Estimating Fingerprint Deformation

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Outline of talk

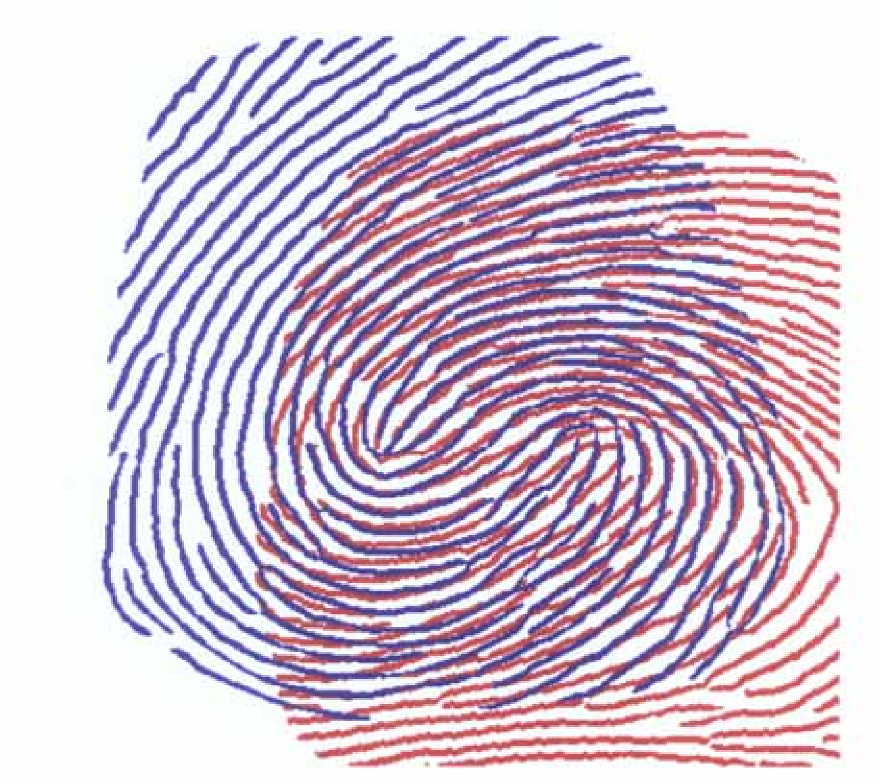
- Fingerprint deformation
    - Fingerprint acquisition
    - Fingerprint matching
- Proposed approach for estimating deformation
    - Average deformation model
    - Index of deformation
- Experimental results
    - Improved alignment between two minutiae sets
    - Optimal template selection

Fingerprint acquisition

- The process of fingerprint imaging introduces non-linear deformations in the ridge structure

Fingerprint matching

- A simple affine transformation does not accurately register the ridge structure of two different impressions of the same finger



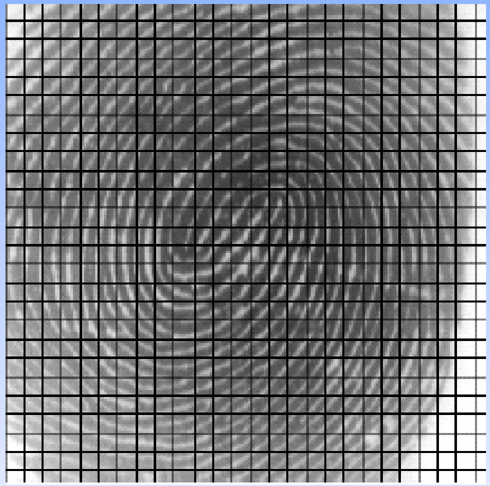
Two different impressions of the same finger using a Digital Biometrics scanner.

- The minutiae points of the two images cannot be accurately matched

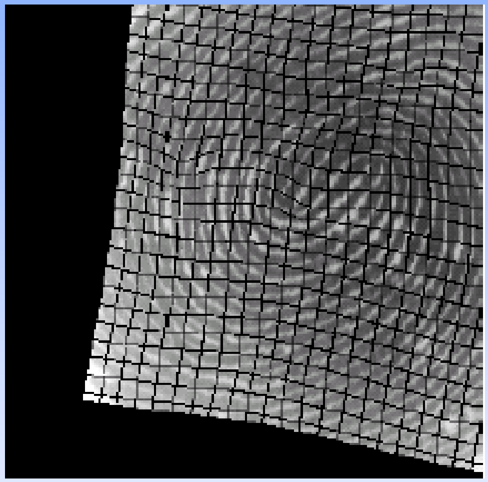
Non-linear deformation

- In order to align (register) two impressions of a finger, the non-linear deformations in the ridge structure have to be considered

(a) Template image



(b) Query image



(c) Aligning query with template

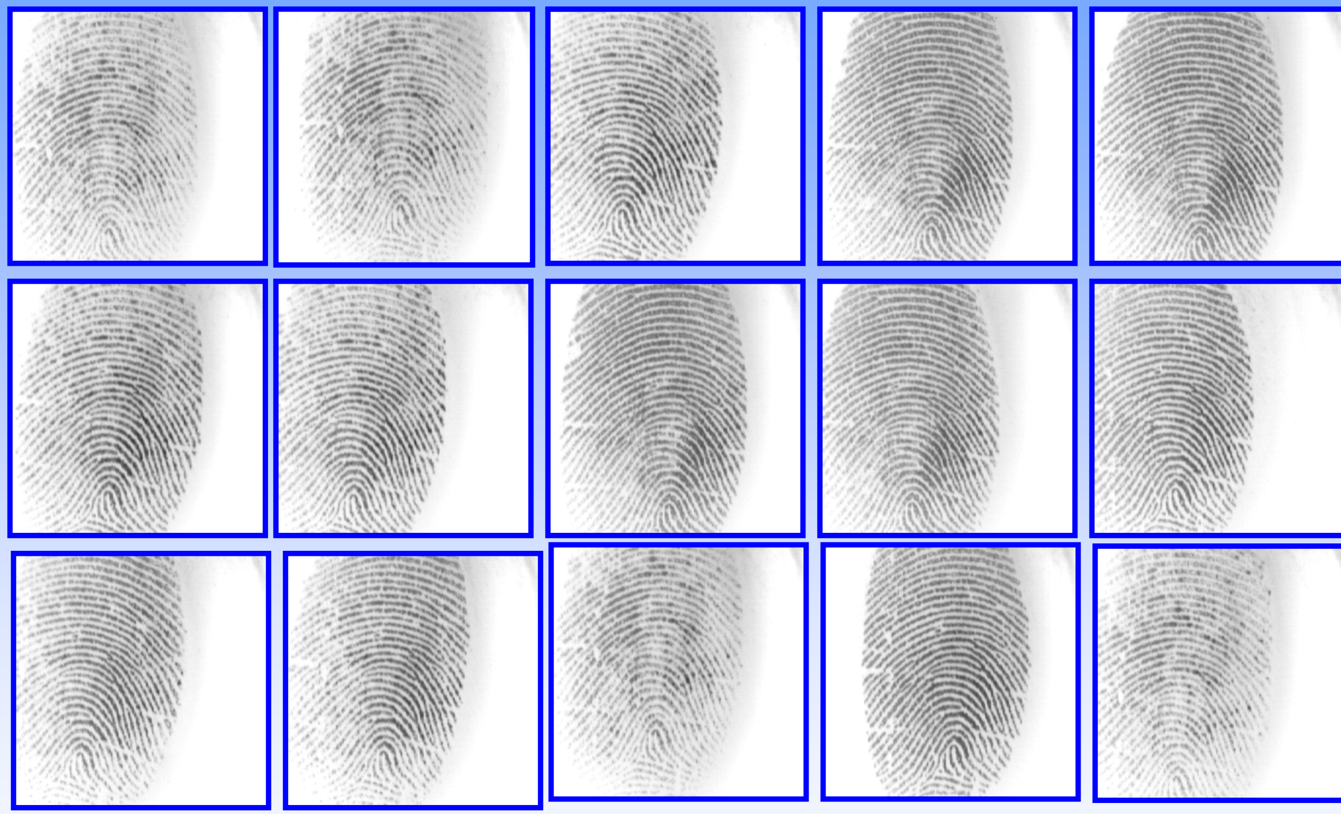
Proposed approach

- Given several impressions of a finger, we develop a finger-specific “average” deformation model
- The average deformation model allows us to pre-distort the template minutiae points before matching them with the query minutiae points
- The deformation model is developed using Thin Plate Splines (TPS)
- Minutiae points and ridge curves are used to establish correspondences between pairs of impressions

Average deformation

- 16 impressions pertaining to a single finger

Baseline impression



Target impressions

- We compute the “average” deformation that relates the baseline impression with the target impressions

The TPS model

- Consider a pair of point patterns $U=\{u_1, u_2,\ldots u_n\}$ and $V=\{v_1, v_2,\ldots v_n\}$, where (u_k,v_k) is the k^{th} corresponding pair; goal is to learn the transformation $\boldsymbol{F}$, s.t. $\boldsymbol{F}(u_k) = v_k$, for $k=1, 2, \ldots n$

- The Thin Plate Spline (TPS) model is given by,

  $$\boldsymbol{F}(u) = c + Au + W^T s(u),$$

  where

  c is a 2x1 translation vector,

  A is a 2x2 affine matrix, and

  W^T is a nx2 weighting matrix;

  $$s(u) = (\sigma(u-u_1),\sigma(u-u_2),\ldots,\sigma(u-u_n))^{\mathrm{T}}$$

  $$\sigma(u) = \begin{cases} ||u||^2 log(||u||), & ||u|| > 0 \\ 0, & ||u|| = 0 \end{cases}$$

Estimating parameters of TPS

- We solve the following equation:

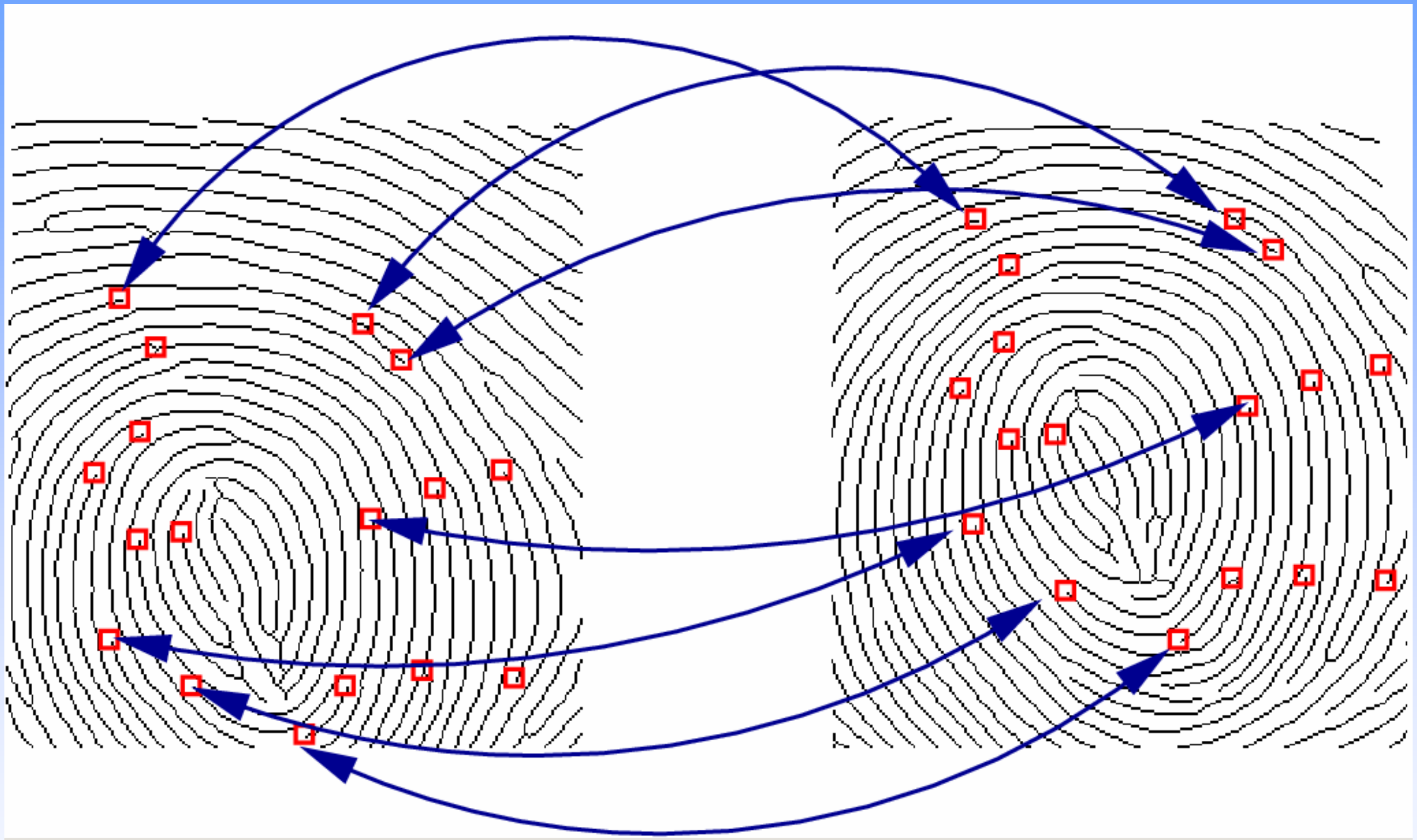
$$\begin{bmatrix} H_{nxn} & 1_n & U \\ 1_n^T & 0 & 0 \\ U^T & 0 & 0 \end{bmatrix} \begin{bmatrix} W_{nx2} \\ c_{2x1}^T \\ A_{2x2}^T \end{bmatrix} = \begin{bmatrix} V \\ 0 \\ 0 \end{bmatrix}, H_{i,j} = \sigma(u_i - u_j)$$

- The constraints are:

$$1_n^T W = 0$$

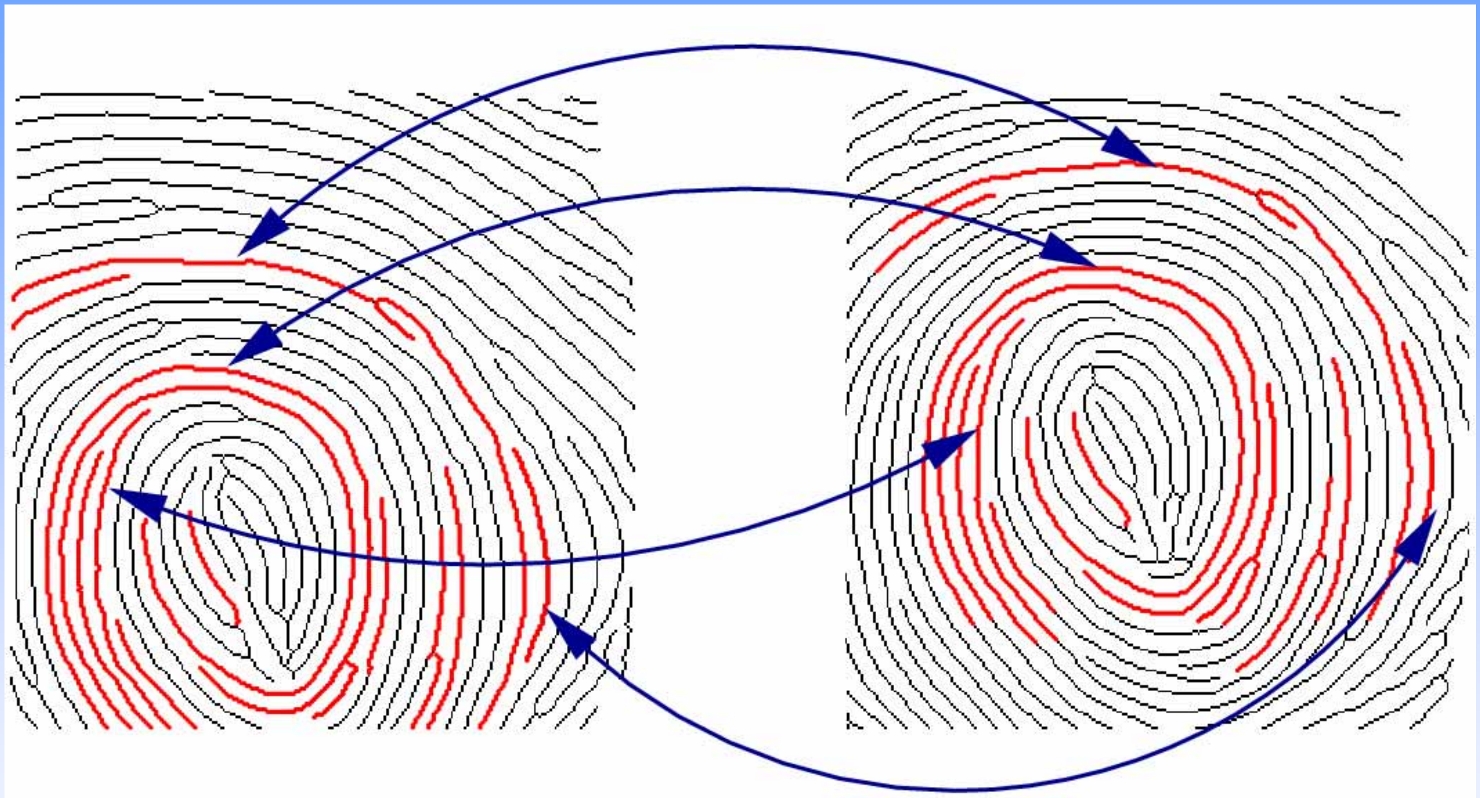
$$U_n^T W = 0$$

Minutiae correspondences



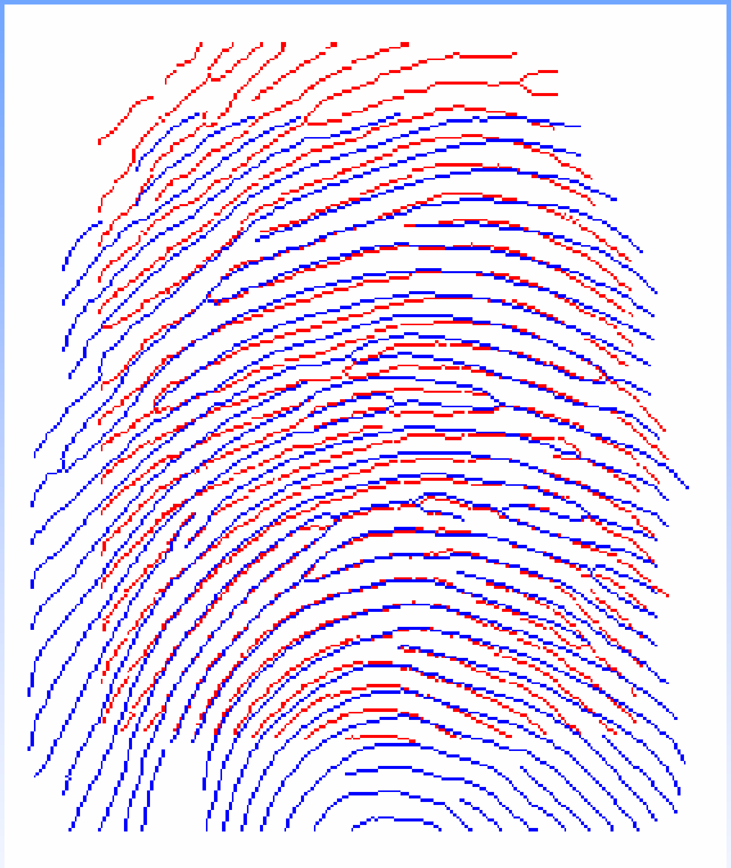
- The TPS model requires point correspondences between image pairs
- We use an elastic string matching technique to obtain minutiae point correspondences

Ridge curve correspondences

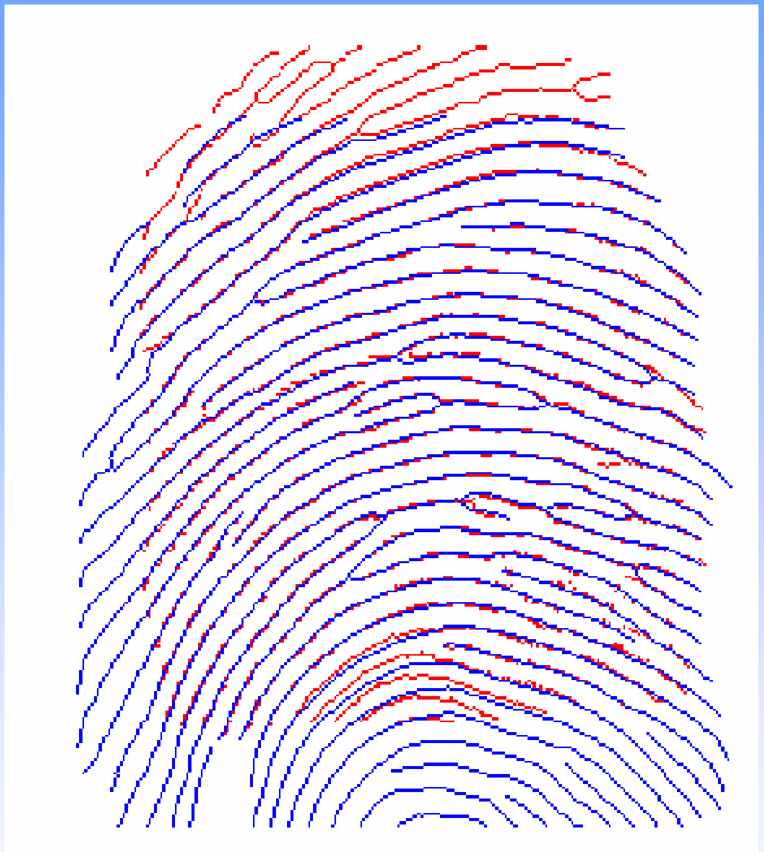


- Ridge curve correspondences are next determined by tracing the ridges in the vicinity of corresponding minutiae points
- These ridge curves are then sampled at regular intervals to obtain point correspondences

Alignment using TPS



(a) Alignment using TPS when minutiae correspondences are used



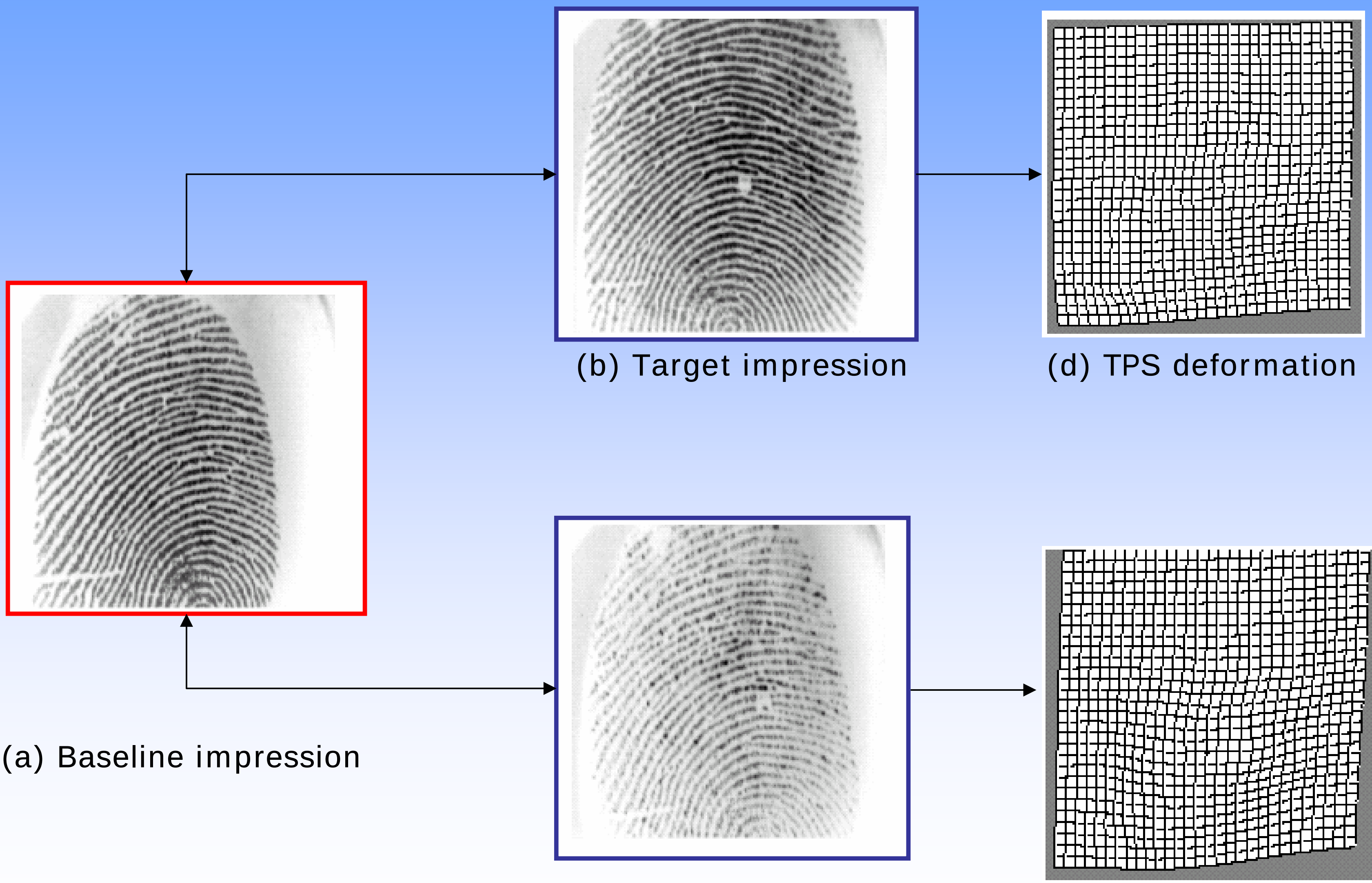
(b) Alignment using TPS when ridge curve correspondences are used

The average deformation model

- Suppose we have L impressions of a finger: T_1, T_2, ..., T_L.
- An impression, T_i, can be paired with each of the remaining (L-1) impressions
- For each pairing $\{T_i, T_j\}$, $j \neq i$, a TPS model, F_{ij}, is computed using sampled ridge curve correspondences
- The average deformation of each pixel u in T_i can then be computed as:

$$\bar{F}_i(u) = \frac{1}{L-1} \sum_{j \neq i} F_{ij}(u).$$

Non-linear deformation



(a) Baseline impression

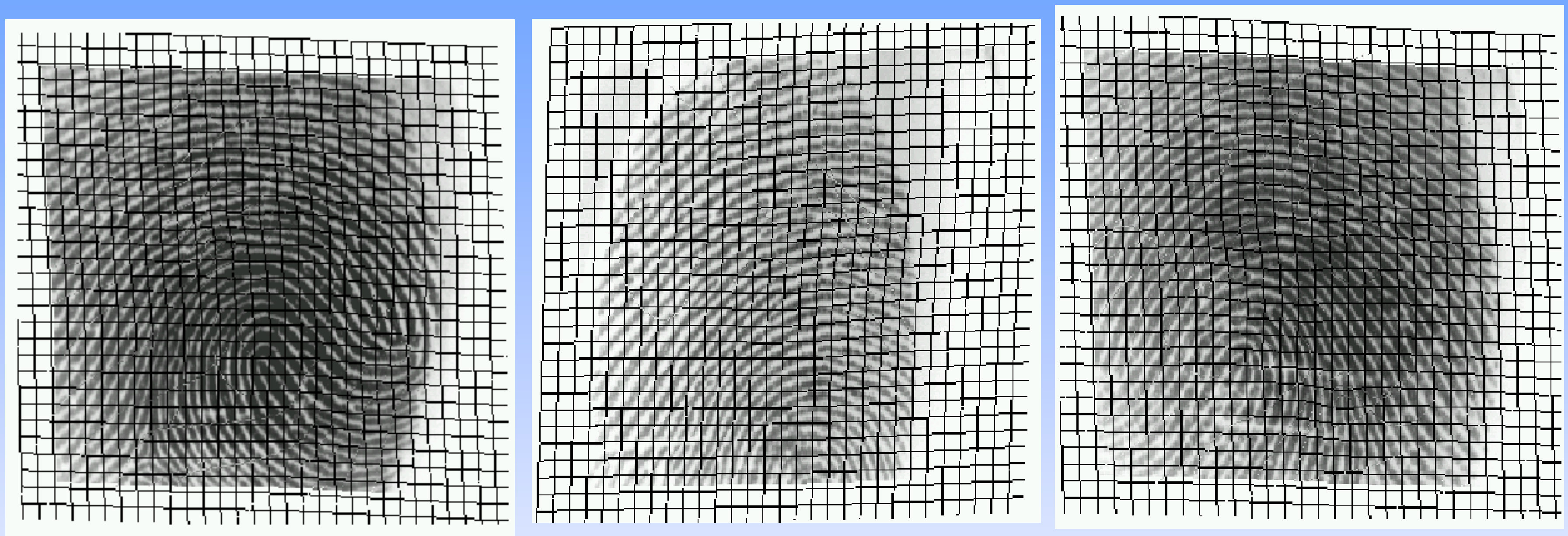
(b) Target impression

(c) Target impression

(d) TPS deformation

(e) TPS deformation

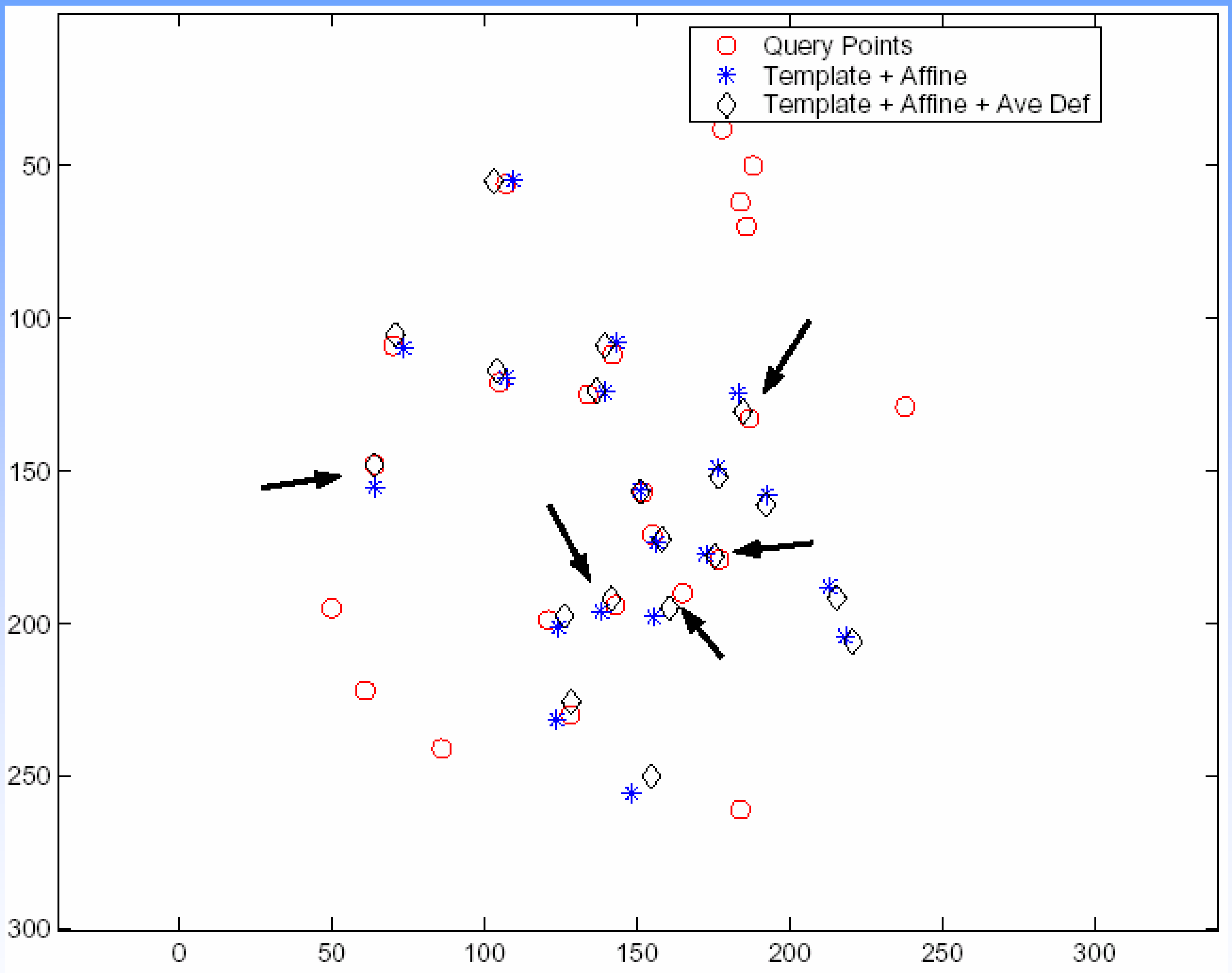
Average deformation model



Finger 1 **Finger 2** **Finger 3**

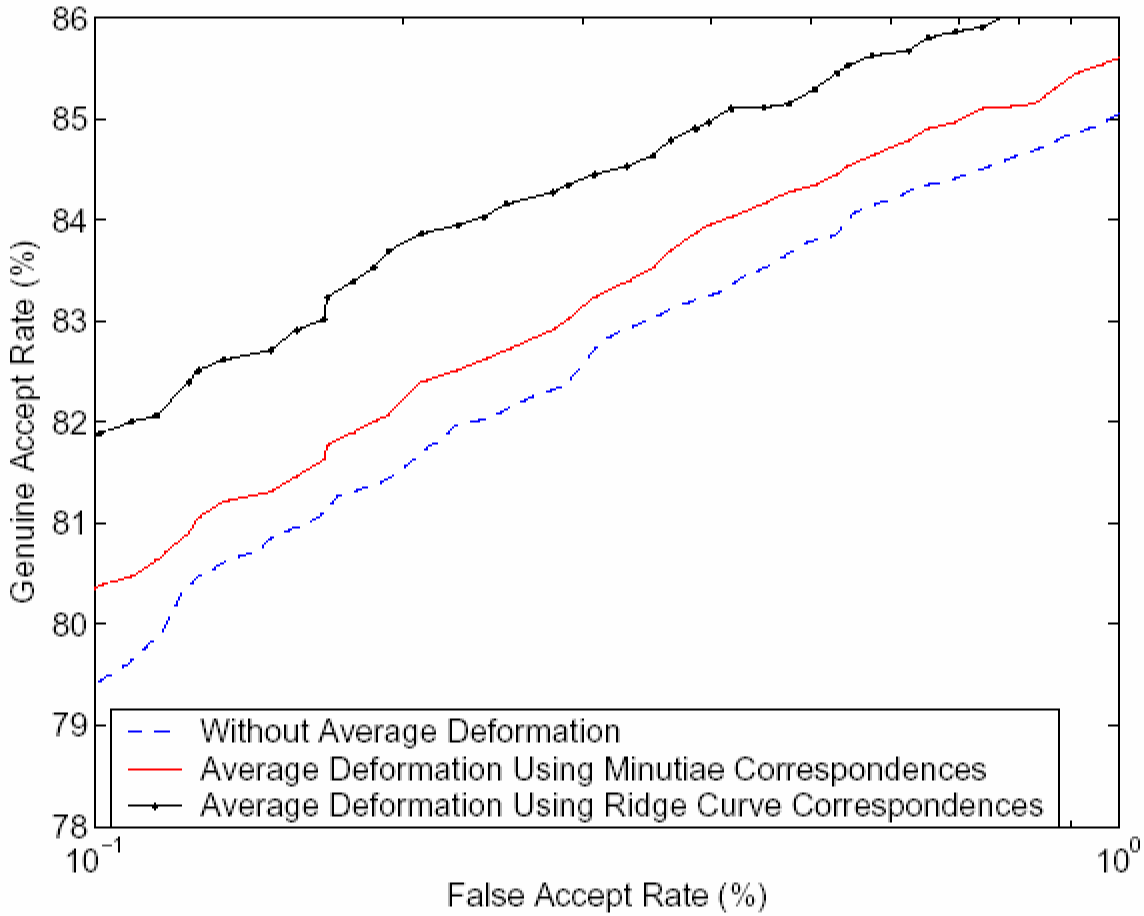
- The average deformation model of three different baseline impressions is shown; each baseline impression was compared against 15 other impressions of the same finger in order to compute the model

Improved alignment



- The average deformable model results in an improved alignment between query and template minutiae points

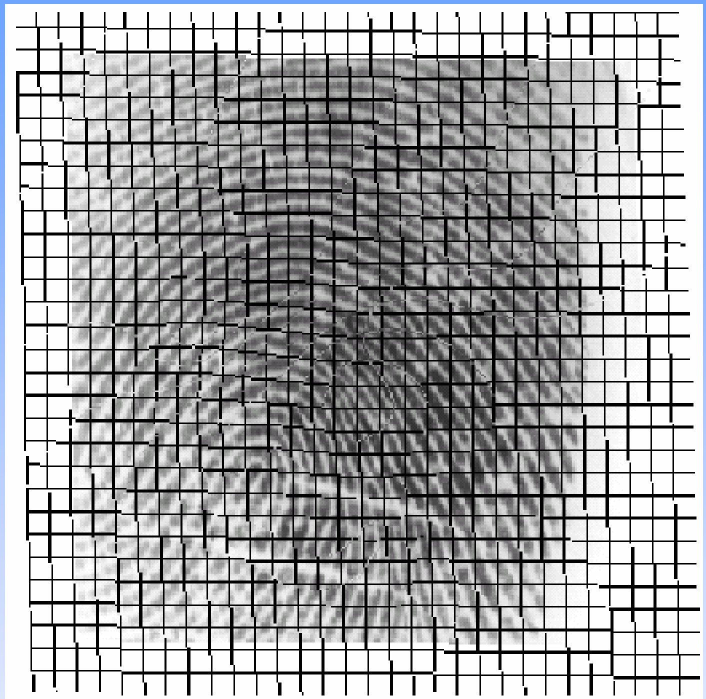
Matching performance



- Data of 50 fingers acquired using Identix sensor
- 32 impressions per finger
- 16 impressions used for computing the average deformation of a finger
- 16 impressions used in testing

- Using distorted minutiae templates results in better alignment

Index of deformation (Φ)

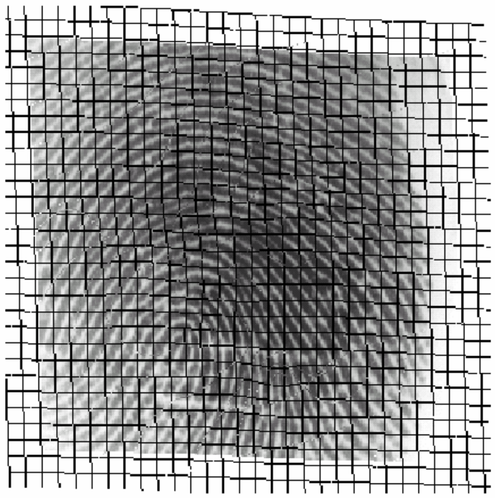


$\Phi = 63.02$

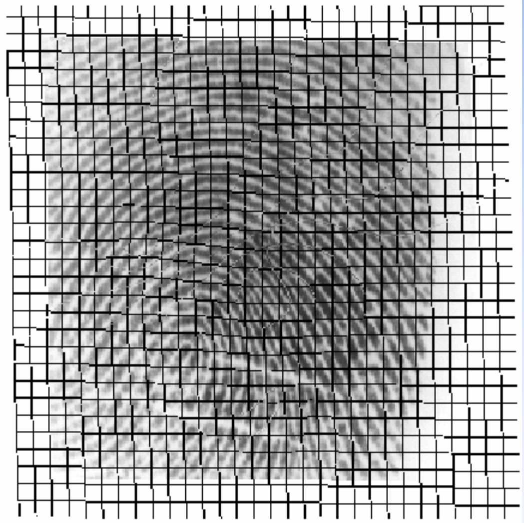
- The index of deformation represents the variability associated with the estimated deformation around the average
- The index of deformation (Φ) is the sum of the trace of the covariance matrix of deformation over all the pixels

Template selection

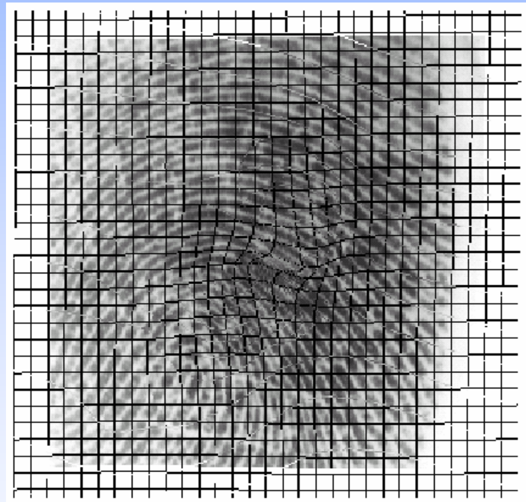
- Given L enrollment images of a finger, select a template such that its index of deformation, Φ, w.r.t. other images is the smallest. Store the average deformable model of this template



$\Phi = 44.68$



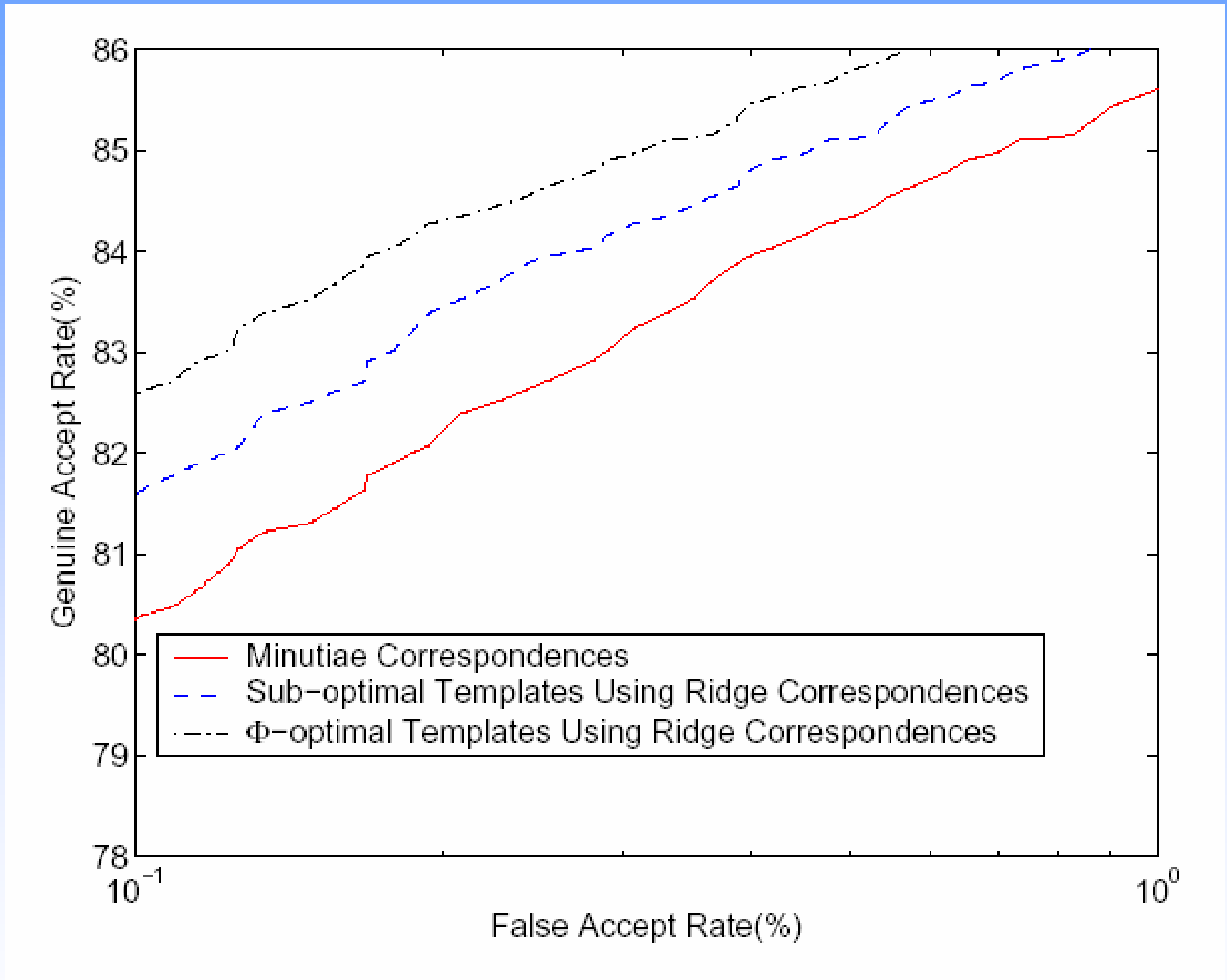
$\Phi = 63.02$



$\Phi = 128.27$

Selected template

Performance using Φ-optimal templates



- Data of 50 fingers acquired using Identix sensor
- 32 impressions per finger
- 16 impressions used for computing the average deformation of a finger
- 16 impressions used in testing

- Using the Φ-optimal templates results in better performance

Summary and future work

- We have developed an *average deformation model* for estimating the non-linear deformations in fingerprint impressions using ridge curve correspondences

- We have proposed an *index of deformation* for selecting the *optimal* average deformation model for a finger

- We are studying the effect of the number of impressions on the average deformation model

- We are examining ways to perform incremental update on the average deformation model when new impressions are made available