Registration Seminar

Biometric Data Indexing using Robust Key Generation Techniques

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Outline

Introduction

What is a Biometric?

Examples of Biometric Traits

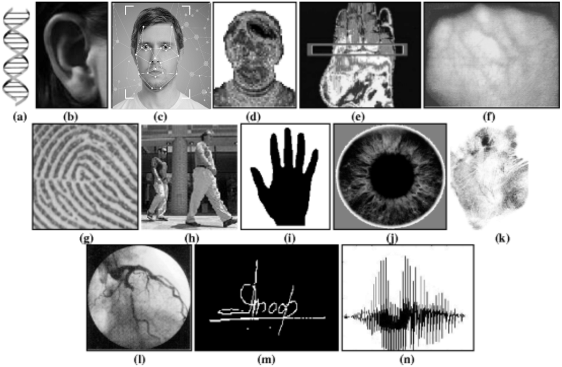

Figure: (a) DNA profiling, (b) ear shape, (c) facial features, (d) facial thermograph, (e) hand thermograph, (f) hand vein profile, (g) fingerprints, (h) gait, (i) hand geometry, (j) iris, (k) palmprint, (l) retina scans, (m) signature, and (n) voice.

How to decide on a Biometric?

- Feasibility of a biometric traits [1]
  - *Universality*
  - *Distinctiveness*
  - *Collectability*
  - *Permanence*
  - *Performance*
  - *Acceptability*
  - *Circumvention*

Comparison of Biometric Traits

- Feasibility comparison of biometric traits [2]

Biometric Trait	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention	Average
Fingerprint	50	100	100	50	100	50	50	71.4
Palmprint	50	100	100	50	100	50	50	71.4
Face	100	0	50	100	0	100	100	64.3
Ear	50	50	100	50	50	100	50	64.3
Facial thermogram	100	100	0	100	50	100	0	64.3
Iris	100	100	100	50	100	0	0	64.3
DNA	100	100	100	0	100	0	0	57.1
Hand geometry	50	50	50	100	50	50	50	57.1
Odor	100	100	100	0	0	50	0	50.0
Retina	100	100	50	0	100	0	0	50.0
Gait	50	0	0	100	0	100	50	42.9
Hand vein	50	50	50	50	50	50	0	42.9
Signature	0	0	0	100	0	100	100	42.9
Voice	50	0	0	50	0	100	100	42.9
Keystroke	0	0	0	50	0	50	50	21.4

Figure: High=100, Medium=50, Low=0[2]

Diffrent Modalities of Biometric

Biometric Modalities

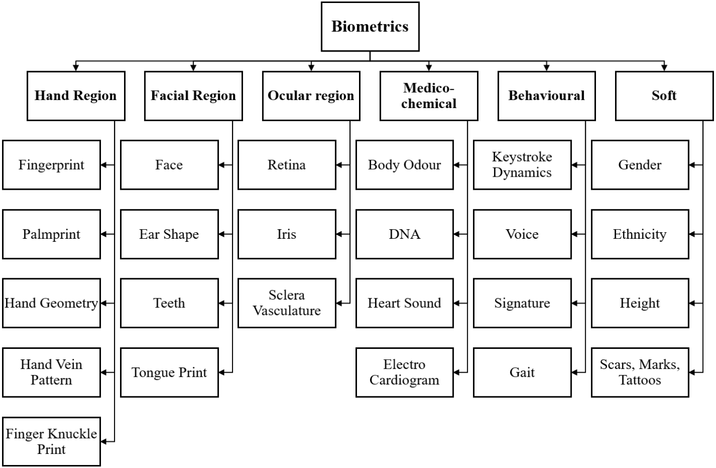

Figure: Classification of Biometric Modalities

Biometric Authentication System

- **Working modes of biometric authentication system**
  - Identification System
  - Recognition System

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Biometric Authentication System

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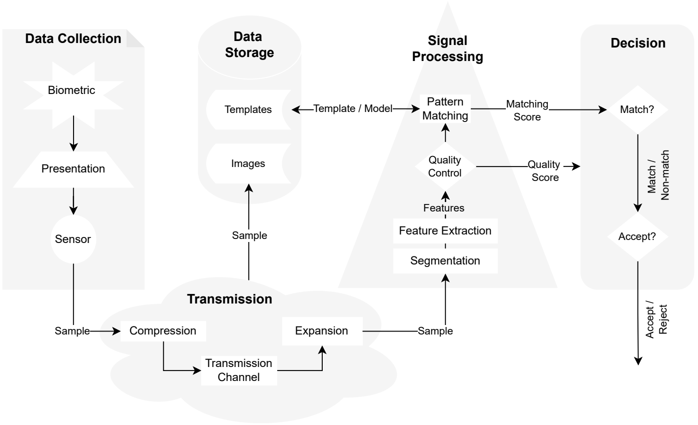

Figure: Block Diagram of a Biometric Authentication System

Database Idexing

Indexing Techniques

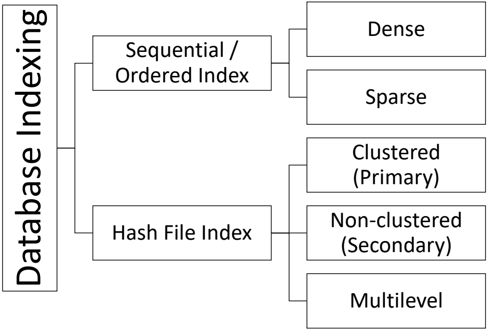

Figure: Classification of Database Indexing

Indexing Techniques

Common Indexing Techniques

- Dense Index
- Sparse Index
- Secondary Index
- Hashing
- B-Tree (B+ Tree)
- kd-Tree

Indexing of Biometric Data

Indexing of Biometric Data

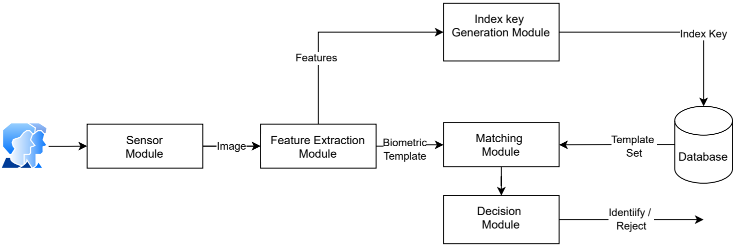

Figure: Steps in Biometric Identification with indexing

Literature Review

Literature Survey

Fingerprint-based Indexing Survey

Table: Summary of the recent approaches for fingerprint indexing

Author(s)	Indexing Approach	Feature	Test Database	Efficiency	Performance
Cappelli [3]	Continuous classification	Local orientations, corresponding con- sistencies, local frequencies, average frequency,average vertical orientation difference	NIST DB4 FVC 2000 FVC 2004	Search complexity is $(O(N + N_T \log N_T))$	Hit Rate = 97.5% Pen Rate = 20%
Park et al. [4]	Classification	Discrete Fourier transform (DFT) based feature	NIST DB4	-	Hit Rate = 90.7% Pen Rate = 20%
Vandana et al. [5]	Kd-Tree	Delaunay Triangulation based minutiae triplet feature	IITK fin- gerprint db	-	Pen Rate = 15%
Jiang et al. [6]	K-means clustering	Orientation field and dominant ridge dis- tance	NIST db-4	Time complexity of O(n2)	Hit Rate = 96% Pen Rate = 15%
Liu and Yap [7]	K-means clustering	Features based on polar complex moments (PCMs)	NIST FVC	The average number of comparisons is $K_f + (N_f / K_f)$ where, N_f = Number of fingerprints and K_f is number of clusters,	Hit Rate = 96.5% Pen Rate = 30%

Literature Survey

Fingerprint-based Indexing Survey(cont.)

Author(s)	Indexing Approach	Feature	Test Database	Efficiency	Performance
Li et al. [7]	Minutiae-Vicinity- based K-means indexing	4-D minutiae vicinity feature, 3-D minutiae triplet feature, average ridge density and average ridge curvature	FVC 2002 DB2 FVC 2004 DB4	Time complexity of O(n2)	Hit Rate = 95% Pen Rate = 9.75%
Cappelli et al. [8]	Locality-Sensitive Hashing (LSH)	Minutia Cylinder Code	NIST-DB4 and DB14, DB2 of FVC2000, DB3 of FVC2000, DB1 of FVC2002	Search time complexity is O(|V|* l* b_s), where |V| = len(feature vector), l = count(hash function), and b_s = entries / bucket	Hit Rate = 96% Pen Rate = 15%
Cappelli et al. [9]	Similarity based matching	Level-1 (local orientation and frequencies) and level-2 (minutiae) feature	NNIST-DB4 & DB14, DB2 of FVC2000, DB3 of FVC2000, DB1 of FVC2002	-	Hit Rate = 98% Pen Rate = 10%
Jayaraman et al. [10]	Geometric hashing	Minutia Binary Pattern	FVC 2004	-	Hit Rate = 96% Pen Rate = 2.26%

Literature Survey

Iris-based Indexing Survey

Author(s)	Indexing Approach	Feature Dimension	Insertion/Update Efficiency	Data Specific Requirement	Performance
Khalaf et. al. [11]	*K - means clustering*	81	May need to restructure the cluster with the insertion/updating of data	No specific requirement	Hit Rate = 95% Pen Rate = 9.75%
Rathgeb et. al. [12]	Bloom filters and binary search trees	<2048	On data deletion the entire tree has to be replace by a tree generated from all remaining leaves	Requires binary Representation of features	Hit Rate = 93.5% Pen Rate = 6.2%
Mehrotra et. al. [13]	Geometric Hashing	128	No need to change the underlying structure. However multiple pairwise insertion require	No specific requirement	Hit Rate = 95.5% Pen Rate = 7.2%
Gadde et. al. [14]	Occurrence of Binary pattern	Variable	No need to change the underlying structure	Requires binary Representation of features	Hit Rate = 99.8% Pen Rate = 12.3%

Literature Survey

Multi-modal Biometric Indexing Survey

Author(s)	Considered Modality	Indexing Approach	Database	Performance
Gyaourova et al. [15]	Fingerprint and Face	Similarity between a biometric image and a fixed set of reference images	Chimeric multimodal dataset using the FERET face database and the WVU fingerprint database	Hit Rate - 98% Pen Rate - 7%
Prabhu et al. [16]	Fingerprints, Palm prints, Hand Geometry	Classification	-	Identification Accuracy - 87%
Soheil et al. [17]	Fingerprint, iris, palm- print, hand geometry, and voice	Classification	WVU multimodal dataset	Classification Accuracy - 98.6%
Goswami et al. [18]	Face, finger and iris	Classification	WVU multimodal dataset	Identification Accuracy - Between 95% to 99%

Scope and Objectives

Scope of Work

Indexing of Biometric Data

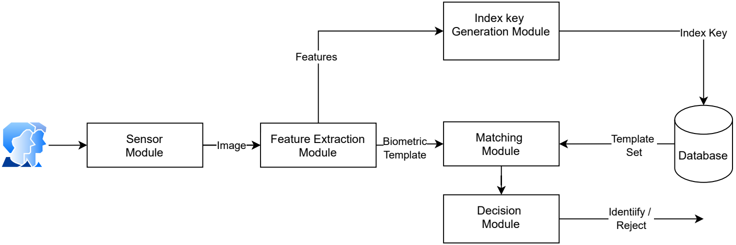

Figure: Steps in Biometric Identification with indexing

Motivation

- **Limitations of Biometric Identification**
  - False Matching
  - Long Response Time

Motivation

- **Limitations of Biometric Identification**
  - False Matching
  - Long Response Time
- **The Solution**
  - Indexing
  - Considering multiple biometric modalities

Objectives

Research Objectives

1. To create a large-scale virtual multi-modal biometric dataset and compare its performance on traditional indexing schemes and the proposed method.
2. To design and implement an effective and scalable indexing scheme using Fingerprint as the biometric modality.
3. To design and implement an effective and scalable indexing scheme using Iris as the biometric modality.
4. To design and implement an effective and scalable indexing scheme in a multi-modal biometric system.

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Work Done

Proposed Approach

- **Overview of the key generation from a fingerprint image.**

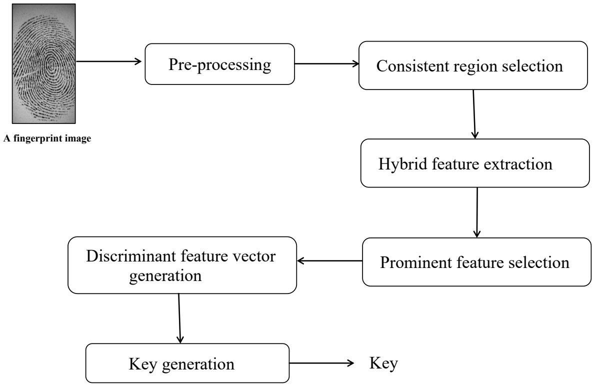


Figure: Block diagram of proposed model

Proposed Approach

Pre-Processing

(a) Original fingerprint image.

(b) Vertically aligned image.

(c) Enhanced image.

Figure: An illustration of pre-processing of a sample fingerprint image.

Proposed Approach

Consistent Region Selection

(a) Original ROI r around central point.
(b) Scaled ROI of r.
(c) Consistent region.

Figure: CRS based on GLCM statistical feature descriptor

Proposed Approach

Hybrid Feature Vector Extraction

- Indirect Features using Delaunay Triangulation [19]
- Texture-based Features by combining:
  - Hilbert curve-based descriptor (HCBD) [20]
  - Gray code-based descriptor (GCBD) [21]
  - Local ternary pattern (LTP) [22]
  - Median ternary pattern (MTP) [23]

Indirect Feature Extraction

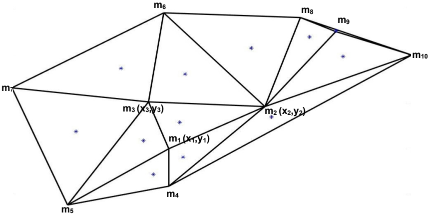
Delaunay Triangulation [19]

- **Indirect Feature Vector (F_v)**

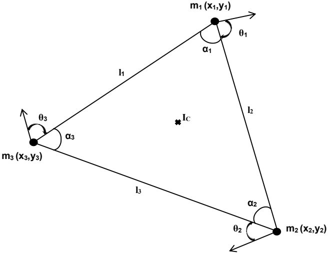
  > F_v = [
  > r_area($\forall$ $\triangle$ $\in$TR) $\|$
  > r_length_of_sides($\forall$ $\triangle i$ $\in$TR) $\|$
  > r_angles_b/w_sides($\forall$ $\triangle$ $\in$ TR) $\|$
  > r_incenter($\forall\triangle$ $\in$ TR) $\|$
  > r_position($\forall$ m_i $\in$ m) $\|$
  > r_orientation($\forall$ m_i $\in$ m)
  >]

Indirect Feature Extraction

Delaunay Triangulation [19]



(a) Delaunay triangular net from a set of minutia points.



(b) Indirect feature extraction from a triangle.

Figure: An example of Delaunay triangulation-based indirect feature generation.

Texture-based Feature Extraction

- **Hilbert curve-based descriptor (HCBD) [20]**

$$HCBD_l(i,j) = \sum_{n=2}^{N/2} sign(I_n^{(i,j)} - I_{n-1}^{(i,j)}) \times 2^{n-1} \tag{1}$$

$$HCBD_u(i,j) = \sum_{n=N/2+2}^{N} sign(I_n^{(i,j)} - I_{n-1}^{(i,j)}) \times 2^{n-1} \tag{2}$$

$$HCBD = \begin{cases} [HCBD_l \oplus HCBD_u || 0], & if sign(I_{N/2+1}^{(i,j)} - I_{N/2}^{(i,j)}) = 1 \\ [HCBD_l \oplus HCBD_u || 1], & if sign(I_{N/2+1}^{(i,j)} - I_{N/2}^{(i,j)}) = -1 \end{cases} \tag{3}$$

where $\oplus$ is *XOR* operator and $||$ is the concatenation operator.

Texture-based Feature Extraction

- **Hilbert curve-based descriptor (HCBD) [20]**

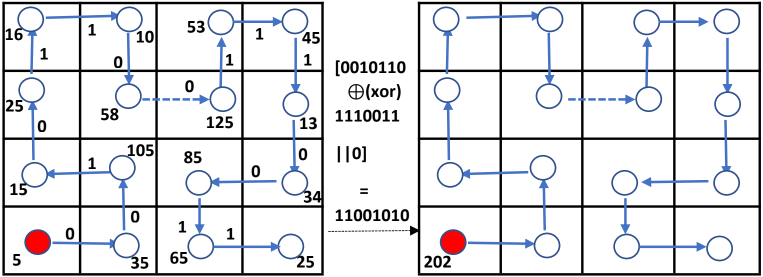


Figure: Illustration of HCBD operation

Texture-based Feature Extraction

- **Gray code-based descriptor (GCBD) [21]**

$$GCBD_l(i,j) = \sum_{n=2}^{N/2} sign(I_n^{(i,j)} - I_{n-1}^{(i,j)}) \times 2^{n-1} \quad (4)$$

$$GCBD_u(i,j) = \sum_{n=N/2+2}^{N} sign(I_n^{(i,j)} - I_{n-1}^{(i,j)}) \times 2^{n-1} \quad (5)$$

$$GCBD = \begin{cases} [GCBD_l \oplus GCBD_u || 0], & ifsign(I_{N/2+1}^{(i,j)} - I_{N/2}^{(i,j)}) = 1 \\ [GCBD_l \oplus GCBD_u || 1], & ifsign(I_{N/2+1}^{(i,j)} - I_{N/2}^{(i,j)}) = -1 \end{cases} \quad (6)$$

where $\oplus$ is *XOR* operator and $||$ is the concatenation operator. The

Texture-based Feature Extraction

- **Gray code-based descriptor (GCBD) [21]**

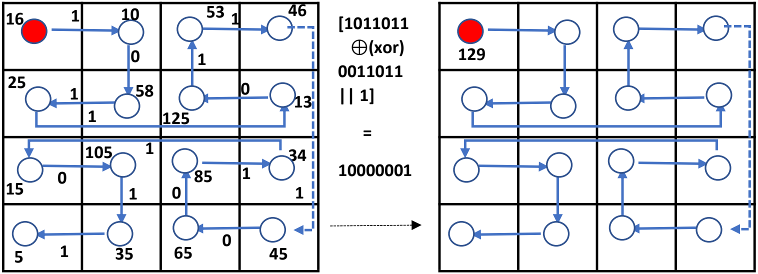


Figure: Illustration of GCBD operator.

Texture-based Feature Extraction

- **Local ternary pattern (LTP) [22]**

$$LTP_{P,R} = \sum_{p=0}^{P-1} 2^P s(i_p - i_c) \tag{7}$$

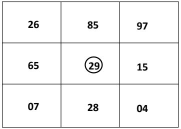
where, i_c = center pixel gray value, i_p $(p = 0, ..., P-1)$ = neighbor pixel (radius R) gray value, P = number of neighbors (estimated using Bilinear Interpolation)

$$s(u) = \begin{cases} 1 & u \geq t \\ 0 & -t < u < t \\ -1 & u < -t \end{cases} \tag{8}$$

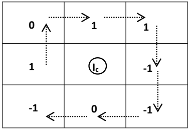
where, u = neighbor gray level, t = threshold.
$LTP = LTP_u || LTP_l$ (size = 512)

Texture-based Feature Extraction

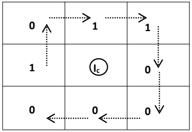
Local ternary pattern (LTP) [22]



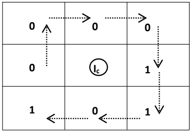
(a) Original image block of size 3×3



(b) LTP code 1011-1-10-1 ($cp = 29, t = 5$)



(c) LTP_u = 10110000, $I_c = 176$.



(d) $LTP_l = 0001101$, $I_c = 13$

Figure: Illustration of LTP operator.

Texture-based Feature Extraction

- **Median ternary pattern (MTP) [23]**

$$s'(u) = \begin{cases} 1 & u \geq m_c + t \\ 0 & m_c - t < u < m_c + t \\ -1 & u < m_c - t \end{cases} \tag{9}$$

where, u =neighbor gray level, m_c=local median, t = threshold. (Size = 3^8).
$MTP = MTP_u || MTP_l$ (Size = 2×2^8)

$$MTP_u = \sum_{p=0}^{7} f_u(s'(i_p)) \times 2^P, f_u(x) = \begin{cases} 1 & x = 1 \\ 0 & otherwise \end{cases} \tag{10}$$

$$MTP_l = \sum_{p=0}^{7} f_l(s'(i_p)) \times 2^P, f_l(x) = \begin{cases} 1 & x = -1 \\ 0 & otherwise \end{cases} \tag{11}$$

Texture-based Feature Extraction

Median ternary pattern (MTP) [23]

60	110	86
70	85	95
80	88	91

(a) Orginal image block of size 3×3.

-1	1	0
-1	I_c	0
0	0	0

(b) MTP code -1-110000, $m = 86$, $t = 10$

0	1	0
0	I_c	0
0	0	0

(c) MTP_u code 0010000,$I_c = 16$

1	0	0
1	I_c	0
0	0	0

(d) MTP_l code 1100000, $I_c = 96$

Figure: Illustration of MTP operator.

Hybrid Feature Vector

- **Texture based features**: HCBD (256 bits), GCBD (256 bits), LTP (512 bits) and MTP (512 bits)
  - For each minutiae point, HCBD features f_{hcbd}, GCBD features f_{gcbd}, LTP features f_{ltp}, and MTP features f_{mtp} are extracted with a window of size $w \times w$.
  - $f_{hcbd}, f_{gcbd}, f_{ltp}, f_{mtp}$ features from all minutia points are combined as $F_{hcbd}, F_{gcbd}, F_{ltp}, F_{mtp}$.
  - Normalized texture feature vector 1, F_{T1} = z-score($F_{hcbd}||F_{gcbd}||F_{ltp}$)
  - Normalized texture feature vector 2, F_{T2} = z-score($F_{hcbd}||F_{gcbd}||F_{ltp}||F_{mtp}$)
- **Hybrid Feature Vector**: Indirect Features (1024 bits), Texture feature 1 (1024 bits), Texture feature 2 (1536 bits)
  - $F_h = \{F_v, F_{T1}, F_{T2}\}$

Prominent Feature Selection

Genetic algorithm based feature selection

- **Step-1:** An initial population size of 10 is generated. The length of each feature vector (F_h), henceforth referred as chromosome, is L.
- **Step-2:** KNN classifier is used to evaluate fitness parameter by dividing the total feature set into training set and testing set.
- **Step-3:** Rank-based selection method is used to find the fittest chromosome for mating.
- **Step-4:** A 2-point crossover is applied on 80% of the selected chromosome, and the rest 20% is added through elitism. This process generates new offsprings.
- **Step-5:** Mutations in the chromosome is performed with probability 0.01
- **Step-6: Step-2** to **Step-5** is performed until number of generations reach 100.

Prominent Feature Selection

Genetic algorithm based feature selection

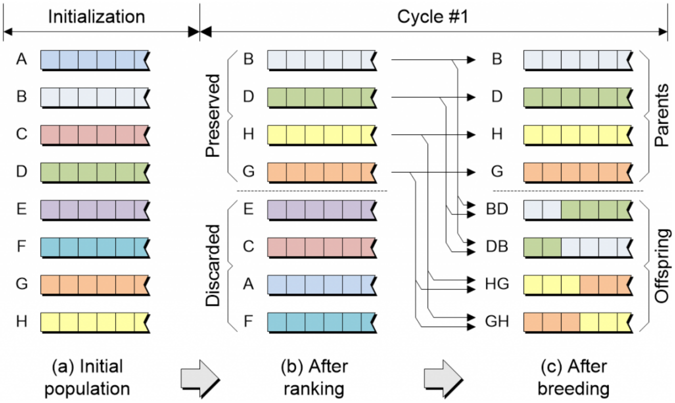


Figure: An illustration of one step in GA.

Prominent Feature Selection

- **Genetic algorithm based feature selection**

Table: GA constraints information.

GA parameters	Value
Initial population size	10
No of generation	100
Crossover probability	0.80
Mutation probability	0.01

Discriminant Feature Vector Generation

Metric learning based discriminant feature vector

- **Distance Metric:** Mahalanobis distance [24]

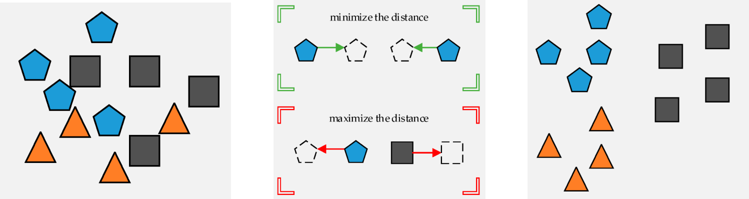
$$d_M = \sqrt{(x_i - x_j)^T M (x_i - x_j)} \tag{12}$$

where $(x_i, x_j) \in R^d$, M is a positive definite matrix and subject to the constraints between pair of points:

$$\begin{cases} d_M(x_i, x_j) \leq u & if(x_i, x_j) \in S(similar) \\ d_M(x_i, x_j) \geq l & if(x_i, x_j) \in D(dissimilar) \end{cases} \tag{13}$$

Discriminant Feature Vector Generation

- **Metric learning based discriminant feature vector**



(a) Original Data Space (b) Purpose of Metric Learning (c) Transformed Data Space

Figure: Metric Learning based Discriminant feature vector

Discriminant Feature Vector Generation

Metric learning based discriminant feature vector

- **Information Theoretic Metric Learning (ITML) technique [25]**
  - > ITML is used to find a distance metric (M),
  - > M should be close to M_0 (initial pre-defined distance)
  - > ITML minimizes Kullback-Leibler (KL) divergence [26] between $p(x|M_0)$ and $p(x|M)$, subject to:

$$\min_{M} \; KL(p(x|M_0) \; || \; p(x|M)) \tag{14}$$

$$s.t. \begin{cases} d_M(x_i, x_j) \leq u & if(x_i, x_j) \in S(similar) \\ d_M(x_i, x_j) \geq l & if(x_i, x_j) \in D(dissimilar) \end{cases} \tag{15}$$

where
$KL(p(x|M_0) \; || \; p(x|M)) = 0.5 \times (trace(MM_0^{-1}) - logdet(MM_0^{-1}) - n)$,
for $n \times n$ matrices M and M_0.

Stable Key Generation

The stable key generation from f_b as follows:

- **Step-1:** Obtain $F_{i,j}$, a combinations of binary feature sequences (f_b),
  where n-fingerprints $1 \leq i \leq n$ and l-samples of each fingerprint $1 \leq j \leq l$.
- **Step-2:** Combine f_b for l-instances of a fingerprint into a $l \times z$matrix M,
  ($l \times z$ is the feature vector dimension).
- **Step-3:** Select the consistent bit positions
  for values of feature sequences across l-columns of M that are same.
  The consistent bit position is set to 1 in a auxiliary vector (A) having dimension $l \times z$).
- **Step-4:** Using A, extract a **key(b_k)** from f_b.

Results and Analysis

Experimental Results

- The proposed method generates a dynamic and scalable key and can be generated without complex hardware and is computationally inexpensive.
- Proposed method is tested with several fingerprint biometric datasets, FVC-2002([27], FVC-2004 [28], Polyu-2016[29]).
- The keys generated passed statistical tests like NIST tests [30] and Diehard tests [31] successfully, thus ensuring randomness.

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Future Plan of Work

Future Plan of Work

- **The plan of work is as follows:**

1. Creation of a virtual dataset containing a large number of multi-modal biometric data
2. Evaluation of traditional indexing methods on the virtual dataset
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Thank You

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