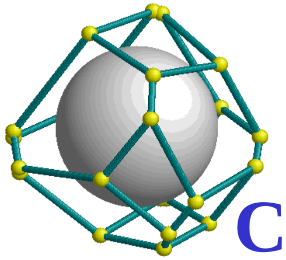
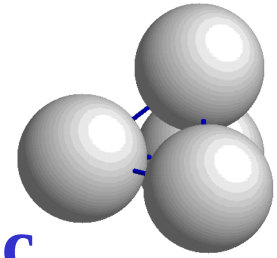


GlobNet 2012
Invited Tutorial
Chaotic Neural Network for Biometric Pattern Recognition



Dr. Marina Gavrilova

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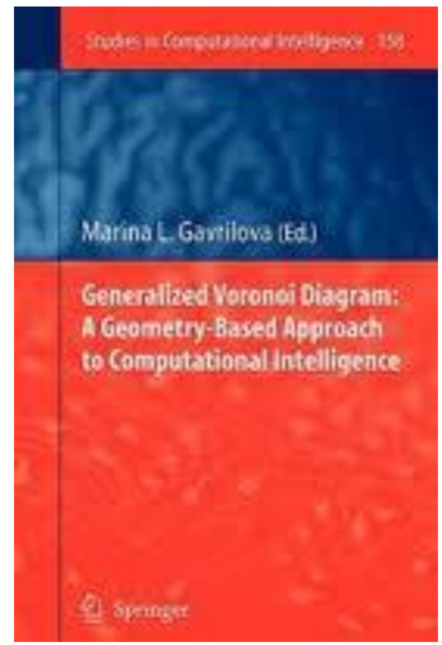
UNIVERSITY OF CALGARY

Talk Overview

- Research Interests
- Biometric authentication
- Biometric fusion
  - Definitions
  - Classification
  - Algorithms
  - Multimodal systems based on Rank-Level Fusion
- Applications
- Conclusions

Activities in Brief



ISVD 2006

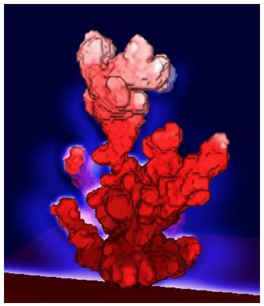
WADS 2009

Activities in Brief

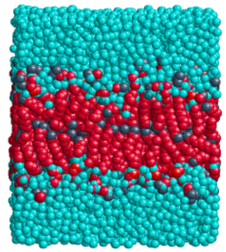
IEEE Robotics & Automation MAGAZINE

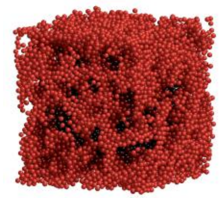
BIOMETRIC TECHNOLOGIES LABORATORY
UNIVERSITY OF CALGARY

Areas of Interests

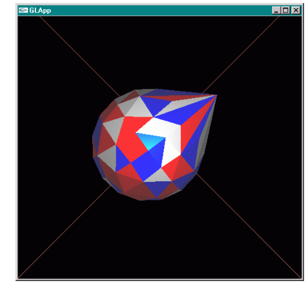


Coral models (with J. Kaandorp)

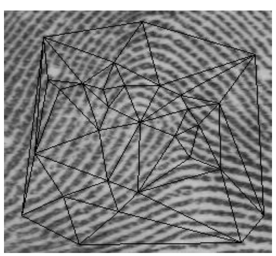




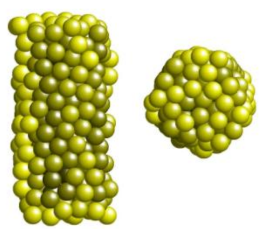
Lipid bi-layers and molecular modeling (with N.N. Medvedev)

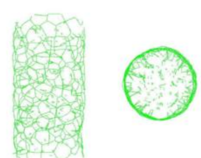


Dynamic data structures (with I. Kolingerova)

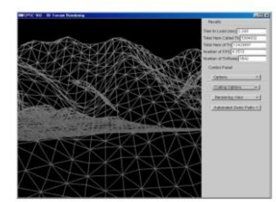


Biometric research





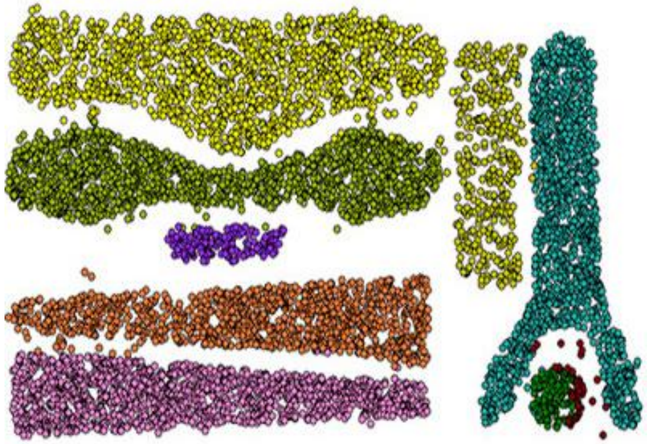
Porous materials



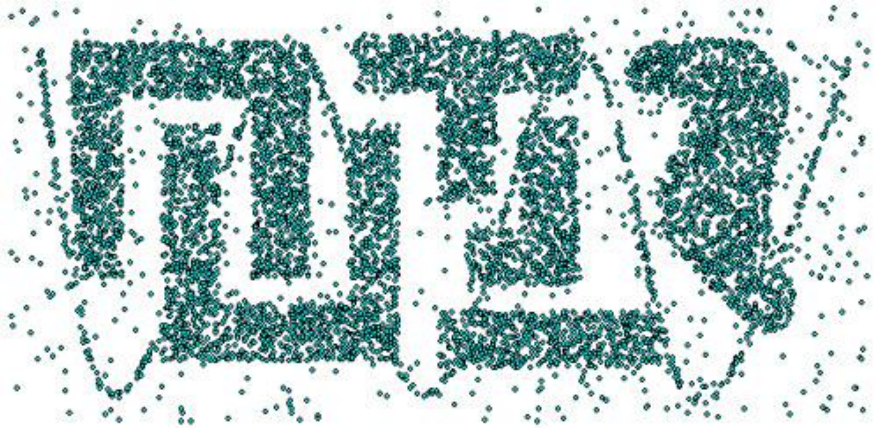
Terrain modeling

Voronoi clustering examples

Original dataset



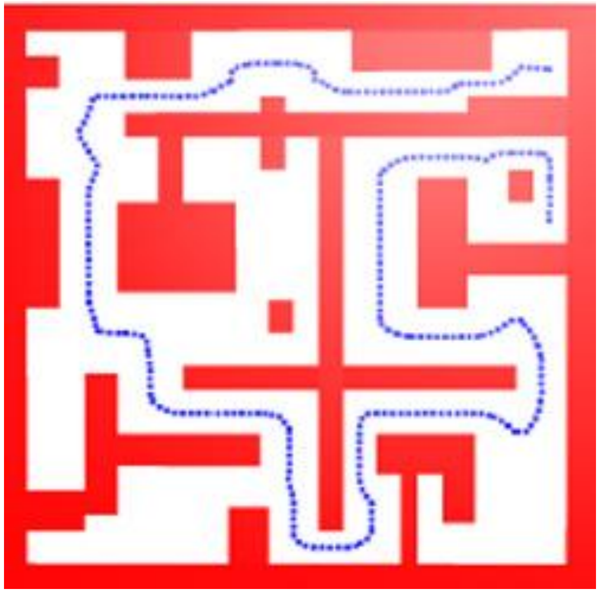
Crystal output (Th = 2.5)



Original dataset

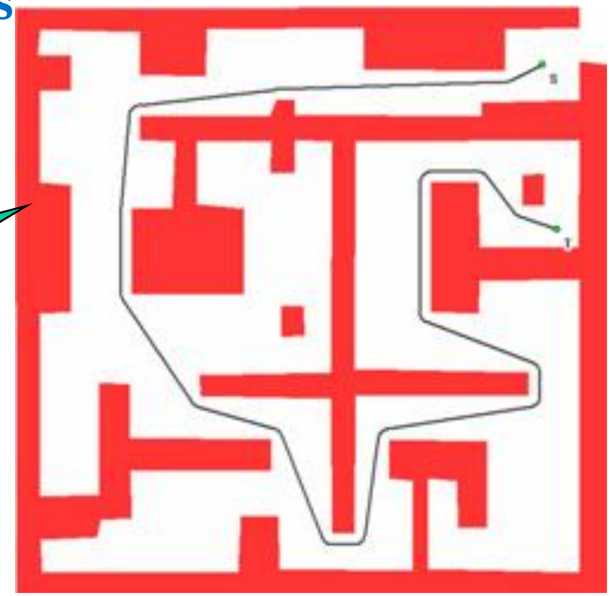
Crystal output (Th = 2.4)

More examples

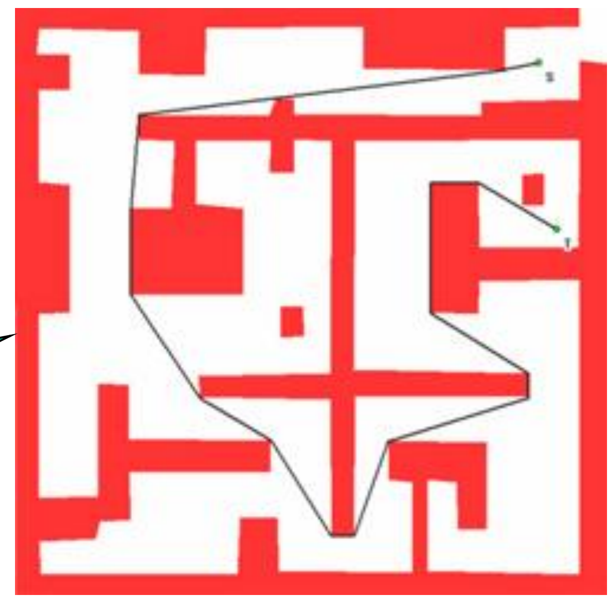


Geraerts, 2004

Cmin = 12



$C_{min} = 0$



Our approach

Authentication

- –**Possession-based**(credit card, smart card)
  - *Use "something that you have"*
- –**Knowledge-based** (password, PIN)
  - *Use "something that you know"*
- –**Biometrics-based** (biometric identifier)
  - *Use something that relies on "what you are"*

What is biometrics

- **Biometrics** is a science which deals with the automated recognition of individuals based on biological and/or behavioral characteristics
  - –Scientific follow-on to Bertillon’s body measurements of 1800s
- **Biometry**–mathematical and statistical aspects of biology
- **Biometric system**–essentially an automatic pattern recognition system that recognizes a person by determining the authenticity of a specific biological and/or behavioral characteristic (biometric) possessed by that person

Biometric System

- **Biometric system**
  An automatic pattern recognition system that recognizes a person by determining the authenticity of a specific biological and/or behavioral characteristic (biometric) possessed by that person

- **Physiological biometric identifiers:**
  - Fingerprints,
  - Hand geometry,
  - Ear patterns
  - Eye patterns (iris and retina),
  - Facial features

- **Behavioral identifiers:**
  - Voice,
  - Signature
  - Typing patterns

Biometric System

Application of Biometric Systems

- **Physical access control** of, for example, an airport. Here the airport infrastructure, or travel infrastructure in general, is the application.

- **Logical access control** of, for example, a bank account; i.e., the application is the access to and the handling of money.

- **Ensuring uniqueness** of individuals. Here the focus is typically on preventing double enrollment in some application, for example, a social benefits program.

Operational Modes of a Biometric System

Verification Mode

- **One-to-One transaction**

- **The user effectively claims an identity by providing some information which is typically used to call up a reference number from a database.**

Identification Mode

- **One-to-Many transaction**

- **The user's information is compared against a database of reference templates and the user's identity determined as a match against one of these templates**

Multibiometric System

- **Most biometric systems deployed in real-world applications are monomodal, i.e. only one source of information is used for authentication.**

- **These systems often face numerous limitations, such as, susceptibility of the result to quality of the sample, its orientation/rotation and distortion, noise, intra-class variability, non-distinctiveness, non-universality, and others.**

- **Some of the limitations imposed by monomodal biometric systems can be overcome by including multiple sources of information for establishing identity. Such systems are known as Multibiometric Systems.**

Advantages of Multibiometric Systems

- **Multibiometric systems can offer substantial improvement in the matching accuracy.**

Reduced FAR and FRR; Increase feature space and hence capacity of identification system

- **Multibiometric addresses the issue of non-universality or insufficient population coverage.**

Achieved a certain degree of flexibility; If a dry finger prevent user from enrolling tc.

- **Multibiometric system makes the life of any impostor harder.**

Facilitates challenge-response mechanism by asking the user to present a random subset of traits; can be used in single biometric system.

Single and Multibiometric Systems

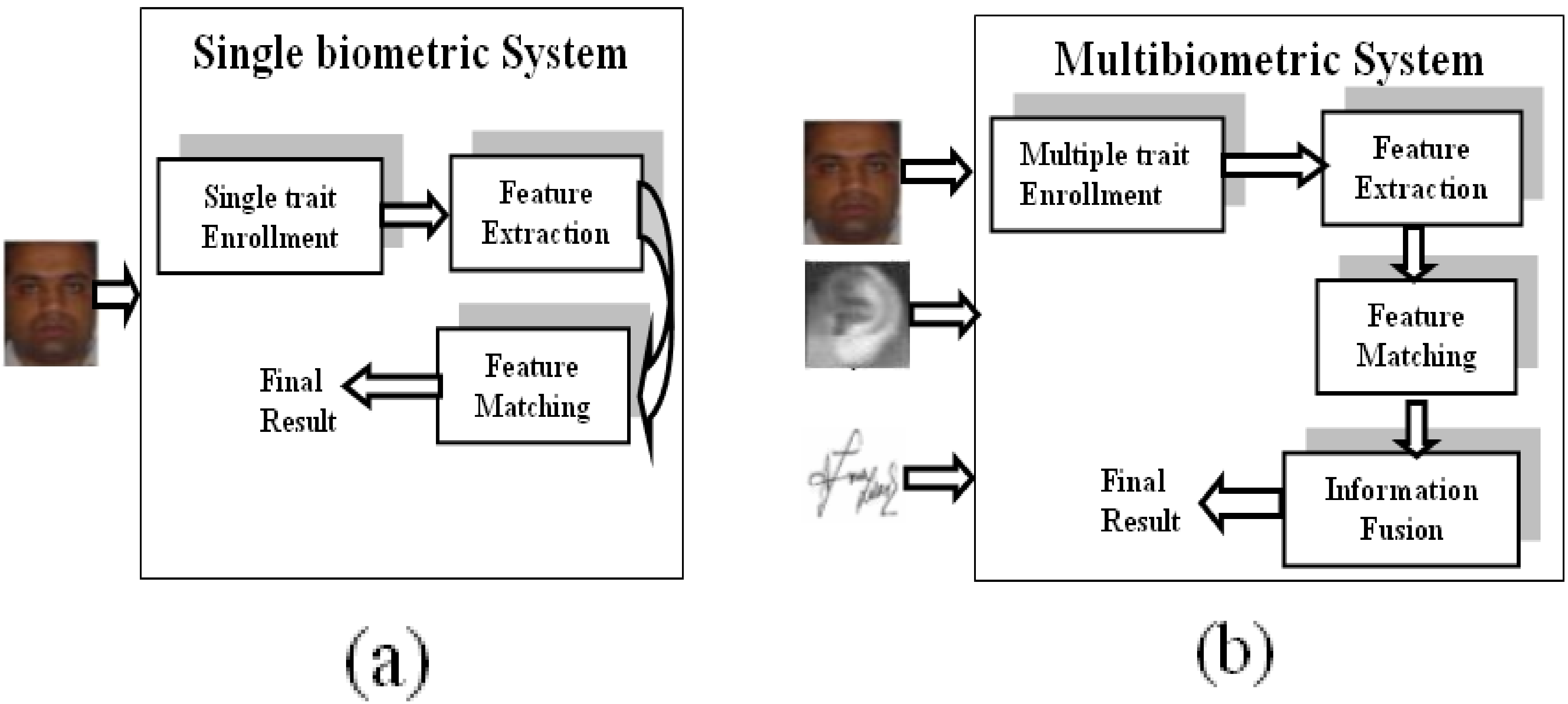


Fig. Block diagram of two biometric systems (a) single biometric (b) multibiometric

Design Issues of Multibiometric Systems

- **Cost benefits**

Tradeoff between the added cost and the improvement in matching

- **Determining sources of biometric information**

Which of the sources are relevant to the application at hand?

- **Acquisition and processing sequence**

Simultaneously or one-by-one; Processing can also be done one after another or simultaneously

- **Type of information used**

What type of information is to be fused?
True or virtual multimodal database

Design Issues of Multibiometric Systems

- **Fusion methodologies adopted**

Sum rule, maximum, minimum, Borda count

- **Operational Mode**

Identification or verification

- **Assigning weights to Biometric**

Weights need to be assigned or not?

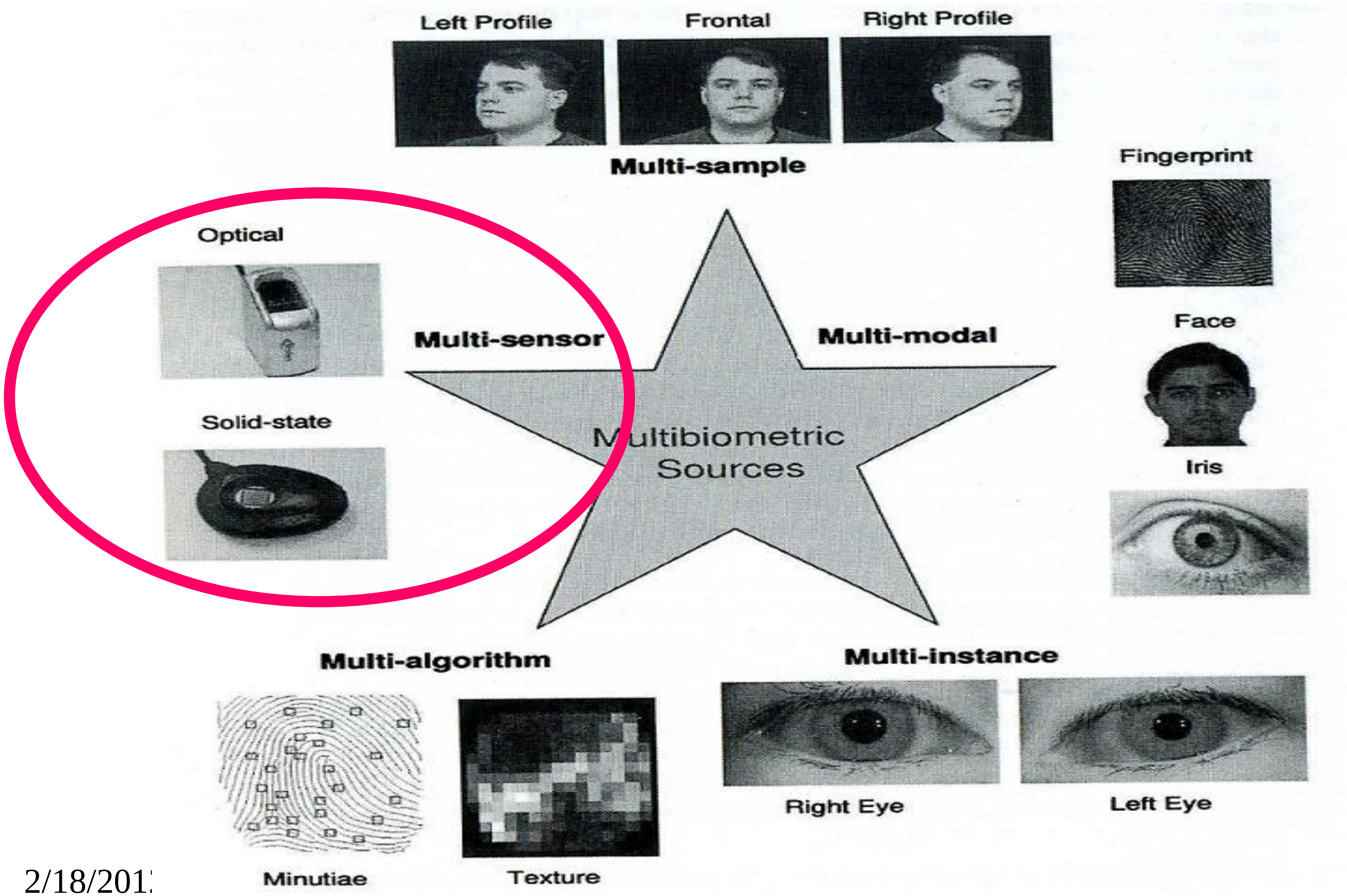
- **Multimodal Database**

True or virtual multimodal database

Sources of Multiple Evidences

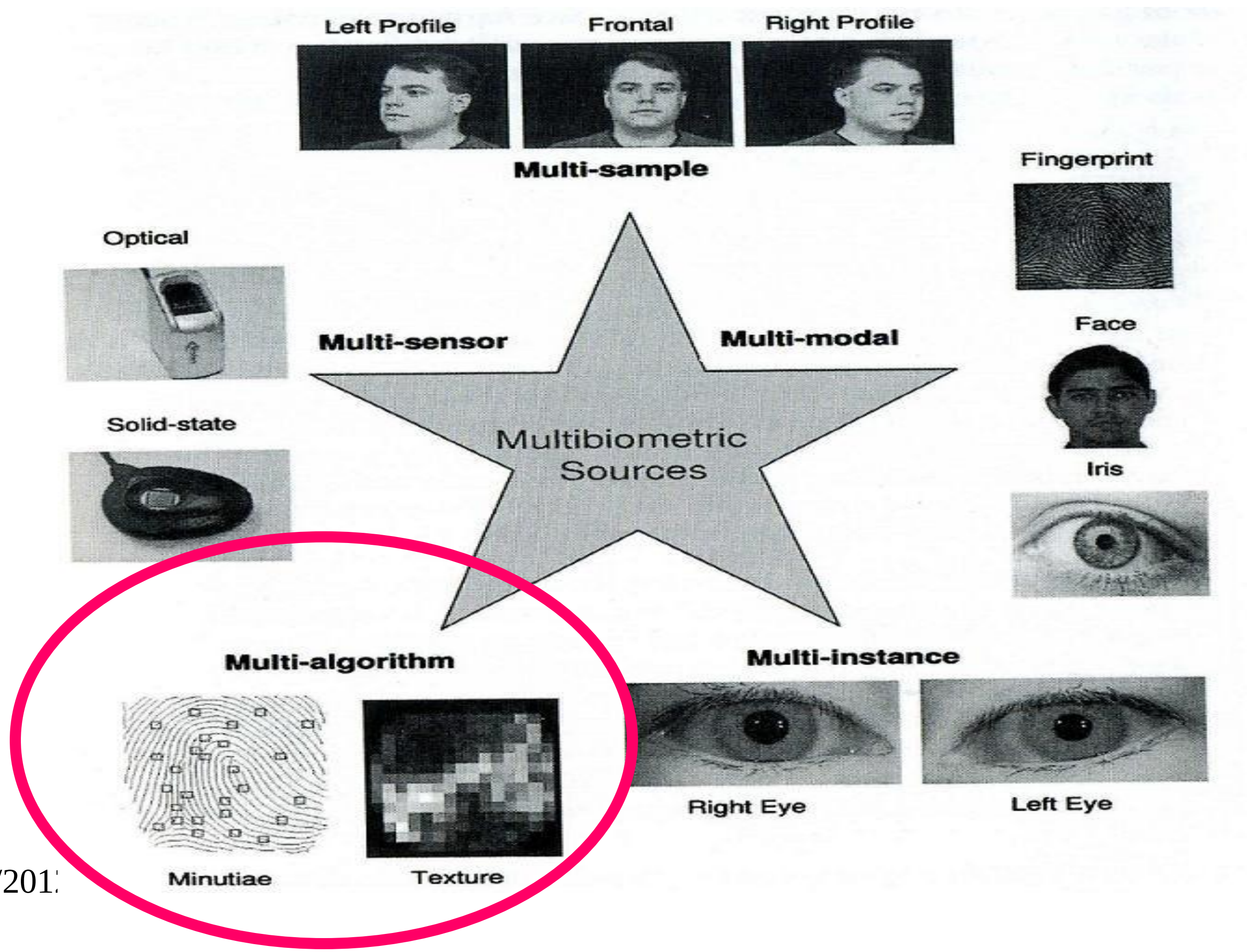
- Multi-sensor systems (single biometric trait-multiple sensors)

2D texture content using CCD and 3D surface shape using range camera



Sources of Multiple Evidences

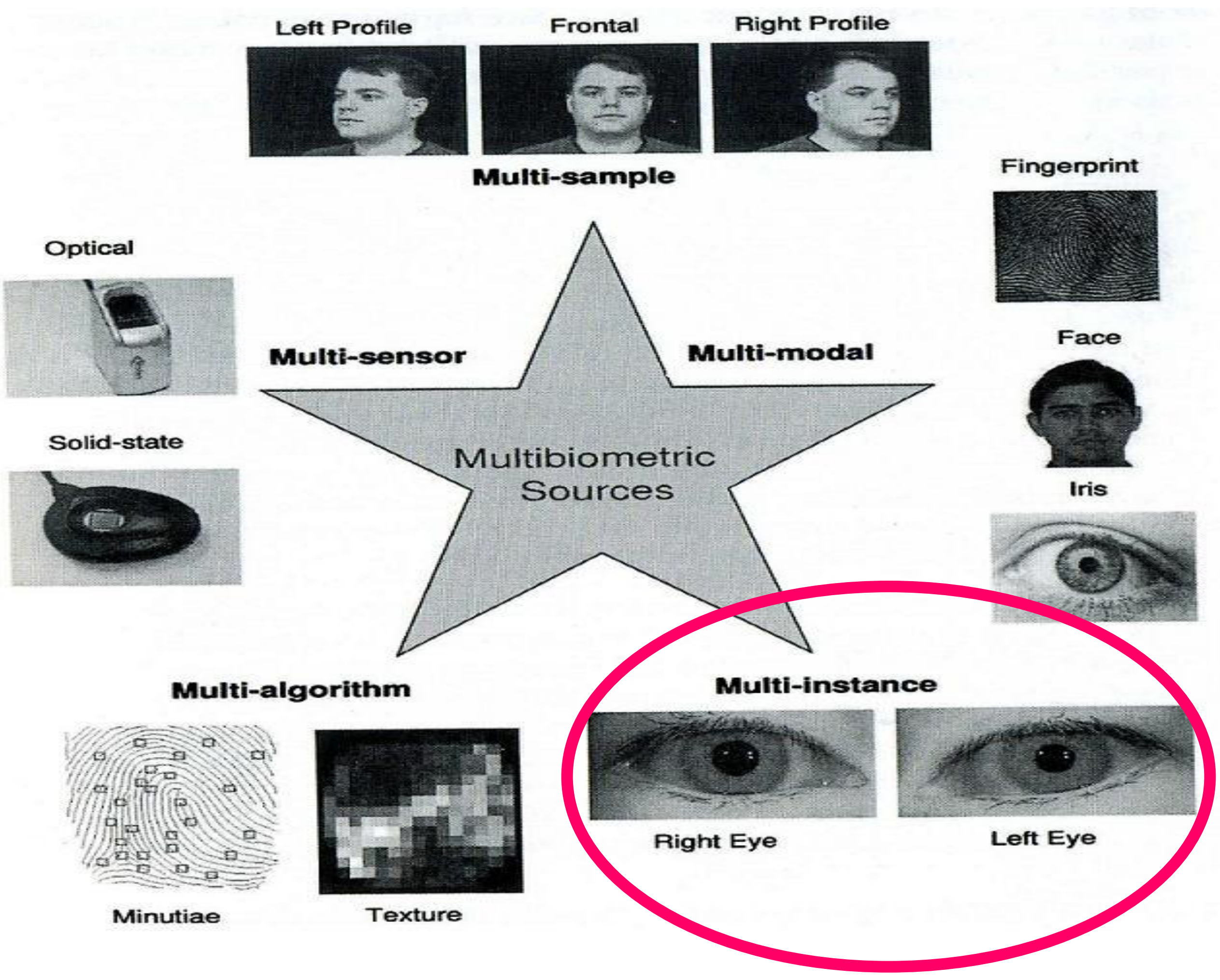
- Multi-algorithm systems (single biometric trait-multiple algorithm)



Sources of Multiple Evidences

- Multi-instance systems (multiple instances of same body traits)

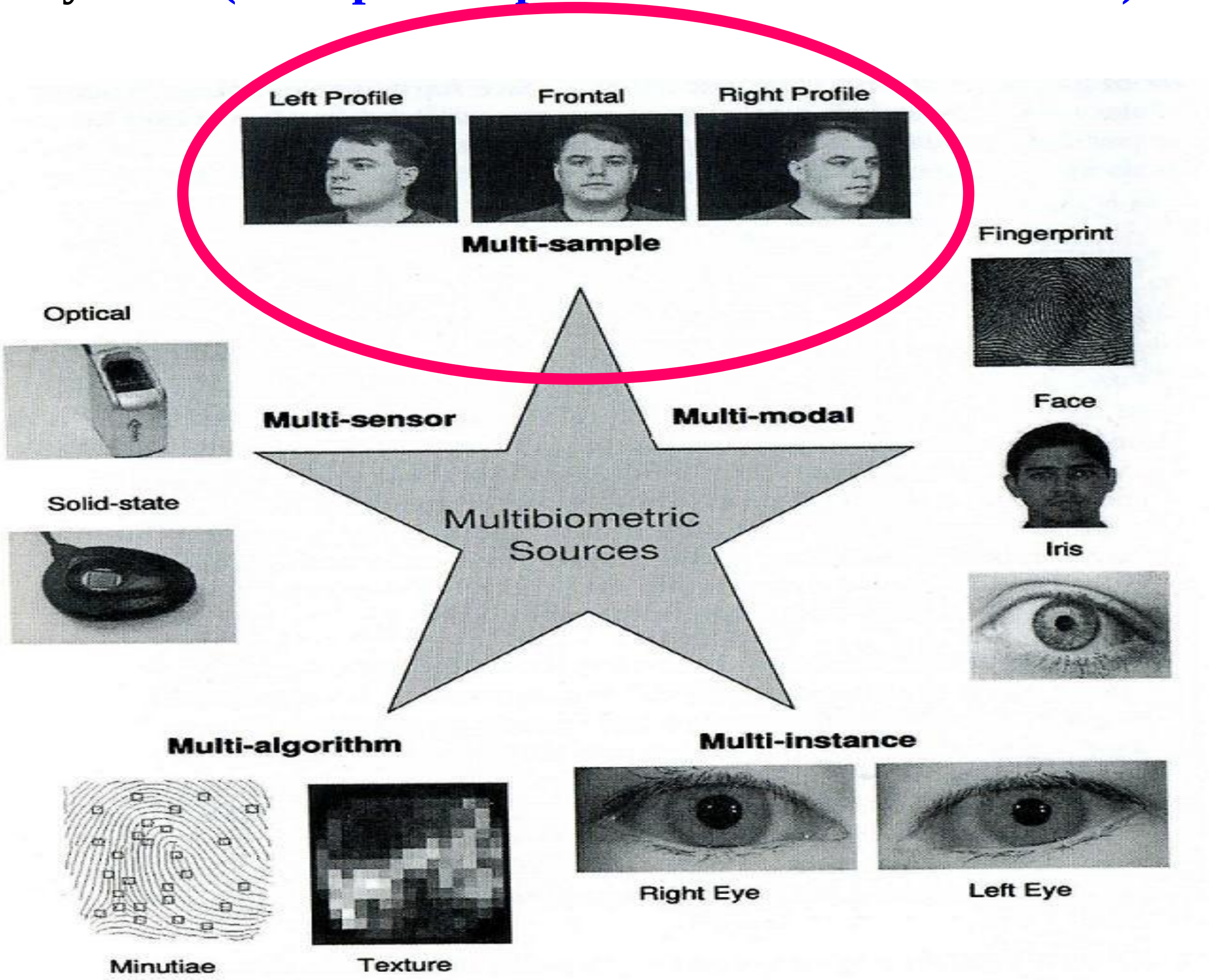
For dry skin, one fingerprint might not work



Sources of Multiple Evidences

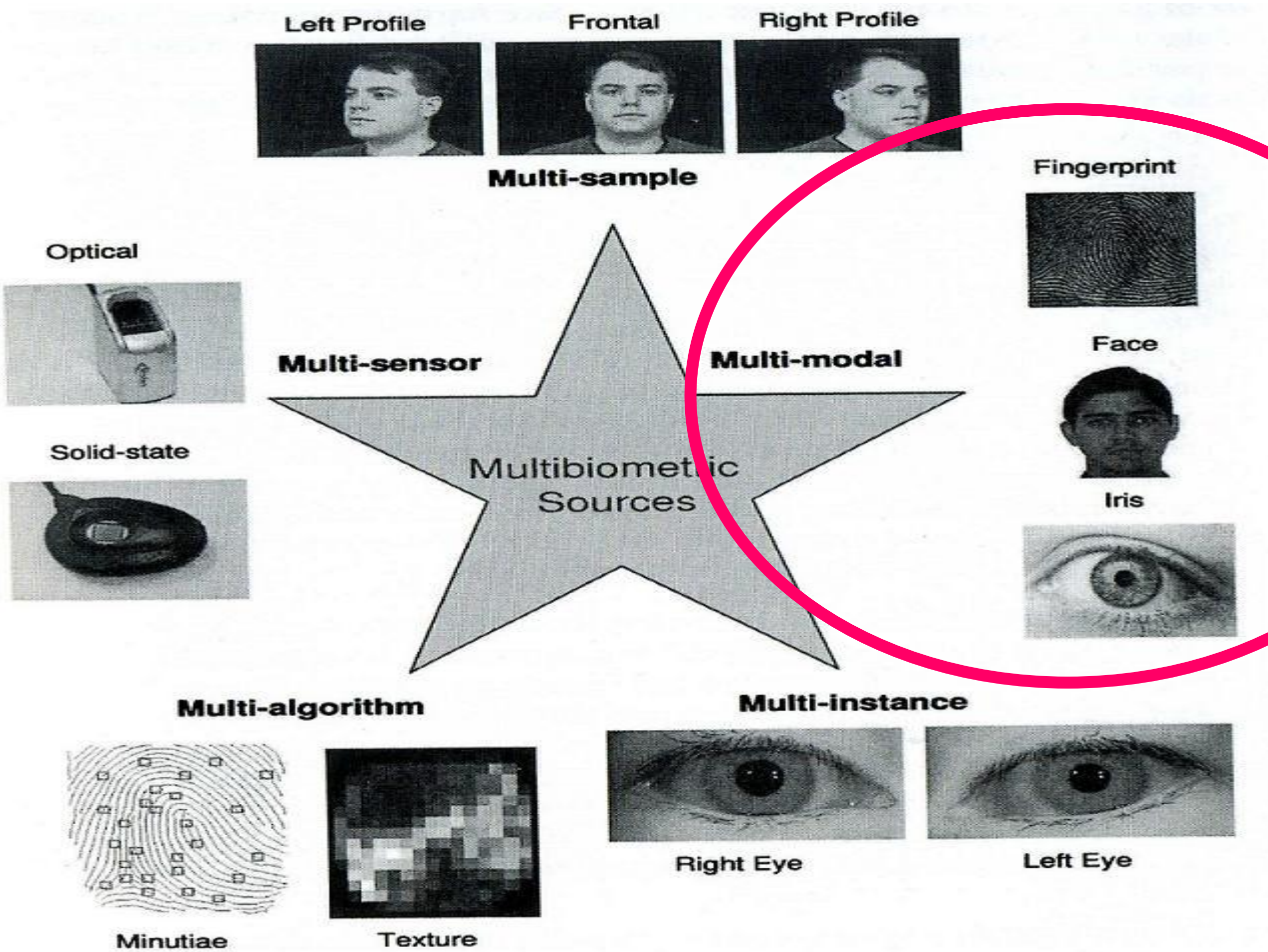
- Multi-sample systems (multiple samples of same biometric traits)

A small size sensor may acquire multiple dab prints of an individual's finger and later done mosaicing



Sources of Multiple Evidences

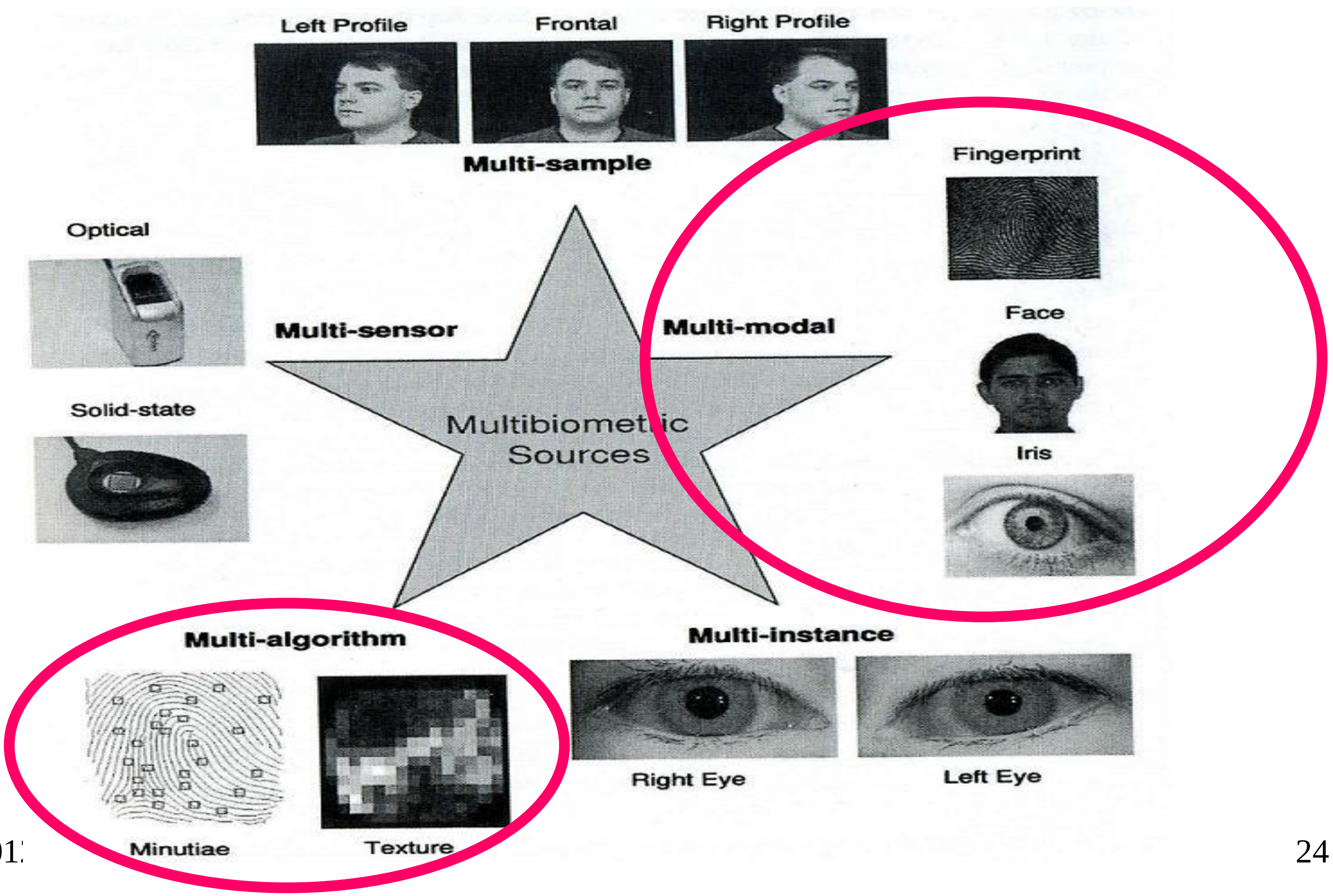
- Multimodal systems (multiple biometric traits)



Sources of Multiple Evidences

- Hybrid systems

Two speaker recognition algorithm combined with three face recognition algorithm



Fusion

The goal of Fusion is to determine the best set of experts in a given problem domain and devise an appropriate function that can optimally combine the decisions rendered by the individual experts.

Two subcategories:

- **Prior to matching**

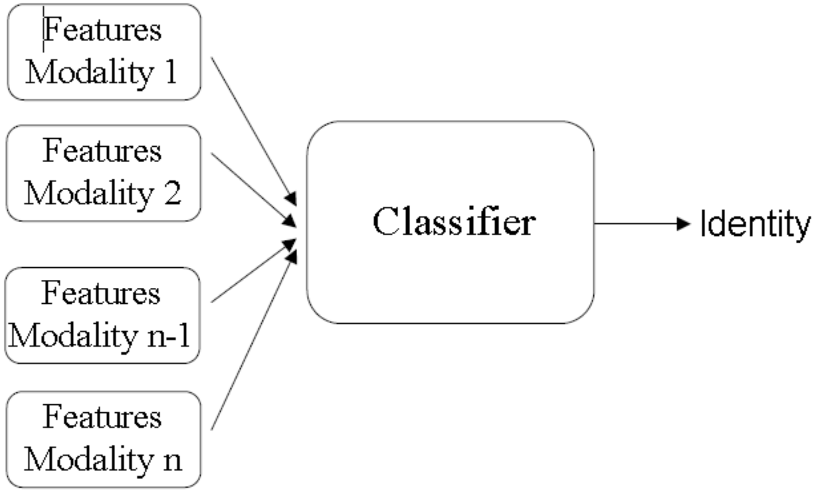
  - Sensor level fusion
  - Feature level fusion

- **After Matching**

  - Rank level fusion
  - Match score level fusion
  - Decision level fusion

Multi-modal Systems: Fusion

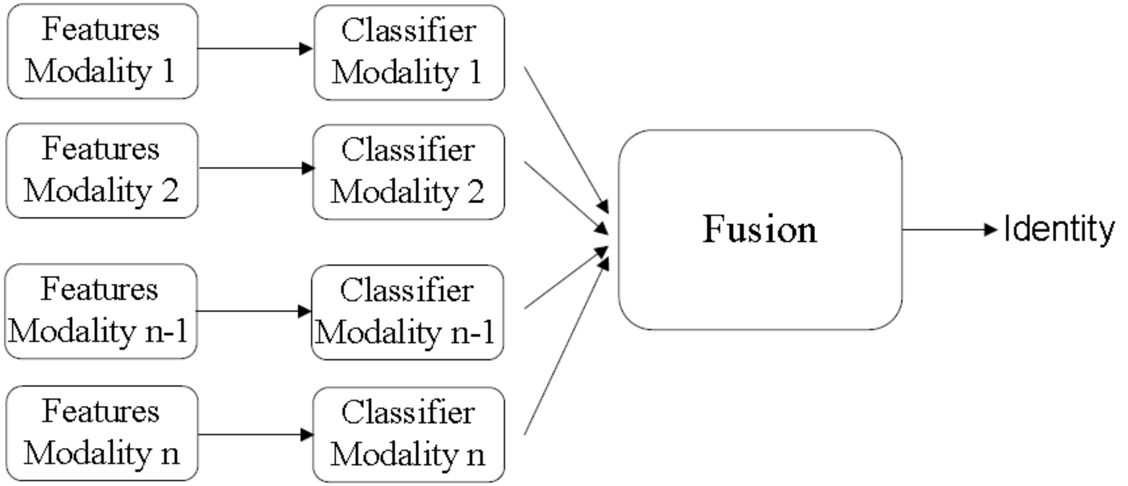
- **Early integration**
  - Integration is performed on the feature level
  - Classification is done on the combined feature vector



Multi-modal Systems: Fusion

Late integration

- Each modality is first pre-classified independently
- The final classification is based on the fusion of the outputs of the different modalities



Prior to Match Fusion

Sensor level

The raw data acquired from multiple sensors can be processed and integrated to generate new data from which features can be extracted.

For example, in the case of face biometrics, both 2D texture information and 3D depth (range) information (obtained using two different sensors) may be fused to generate a 3D texture image of the face which could then be subjected to feature extraction and matching.

Feature level

The feature sets extracted from multiple data sources can be fused to create a new feature set to represent the individual.

The geometric features of the hand, for example, may be augmented with the eigen-coefficients of the face in order to construct a new high-dimension feature vector. A feature selection/transformation procedure may be adopted to elicit a minimal feature set from the high-dimensional feature vector .

After Matching Fusion

Match Score Level

Multiple classifiers output a set of match scores which are fused to generate a single scalar score.

As an example, the match scores generated by the face and hand modalities of a user may be combined via the simple sum rule in order to obtain a new match score which is then used to make the final decision.

Rank level

This type of fusion is relevant in identification systems where each classifier associates a rank with every enrolled identity (a higher rank indicating a good match).

Thus, fusion entails consolidating the multiple ranks associated with an identity and determining a new rank that would aid in establishing the final decision. Techniques such as the Borda count may be used to make the final decision

After Matching Fusion

Decision level

When each matcher outputs its own class label (i.e., accept or reject in a verification system, or the identity of a user in an identification system), a single class label can be obtained by employing techniques such as majority voting or AND/OR rules.

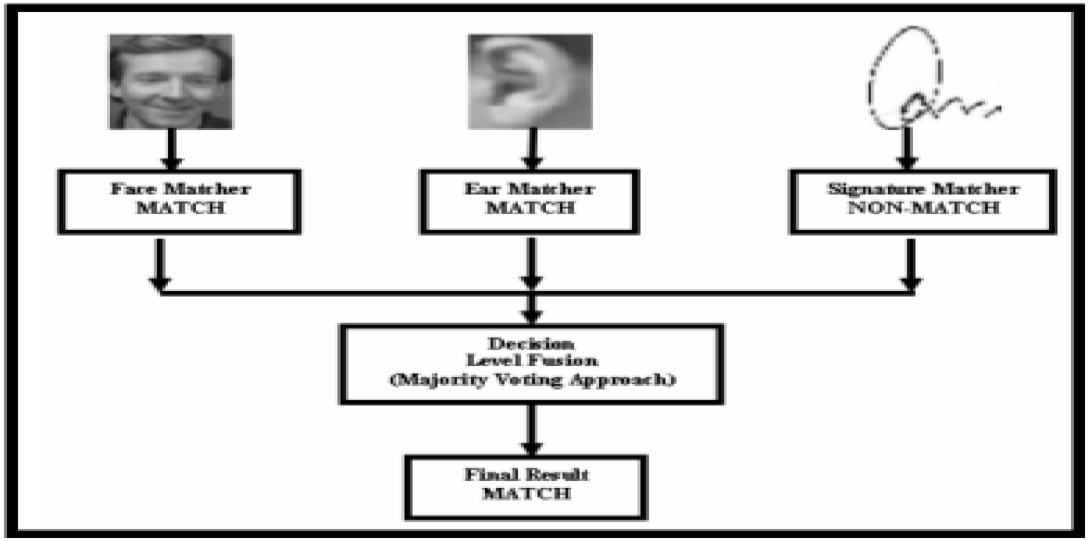
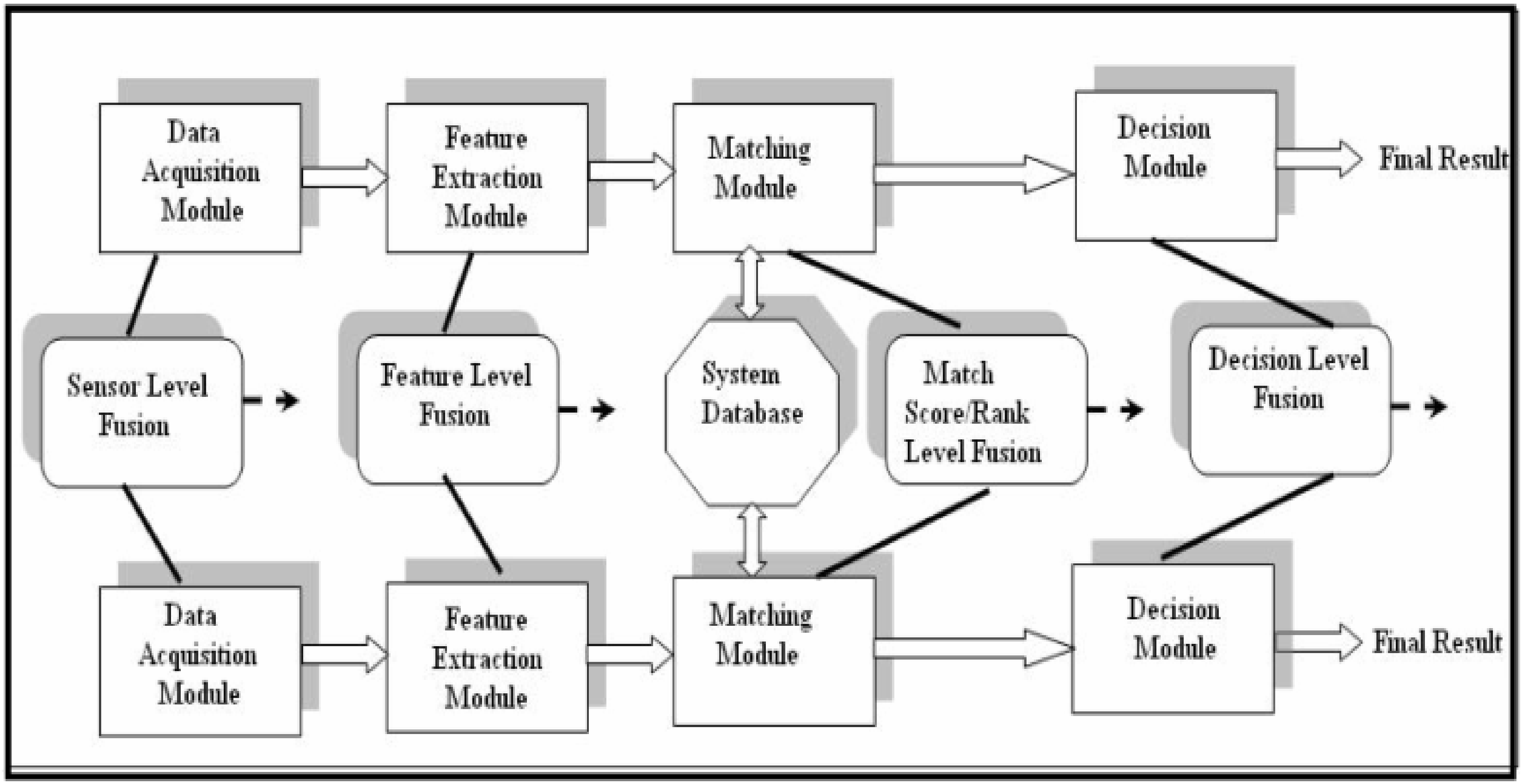


Fig. Example of the majority voting approach of decision level fusion method

Various Fusion Level Possibilities



- Diagram is courtesy of Md. Maruf Monwar

Some Multibiometric Systems

Author & Year	Multibiometric Systems	Level of fusion
Kumar and Zhang, 2003 [13]	Face, Palm	Match Score
Kumar et al., 2003 [14]	Palm, Hand	Match score, Feature
Chang et al., 2003 [15]	Face, Ear	Feature
Jain and Ross, 2002 [7]	Fingerprint (2 impressions)	Sensor, Feature
Shakhnarovich and Darrell, 2002 [16]	Face, Gait	Match score
Marcialis and Roli, 2004 [6]	Face (PCA, LDA, ICA)	Match score
You et al., 2004 [17]	Palmprint (global geometry, global ad local texture energy, fuzzy 'interest' line	Decision
Ross and Govindarajan, 2005 [10]	Red, Green, Blue channels for face	Feature, Match Score
Marcialis and Roli, 2004 [5]	Optical and capacitive fingerprint sensors	Match score
Monwar and Gavrilova, 2007 [3]	Face, ear and signature	Rank, Decision

Table . Examples of multibiometric systems

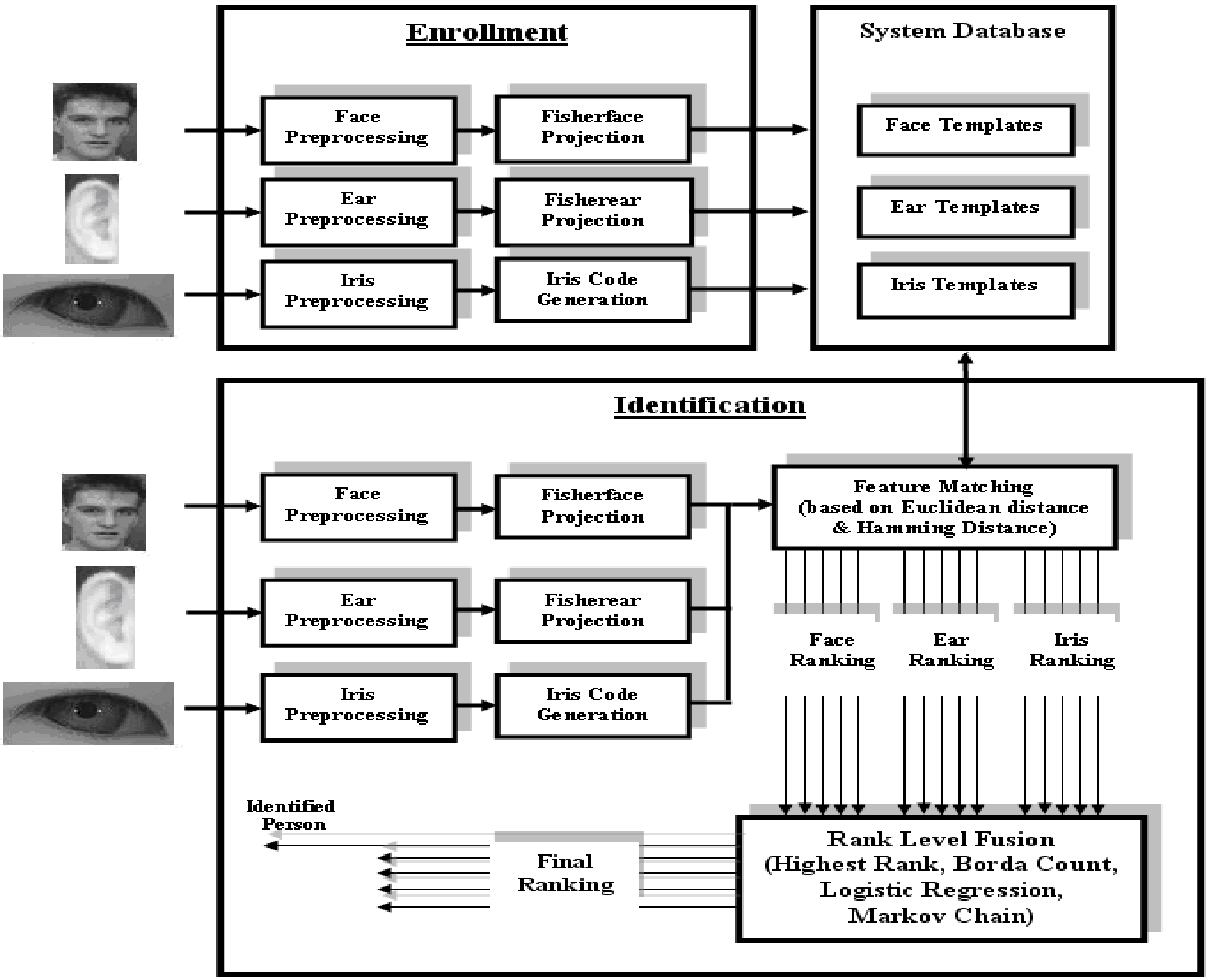
Rank-level Fusion Multibiometric System

<u>Based on rank level fusion</u>

- *Rank level fusion is significantly understudied and highly potential for identification systems.*
- *Rank fusion use similarity/distance scores based biometric rank information but no normalization is needed.*
- *Ranking lists as outputs from unimodal systems can be easily obtained using Fisherimage and Hamming distance methods.*
- *Successfully used in web ranking.*

<u>Uses face, ear and iris obtained from the same region (facial) using simple camera</u>

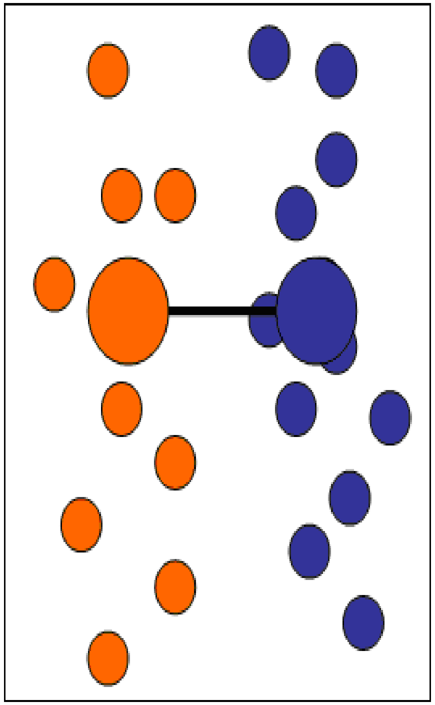
System Architecture



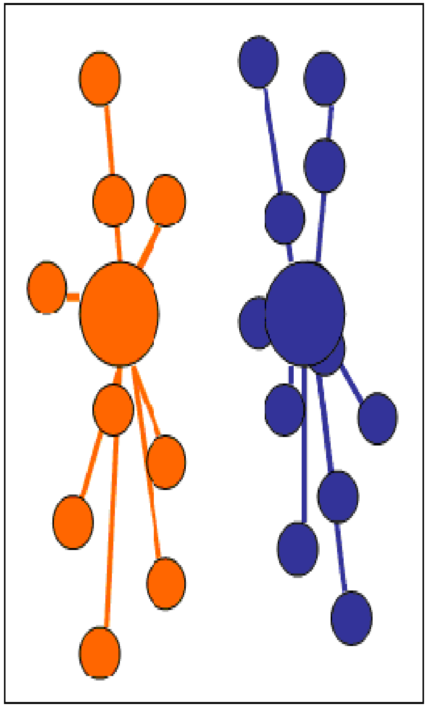
Unimodal Matchers (Face and Ear)

Fisherimage

- *Use PCA and FLDA.*
- *Maximize between class scatter and minimize within class scatter.*



Between Class Scatter

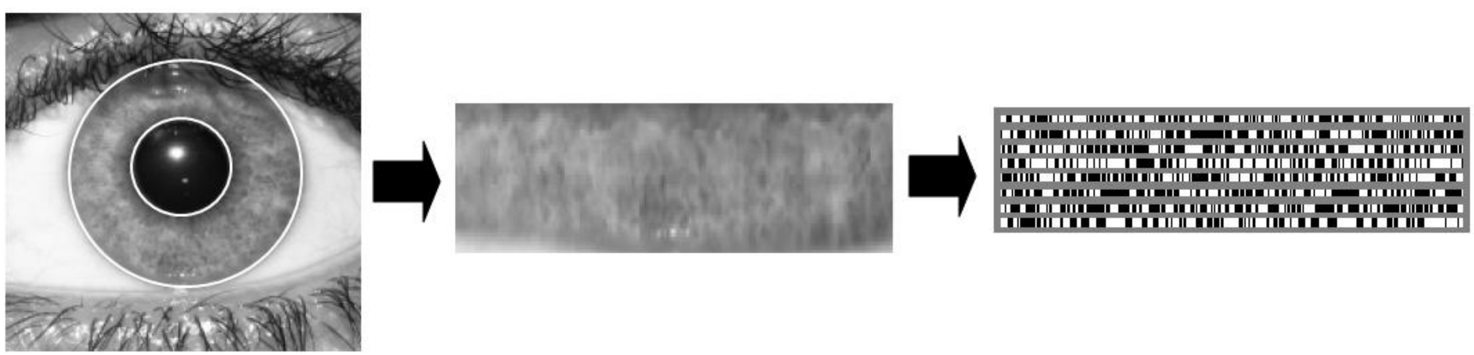


Within Class Scatter

Unimodal Matcher (Iris)

Four steps -

- ***Locating iris* -** *Hough transform.*
- ***Unwrapping iris data* -** *Rubber sheet model.*
- ***Generating iris code* -** *Haar wavelet.*
- ***Comparing iris codes*** - *Hamming distance.*



Iris code generation process

Rank Level Fusion

Highest rank method -

The consensus ranking list is obtained by arranging the identities based on their highest rank in ascending order.

- Simple and has the ability to utilize the strength of each matcher.
- The final ranking may have many ties which are broken randomly.

Rank Level Fusion

<u>Borda count method</u> -

The sum of the ranks assigned by individual matchers, called the Borda score, is used to calculate the final rank.

- Simple, easy to implement and requires no training.
- Does not take into account the differences in the individual matcher's capabilities and assumes that all the matchers perform equally, which may not be true in most of the biometric recognition cases.

Rank Level Fusion

Logistic regression method -

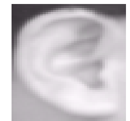
The weighted Borda scores are used to calculate the final rank.

- The weight to be assigned to the different matchers is determined by some function.
- Very useful when different matchers have significant differences in their accuracies.
- Needs a training phase to determine the weights.

Rank Level Fusion

Face Matcher

Identity	Rank
Person 1	1
Person 2	5
Person 3	3
Person 4	2
Person 5	4



Ear Matcher

Identity	Rank
Person 1	2
Person 2	1
Person 3	5
Person 4	4
Person 5	3

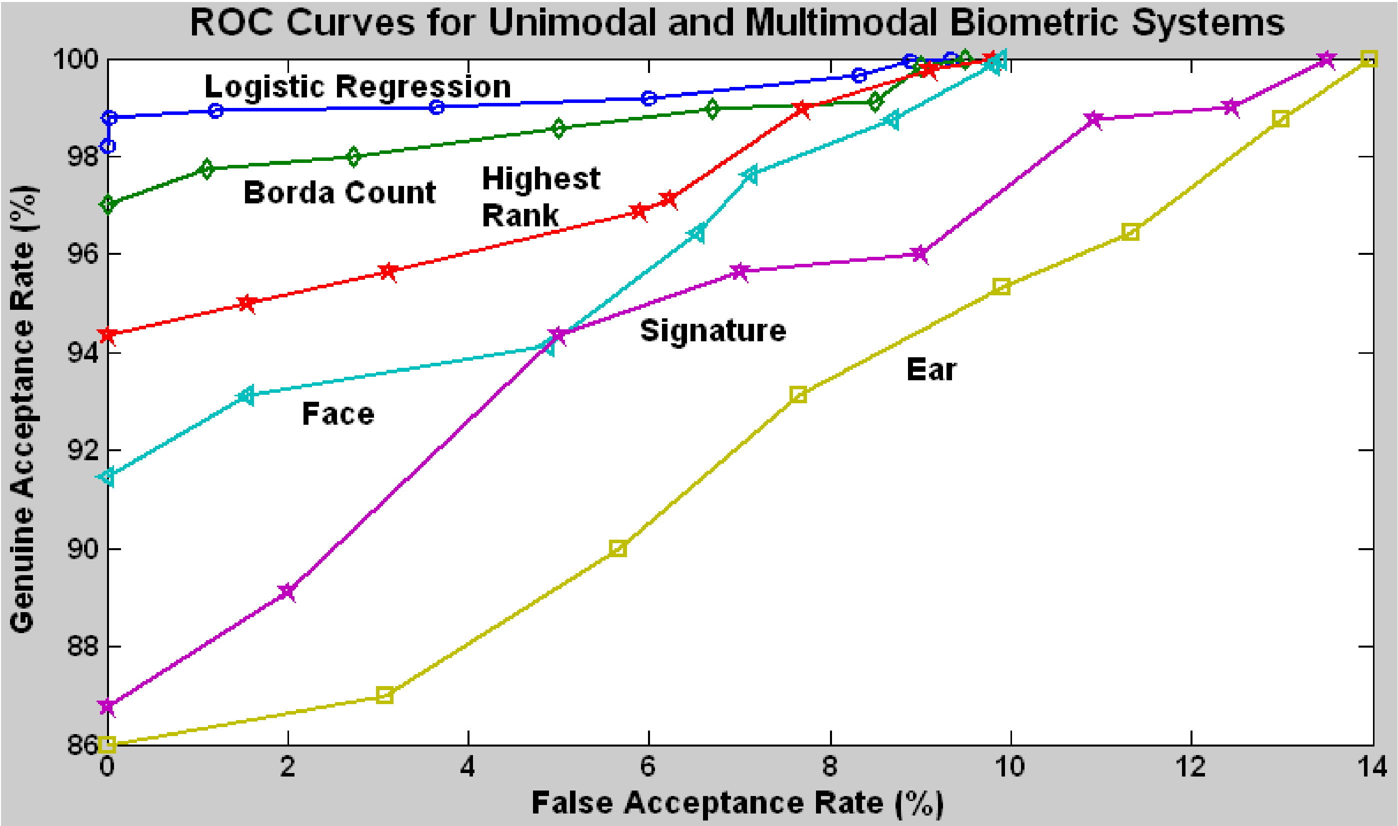
Signature Matcher

Identity	Rank
Person 1	2
Person 2	1
Person 3	5
Person 4	3
Person 5	4

Rank Level Fusion

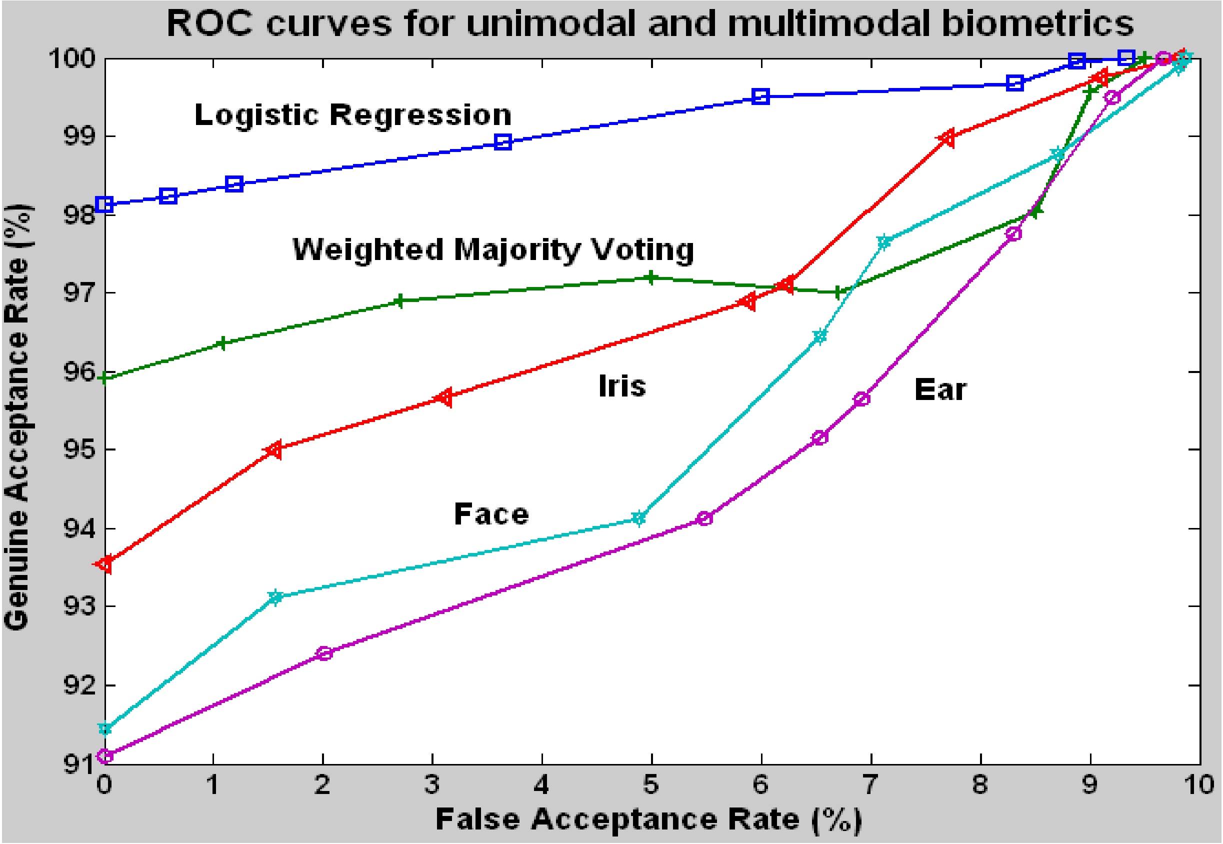
method →	Highest Rank		Borda Count		Logistic Regression Weights: Face = 0.1; Ear = 0.5; Sig. = 0.4	
Identity ↓	Fused Score	Reordered Rank	Fused Score	Reordered Rank	Fused Score	Reordered Rank
Person 1	1	1	5	1	2.2	2
Person 2	1	2	7	2	1.4	1
Person 3	3	4	13	5	4.8	5
Person 4	2	3	9	3	3.4	3
Person 5	3	5	11	4	3.5	4

Preliminary Results



Receiver Operating Characteristic (ROC) curves for unimodal (face, ear and signature) and multimodal (with three rank fusion approaches based) biometric systems.

Preliminary Results



Receiver Operating Characteristic (ROC) curves for unimodal (face, ear and iris) and multimodal (with rank and decision fusion methods based) biometric systems.

Preliminary Results

Summary of results –

- *Various rank and decision fusion approaches can be used in multimodal systems for evaluating the performances. The results show that rank level fusion outperforms decision level fusion.*
- *The enrollment and recognition time of the multimodal systems are larger than any unimodal systems.*
- *ORL face database, CASIA iris database, RUSign signature database and a public domain ear database from University of Madrid are used in these systems. Images from these databases are matched again each other to form multimodal database.*

Markov Chain

Markov Chain, which is a stochastic process with the property that, given the present state, future states are independent of the past states.

Advantages -

- *Can handle partial ranking lists.*
- *Can ensure Condorcet winner if one exists.*
- *Natural extensions of other heuristics.*

Fairness Criteria

Fairness Criteria for meaningful ranking:

- ***Pareto Criterion:***
  If every matchers prefers alternative ***a*** over alternative ***b***, then ***b*** should not be declared the winner.

- ***Condorcet Winner Criterion:***
  If there exists an alternative ***a*** which would win in pairwise comparison against each other alternative, then ***a*** should be declared the winner. This alternative is called the **Condorcet winner**.

- ***Condorcet Loser Criterion:***
  If there exists an alternative ***a*** which would loose in pairwise against each other alternative, then ***a*** should not be declared the winner.

- ***Monotonicity Criterion:***
  If alternative ***a*** is declared the winner under a ranking method, and one or more matchers change their preferences in a way favour to ***a*** (making no other changes), then ***a*** should still win.

Independency and ***Neutrality*** (un-biasness) are also criteria for meaningful ranking.

Consistency, **manipulability** etc. criteria are for election (voting) system.

Fuzzy Logic

Fuzzy Logic confidence (0-100) instead of Yes/No.

Advantages -

- *Can be applied at multiple levels.*
- *Can ensure Condorcet winner if one exists.*
- *Provides ore information to system user.*

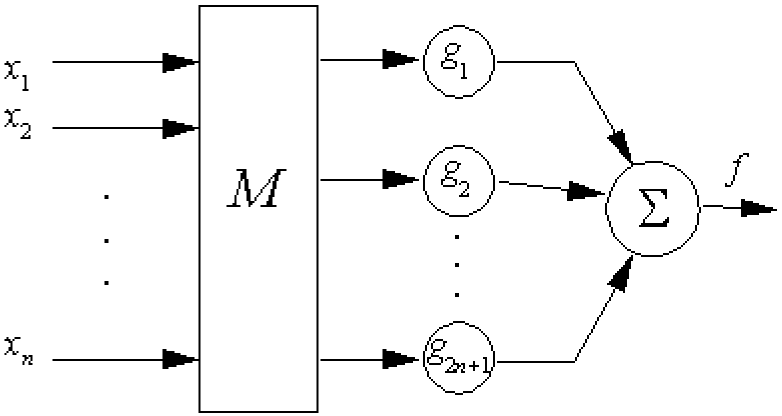
Neural Network

Neural network –resembles how human brain works, establishes connections among individual data.

Advantages -

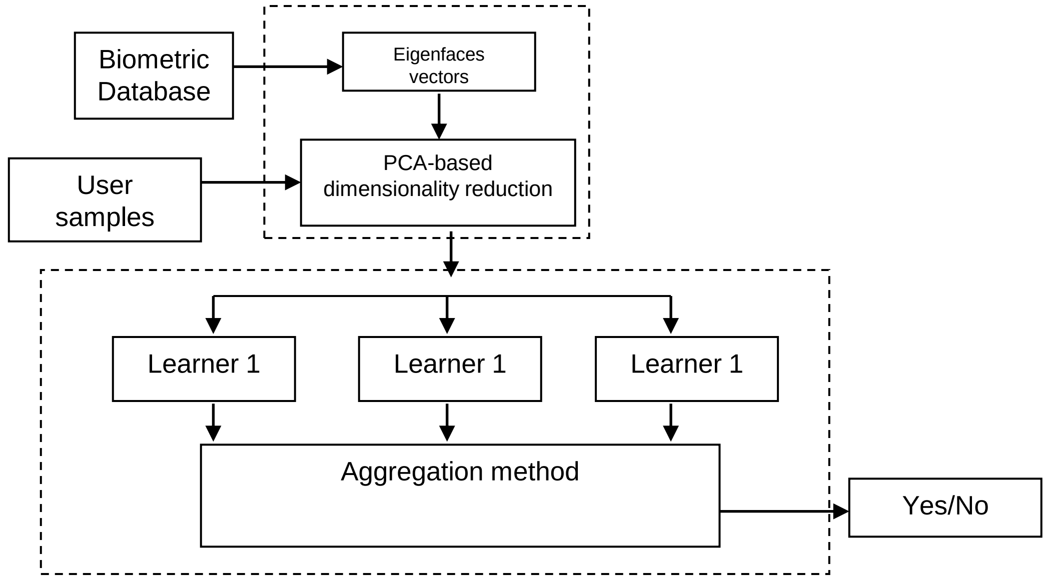
- *Learning process – system can be trained on data sets.*
- *Can integrate features of all multiple biometrics as vectors in high-dimensional space.*
- *Can support multiple architectures.*

Neural network



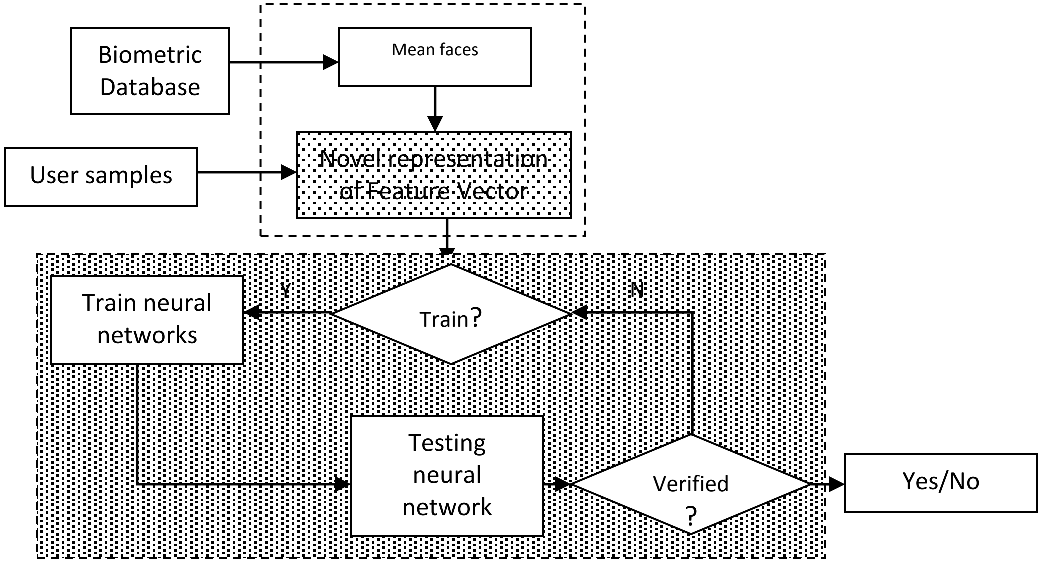
- Chaotic Neural Networks un pattern Rec.(Wang, 2006)
- CSA (Chen and Aihara, 1997)
- Applications of Optimization (Wang, 1998)

Traditional System Architecture

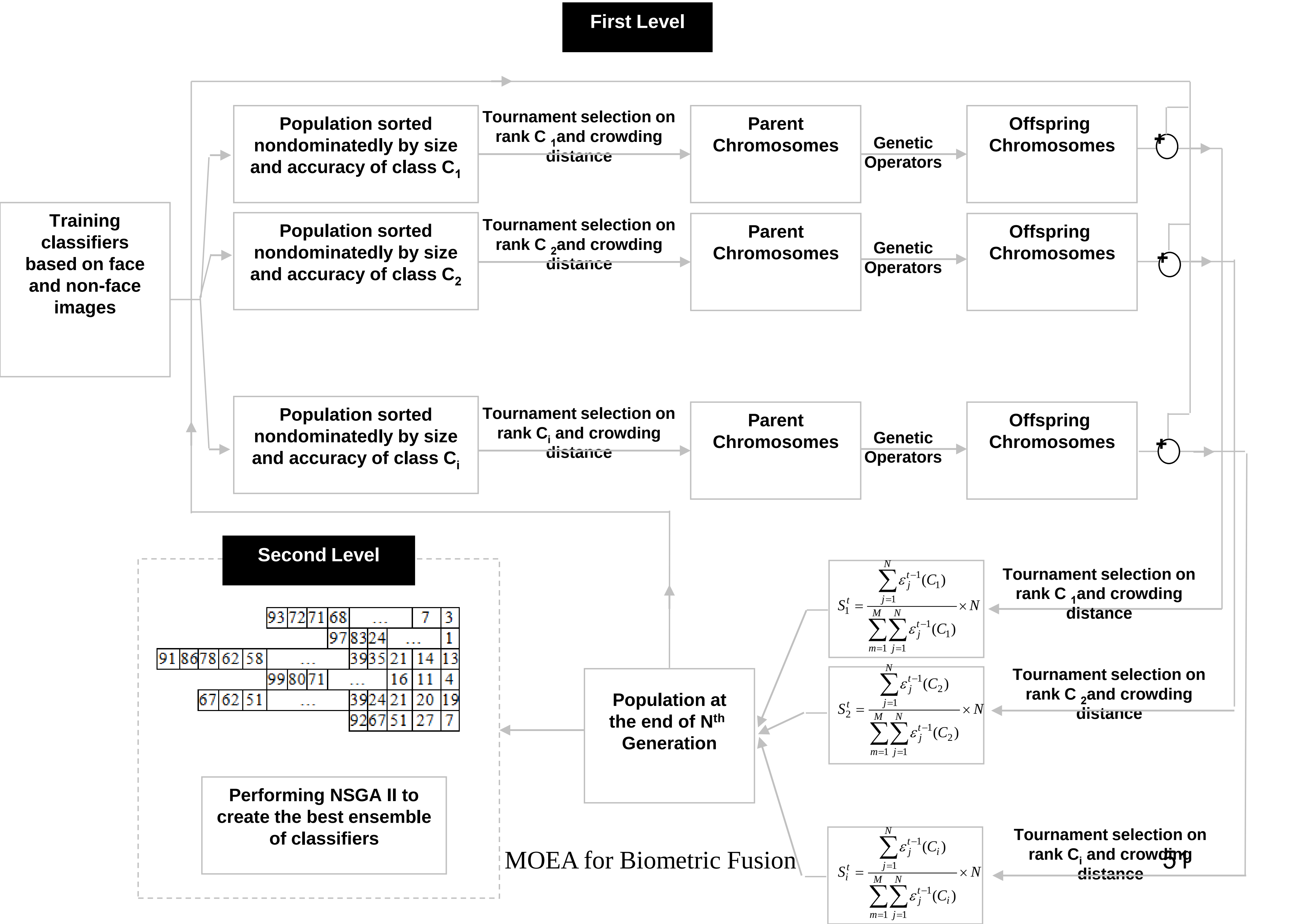


Traditional multimodal architecture

Chaotic NN System Architecture



Proposed biometric recognition system


First Level
Training classifiers based on face and non-face images
Population sorted nondominatedly by size and accuracy of class C_1
Tournament selection on rank C_1 and crowding distance
Parent Chromosomes
Genetic Operators
Offspring Chromosomes
Population sorted nondominatedly by size and accuracy of class C_2
Tournament selection on rank C_2 and crowding distance
Parent Chromosomes
Genetic Operators
Offspring Chromosomes
Population sorted nondominatedly by size and accuracy of class C_i
Tournament selection on rank C_i and crowding distance
Parent Chromosomes
Genetic Operators
Offspring Chromosomes
Second Level
93 72 71 68 … 7 3
97 83 24 … 1
91 86 78 62 58 … 39 35 21 14 13
99 80 71 … 16 11 4
67 62 51 … 39 24 21 20 19
92 67 51 27 7
Performing NSGA II to create the best ensemble of classifiers
Population at the end of N^{th} Generation
$S_1^t = \frac{\sum_{j=1}^{N} \varepsilon_j^{t-1}(C_1)}{\sum_{m=1}^{M}\sum_{j=1}^{N} \varepsilon_j^{t-1}(C_1)} \times N$
Tournament selection on rank C_1 and crowding distance
$S_2^t = \frac{\sum_{j=1}^{N} \varepsilon_j^{t-1}(C_2)}{\sum_{m=1}^{M}\sum_{j=1}^{N} \varepsilon_j^{t-1}(C_2)} \times N$
Tournament selection on rank C_2 and crowding distance
$S_i^t = \frac{\sum_{j=1}^{N} \varepsilon_j^{t-1}(C_i)}{\sum_{m=1}^{M}\sum_{j=1}^{N} \varepsilon_j^{t-1}(C_i)} \times N$
Tournament selection on rank C_i and crowding distance

Subspace Clustering

For each person (class) compute the mean image

Input Data

$$\Psi = \frac{1}{m}\sum_{i=1}^{m}\Gamma_i$$

Mean image for each class

Eigenface images

- The eigenvectors are sorted in order of descending eigenvalues and the greatest eigenvectors are chosen to represent face space.
- This reduces the dimensionality of the image space, yet maintains a high level of variance between face images throughout the image subspace.
- Any face image can then be represented as a vector of coefficients, corresponding to the 'contribution' of each eigenface.

Each eigenvector can be displayed as an image and due to the likeness to faces (FERET database)

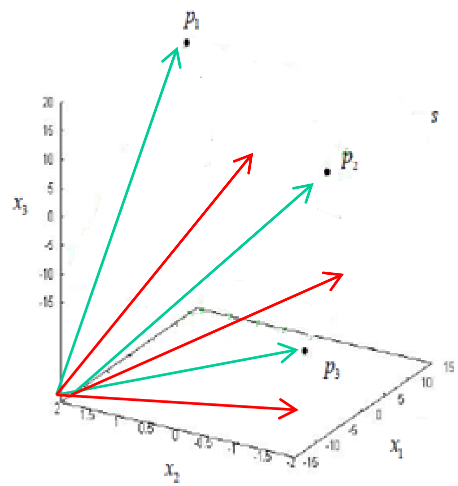
Reducing Dimensionality by Subspace Analysis

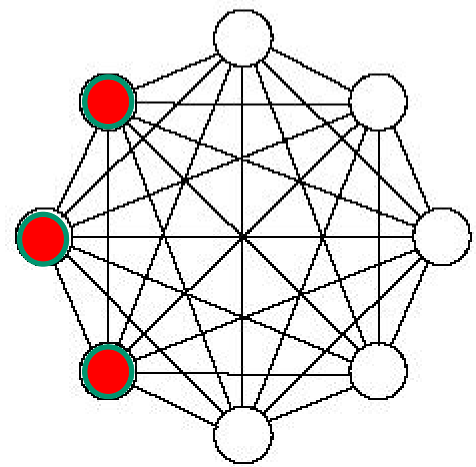
- Find the clusters within an error range of ε.
- Use the mean vector as the candidate for the members of a cluster and create the new vector space. The number of points of the new space is:

$$M \ll x*y$$

Next, we try to learn the pattern using a learner (Chaotic Neural Network)

Associative Memory





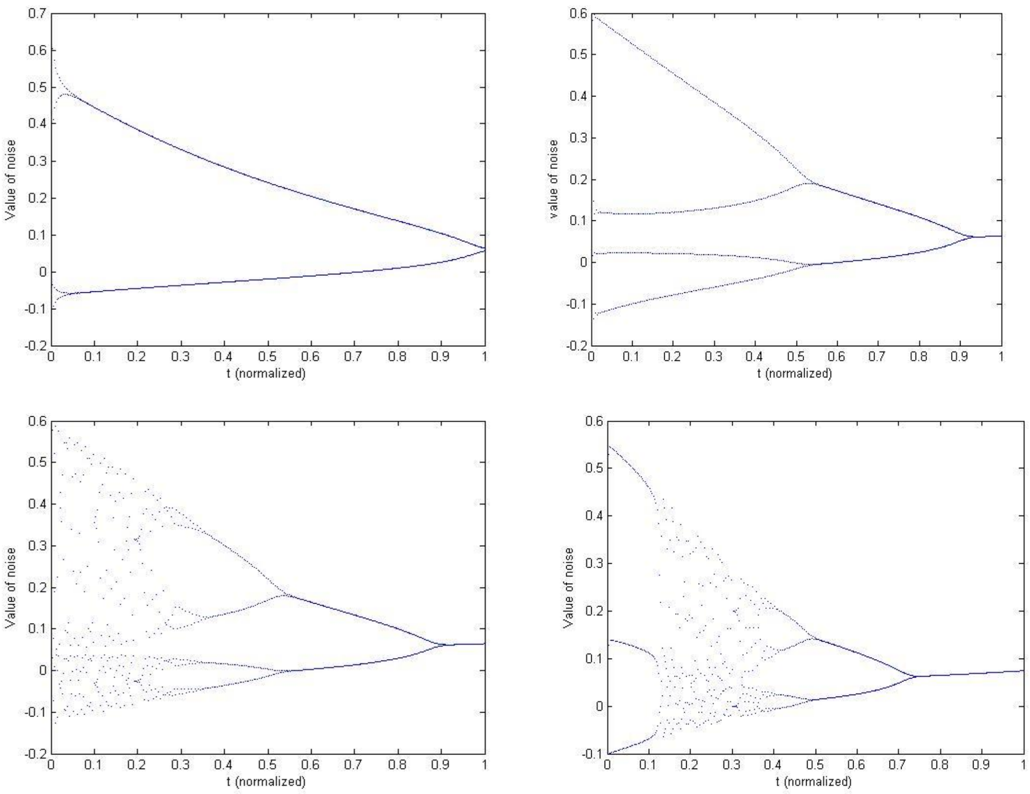
- The neuron signals comprise an output pattern.
- The neuron signals are initially set equal to some input pattern.
- The network converges to the nearest stored pattern

Chaotic Associative Memory

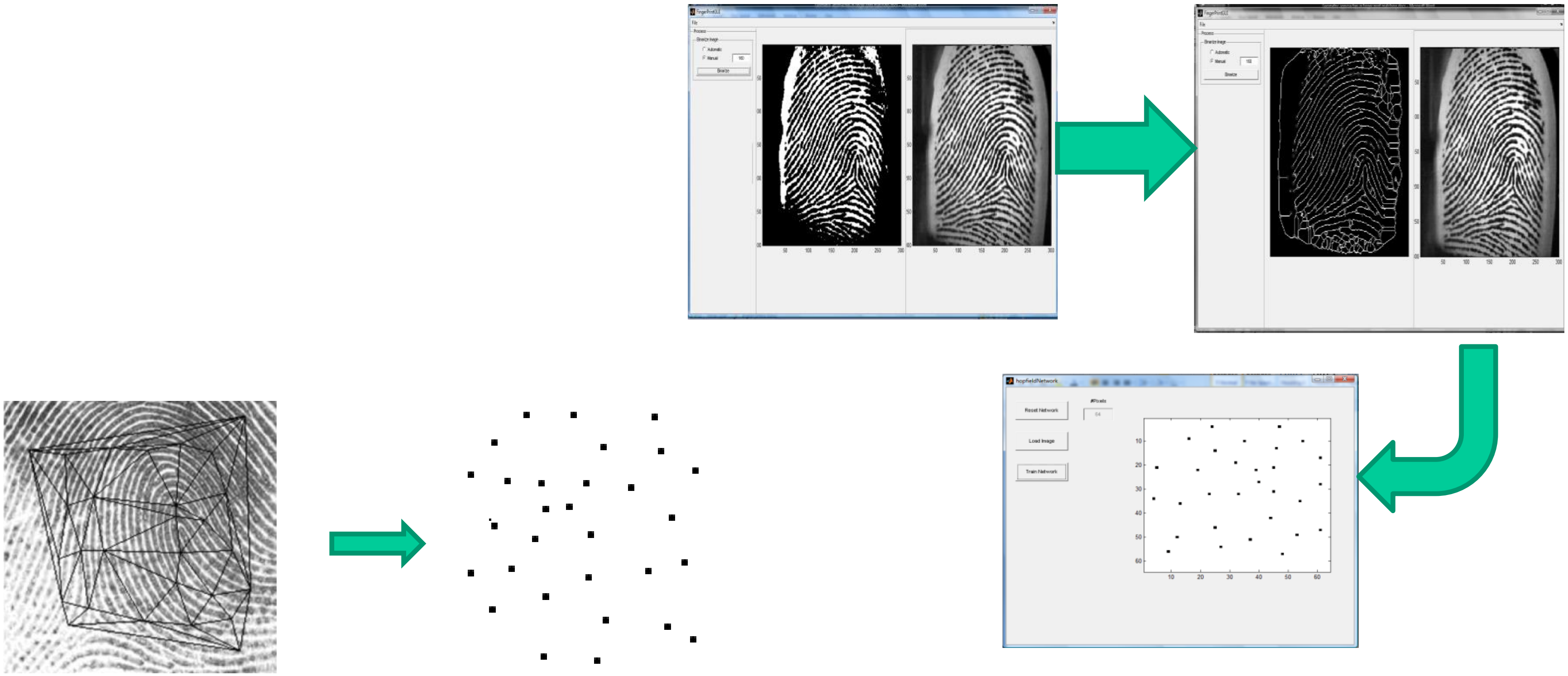
Chaotic and period doubling noise injection policies

• To overcome the drawback of non-autonomous methods is their *blind* noise-injecting strategy

• Proposing the adjacency matrix to evaluate the chances of a neuron to receive chaotic noise



Fingerprint Neural Based Method – Case Study

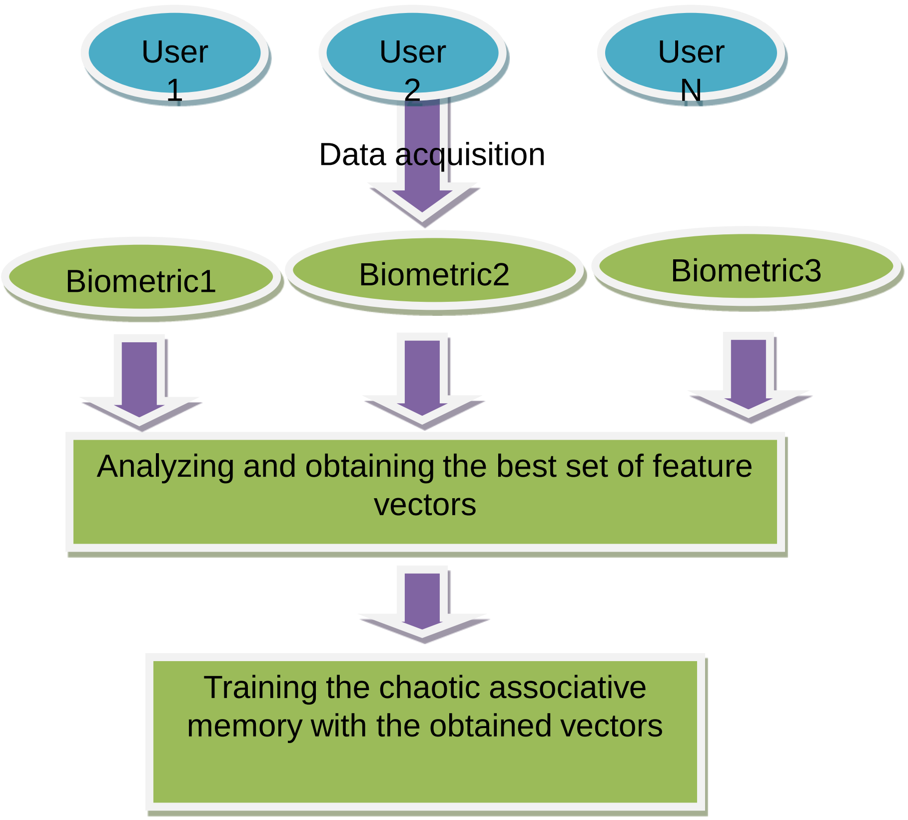


The general goal is to train the network using the Delaunay triangulation of minutiae points.

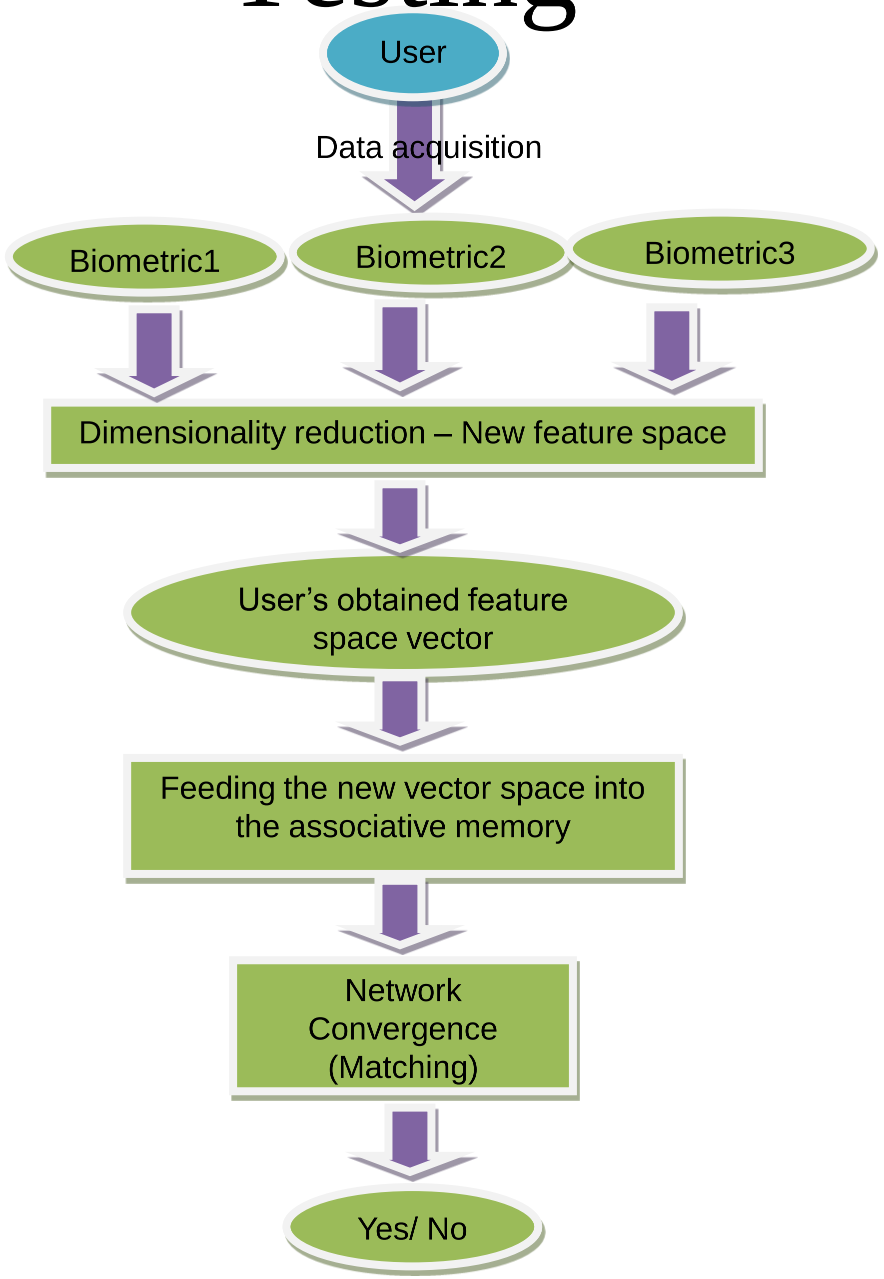
DT based Matching -Experimental Results

Method	FRR	FAR	Time
HNN	23.7%	45.6%	33ms
Standard minutiae methods	17.09%	0.84%	98 ms
Delaunay Tr. Matching	8.48%	0.18%	27ms
Delaunay Tr. matching (rigid)	5.46%	0.19%	29ms
Dual of DT and HNN	0.047%	1.17%	41ms

Multimodal Training Phase



Testing


User
Data acquisition
Biometric1
Biometric2
Biometric3
Dimensionality reduction – New feature space
User's obtained feature space vector
Feeding the new vector space into the associative memory
Network Convergence (Matching)
Yes/ No

Experimental Results

New method: Subspace Clustering (SC) and Chaotic Noise Neural Network (CNNN)

- Compared methods:
  - Simple-Sum (SS), Min-Score (MIS), Max-Score (MAS), Matcher Weighting (MW), User Weighting (UW)

Normalization Method	*Fusion Method*					
	SS	MIS	MAS	MW	UW	CNNN
MM	0.99	5.43	0.86	**1.16**	**0.63**	**0.54**
ZS	1.71	5.28	1.79	1.72	1.86	2.27
TH	1.73	4.65	1.82	1.50	1.62	3.18
QLQ	**0.94**	5.43	0.63	**1.16**	**0.63**	**0.58**
SC	1.64	**4.43**	**0.61**	1.72	**0.63**	**0.51**

  - Min-Max Score (MM), Zero Score (ZS), Tanh (TH), Quadratic Line Quadric (QLQ), Subspace Clustering (SC)

Experimental Results

Normalization Method	*Fusion Method*					
	SS	MIS	MAS	MW	UW	CNNN
MM	0.99	5.43	0.86	**1.16**	**0.63**	**0.54**
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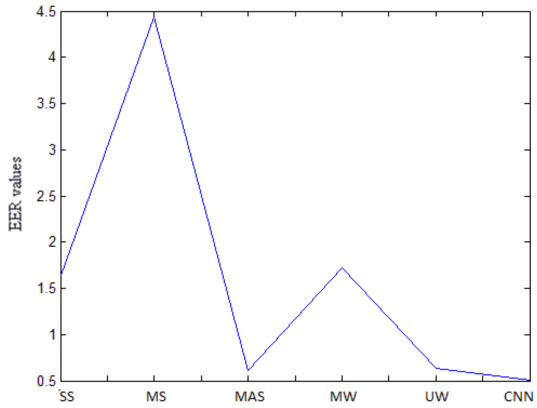
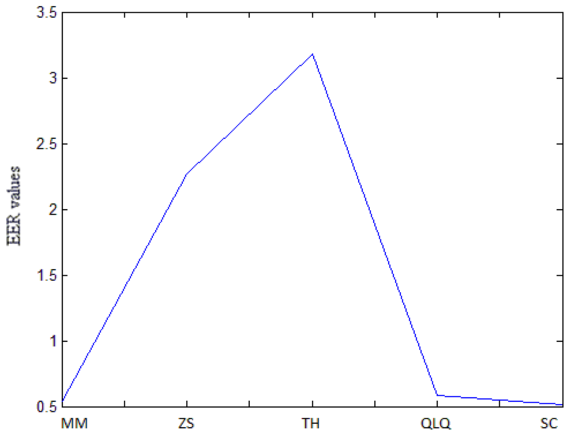


EER rate, SC with different fusion techniques



EER rate, CNN with different normalization techniques

Experimental Results

Normalization Method	*Fusion Method*					
	SS	MIS	MAS	MW	UW	CNNN
MM	0.99	5.43	0.86	**1.16**	**0.63**	**0.54**
ZS	1.71	5.28	1.79	1.72	1.86	2.27
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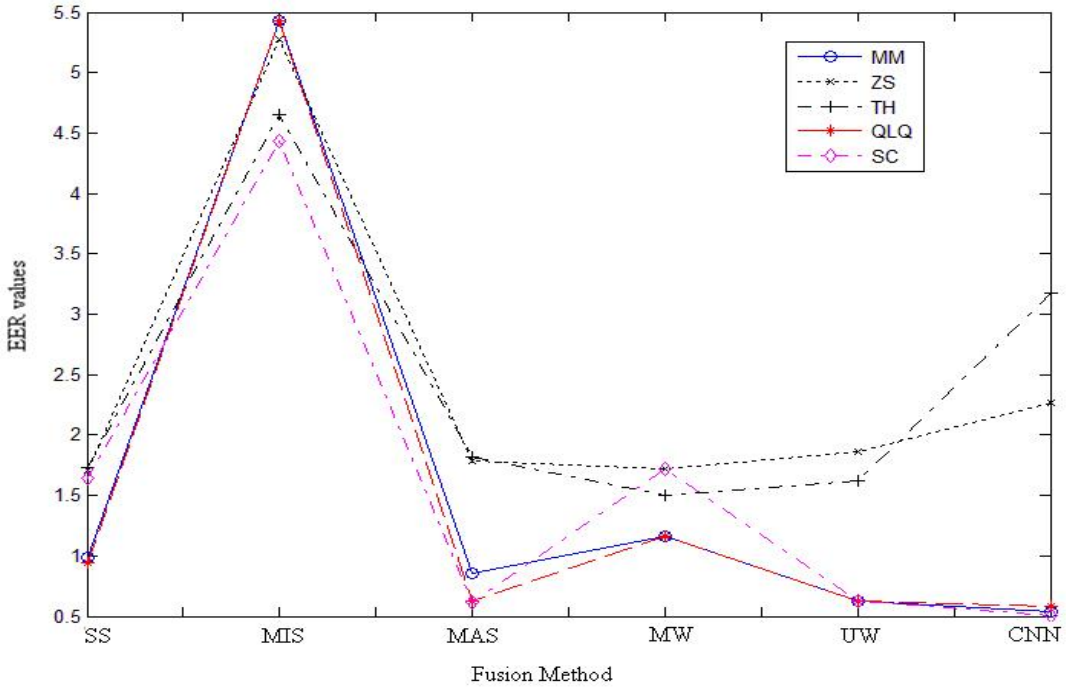


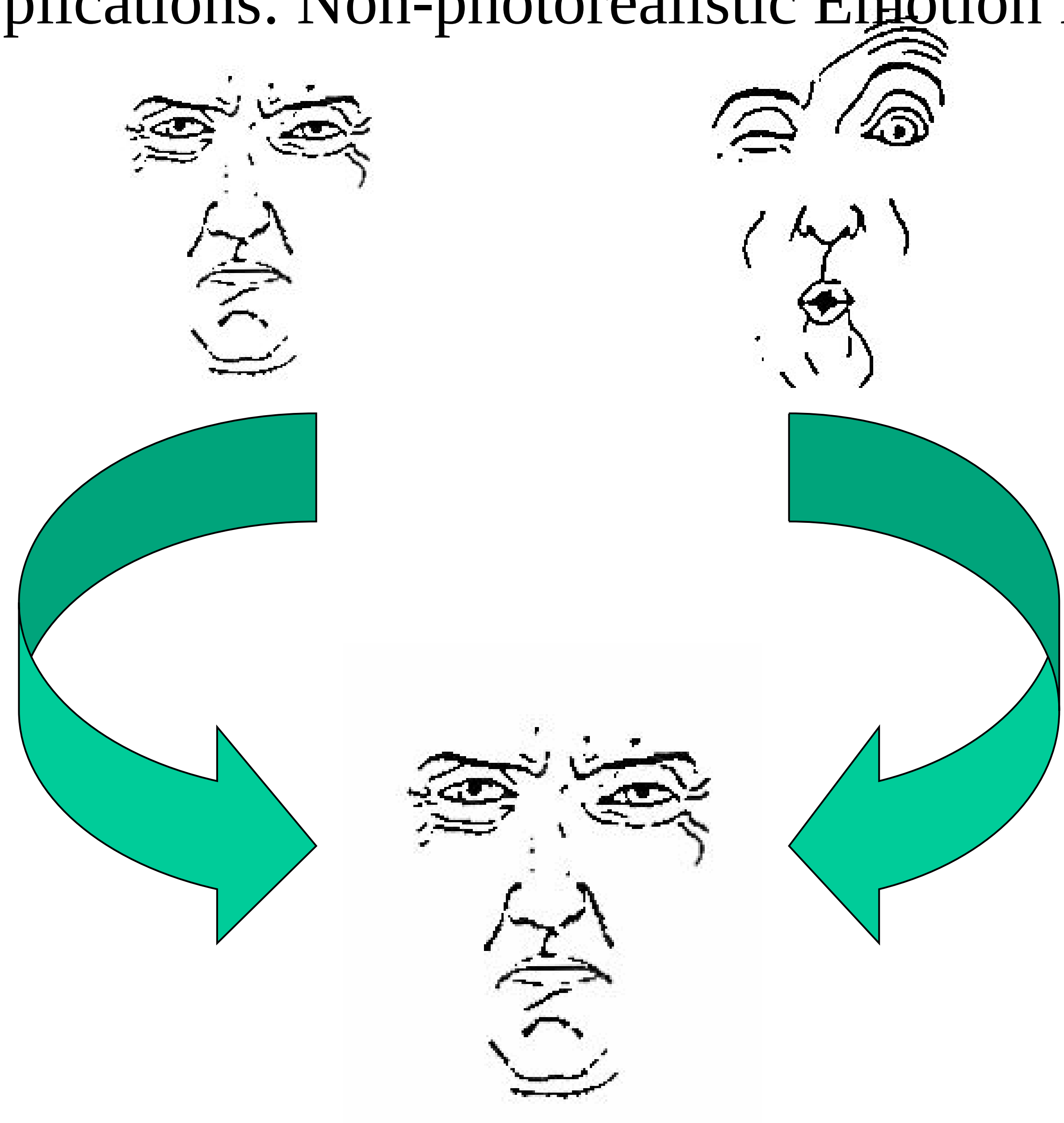
EER rate, Combination of different fusion and normalization techniques

Benefits

- The benefits are :
  - New method for selecting a proper set of input features to reduce the dimensionality of biometric data and consequently enhancing the performance of the system.
  - Introducing chaotic associative memories in biometric system has significant advantages over conventional memories in terms of capacity of the memory
  - Implementing and enhancing performance of the biometric multimodal verification system in presence of noise or missing data.

Applications: Sign Recognition and Navigation

Applications: Non-photorealistic Emotion Morphing



Artimetric - Avatar Recognition

(with R. Yampolskii, U of Louisville, USA)

CONNECTING VIRTUAL ROOMMATES VIA FEATURE-BASED SPATIAL MAPPING

In collaboration with A. Sherstyuk, Avatar realty, USA

Summary

Advantages of multibiometric systems over single biometric systems and the issues that need to be considered during designing such systems have been discussed.

Information fusion plays a key role in a multibiometric system and the success of such system depends heavily on fusion methods.

Active research in the area is focused on using various fusion schemes in combination with specific system design, biometric types and applications.

Rank level fusion in combination with Markov chain approach, fuzzy logic provide better accuracy rates.

Neural networks are recent directions of research which allow for better learning of patterns in complex biometrics, increased accuracy rates and better system circumvention in presence of noisy/missing data.

Thank You

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