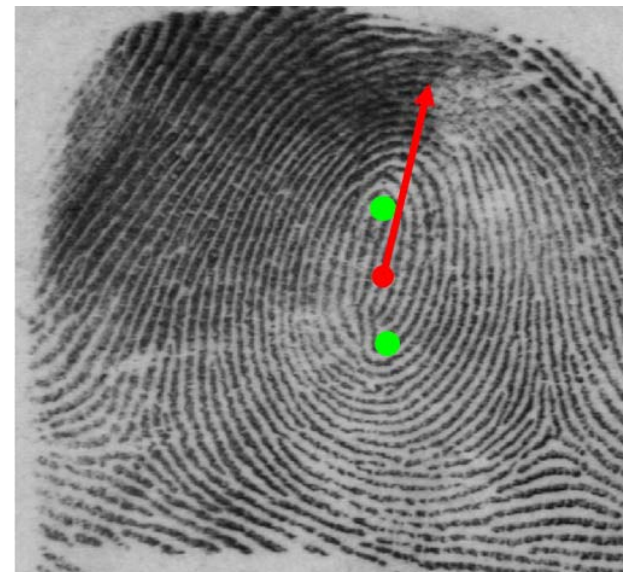
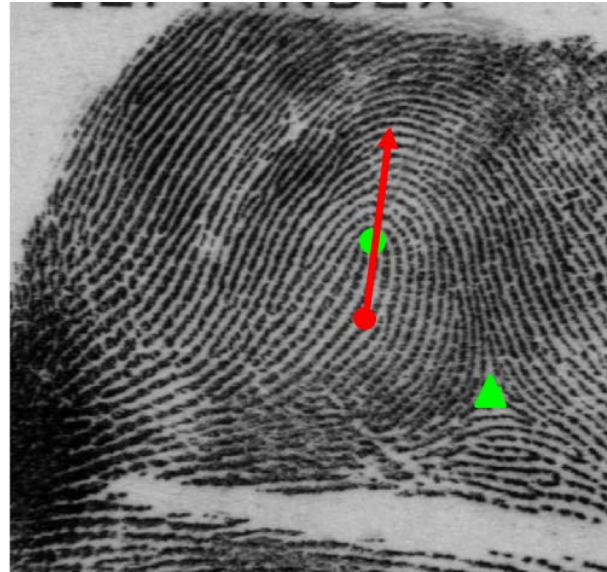


# Finger coordinate system

- Premise of using localized dictionaries is defining a finger coordinate system and designing an algorithm to estimate it from fingerprints.
- Finger pose or coordinate system is given by  $(x, y, \theta)$ .
- Origin (finger center) is geometric center of a frontal finger.
- $y$  axes (finger direction) is normal to finger joint and points to fingertip.
- Finger pose or coordinate system is given by  $(x, y, \theta)$ .
- Easy to define in photograph of finger, not easy in fingerprint.

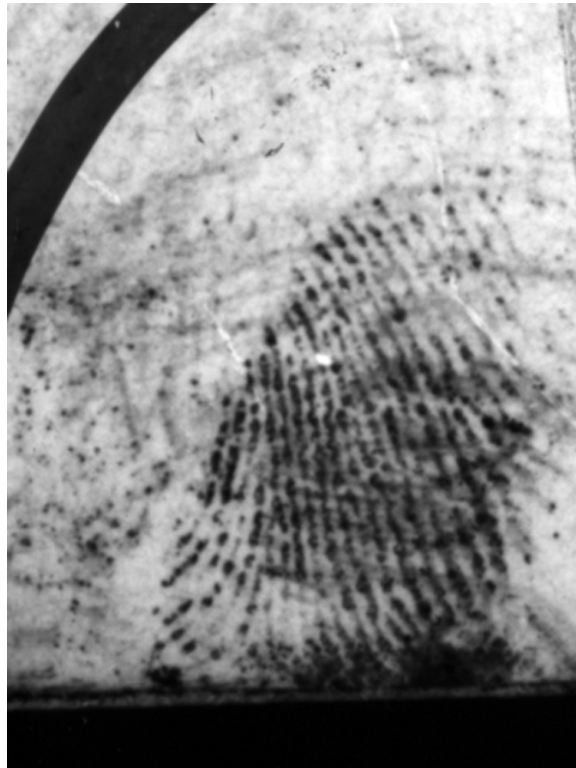


# Finger center & direction

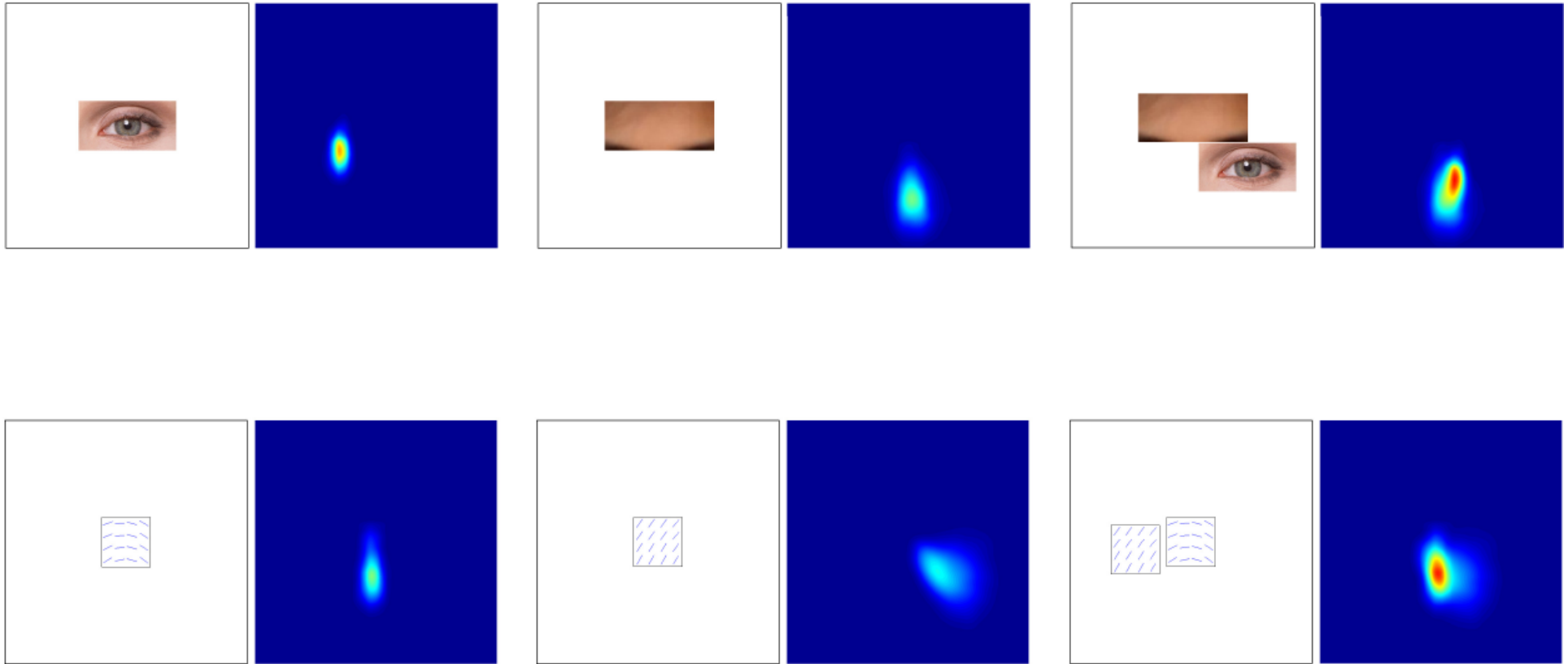


The direction normal to the finger joint or the ridges located at the bottom area of fingerprint is chosen as the finger direction.

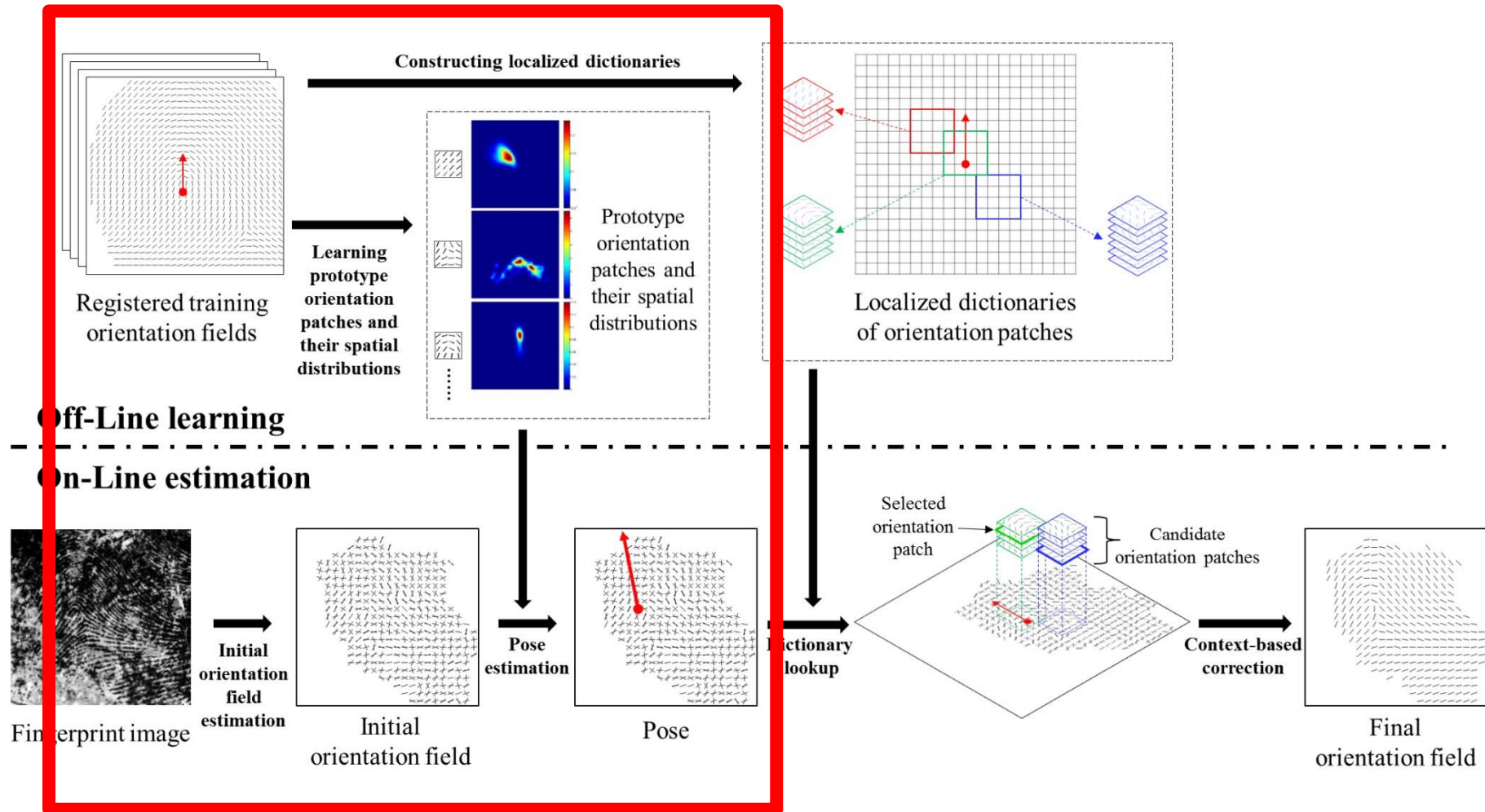
# Pose estimation of latent



# Pose estimation



# Flowchart

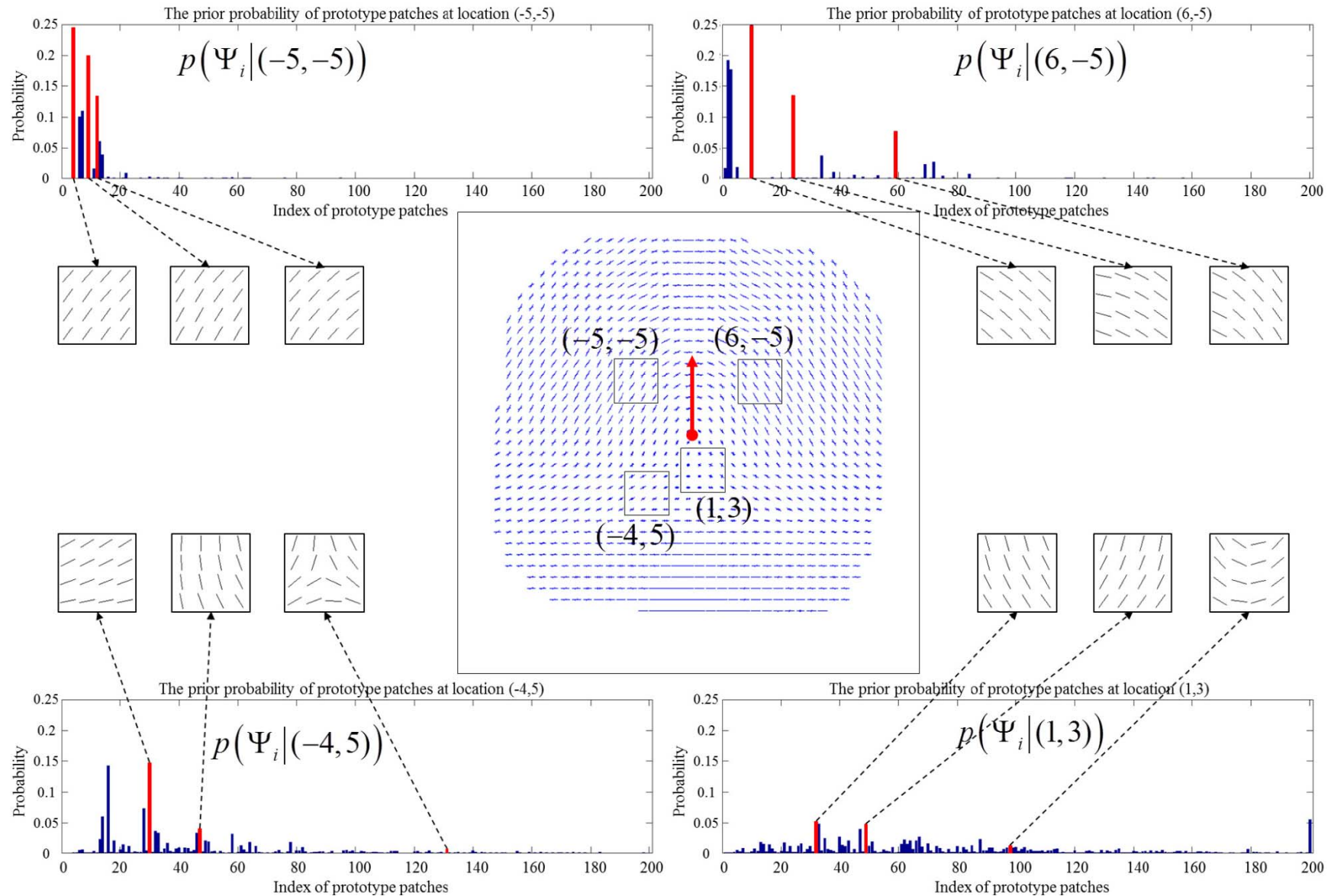


X. Yang, J. Feng, J. Zhou, "Localized Dictionaries Based Orientation Field Estimation for Latent Fingerprints", under review in PAMI.

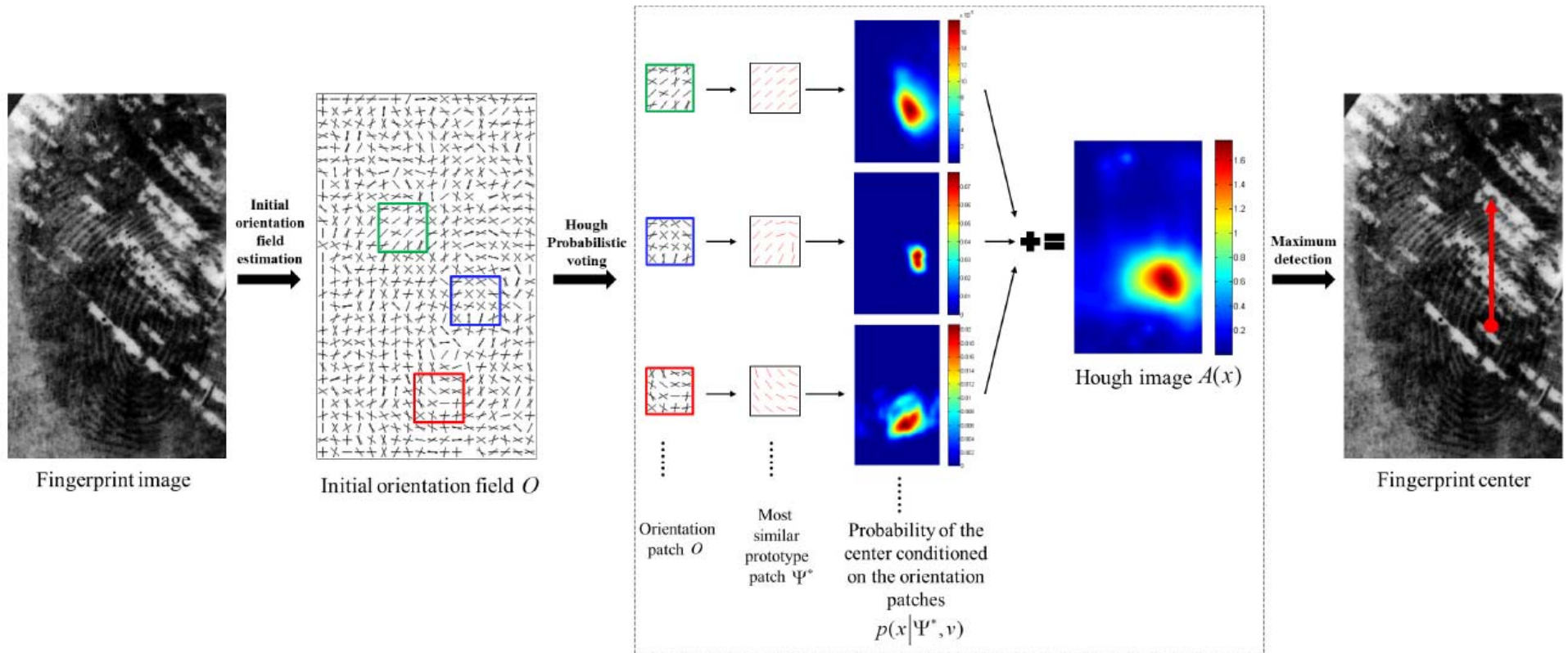




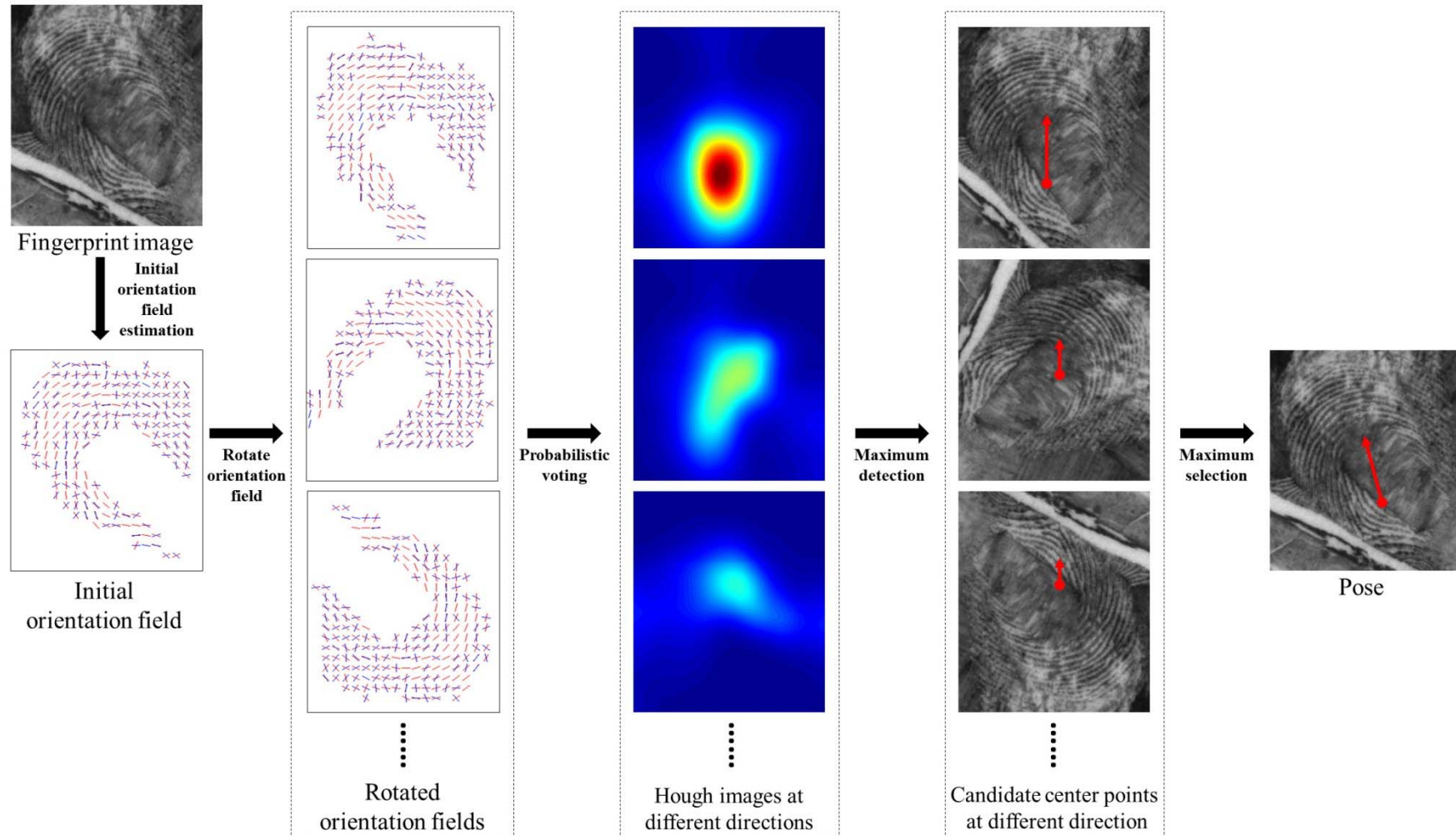
# Distribution of prototype at given location



# Pose estimation: finger center

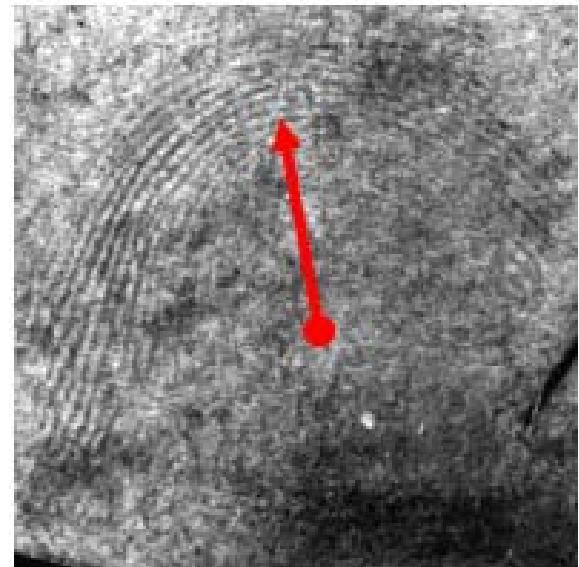
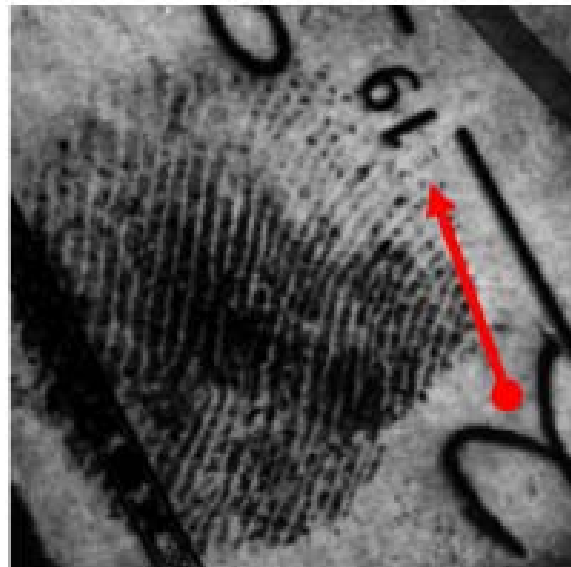
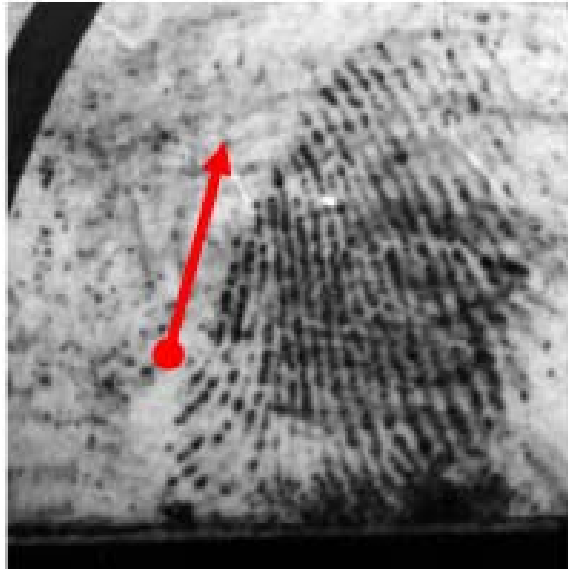


# Pose estimation: finger direction

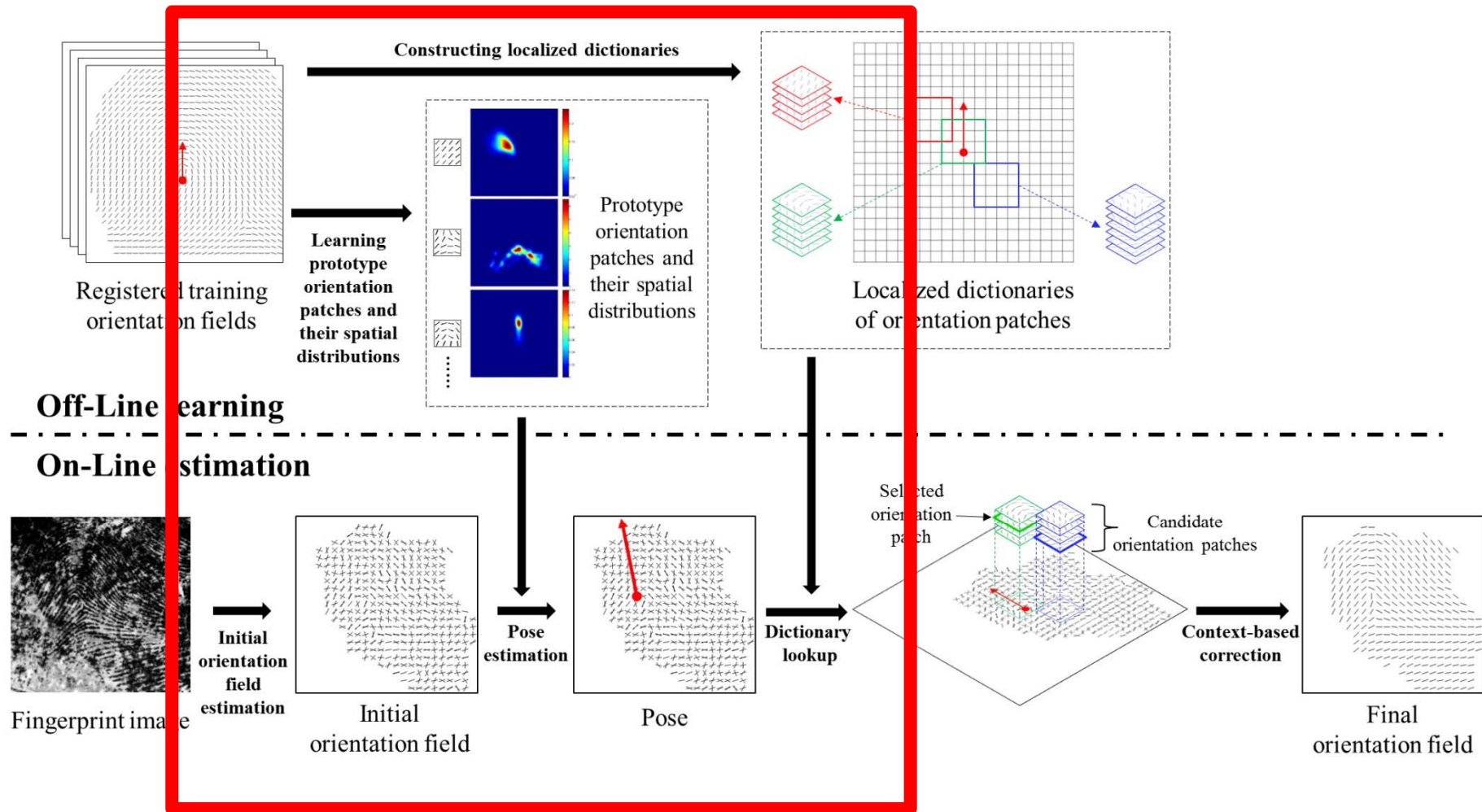


Analogous to detecting rotated face in an image

# Pose estimation: results



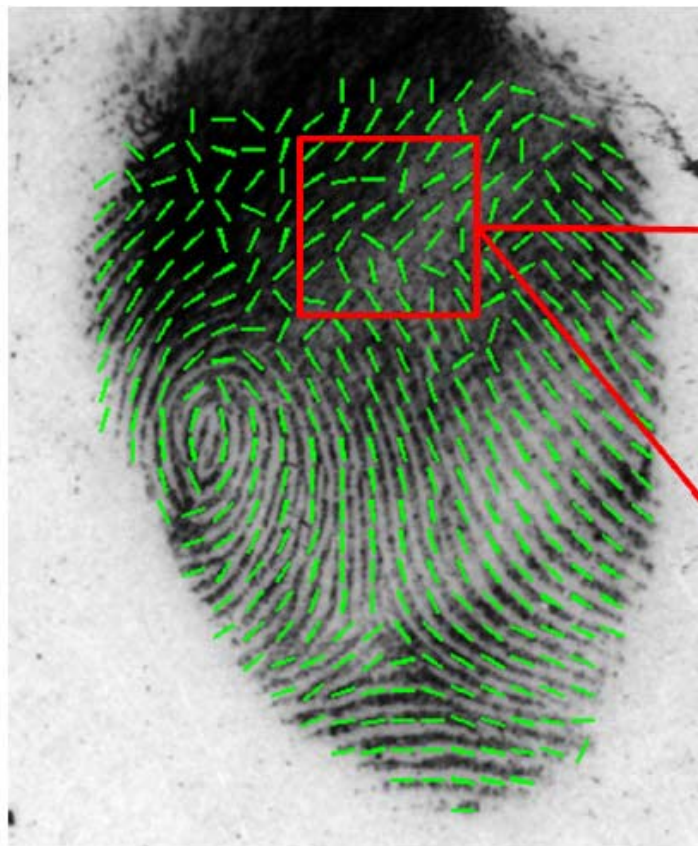
# Flowchart



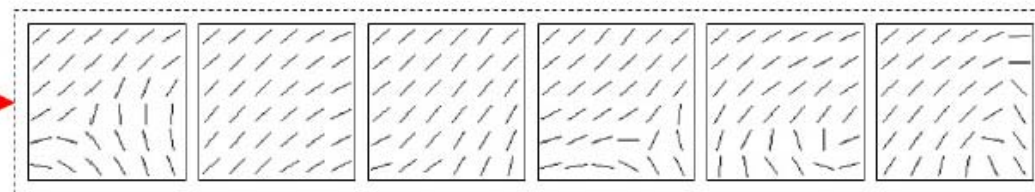
- Clustering algorithm for dictionary construction is the same as GlobalDict
- Dictionary lookup and context-based correction algorithms are also similar

# Advantages of localized dictionaries

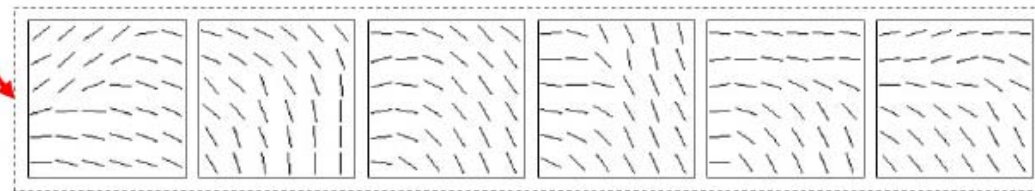
- Reasonable candidate orientation patches
- Small dictionary



Initial orientation field overlaid on the latent fingerprint



Top-6 similar patches in the global dictionary (total number is 30176)



Top-6 similar patches in the localized dictionary (total number is 180)

# Size of localized dictionaries

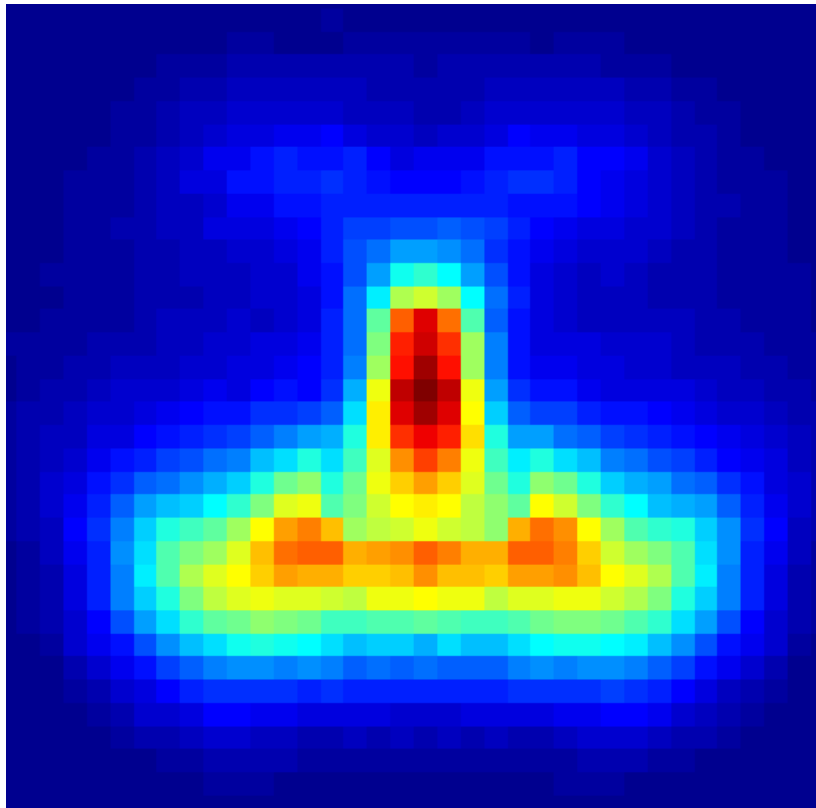


Image value at  $(x, y)$  is the size of localized dictionary at  $(x, y)$

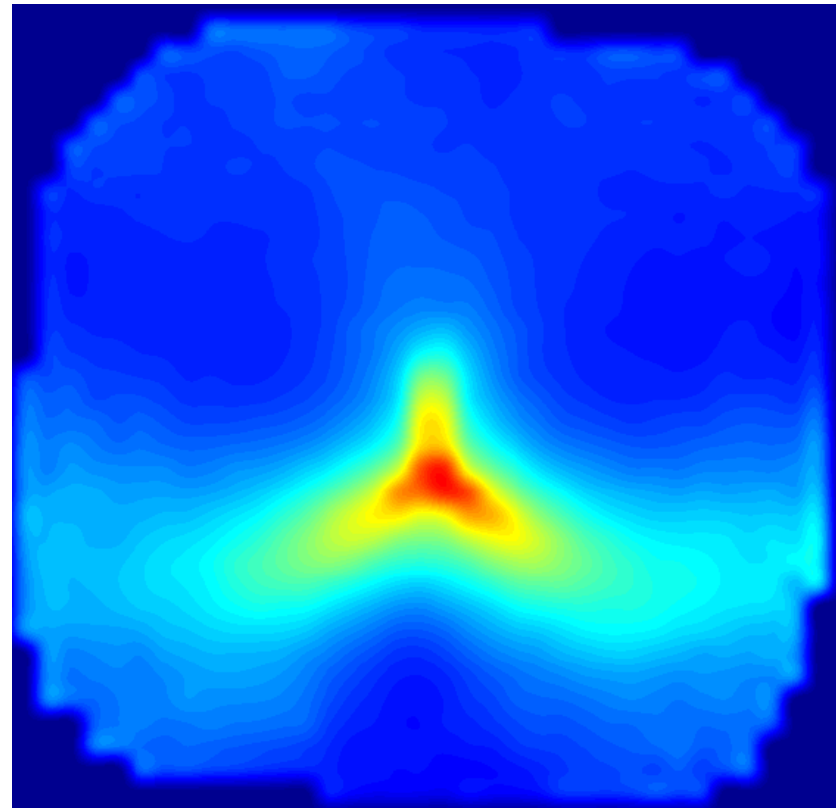
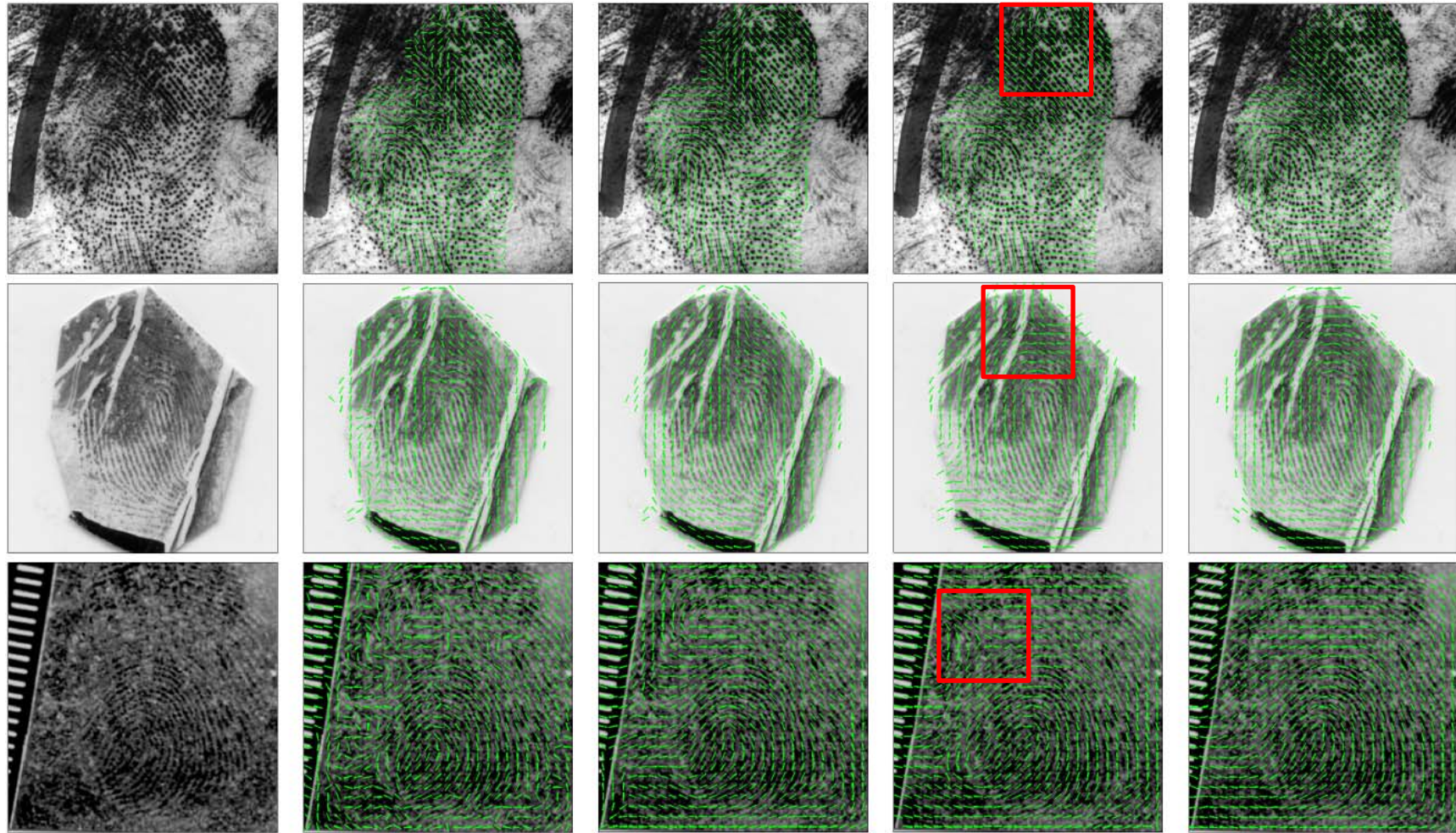


Image value at  $(x, y)$  is standard deviation of orientation in training samples

Larger orientation deviation corresponds to larger dictionary size.

# Experimental results



Latent fingerprints

STFT

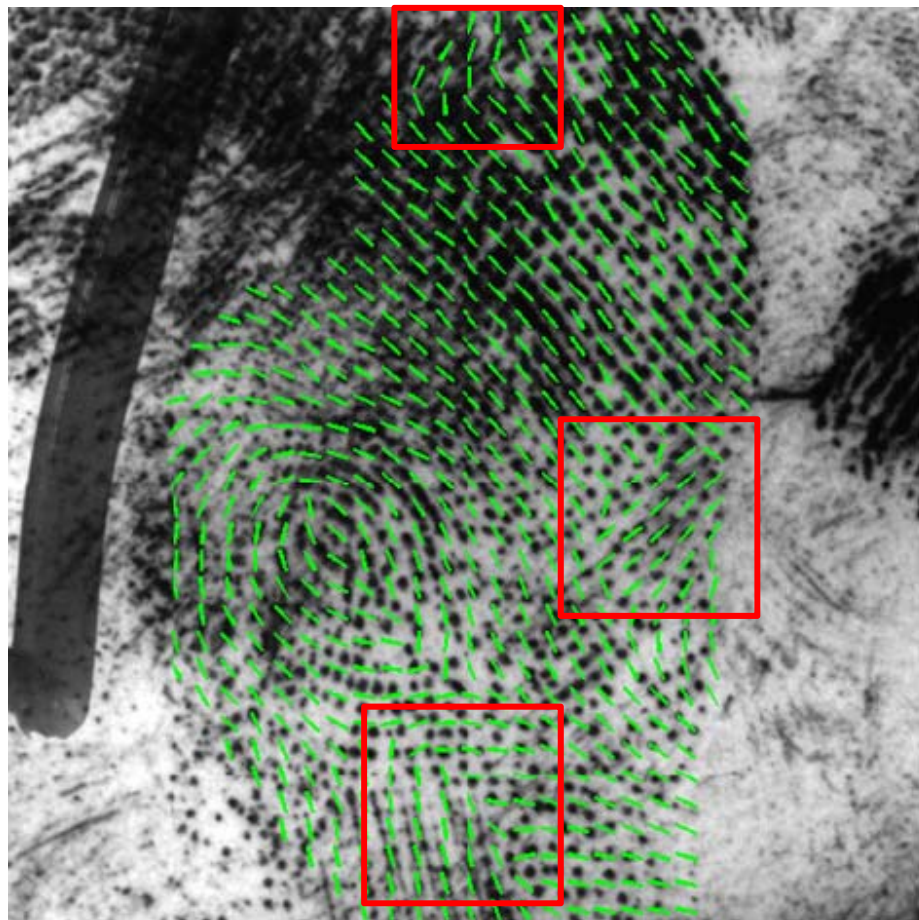
FOMFE

GlobalDict

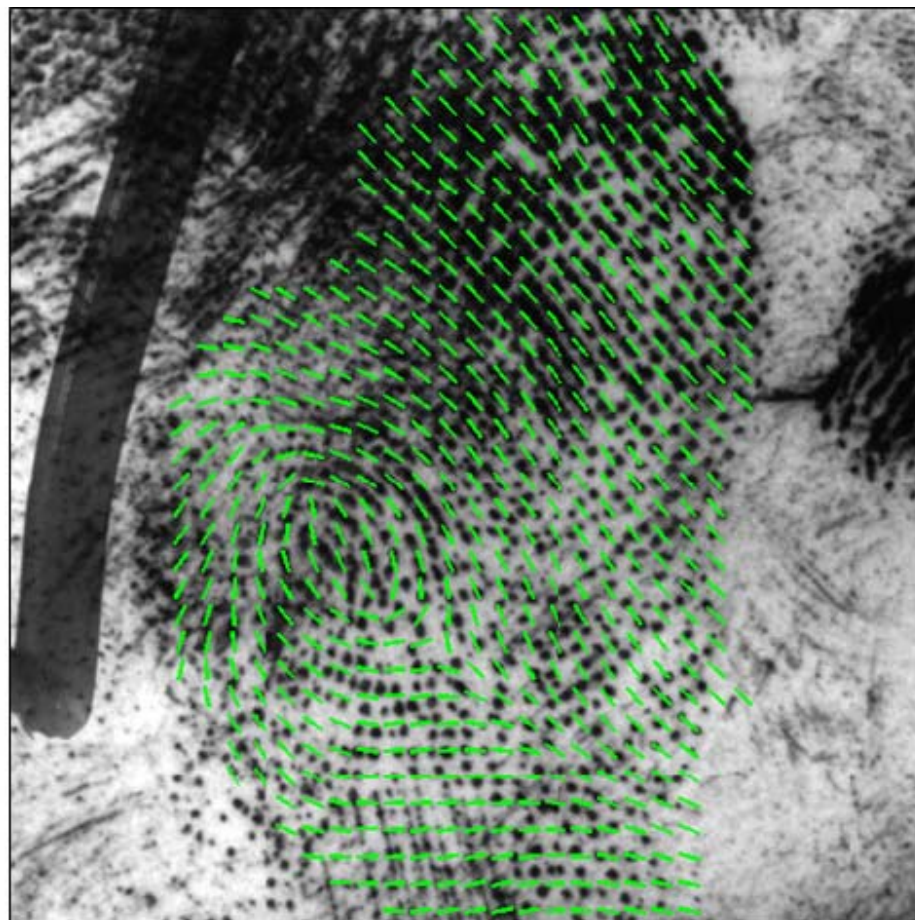
LocalDict



# Experimental results

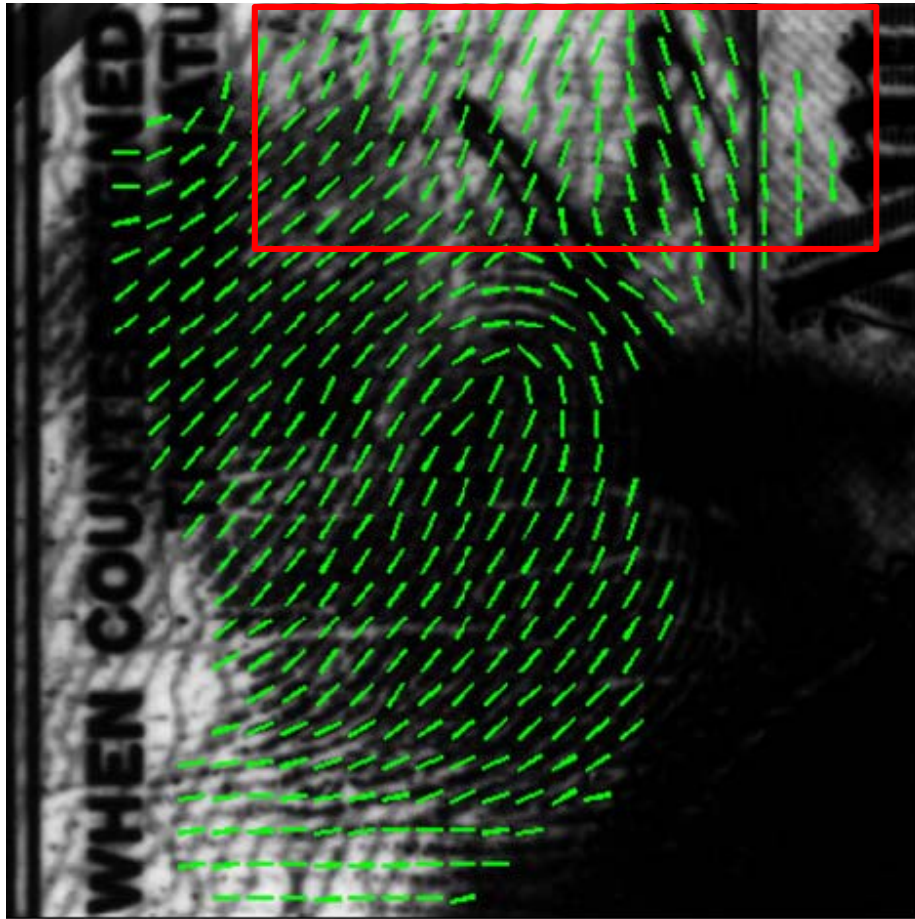


GlobalDict

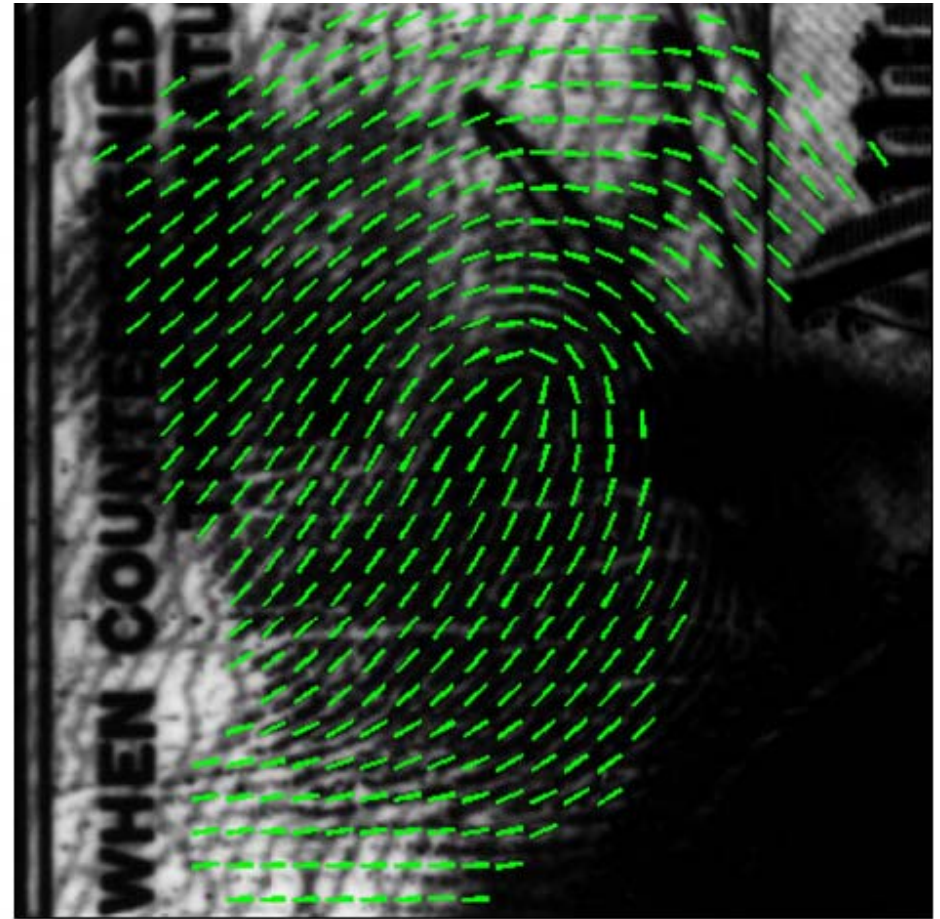


LocalDict

# Experimental results



GlobalDict



LocalDict

# Accuracy of OF estimation (1)

- Average OF estimation errors (RMSE, in degrees) of 5 algorithms on NIST-27 and 3 subsets
- To understand the impact of pose estimation on OF estimation, we combine manually marked pose with localized dictionaries based algorithm.

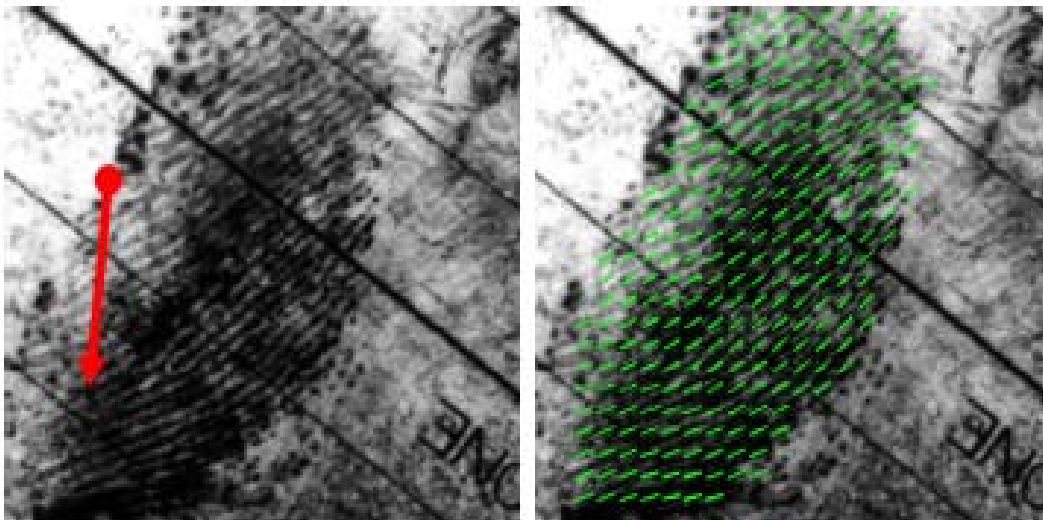
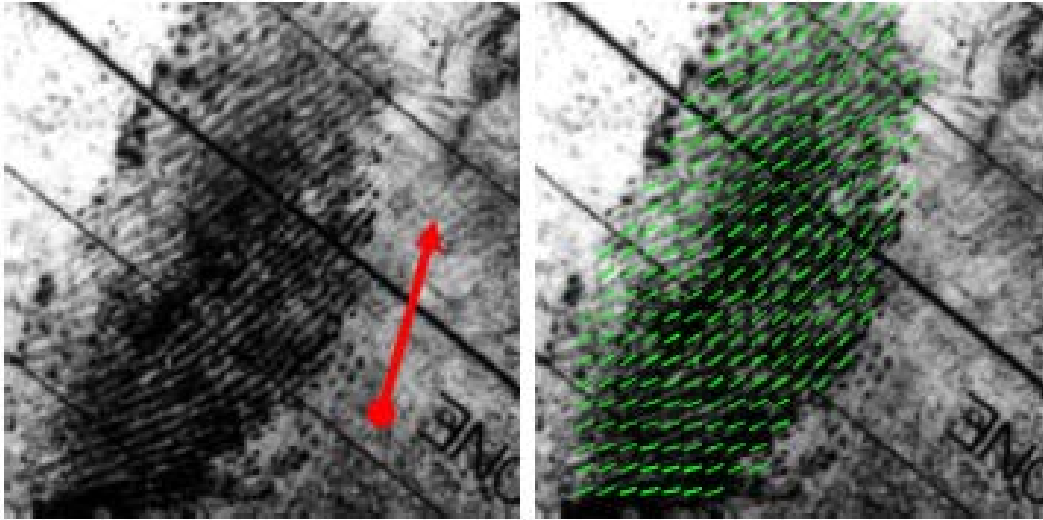
| <b>Algorithm</b>                | <b>All</b> | <b>Good</b> | <b>Bad</b> | <b>Ugly</b> |
|---------------------------------|------------|-------------|------------|-------------|
| Proposed (manually marked pose) | 13.76      | 10.87       | 14.12      | 16.40       |
| Proposed                        | 14.35      | 11.15       | 15.15      | 16.85       |
| GlobalDict [7]                  | 18.44      | 14.40       | 19.18      | 21.88       |
| FOMFE [31]                      | 28.12      | 22.83       | 29.09      | 32.63       |
| STFT [6]                        | 32.51      | 27.27       | 34.10      | 36.36       |

# Impact of pose estimation

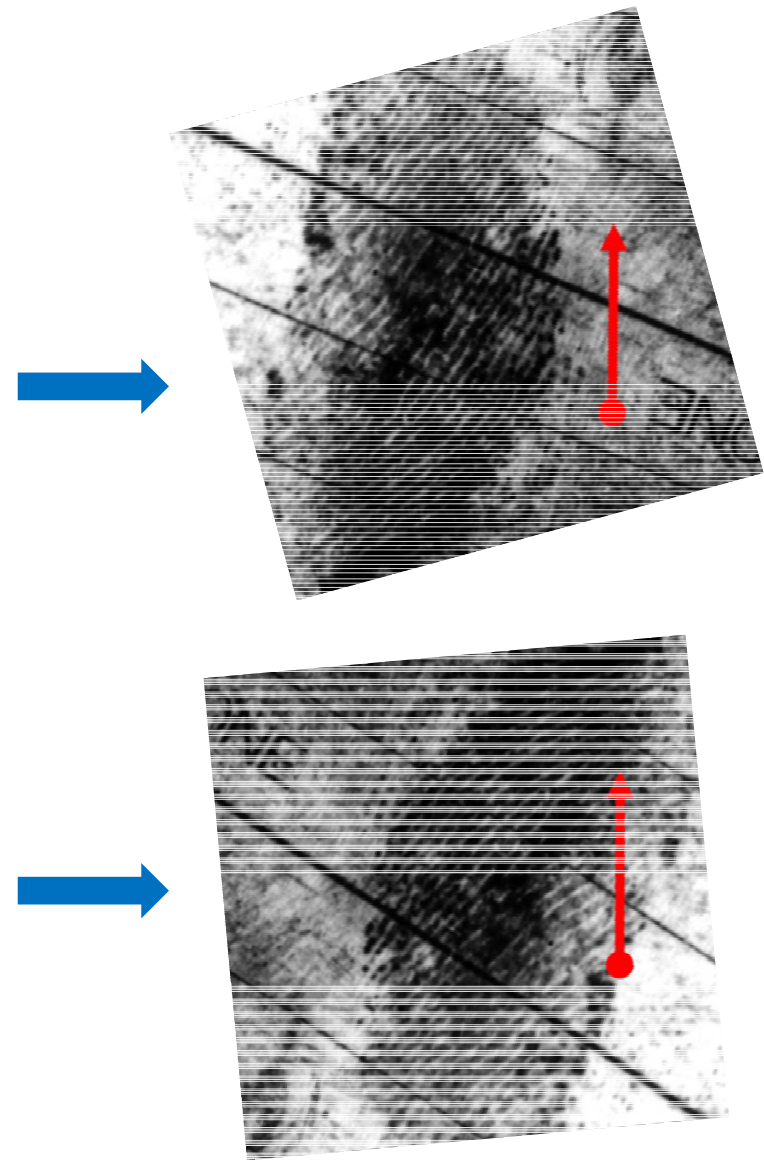
- Why is manually marked pose only slightly better?
- Not because automatic estimate of pose is as good as manual markup
- It is because orientation field of partial fingerprints can be explained by different poses.

# Impact of pose estimation

Manually marked pose

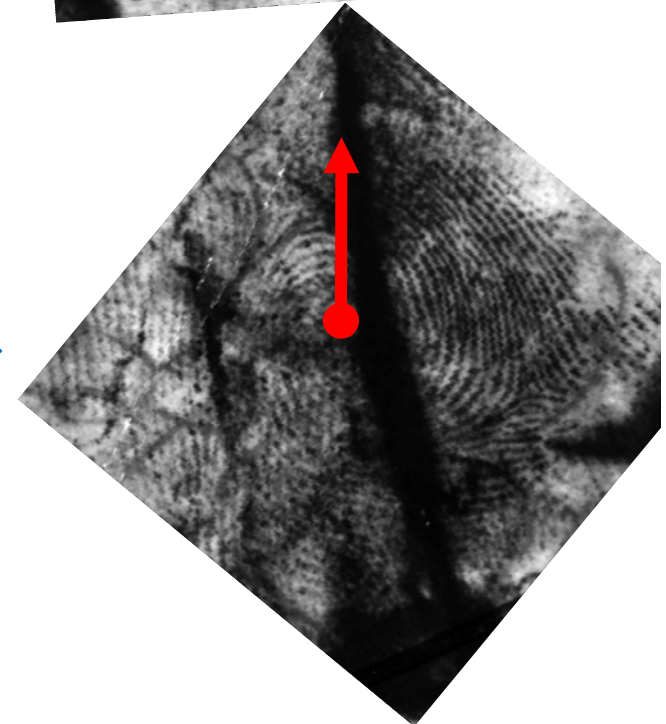
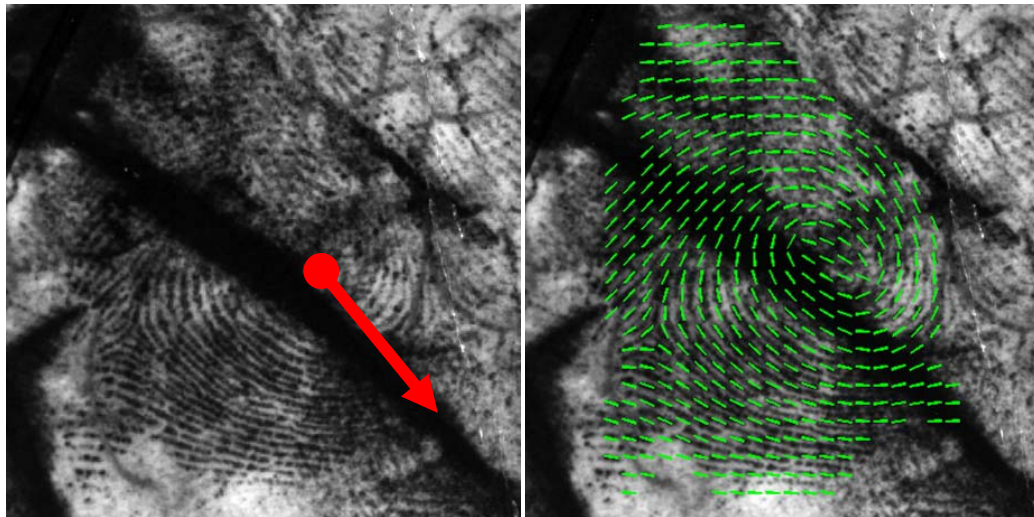
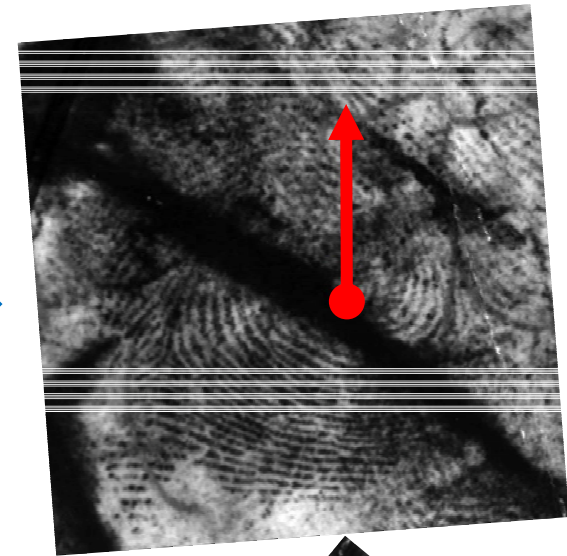
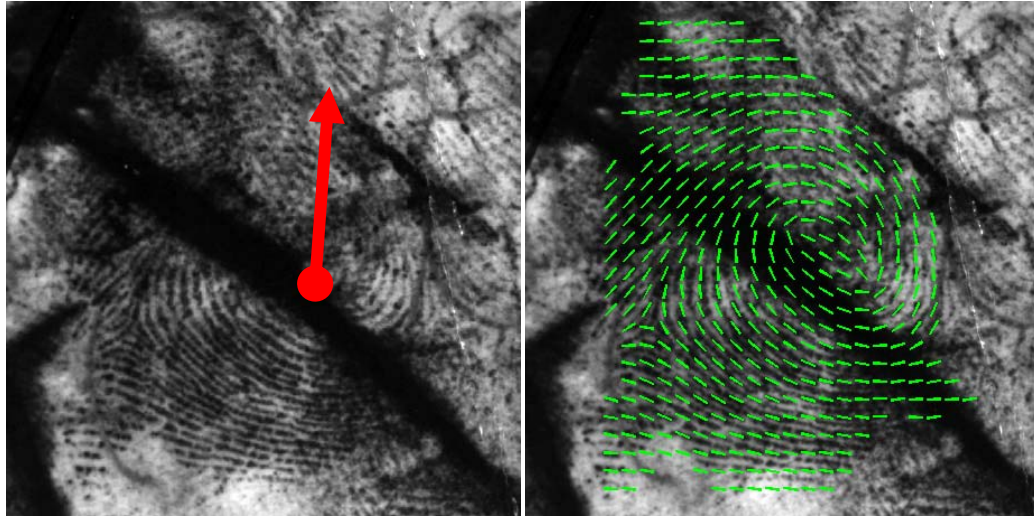


Automatically estimated pose



# Impact of pose estimation

Manually marked pose



Automatically estimated pose

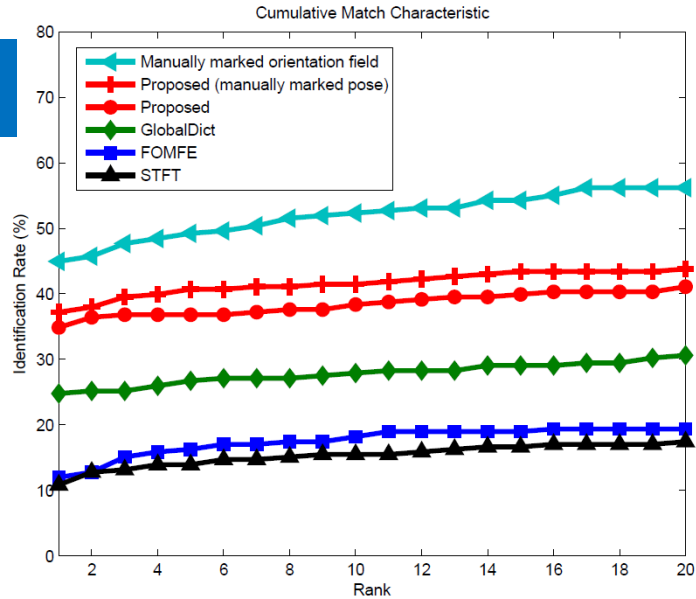
# Accuracy of OF estimation (2)

- FVC-onGoing FOE benchmark is an online evaluation for fingerprint orientation field estimation algorithms.
- 2 fingerprint datasets: good quality (10), bad quality (50)
- Ground truth orientation fields are marked by human.
- Measure: RMSD between ground-truth and estimated OF

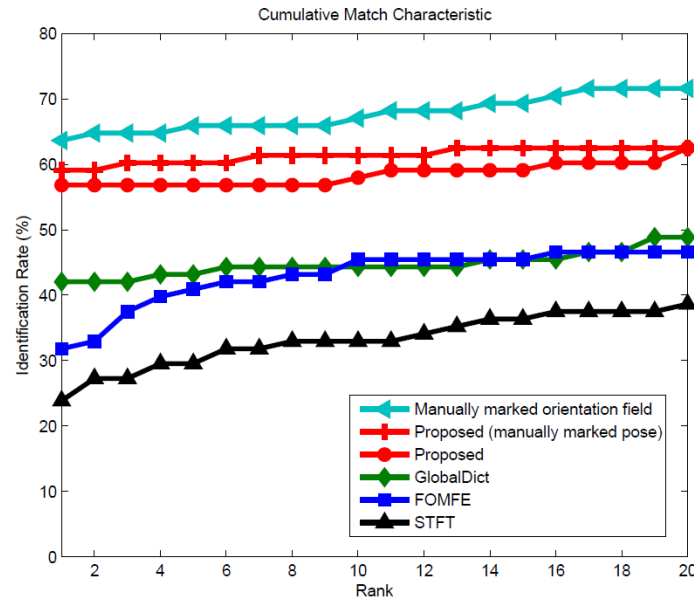
| Published on | Benchmark   | Participant   | Type                    | Algorithm             | Version | AvgErr <sub>GQ</sub> | AvgErr <sub>BQ</sub> ▲ |
|--------------|-------------|---|-------------------------|-----------------------|---------|----------------------|------------------------|
| 09/05/2013   | FOE-STD-1.0 | Department of Automation, Tsinghua University               | Academic Research Group | LocalDict             | 0.1     | 6,08°                | 9,66°                  |
| 08/04/2012   | FOE-STD-1.0 | Institute of Automation, Chinese Academy of Sciences        | Academic Research Group | ROF                   | 1.1     | 5,24°                | 11,20°                 |
| 18/11/2011   | FOE-STD-1.0 | Zengbo Xu   | Independent Developer   | MXR                   | 1.0.5   | 5,59°                | 11,36°                 |
| 08/11/2011   | FOE-STD-1.0 | Biometric System Laboratory                                 | Academic Research Group | Adaptive-3 (Baseline) | v0.2    | 5,93°                | 13,27°                 |
| 22/11/2011   | FOE-STD-1.0 | Antheus Technology, Inc.                                    | Company                 | AntheusOriEx          | 1.1.4   | 5,46°                | 17,06°                 |
| 22/11/2010   | FOE-STD-1.0 | School of Engineering and Information Technology, UNSW@ADFA | Academic Research Group | FOMFE                 | 1.0     | 6,70°                | 21,44°                 |
| 19/07/2010   | FOE-STD-1.0 | Biometric System Laboratory                                 | Academic Research Group | Gradient (baseline)   | 1.0     | 5,86°                | 21,83°                 |

# Match accuracy (1)

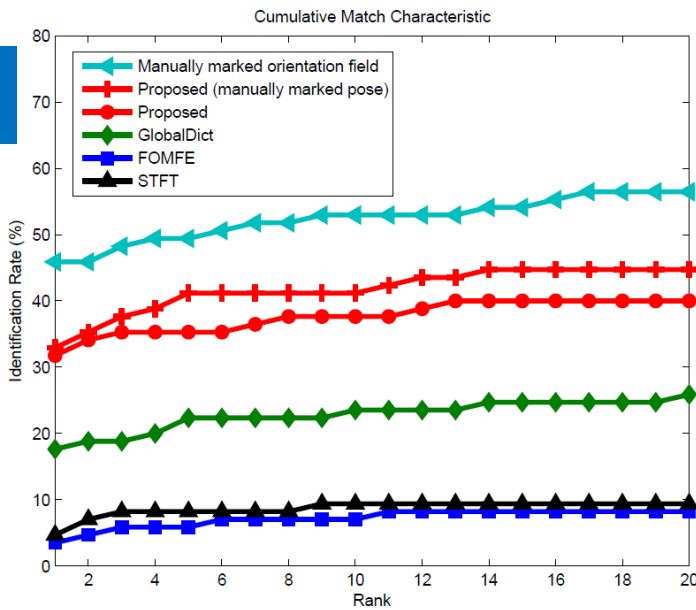
All



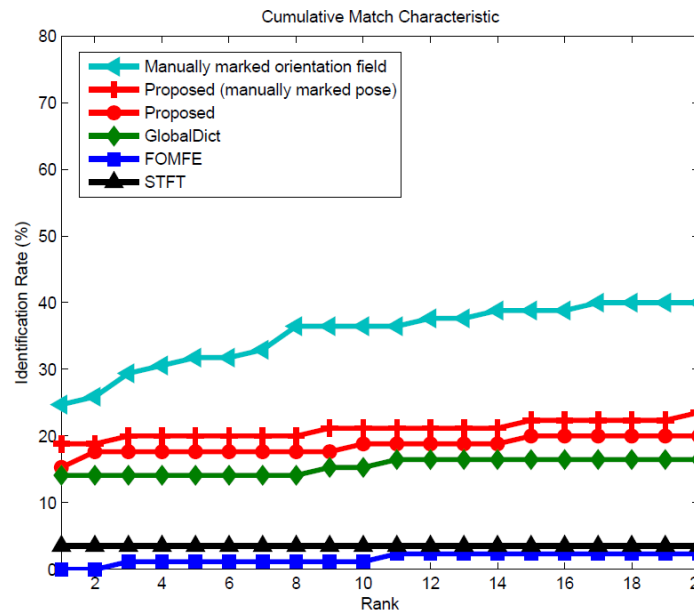
Good



Bad

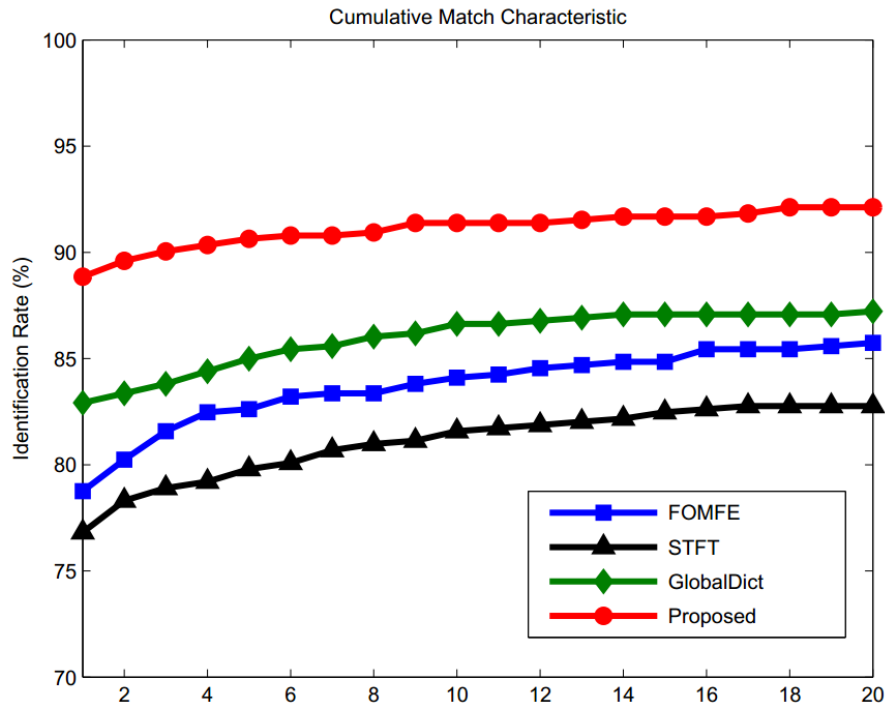


Ugly



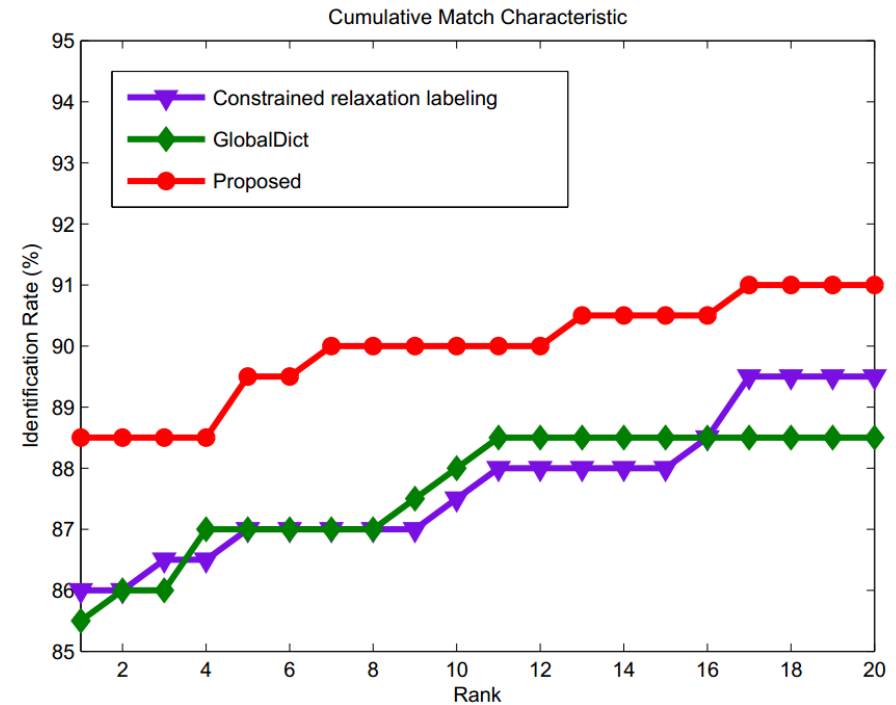


# Match accuracy (2)



## Hisign latent database

- 673 pairs of latent and mated rolled prints from solved cases
- NIST-14 as background



## Tsinghua overlapped latent fingerprint database

- 100 pairs of latent and mated plain fingerprints collected in lab
- NIST-14 as background

# Outline

- Basics of fingerprint recognition
- Fingerprint orientation field estimation
- Detection and rectification of distorted fingerprint

# Distorted fingerprints

Skin distortion is introduced due to inherent flexibility of fingertips, contact-based acquisition procedure, and lateral force or torque.

First frame

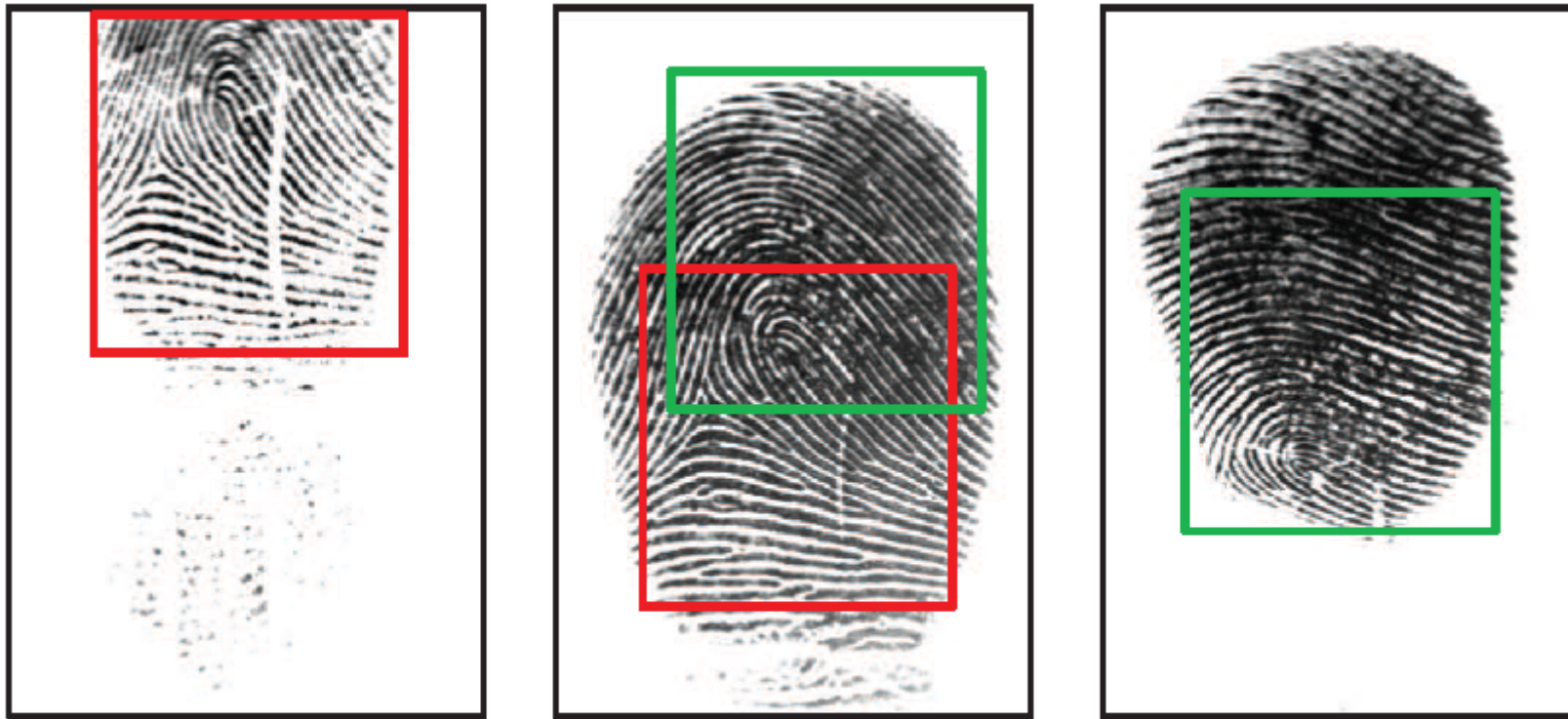


Last frame

Video of fingerprint distortion

# Distortion causes false non-match

Skin distortion increases the difference among fingerprints from the same finger and thus leads to false non-matches.



**Match score: 329**

**Match score: 12**

Computed by  
VeriFinger SDK

# Danger of distortion

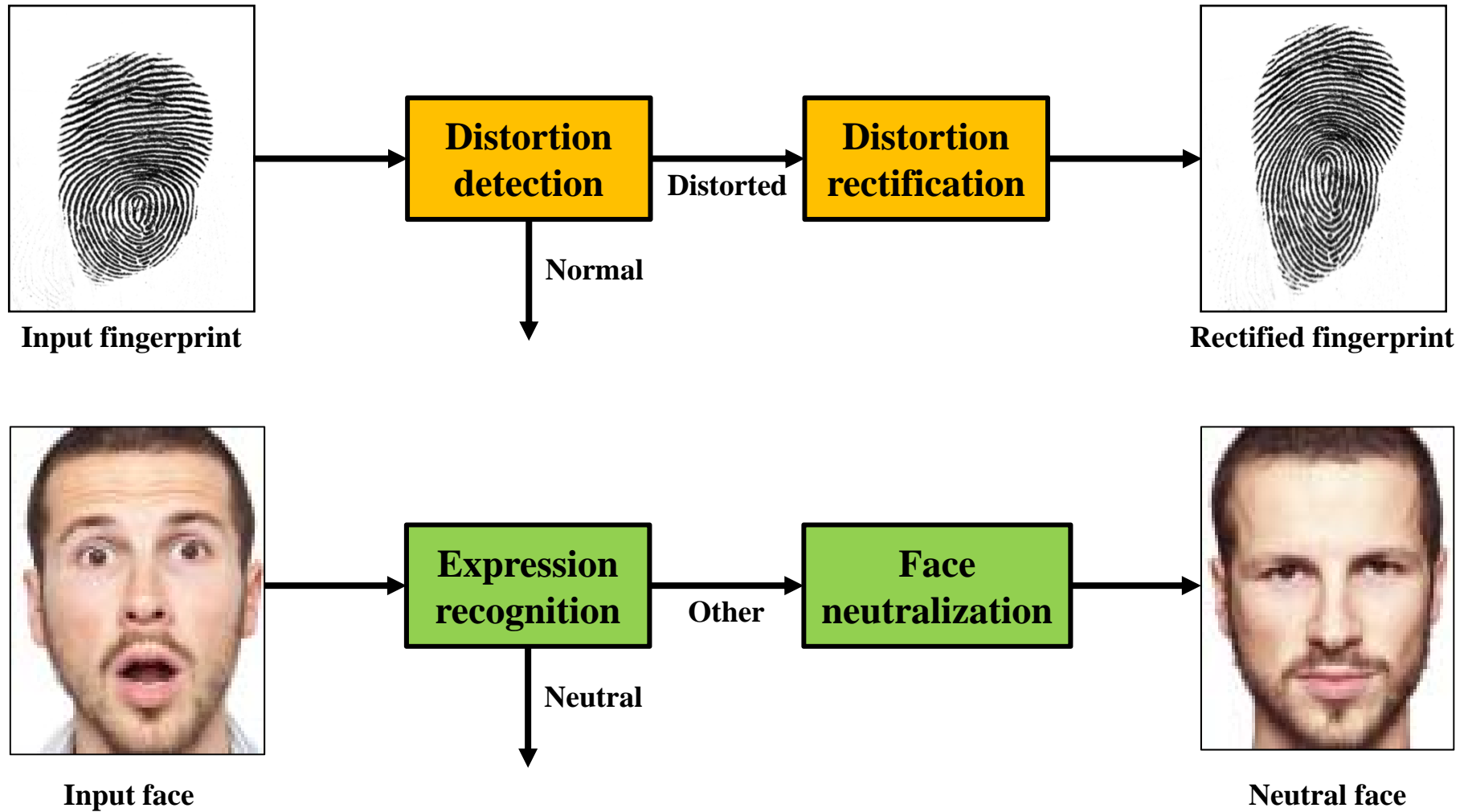
- For crime investigation, criminals cannot be identified.
- For watch-list applications, bad guys may purposely utilize this hole.
- So, it is urgent to solve the problem.



# Existing methods for handling distortion

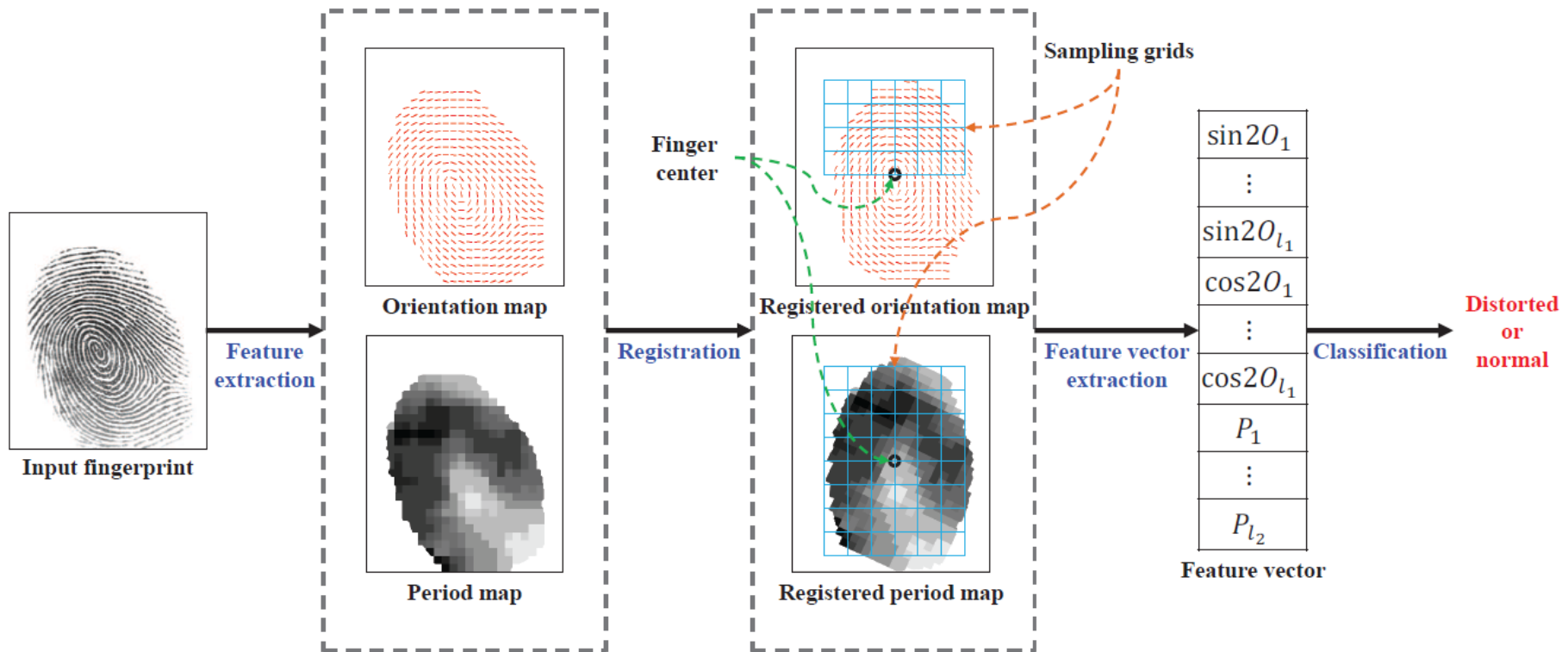
- Distortion-tolerant matching: allowing larger distortion in matching (?)
  - Result in higher false match rate
  - Slow down the matching speed
- Distortion detection using special hardware
  - Require special force sensors (?) or fingerprint sensors with video capturing capability (?)
  - Cannot detect distorted fingerprint images in existing fingerprint databases
- Ridge distance normalization (Senior & Bolle)
  - Introduce further distortion

# Distortion detection & rectification



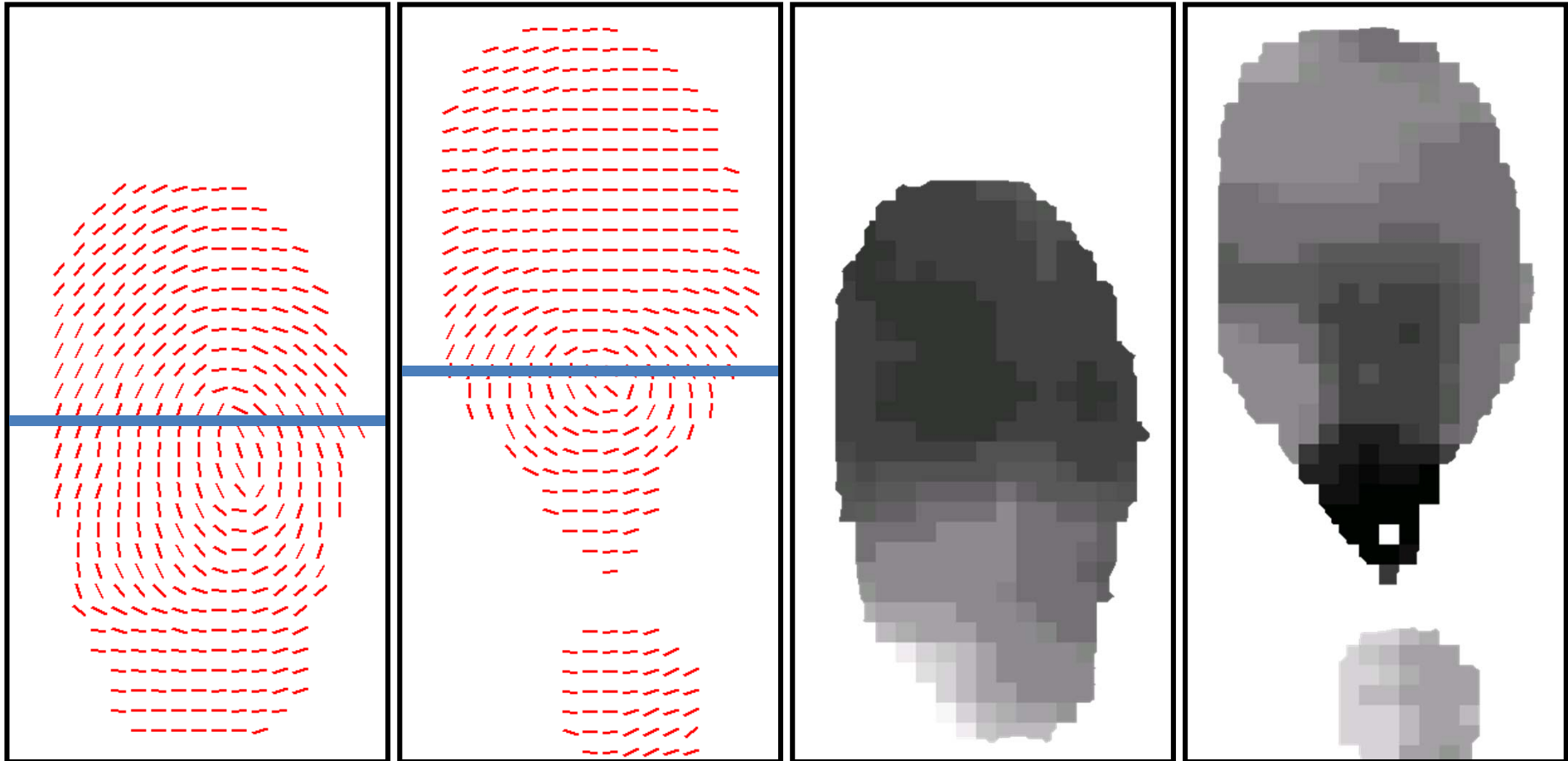
# Distortion detection

- It is viewed as a 2-class classification problem.
- Training data: normal & distorted fingerprints
- Feature: registered ridge orientation and period maps.
- Classifier: SVM





# Features for distortion detection



**Normal  
orientation field**

**Distorted  
orientation field**

**Normal  
period map**

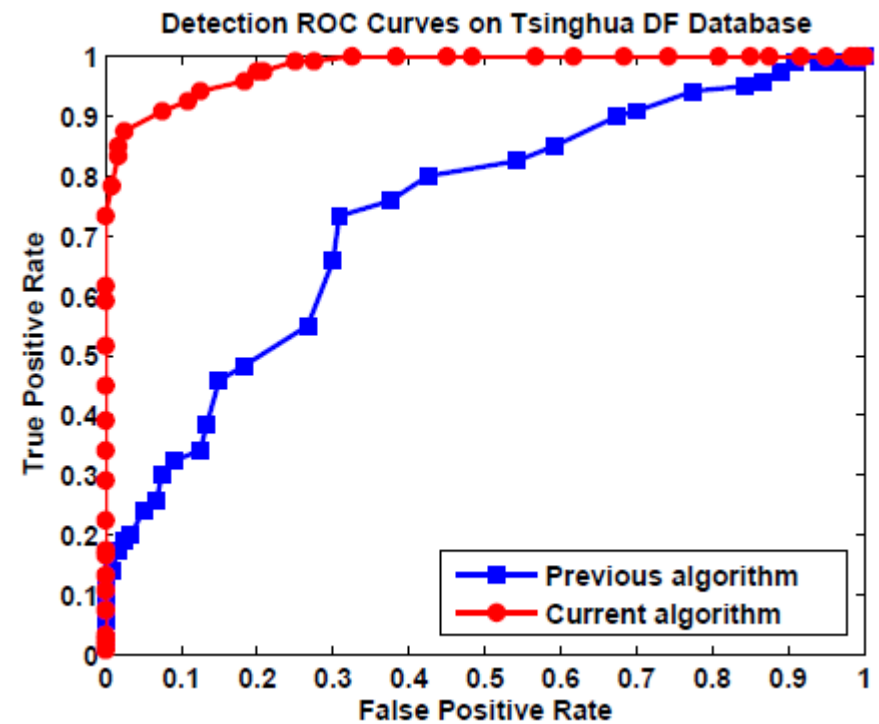
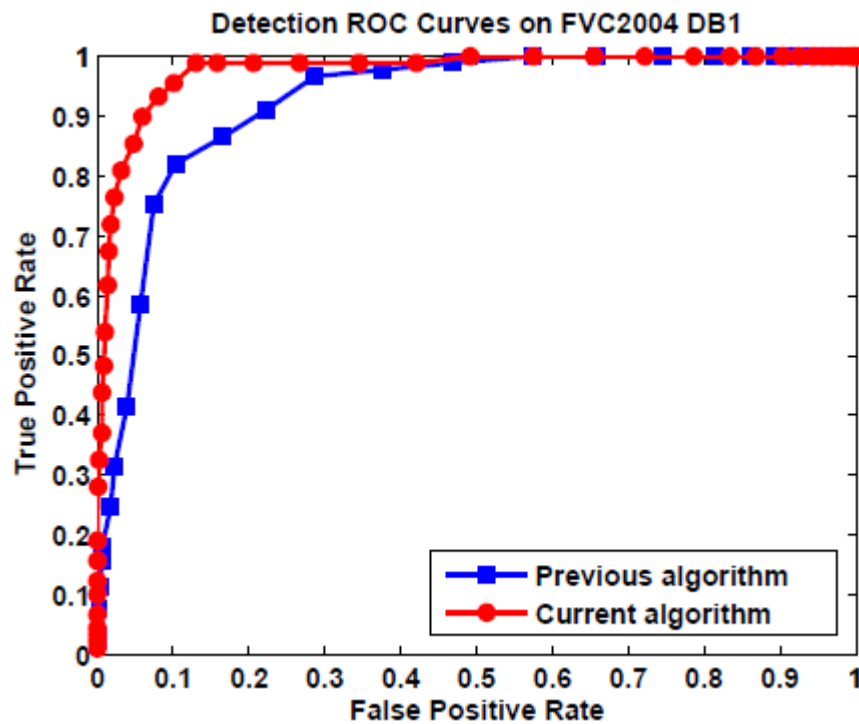
**Distorted  
period map**

# Registration

- Fingerprints need to be registered so that the feature vector is meaningful.
- A set of reference fingerprints are chosen. They are registered using manually marked core point and finger direction.
- Given a test fingerprint, registration is done as follows:
  - Find the best registration parameters with each reference fingerprint under which two OFs are most similar.
  - Choose the registration parameters with highest similarity.



# Accuracy of distortion detection

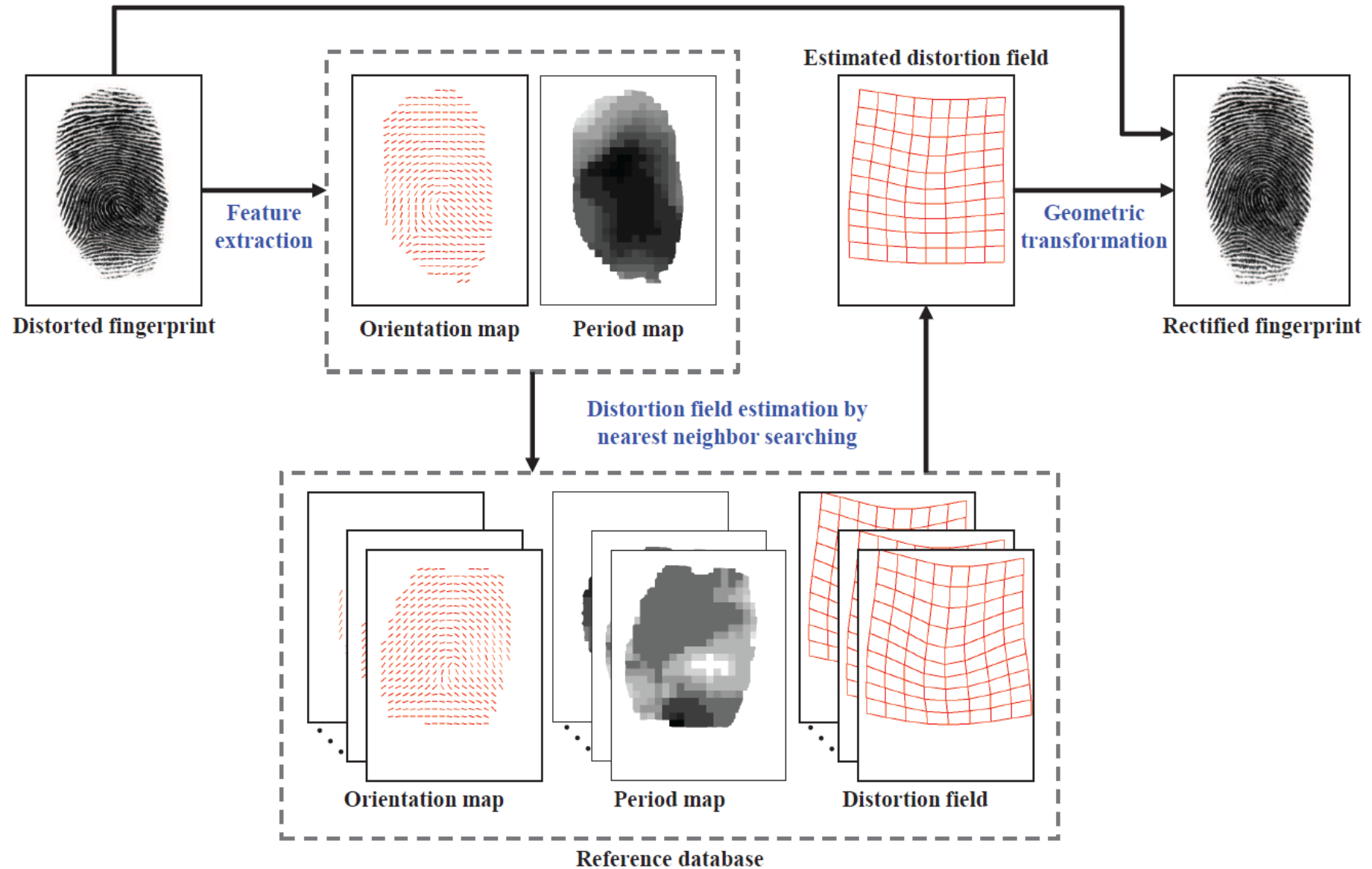


Detection ROC curves of our previous algorithm and current algorithm on the FVC2004 DB1 (left) and Tsinghua DF database (right).

# Distortion rectification = Distortion field estimation

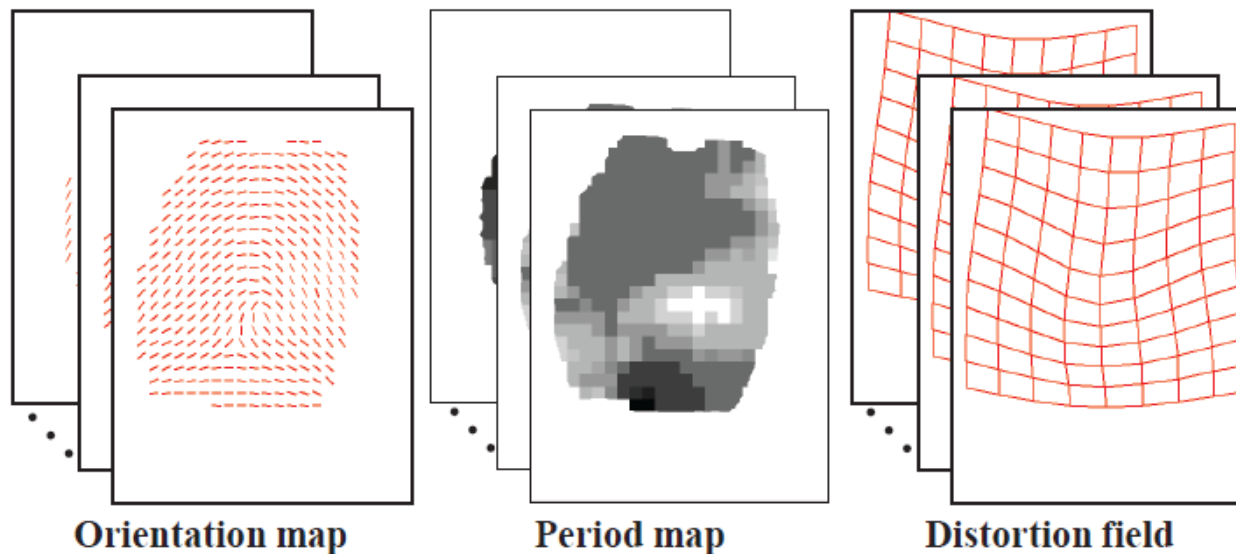
- A distorted fingerprint can be thought of being generated by applying an unknown distortion field  $d$  to the normal fingerprint (also unknown).
- If we can estimate  $d$  from the given distorted fingerprint, we can rectify it into a normal fingerprint by applying the inverse of  $d$ .
- So we need to address a regression problem, which is quite difficult because of the high dimensionality of the distortion field (even if we use a block-wise distortion field).

# Distortion field estimation by nearest neighbor search



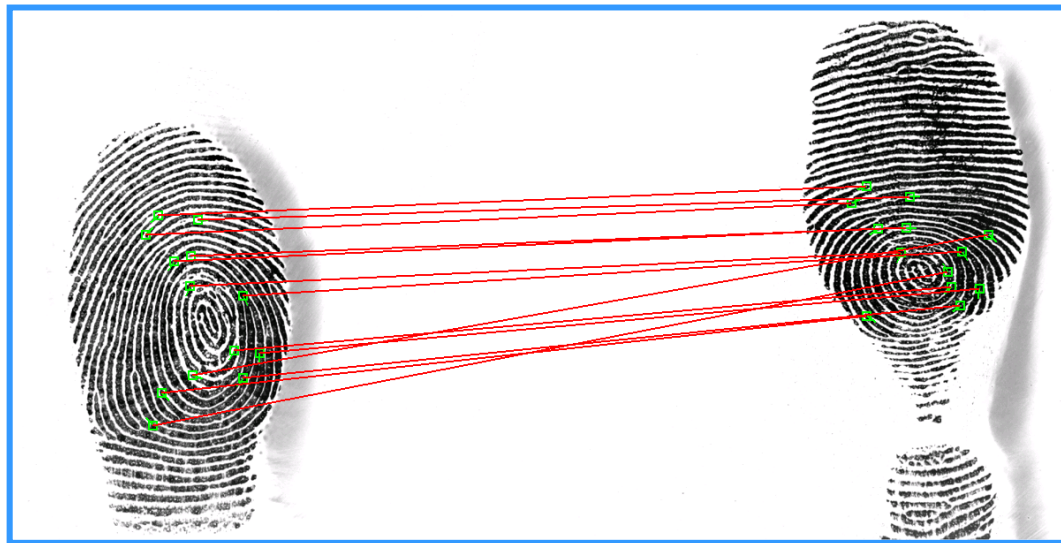
# Generation of distorted fingerprints with known distortion fields

- Obtain training distortion fields
- Use PCA to get a statistical distortion model that captures the statistical variations of training distortion fields.
- Generate synthetic distortion fields
- Apply these distortion fields to selected fingerprints and compute the orientation and period maps



# Obtain training distortion fields

- In order to learn statistical fingerprint distortion model, we need to know the distortion fields (or deformation fields) between paired fingerprints (the first frame and the last frame of each video) in the training set.
- Distortion field between two fingerprints can be estimated based on corresponding minutiae of them. Given the matching minutiae of a pair of fingerprints, we estimate the transformation using thin plate spline (TPS) model.
- Unfortunately, due to severe distortion between fingerprints, existing minutiae matchers cannot find corresponding minutiae reliably.



Corresponding minutiae found by VeriFinger

# Tracking based minutiae matching

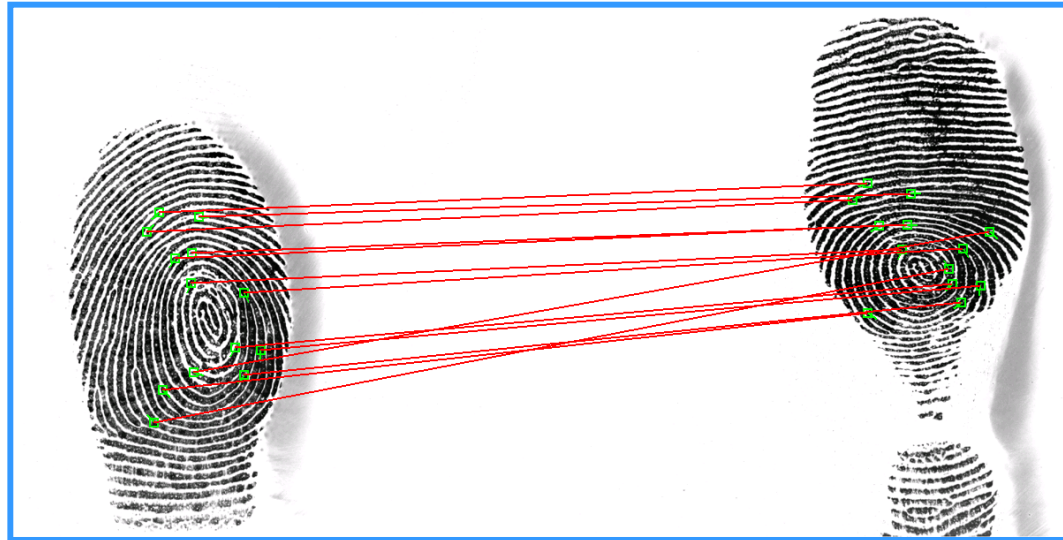
- Thus, we extract minutiae in the first frame using VeriFinger and perform minutiae tracking in each video. Since the relative motion between adjacent frames is small, reliable minutiae correspondences between the first frame and the last frame can be found by this method.



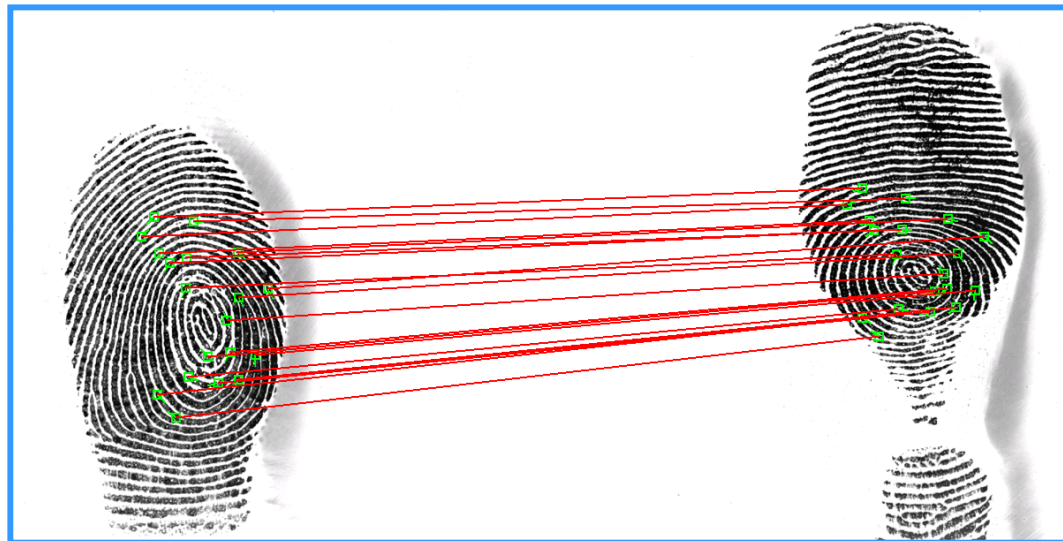
Demo of tracking method



# Tracking based minutiae matching



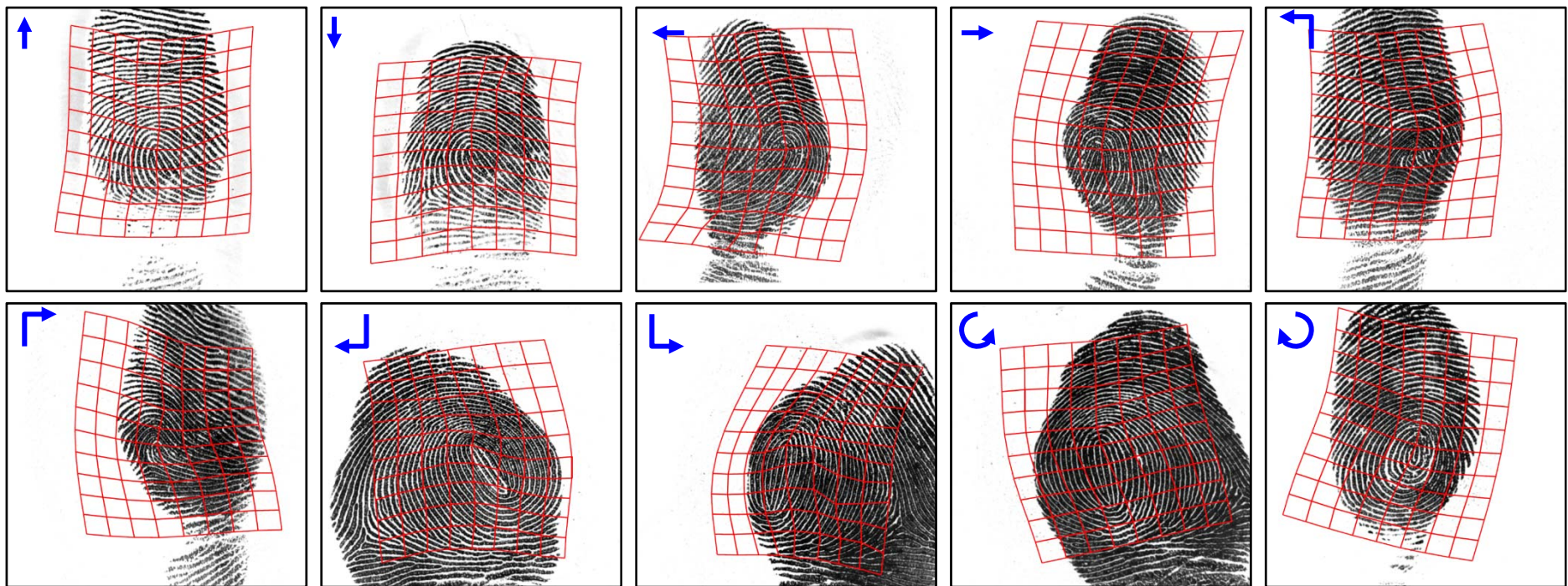
Corresponding minutiae found by VeriFinger



Corresponding minutiae found by tracking method

# Training distortion fields

- Given the matching minutiae of a pair of fingerprints, we estimate the transformation using thin plate spline (TPS) model.
- We define a regular sampling grid on the normal fingerprint and compute the corresponding grid (called distortion grid) on the distorted fingerprint using the TPS model.



# PCA of distortion fields

- The distortion field of the  $i$ -th pair of fingerprints is given by  $\mathbf{d}_i = \mathbf{x}_i^D - \mathbf{x}_i^N$

- The difference matrix

$$\mathbf{D} = ((\mathbf{d}_1 - \bar{\mathbf{d}}), \dots, (\mathbf{d}_{n_{\text{train}}} - \bar{\mathbf{d}}))$$

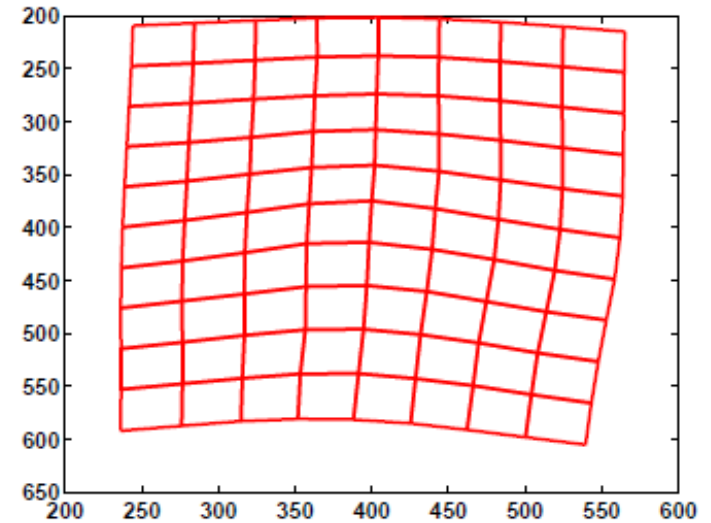
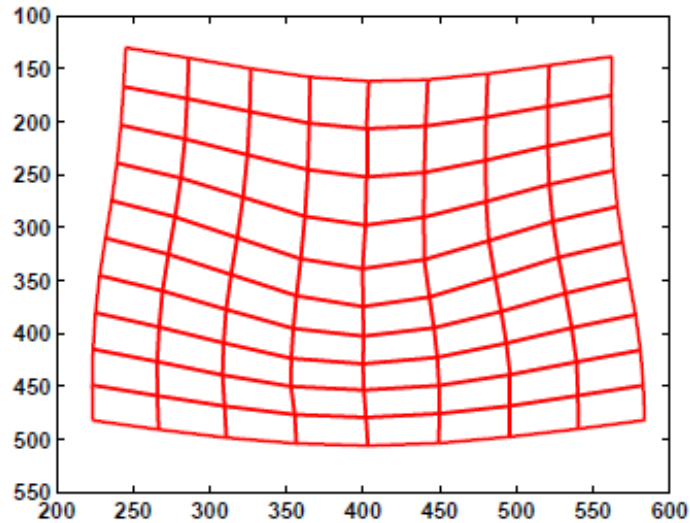
- The covariance matrix  $\text{Cov}(\mathbf{D}) = \frac{1}{n_{\text{train}}} \mathbf{D}\mathbf{D}^T$

- A new distortion field can be approximated as

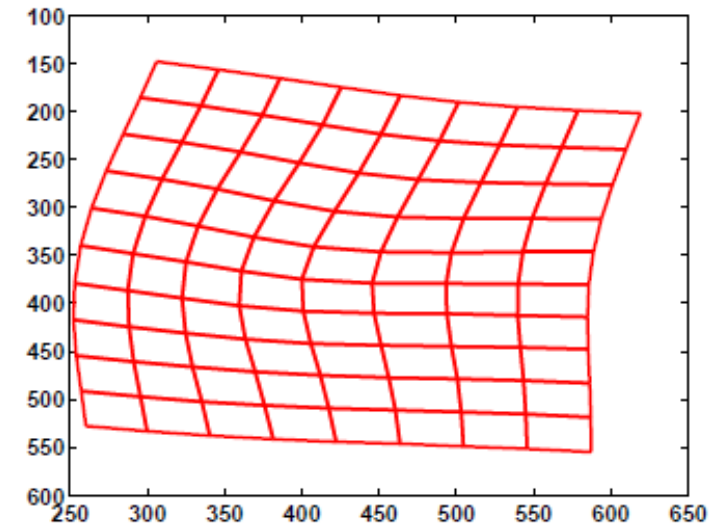
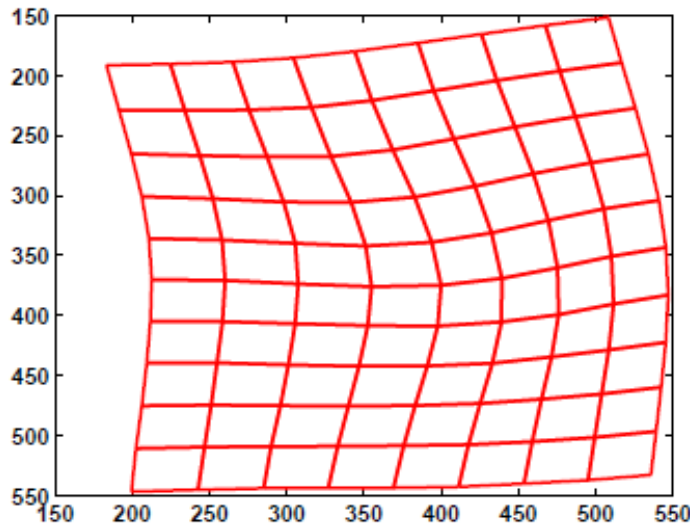
$$\mathbf{d} \approx \bar{\mathbf{d}} + \sum_{i=1}^t c_i \sqrt{\lambda_i} \mathbf{e}_i$$

# Top 2 principle components

1st principle component



2nd principle component

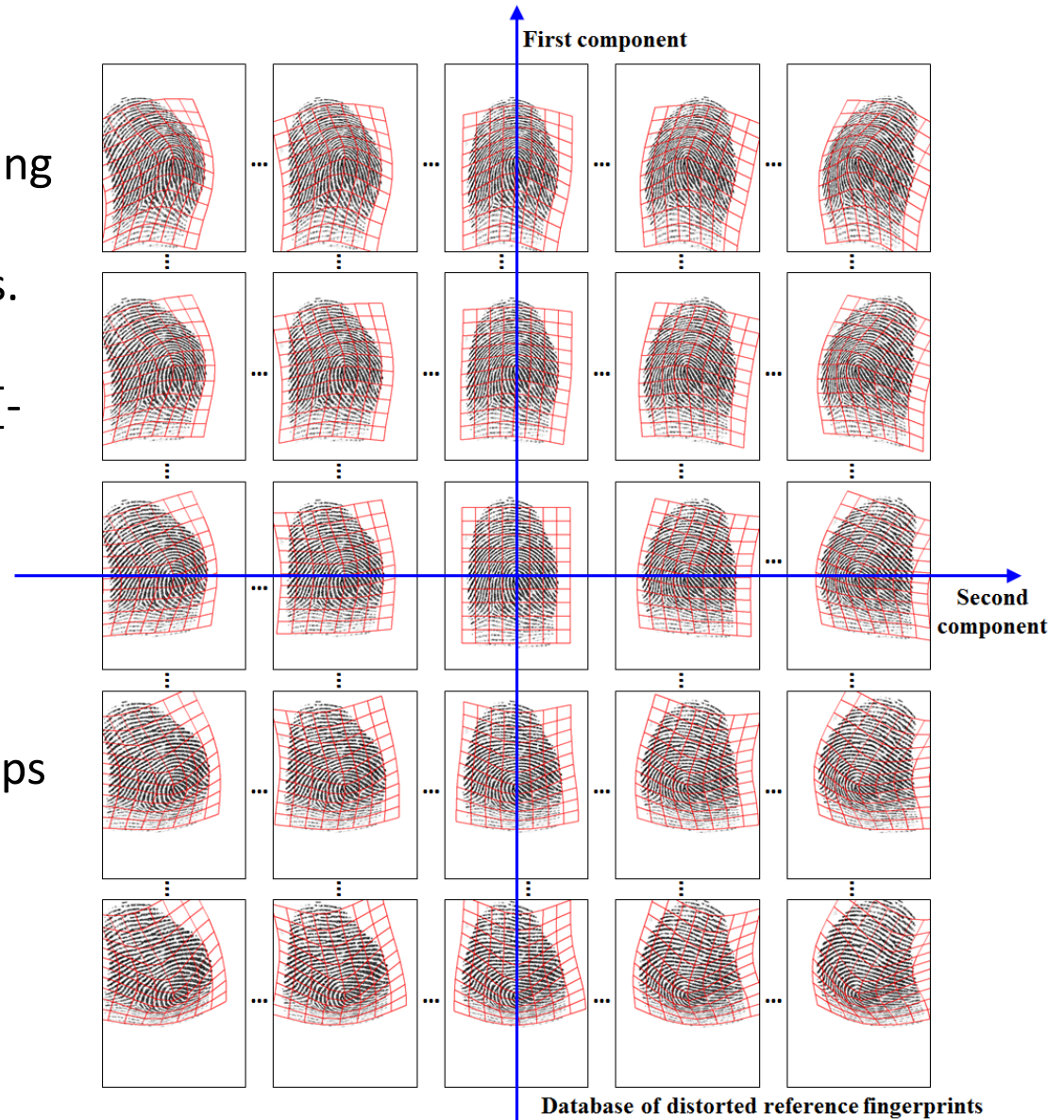


positive

negative

# Generation of Distorted Reference Fingerprint Database

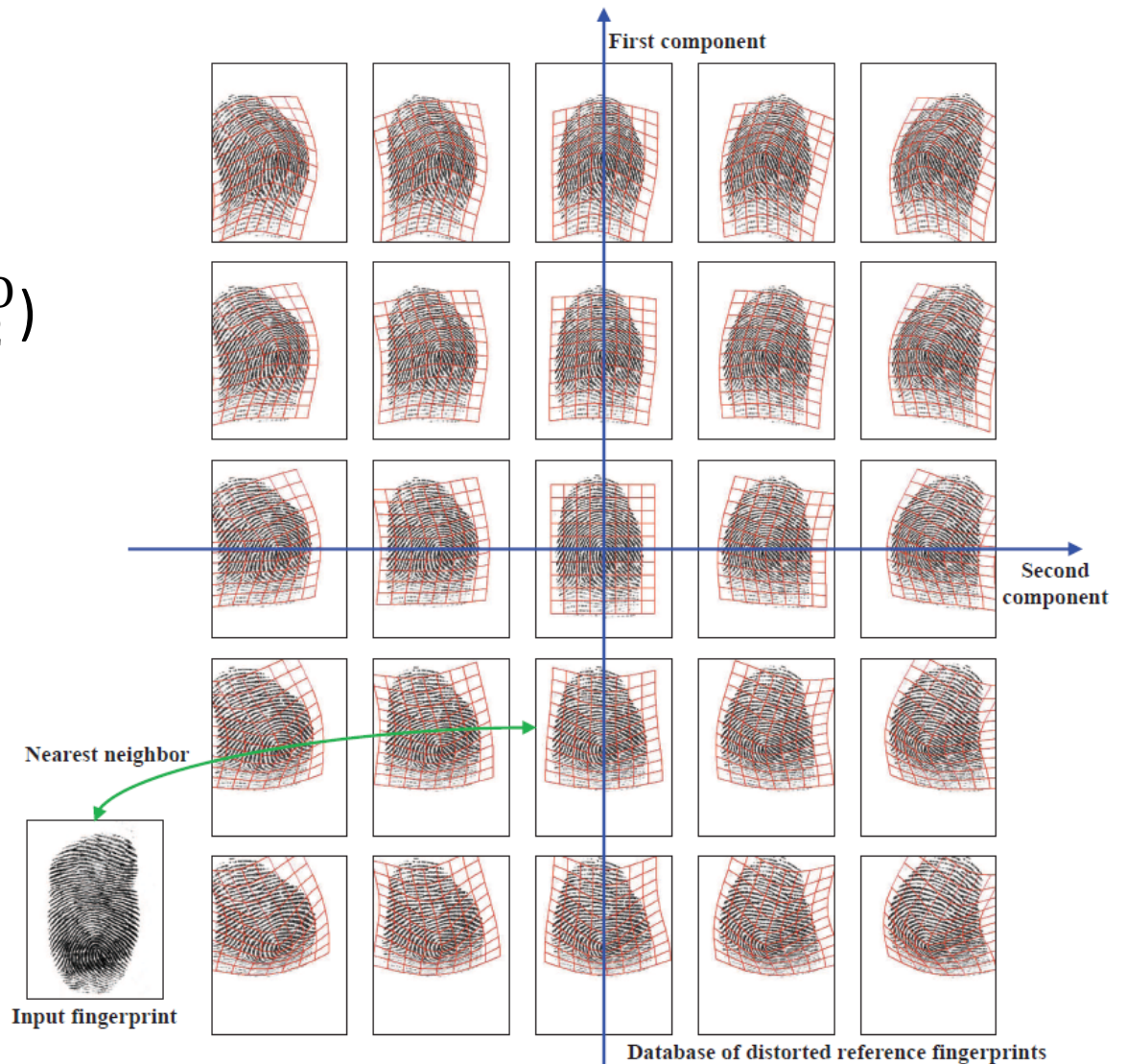
- The distortion fields are generated by uniformly sampling the subspace spanned by the first two principle components. For each basis, 11 points are uniformly sampled in interval  $[-2,2]$ .
- Distorted fingerprints are obtained by transforming reference fingerprints using generated distortion fields.
- Ridge orientation & period maps of distorted fingerprints are computed.



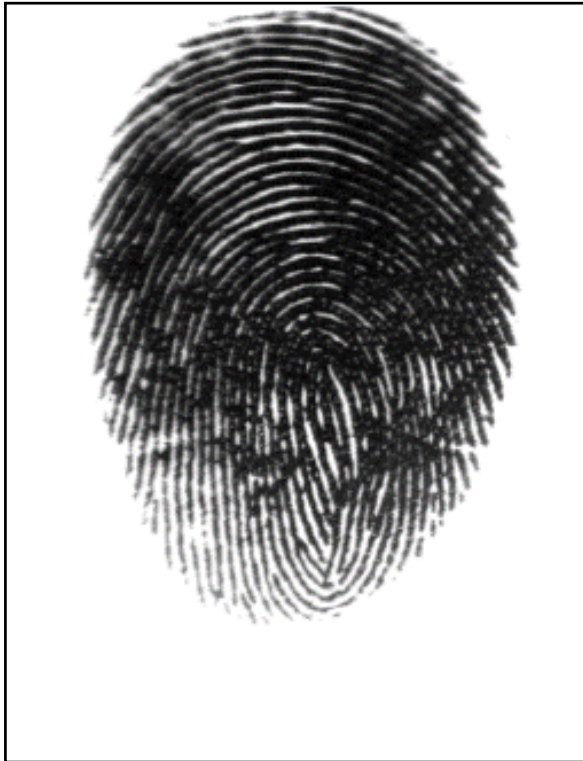
# Nearest neighbor

Similarity measure:

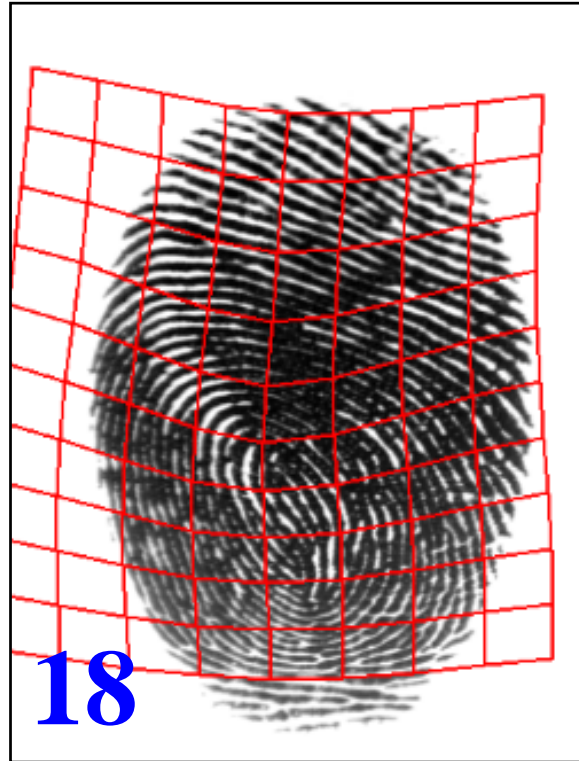
$$s = \frac{s_1^O + s_2^O}{m} (w_1^O s_1^O + w_2^O s_2^O) + \frac{s_1^P + s_2^P}{m} (w_1^P s_1^P + w_2^P s_2^P)$$



# Example of distortion rectification



**Gallery  
fingerprint**



**Original query  
fingerprint**



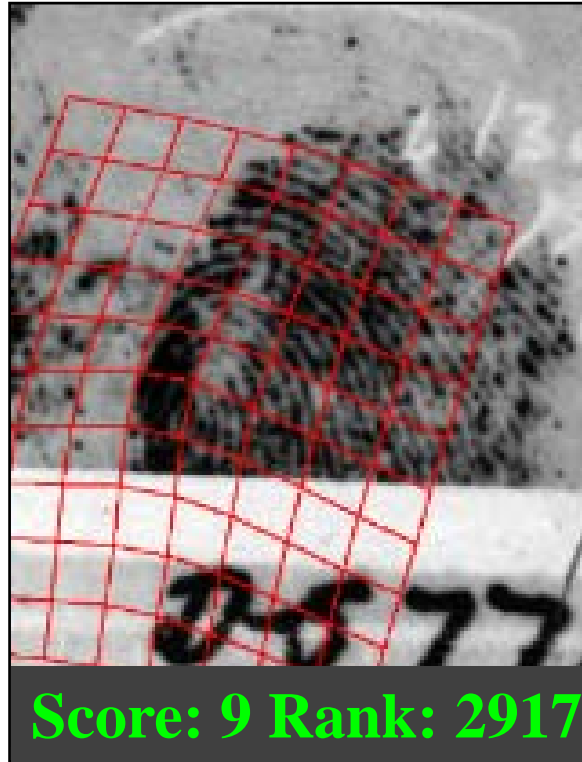
**Rectified query  
fingerprint**

- From FVC2004 DB1;
- Transformation grid (in red) is estimated by our method;
- Scores (in blue) between query & gallery are computed by VeriFinger.

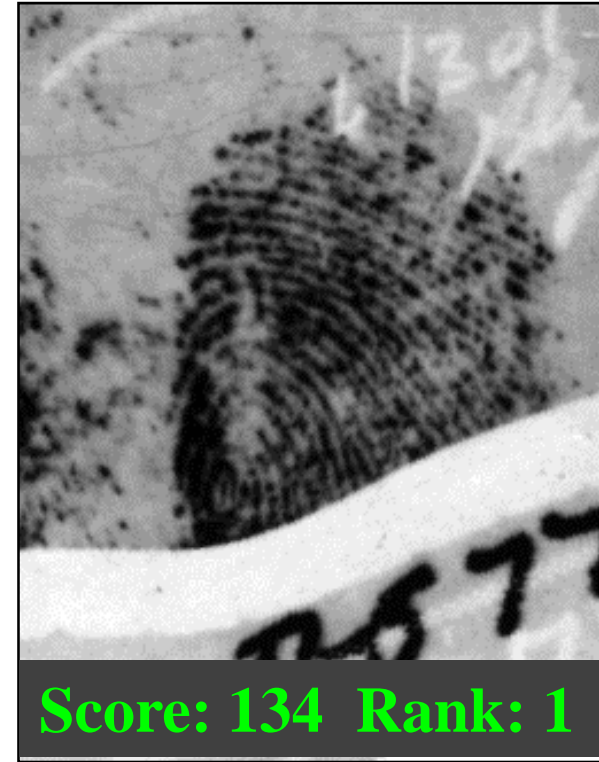
# Example of distortion rectification



**Rolled  
fingerprint**



**Original  
latent fingerprint**



**Rectified  
latent fingerprint**

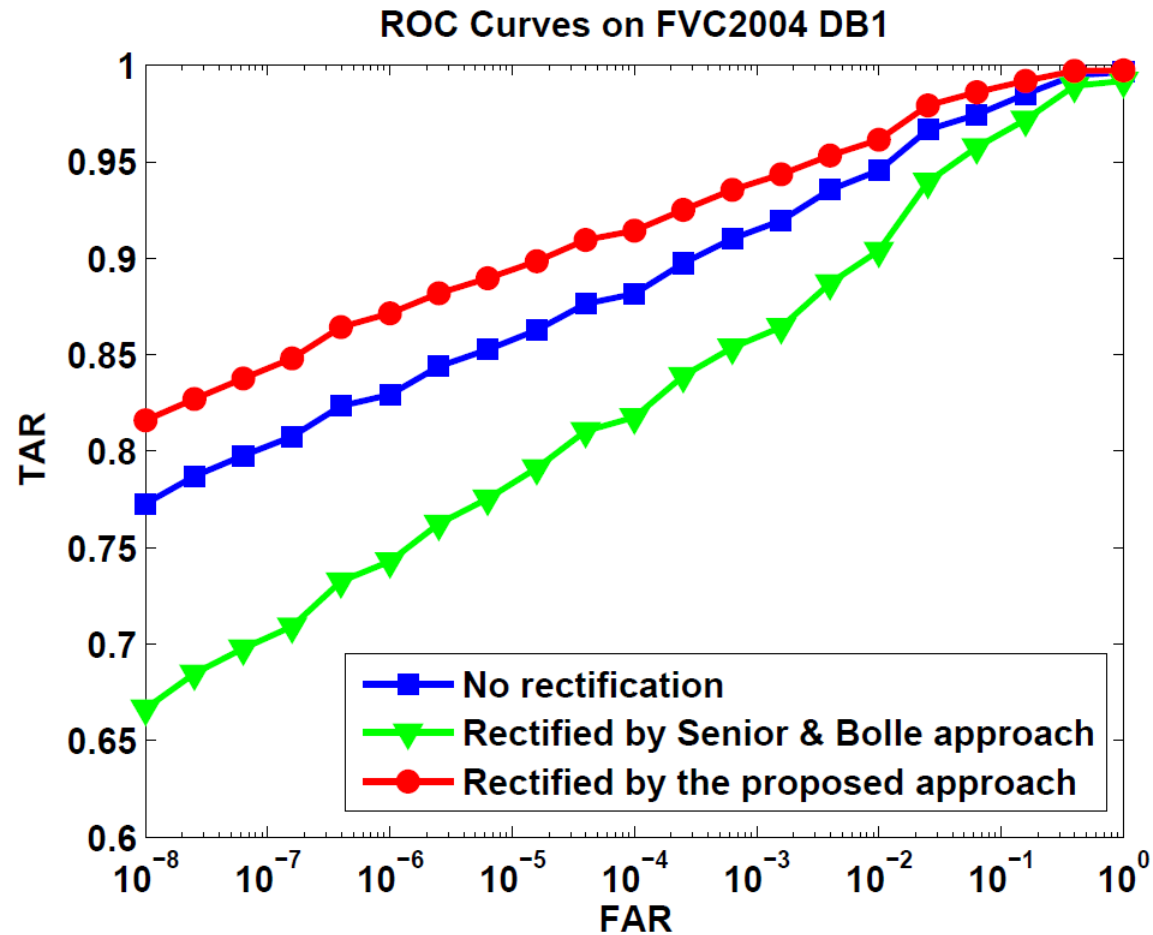
- From NIST-27;
- Transformation grid (in red) is estimated by our method;
- Scores are computed by VeriFinger. A large background database (NIST-14) is used to compute rank.



# Matching experiments

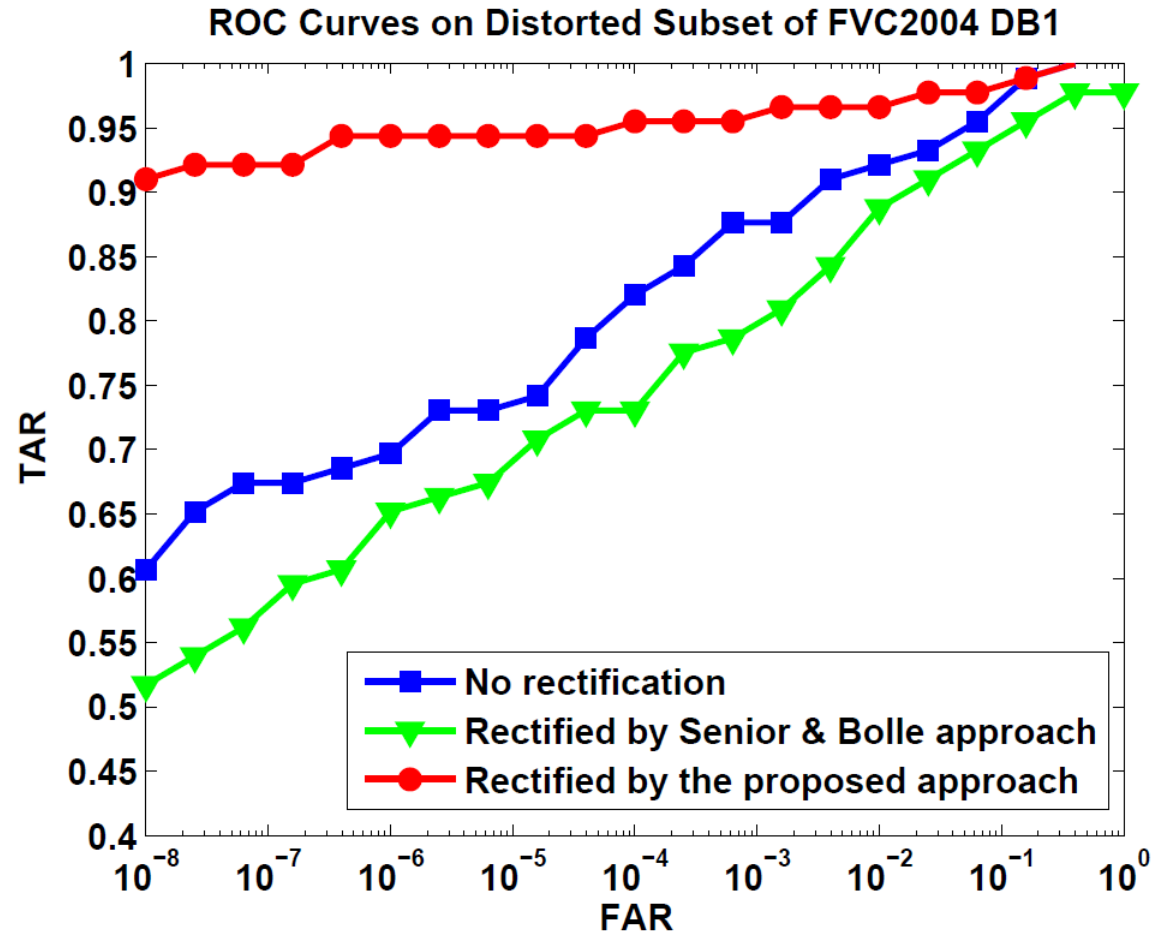
- To systematically evaluate the algorithm, we perform 3 fingerprint matching experiments on each of the following 4 databases:
  - FVC2004 DB1
  - distorted subset of FVC2004 DB1
  - Tsinghua DF database
  - FVC2006 DB2\_A.
- The input images to VeriFinger in 3 matching experiments are:
  - original fingerprints (no rectification is performed)
  - fingerprints rectified by Senior & Bolle approach
  - fingerprints rectified by our approach.

# Matching performance



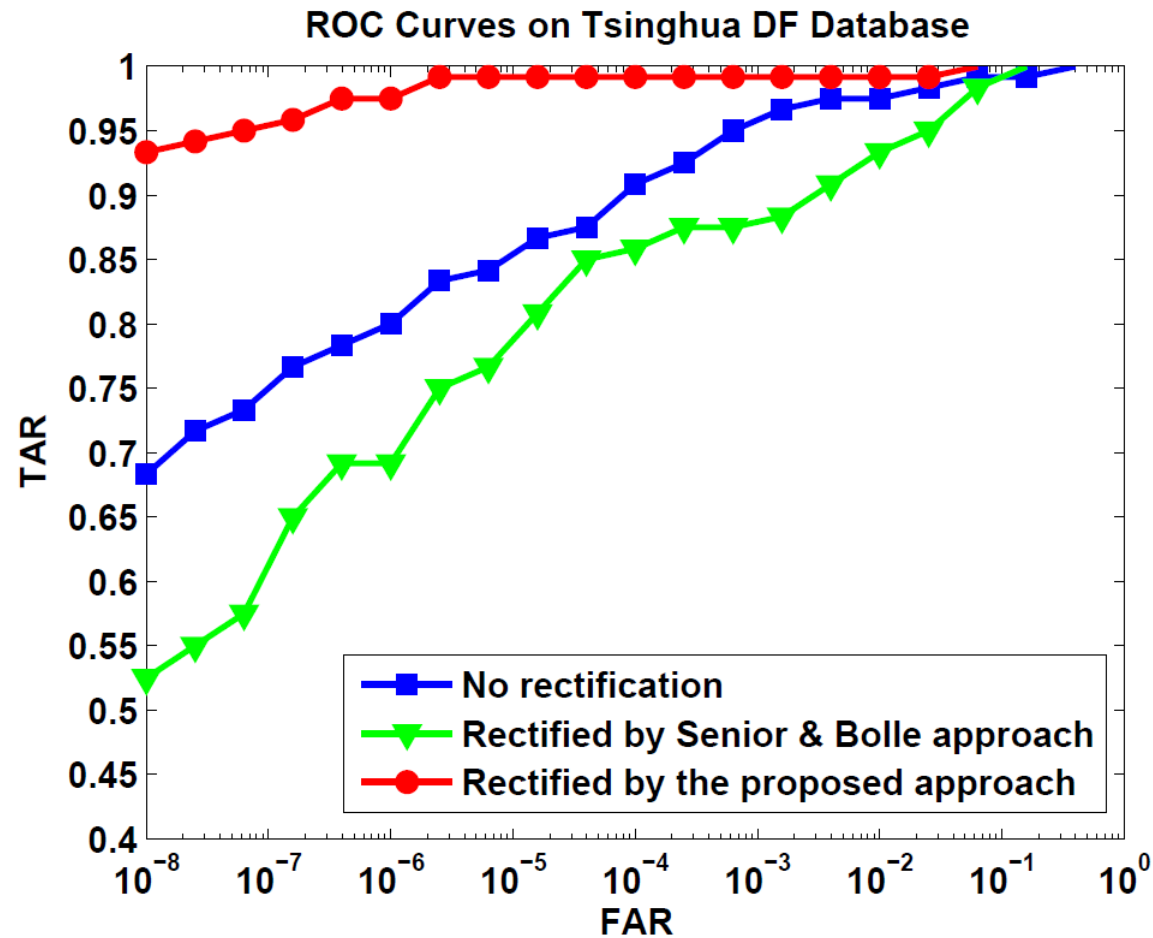
In FVC2004 DB1, ~10% fingerprints are distorted.

# Matching performance



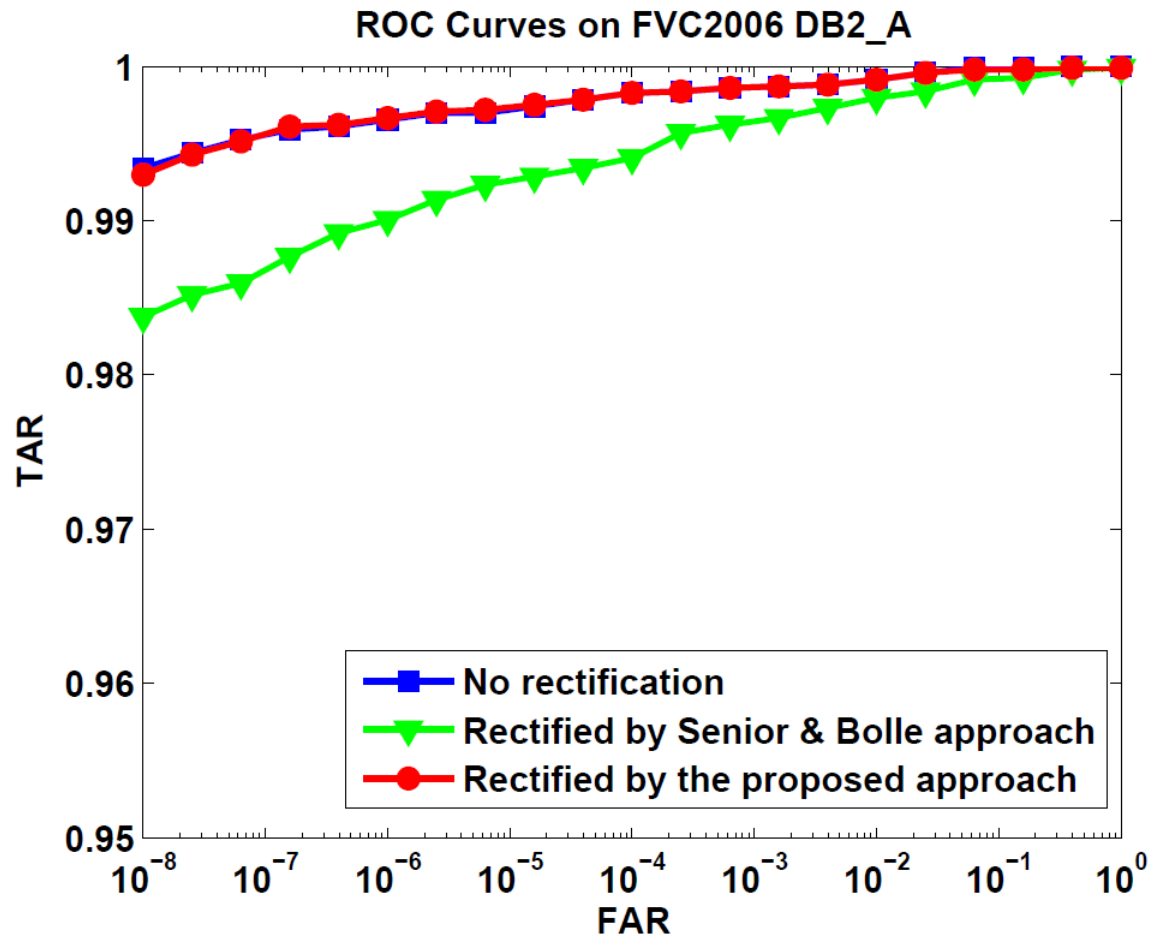
To evaluate the distortion rectification algorithm more clearly, we perform the same experiments on the distorted subset of FVC2004 DB1.

# Matching performance



Half fingerprints in this database are distorted.

# Matching performance



On database without severely distorted fingerprints (FVC2006 DB2\_A), the proposed algorithm has no negative impact.

# Reference

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- D. Maltoni, D. Maio, A. K. Jain, S. Prabhakar, Handbook of Fingerprint Recognition, Springer Verlag, 2009.
- J. Feng, J. Zhou, A. K. Jain, "Orientation field estimation for latent fingerprint enhancement", PAMI 2013.
- X. Yang, J. Feng, J. Zhou, "Localized Dictionaries Based Orientation Field Estimation for Latent Fingerprints", PAMI 2014.
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