FILTERBANK-BASED FINGERPRINT MATCHING

- Dinesh Kapoor(2005EET2920)
- Sachin Gajjar(2005EET3194)
- Himanshu Bhatnagar(2005EET3239)

Papers Selected

- FINGERPRINT MATCHING USING MINUTIAE AND TEXTURE FEATURES
  - *By Anil Jain, Arun Ross and Salil Prabhakar*
- FILTERBANK-BASED FINGERPRINT MATCHING
  - *By Anil Jain,Salil Prabhakar,Lin Hong and Sharath Pankanti.*

Outline

- Advantages/Disadvantages of using Fingerprint for Personal Identification
- Fingerprint Anatomy
- Disadvantages of Minutiae based approach for Fingerprint Matching
- Filter bank-based Fingerprint Matching
- System performance
- Strengths of the Paper
- Weakness of the Paper
- Contribution to the State-of-Art
- Areas unexplored
- Hybrid approach for Fingerprint Matching

Advantages of using Fingerprint for Personal Identification

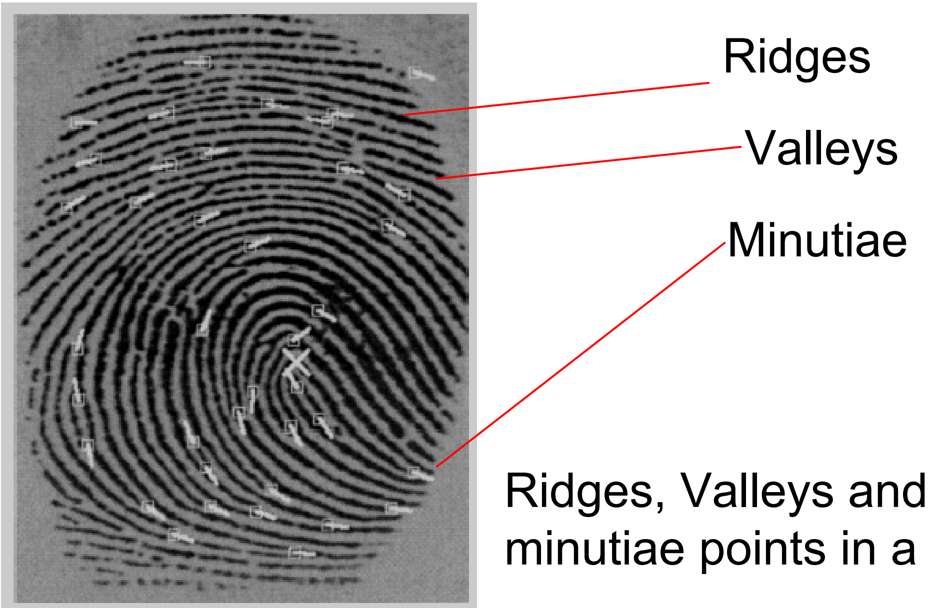
- The most mature and proven technique
- Fingerprint of identical twins and prints on each finger of the same person are different
- Satisfies performance requirements (matching speed and accuracy)
- Sensors are becoming cheaper and smaller
- Compact representation makes Fingerprint based smartcards possible

Disadvantages of using Fingerprint for Personal Identification

- Requires a large amount of computational resources
- Fingerprint of small population is unsuitable for automatic identification
- User acceptance is low
- Patterns scanned require high resolution images, storage requires lot of memory

Fingerprint Anatomy

- Fingerprint is pattern of ridges and valleys on the surface of finger
- Uniqueness determined by overall pattern of ridges and valleys and the local ridge anomalies like ridge bifurcation or ridge ending (minutiae points)



Ridges, Valleys and automatically detected minutiae points in a fingerprint image

Disadvantages of Minutiae based approach for Fingerprint Matching

- A good quality fingerprint contains between 60 and 80 minutiae, but different fingerprints have different numbers
- Reliably extracting minutiae from poor quality fingerprints is very difficult
- Minutiae extraction is time consuming
- Variable sized minutiae-based representation does not easily help in indexing fingerprint database

Advantages of Filter bank based Fingerprint Matching

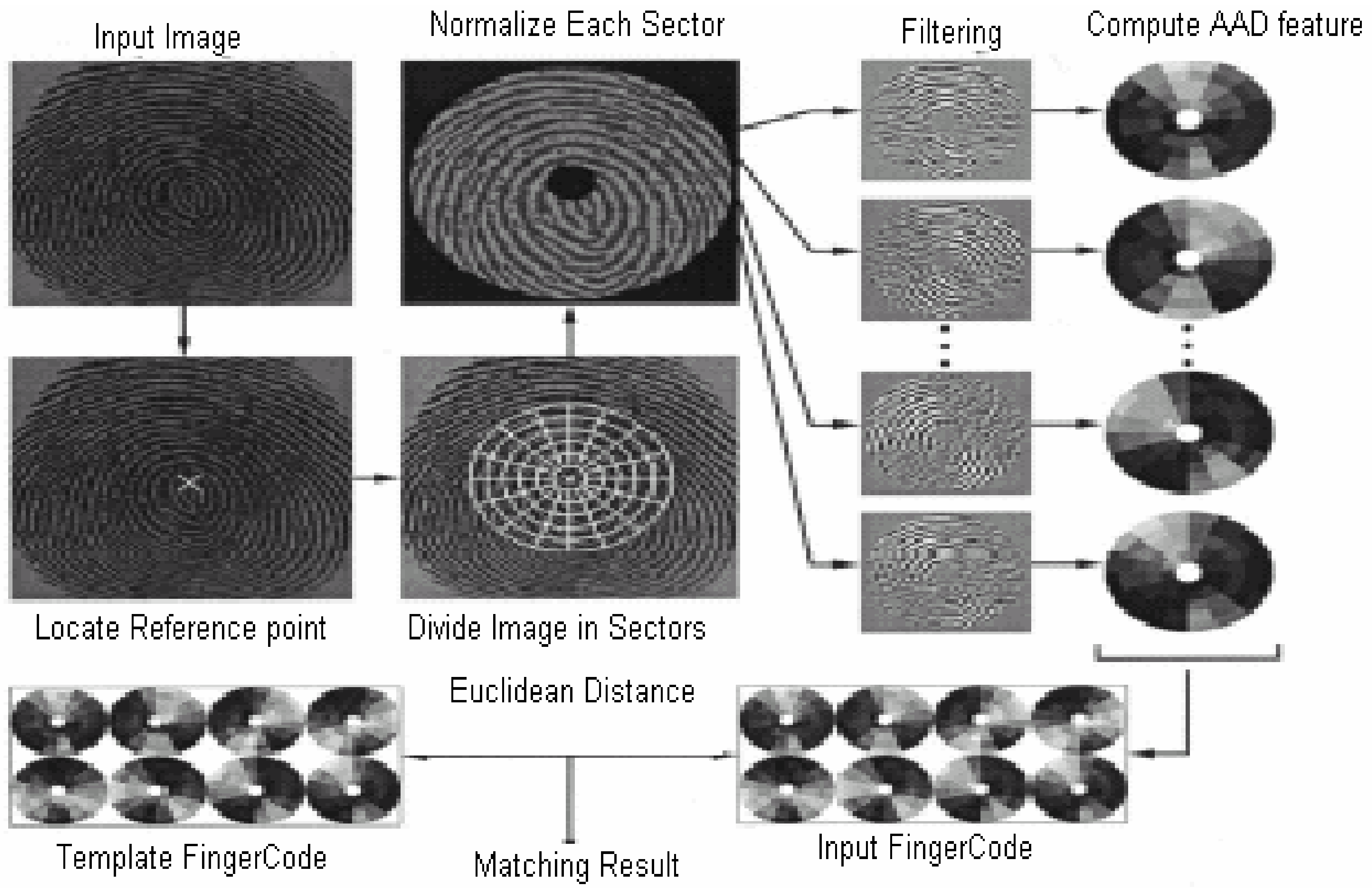
- Both the global flow pattern of ridges and valleys and local characteristics (inter-ridge distances, ridge orientation) are used for feature extraction
- They generate a short fixed length code, ***FingerCode*** (Feature vector) for fingerprint
- ***FingerCode*** is suitable for fast matching (by Euclidean distance), storage on smartcard and indexing
- The obtained representation is scale, translation and rotation invariant

Filter bank-Based Fingerprint Matching

- Steps in feature extraction

1. Determine a reference point and region of interest for the fingerprint image
2. Tessellate the region of interest around the reference point
3. Filter the region of interest in eight different direction using a bank of Gabor filters (to completely capture the local ridge characteristics and the global configuration in a fingerprint)
4. Compute the average absolute deviation from the mean (AAD) of gray values in individual sectors in filtered images to define the ***FingerCode*** (feature vector)

System diagram of Filterbank-Based Fingerprint Matching



Reference Point Location

- Reference Point is point of maximum curvature of concave ridges in fingerprint images
- Steps in determining the Reference Point Location

1. Divide the input image into nonoverlapping blocks of size *w x w*
2. Compute the gradients ∂x(i,j) and ∂y(i,j) at each pixel (i,j)
3. Estimate the Local ridge orientation of each block centered at pixel (i,j) by the following equations

$$\mathcal{V}_x(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} 2\partial_x(u,v)\partial_y(u,v)$$

$$\mathcal{V}_y(i,j) = \sum_{u=i-w/2}^{i+w/2} \sum_{v=j-w/2}^{j+w/2} (\partial_x^2(u,v) - \partial_y^2(u,v))$$

$$\mathcal{O}(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{\mathcal{V}_y(i,j)}{\mathcal{V}_x(i,j)}\right)$$

Reference Point Location (Contd.)

4. Smoothen the Orientation field by low pass filtering. For this Convert the orientation image into a continuous vector field with the following *x* and *y* components

$$\Phi_x(i,j) = \cos(2\mathcal{O}(i,j)) \quad \Phi_y(i,j) = \sin(2\mathcal{O}(i,j))$$

With resulting vector field do Low pass filtering with *W* filter

$$\Phi'_x(i,j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} W(u,v) \cdot \Phi_x(i-uw, j-vw)$$

$$\Phi'_y(i,j) = \sum_{u=-w_\Phi/2}^{w_\Phi/2} \sum_{v=-w_\Phi/2}^{w_\Phi/2} W(u,v) \cdot \Phi_y(i-uw, j-vw)$$

The smoothed orientation field at (i,j) is computed as follows

$$\mathcal{O}'(i,j) = \frac{1}{2}\tan^{-1}\left(\frac{\Phi'_y(i,j)}{\Phi'_x(i,j)}\right).$$

Reference Point Location (Contd.)

5. Compute *E*, image containing only sine component of smoothed orientation field

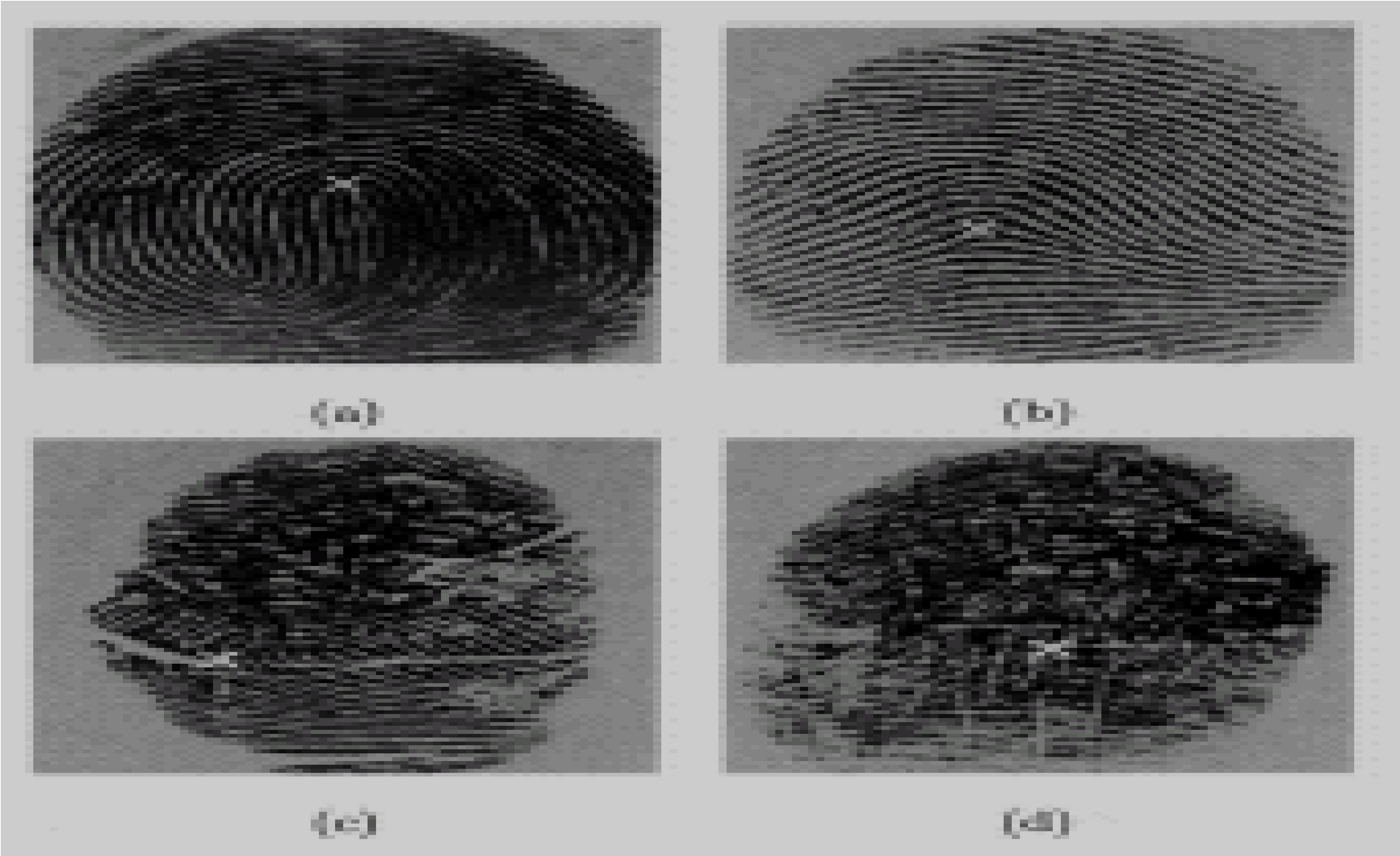
$$\mathcal{E}(i, j) = \sin(\mathcal{O}'(i, j)).$$

6. Regions RI and RII are determined by applying the reference point location algorithm over a large database to capture the maximum curvature in concave ridges
7. For each pixel in *E*, integrate sine component of the orientation field in regions RI and RII and assign the corresponding pixels in *A* (label image to indicate the reference point) the value of their difference

$$\mathcal{A}(i, j) = \sum_{R_I} \mathcal{E}(i, j) - \sum_{R_{II}} \mathcal{E}(i, j).$$

8. Find the maximum value in *A* and assign its co-ordinates to the reference point
9. Repeat steps 1-8 for fixed number of times using window size *w' x w'* *(w'<w)* and restrict the search for the reference point in the local neighborhood of the detected reference point.

Example Results



Divide the Image into Sectors

- Let *I(x,y)* be gray level at pixel *(x,y)* in an *M x N* fingerprint image and *(xc,yc)* be reference point
- The region of interest is divided into collection of all the sectors Si, where

$$S_i = \{(x, y) | b(T_i + 1) \leq r < b(T_i + 2), \\ \theta_i \leq \theta < \theta_{i+1}, 1 \leq x \leq N, 1 \leq y \leq M\}$$

where

$$T_i = i \ div \ k$$
$$\theta_i = (i \mod k) \times (2\pi/k)$$
$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2}$$
$$\theta = \tan^{-1}((y - y_c)/(x - x_c))$$

- b is width of each band, *k* is number of sectors considered in each band and *i=0…..(B x k-1)* where *B* is number of concentric bands considered around the reference point for feature extraction
- Parameters depend upon the image resolution and size

Example Results

- Reference point (x), the region of interest, and 80 sectors superimposed on a fingerprint

Filtering

- Step 1:Normalisation.
  - Done to remove effects of sensor noise and gray level deformation due to finger pressure differences.
  - Normalize each sector separately to a constant mean and variance.
  - Normalization is a pixel wise operation which does not change the clarity of the ridge and valley structures.

Filtering: Normalization

- For all the pixels in sector S_i, the normalized image is defined as,

$$N_i(x,y) = \begin{cases} M_0 + \sqrt{\frac{V_0 \times (I(x,y)-M_i)^2)}{V_i}}, & if \quad I(x,y) > M_i \\ M_0 - \sqrt{\frac{V_0 \times (I(x,y)-M_i)^2)}{V_i}}, & otherwise, \end{cases}$$

- $I(x,y)$:gray level at pixel (x,y)
- M_i and V_i :estimated mean and variance of sector S_i.
- $N_i(x,y)$: Normalised gray level at pixel (x,y).
- M_o and V_o : Desired mean and variance values.

Filtering: In Spatial Domain

- Step2: Filtering in Spatial-Domain with 33 × 33 Mask
  - Gabor Filters. Can remove noise, preserve true ridge and valley structures and provide information contained in a particular orientation.
  - Minutia viewed as anomaly in parallel ridges.
  - General Form of Gabor Filter in the Spatial Domain

$$G(x, y; f, \theta) = \exp\left\{\frac{-1}{2}\left[\frac{x'^2}{\delta_{x'}^2} + \frac{y'^2}{\delta_{y'}^2}\right]\right\}\cos(2\pi f x')$$

$$x' = x\sin\theta + y\cos\theta$$

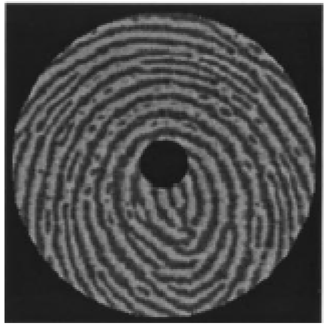
$$y' = x\cos\theta - y\sin\theta$$

- f : frequency of the sinusoidal plane wave along the direction θ from the x-axis
- $\delta_{x'}$ and $\delta_{y'}$: space constants of the Gaussian envelope along x' and y' axes respectively.

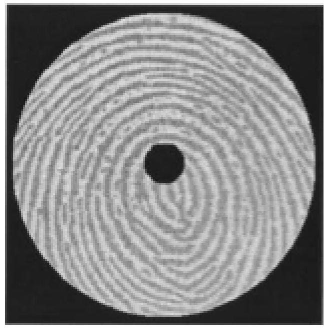
Filtering

- Filtering Characteristics.
  - Filter frequency = Average ridge frequency (1/K)
  - K : Average inter-ridge distance. It is approx 10 pixels in 500 dpi images
  - Eight different filter directions: 0^o, 22.5^o, 45^o, 67.5^o, 90^o, 112.5^o, 135^o, 157.5^o wrt x axis.
  - Normalized region of interest is convolved with each of the eight filters.
  - Eight directional-sensitive filters capture most of the global ridge directionality information and local ridge characteristics present in a fingerprint.

Filtering: Normalized, filtered, and reconstructed fingerprint images

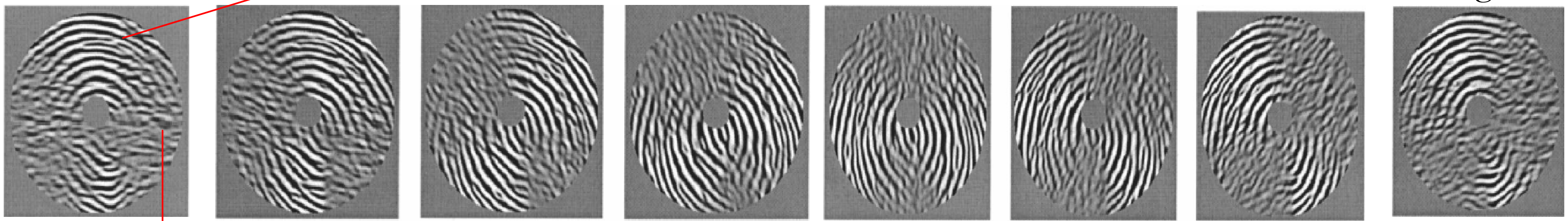


area of interest



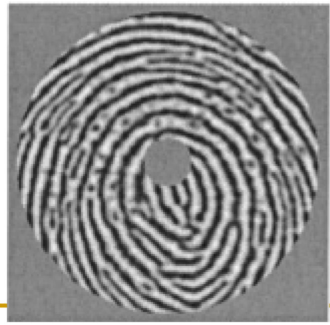
normalized image,

SMOOTHEN



0 , 22.5 , 45 , 67.5 , 90 , 112.5 , 135 ,157.5 filtered images,

ACCENTUTE(0)



reconstructed image with eight filters.

Filtering: Feature Vector

- Average absolute deviation from the mean for every i Є {0,1,…,79} and θ Є {0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135°, 157.5°} is defined as

$$V_{i\theta} = \frac{1}{n_i}\left(\sum_{n_i} |F_{i\theta}(x, y) - P_{i\theta}|\right)$$

- $F_{i,\theta}(x,y)$:θ-direction filtered image for sector S_i .
- $P_{i\theta}$ is the mean of the pixel values of $F_{i,\theta}(x,y)$ in sector $S_{i.}$
- n_i is the number of pixels in sector $S_{i.}$

Matching

- Based on finding the Euclidean distance
- Translation invariance achieved by reference point.
- Approx rotational invariance is achieved by cyclically rotating the features of the FingerCode.
- A rotation by steps R steps corresponds to a R x 22.5^0 rotation of the image.
- A positive rotation implies clockwise rotation while a negative rotation implies counterclockwise rotation.
- The FingerCode obtained after R steps of rotation is given by

$$
\begin{aligned}
V_{i\theta}^{R} &= V_{i'\theta'} \\
i' &= (i + k + R) \bmod k + (i \operatorname{div} k) \times k \\
\theta' &= (\theta + 180^\circ + 22.5^\circ \times R) \bmod 180^\circ
\end{aligned}
$$

- K (= 16) is the number of sectors in a band, i Є {0,1,…,79} and θ Є {0^o, 22.5^o, 45^o, 67.5^o, 90^o, 112.5^o, 135^o, 157.5^o }

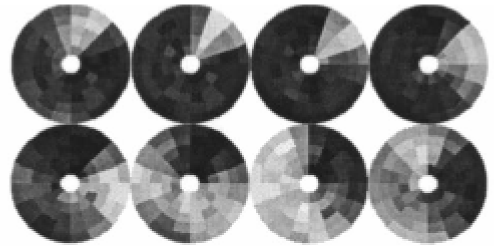
Matching :Alignment

- For each fingerprint in the database, store five templates corresponding to the following five rotations of the corresponding FingerCode: $V_{i\theta}^{-2,}$ $V_{i\theta}^{-1,}$ $V_{i\theta}^{0,}$ $V_{i\theta}^{1,}$, $V_{i\theta}^{2}$
- Due to the nature of the tessellation, features are invariant to only small perturbations that are within ± 11.25^0.
- Generate another feature vector for each fingerprint during the time of registration which corresponds to a rotation of 11.25^0 .
- The original image is rotated by an angle of 11.25^0 and its FingerCode is generated.
- Thus, the database contains ten templates for each fingerprint. These ten templates correspond to all the rotations on the fingerprint image in steps of 11.25^0.
- The final matching distance score is taken as the minimum of the ten scores, i.e., matching of the input FingerCode with each of the ten templates.
- This minimum score corresponds to the best alignment of the two fingerprints being matched.

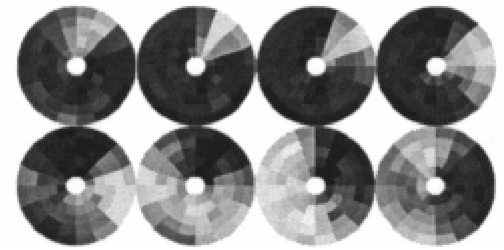
Examples of 640-dimensional feature vectors:

(a) First impression of finger

(b) Second impression of finger

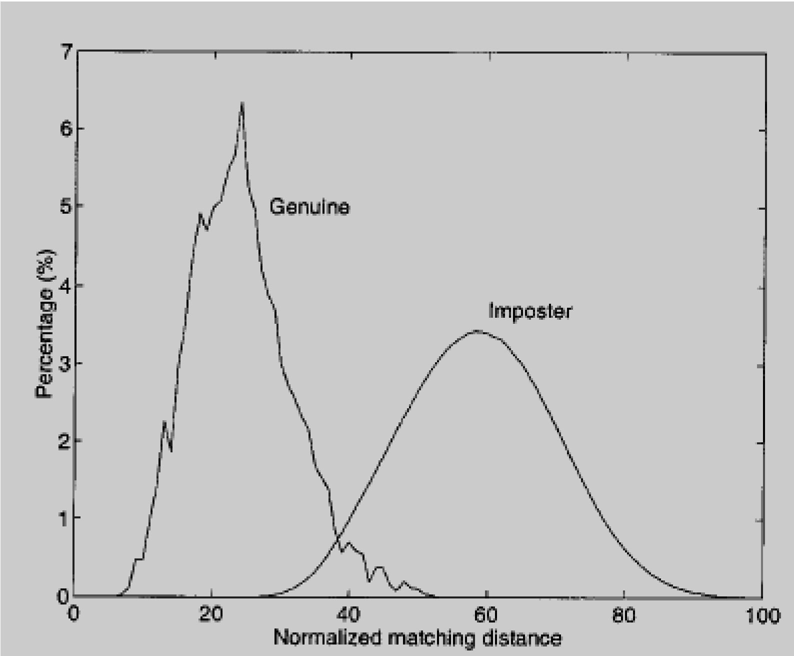


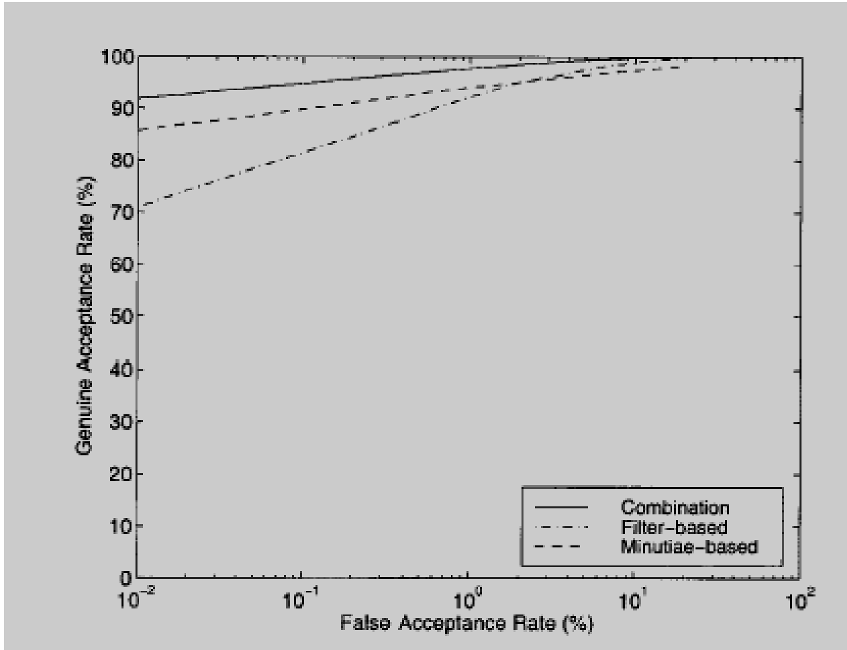
(c) FingerCode of (a)



(d)   FingerCodeof (b),

System Performance





Genuine and imposter distributions

ROC curves for several matchers:

Contributions to the State of the Art

- Presents an entirely new technique for fingerprint detection.
- Technique amenable to hardware implementation.
- Faster as it uses Euclidean distance for matching and computationally attractive, if FingerCodes of all enrolled fingerprints are stored as templates.
- It taps both the global flow pattern of ridges and valleys and local characteristics (inter-ridge distances, ridge orientation) are used for feature extraction.

Weaknesses of the Paper

- Assumptions made for calculations of the reference point.
- Assumes that entire region of interest is available.
- Does not take into account occlusion or obliteration of a part of the fingerprint.
- Susceptible to non-elastic distortions.
- Results based on highly accurate test samples.

Strengths of the Paper

- Paper written in fair detail.
- Well supported by graphs, figures and mathematical expressions.
- Starts from a very basic platform and the progress is gradual with adequate explanations on implementation and technical jargon.
- Paper talks about its own weaknesses.

Areas Unexplored

- Handling nonlinear distortion.
- Refinements to initial strategies for feature extraction and matching.
- Indexing techniques based on the proposed representation.
- Methods for faster search: classifing data.
- Enhancement techniques for the image.
- Use of multiple frames to obtain multiple representations for more robust performance.
- Combination of both techniques :Minutia and Filterbank.

NEED FOR THE HYBRID APPROACH

•SSolid state sensors have small sensing area, so sense only a portion of the total fingerprint.

•MMultiple images of the same fingerprint may have a small region of overlap due to rotation or translation.

•MMinutiae-based algorithms fail, because they consider ridge activity in the vicinity of the minutiae.

•mMinutiae (point) information and texture(region) information for matching the fingerprints.

•SStatistics from the MSU VERIDICOM database shows an improvement in the performance.

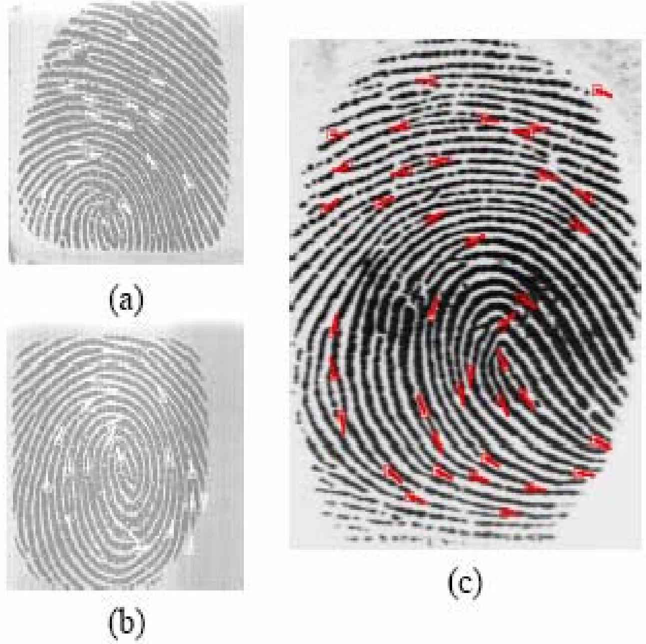


Fig. 1. Fingerprint images acquired using the solid state Veridicom sensor (a,b) and the optical Digital Biometrics sensor (c). The detected minutiae points have been marked in the fingerprint images (17 in (a), 21 in (b), 39 in (c)).

FINGERPRINT MATCHING USING MINUTIAE AND TEXTURE FEATURES

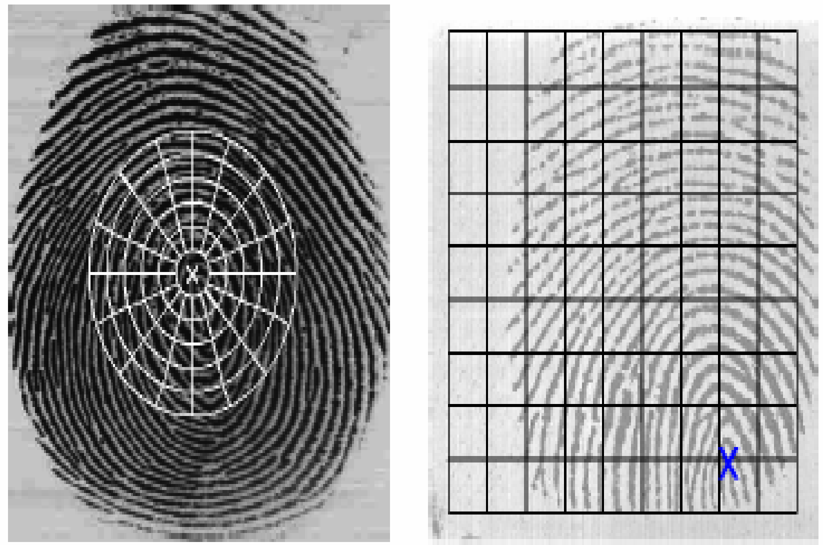
- Combines a minutiae-based representation of the fingerprint with a Gabor-filter (texture-based) representation for matching purposes.
- Algorithm first aligns the two fingerprints using the minutiae points extracted from both the images, then uses texture information to perform detailed matching.
- More information than minutiae points is being used to match fingerprints.
- Verification results suggest better suitability of the hybrid approach.

ALGORITHM APPROACH

1. TRY TO ALIGN THE MINUTIAE POINTS OF TEMPLATE AND INPUT IMAGES.
2. CALCULATE THE ROTATION AND THE TRANSLATION PARAMETERS.
3. SEGMENT THE INPUT AND THE TEMPLATE IMAGES USING FOREGROUND SEGEMENTATION ALGORITHM.
4. DEFINE A ***RECTANGULAR*** TESSELATION ON THE TWO ALIGNED IMAGES.
5. EXTRACT THE TEXTURE FATURES USING GABOR FILTERS.
6. MATCH THE DISTANCE BETWEEN THE OVERLAPPING REGIONS AND WEIGH THE MATCHING DISTANCE BY THE AMOUNT OF OVERLAP.

REASON FOR RECTANGULAR TESSELATION

- Due to small sensor area, core point may not be detected or may lie at the boundary area,so the tessellated sectors will be few.
- The reduced size of the sensor limits the amount of non-linear deformation of the image. Thus every region in the image is given equal importance while extracting features. This is achieved by having equal-sized cells in a rectangular mesh



(a) (b)

Fig. 2. (a) Circular tesselation (80 sectors) about a core point. (b) Rectangular tessellation (81 cells) of a Veridicom image. Since the core point in (b) is located at the lower right corner of the image, we propose to use a rectangular tesselation.

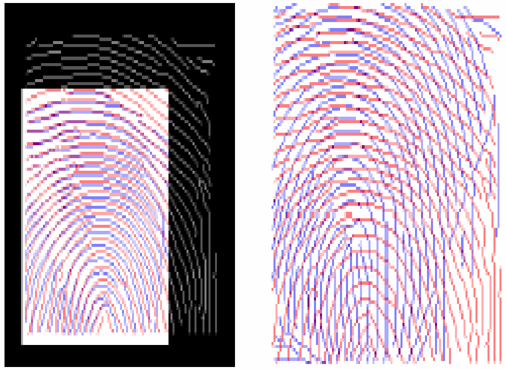
IMAGE ALIGNMENT

- Minutiae extraction algorithm gives two outputs:

(a) A set of minutiae points, each characterized by its spatial position and orientation in the fingerprint image.

(b) Local ridge information in the vicinity of each minutiae point.

- The two sets of minutiae points are then matched using a point matching algorithm.
- The algorithm first selects a reference minutiae pair (one from each image) and then determines the number of corresponding minutiae pairs using the remaining set of points.
- maximum number of corresponding pairs determines the best alignment.
- Exhaustive matching avoided due to the availability of local ridge information at every minutiae point.



(a) (b)

Fig. 3. Aligning the input image with the template image. The red thinned image is the template, and the blue thinned image is the input. (a) Alignment of two impressions of the same finger (the non-overlapping regions appear as white on black); (b) Alignment of two impressions of different fingers.

IMAGE ALIGNMENT

- the rotation and translation parameters are computed.
- Estimated rotation parameter is the average of rotation parameters of all minutiae points.
- The translation parameter is computed using the spatial coordinates of the reference minutiae pair.

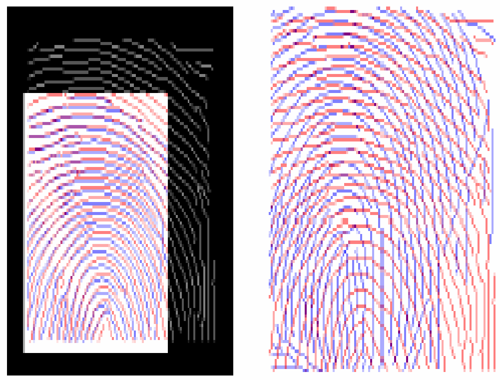


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IMAGE TESSELATION

- The background of the input image is removed.
- Input and the template images are normalized by constructing equal-sized non-overlapping windows and normalizing each block to a constant mean and variance.
- Normalized image is tessellated into non-overlapping rectangular cells of predefined dimensions.
- Dimensions chosen on the basis of inter-ridge span.

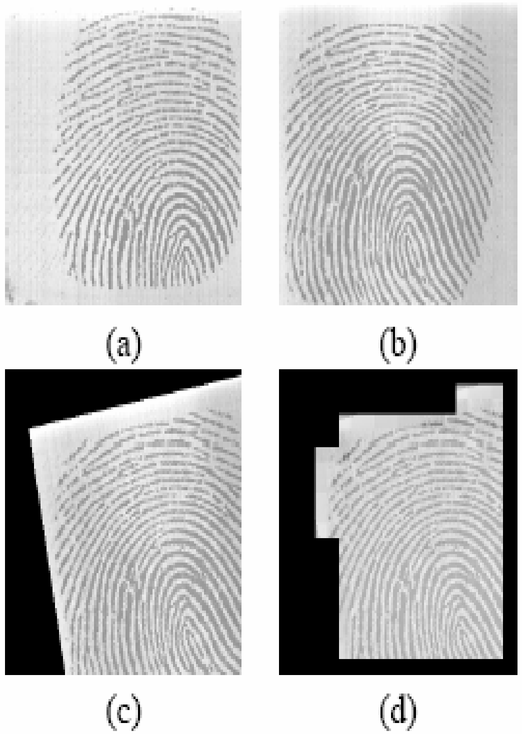

Fig. 4. Masking out background regions: (a) Template image, (b) Input image, (c) Input image after translation and rotation, (d) Masked input image.

FEATURE EXTRACTION

- A bank of 8 gabor filters of different to each of the tessellated cell.
- Gabor filters will have same frequency but different orientations.

  (0 to 157.5 degree,22.5 degree steps)
- Frequency determined by the average inter-ridge distance(in pixels)
- So 8 filtered images for each cell.
- The absolute average deviation in intensity is treated as a feature value.
- Feature values that reside in the masked regions of the input image are not used in the matching stage of the process, and are marked as missing values in the feature vector.

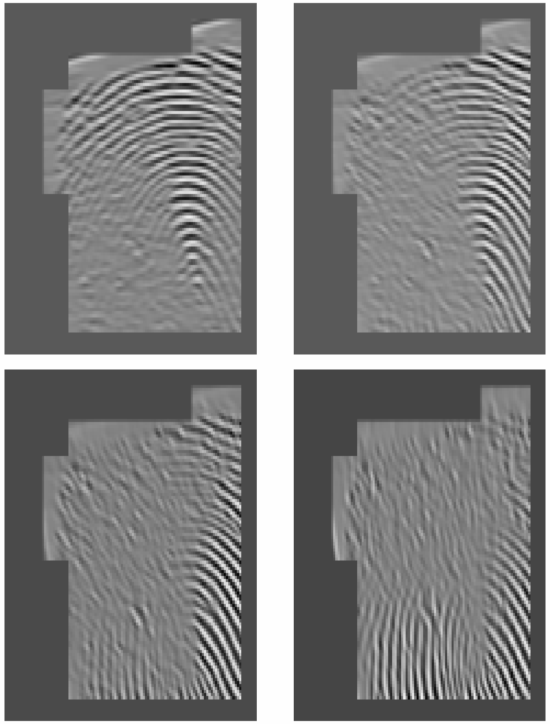

Fig. 5. Result of applying Gabor filters to Fig 4(d). Filtered images for orientations 0°, 22.5°, 45°, and 67.5° are shown.

MATCHING

- Matching involves computing the sum of the squared differences between the two feature vectors after discarding the missing values.
- Distance is normalized by the number of valid feature values used to compute the distance.
- The matching score is combined with that obtained from the minutiae-based method,using the sum rule of combination.
- If the matching score is less than a predefined threshold, then successful match, else failure.

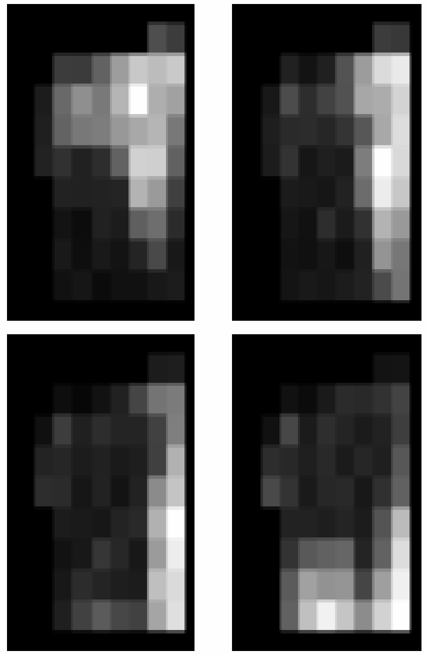

Fig. 6. Feature values derived from the filtered images of Fig 5. For purposes of visualization, the feature values have been scaled to the 0 - 255 range.

EXPERIMENTAL RESULTS

- MSU-VERIDICOM consisting of fingerprints of 160 users using the Veridicom sensor.
- Each user provided 4 impressions for 4 different fingers.
- Total of 2560 images (160 X 4 X 4) collected.
- Quality checker to remove bad quality images.
- ROC curve is shown at different thresholds.
- Hybrid approach outperforms the minutiae based approach over a wide range of FAR values.
- For example, at 1% FAR,

GAR(Hybrid) = 92%

GAR(Minutiae) = 72%

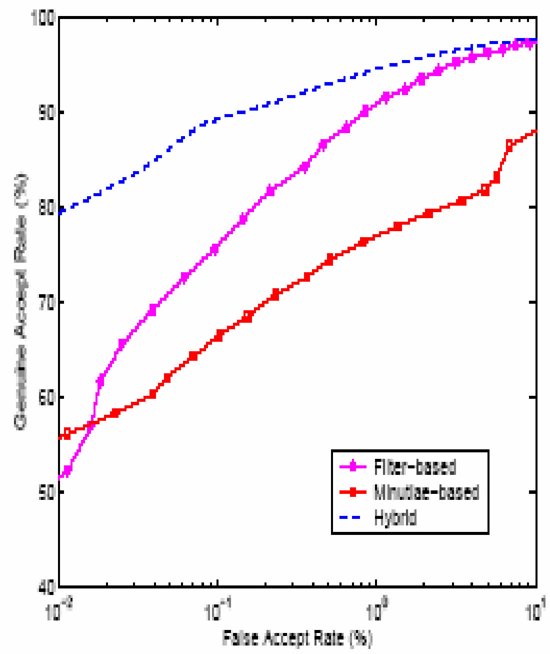

Fig. 7. The ROC curve comparing the performance of the proposed hybrid approach with the minutiae based approach.

PERFORMANCE STATS AND ENHANCEMENTS

- The computational requirement of the hybrid matcher is dictated by the convolution operation associated with the eight Gabor filters.
- The entire algorithm takes around 8 seconds of CPU time in Ultra 10 SPARC machine.
- The speed of the algorithm can be enhanced by implementing the convolution in a dedicated DSP chip.

ADVANTAGES/DISADVANTAGES

- Computationally expensive than the other methods.
- Non real-time performance.
- Doesn’t account for non-linear deformations.
- But small contact area of the sensors alleviates the deformation problem.
- Rotational and translation independent.
- Works better than other approaches.
- Ability to work with incomplete input images.
- But stats provided were of one database with only 4 input finger images.
- GAR may go down for more than four finger input images.

Thank You