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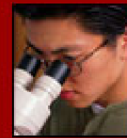


3D Face Recognition Using Multi-Region Summation Invariants

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This research is partially supported by the NSF under Grant No. CCF-0434355

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Agenda

1. ***Introduction***
   - Focus of FR research
2. Invariant Theory
3. MSI Algorithm and Results
4. Conclusion

Focus of FR Research

1. Currently focus on 3D FR algorithm
2. A novel family of geometrical invariants based on the method of moving frame
3. Extract summation invariants from local profiles on multi-regions
4. LDA-based fusion method

Agenda

1. Introduction
2. ***Invariant Theory***
   - Method of Moving Frame
   - Summation Invariants
   - Feature Extraction on 3D surface
3. MSI Algorithm and Results
4. Conclusion

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Method of Moving Frame

- A power tool for finding invariants under group actions (É. Cartan, 1935).
- Definition: a **moving frame** is a G-equivariant mapping $\rho : M \to G$, i.e.

$$\rho(g \circ x) = g\rho(x)$$

Summation Invariants

- Procedures
  1. Given a transformation over points of a curve, surface, etc.
  2. Define ***jet space***.
  3. Solve the moving frame from the ***normalization equations***.
  4. Invariants can be derived by applying moving frame on jet space.
- A systematical way to derive geometrical invariants for pattern recognition

Example

STEP 1 : A point (x,y) under rotation

STEP 2 : Define jet space as $(\bar{x}, \bar{y})$

STEP 3 : Normalization equation

$$\boxed{\bar{y} = x\sin\theta + y\cos\theta = 0} \rightarrow \theta = \arctan(\frac{-y}{x})$$

STEP 4 :Apply moving frame to jet space

$$\bar{x} = x\cos\theta - y\sin\theta = \boxed{\sqrt{x^2 + y^2}}$$

Example : Euclidean Summation Invariants for Curves

STEP 1 : Given a curve (x[n], y[n]) under Euclidean transformation

$$\begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}\begin{bmatrix} x[n] \\ y[n] \end{bmatrix} + \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} \bar{x}[n] \\ \bar{y}[n] \end{bmatrix}$$

STEP 2 : Jet space is defined as

$$(\bar{x}[1], \bar{y}[1], \bar{y}[N], P_{1,0}, P_{0,1}, \ldots) \qquad P_{i,j} = \sum_{n=1}^{N} x^i[n] \cdot y^j[n]$$

Example : Euclidean Summation Invariants of Curves

STEP 3 : We can find a **moving frame** by solving the normalization equations

$$(\bar{x}[1], \bar{y}[1], \bar{y}[N]) = (0,0,0)$$

STEP 4 : Invariants can be obtained by applying moving frame

$$\eta_{i,j} = \sum_{n=1}^{N} \bar{x}^{i}[n] \cdot \bar{y}^{j}[n]$$

where $\bar{x} = \rho^{-1} \circ x$ and $\bar{y} = \rho^{-1} \circ y$

Example : Euclidean Summation Invariants of Curves

- The first-order summation invariants are explicitly shown below

$$\eta_{1,0} = P_{1,0}(x_1 - x_0) + P_{0,1}(y_1 - y_0) + Nx_0(x_0 - x_1) + Ny_0(y_0 - y_1)$$

$$\eta_{0,1} = P_{1,0}(y_1 - y_0) + P_{0,1}(x_0 - x_1) + N(x_1 y_0 - x_0 y_1)$$

where

$$x_0 = x[1], x_1 = x[N], y_0 = y[1], y_1 = y[N]$$

$$P_{i,j} = \sum_{n=1}^{N} x^i[n] \cdot y^j[n]$$

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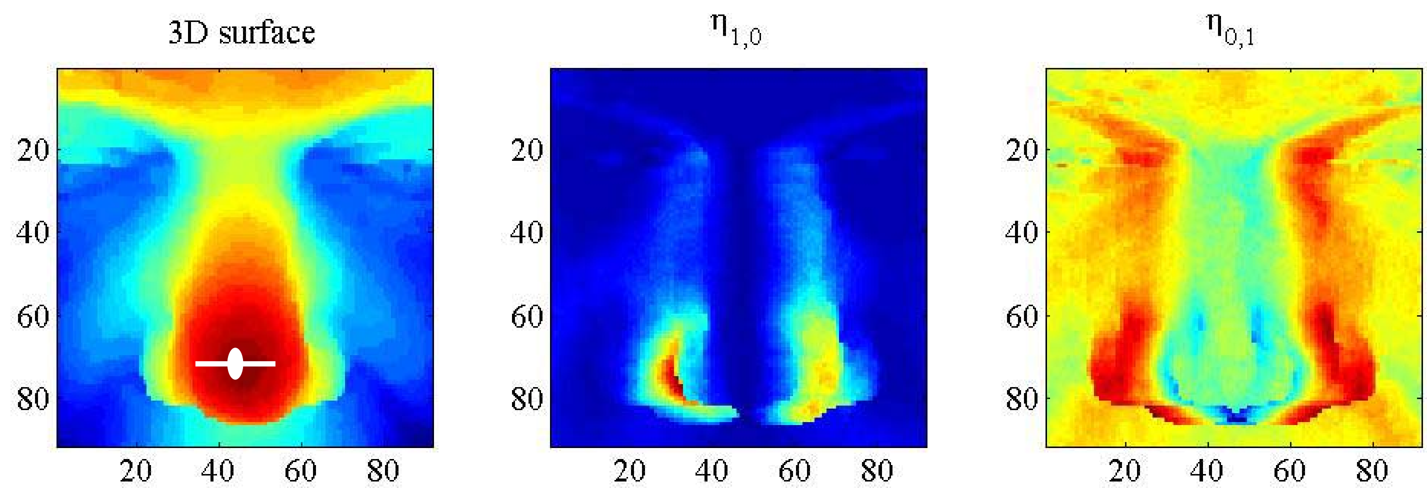
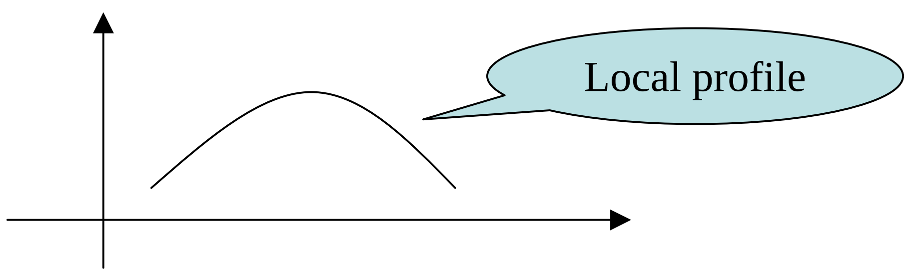
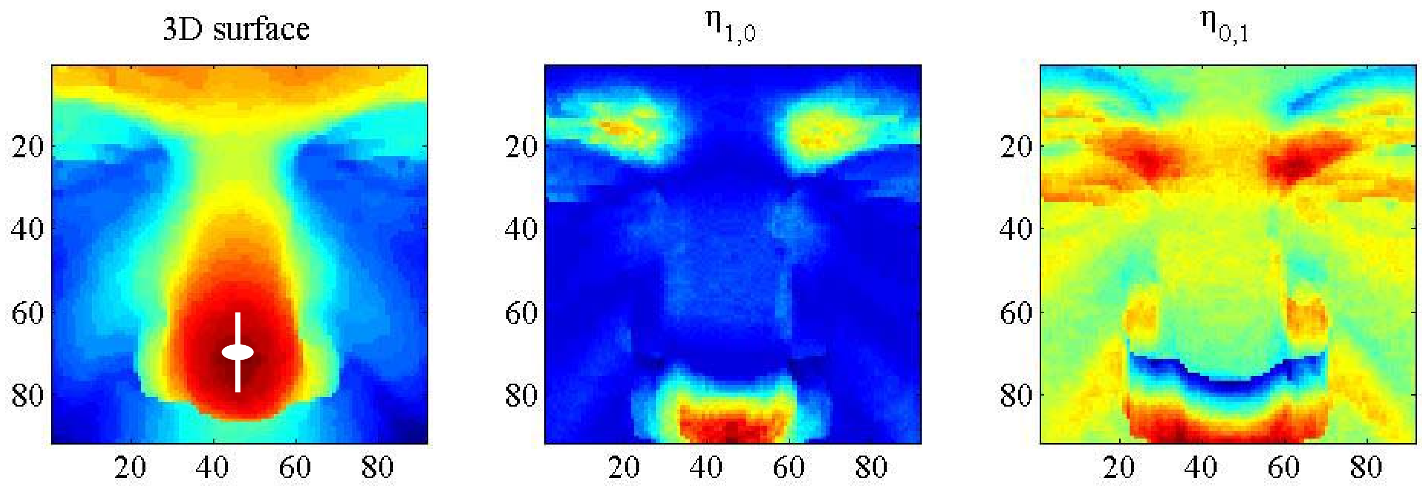
Feature extraction on 3D surface





Feature extraction on 3D surface



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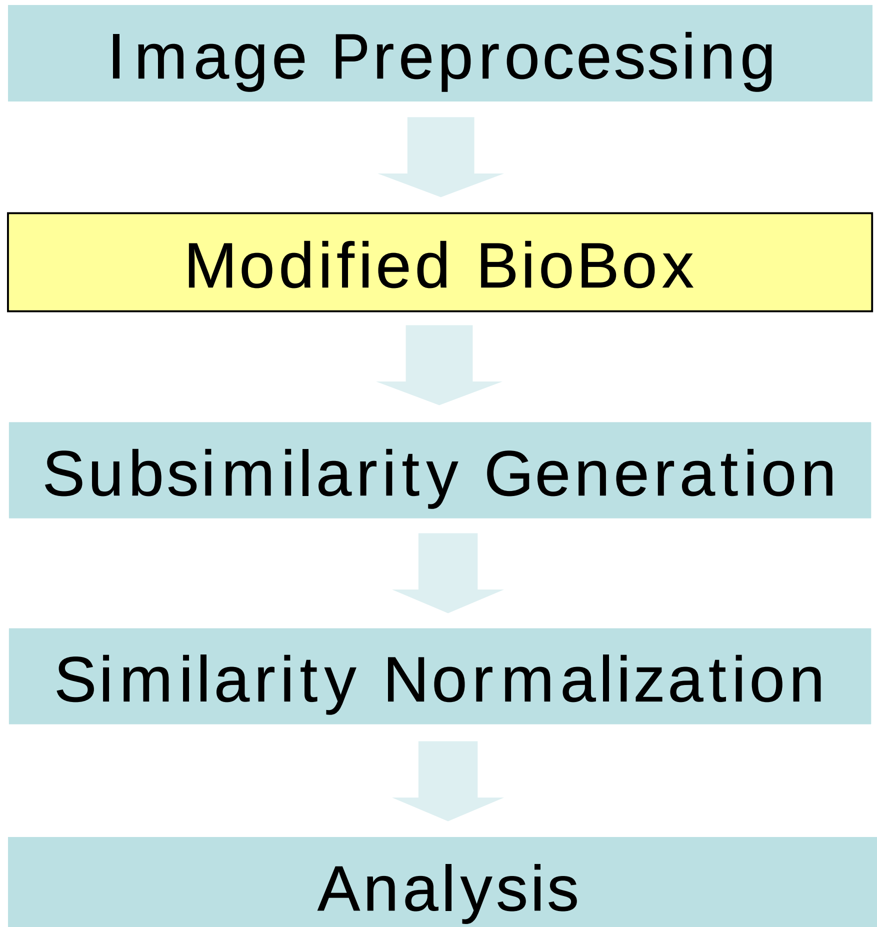
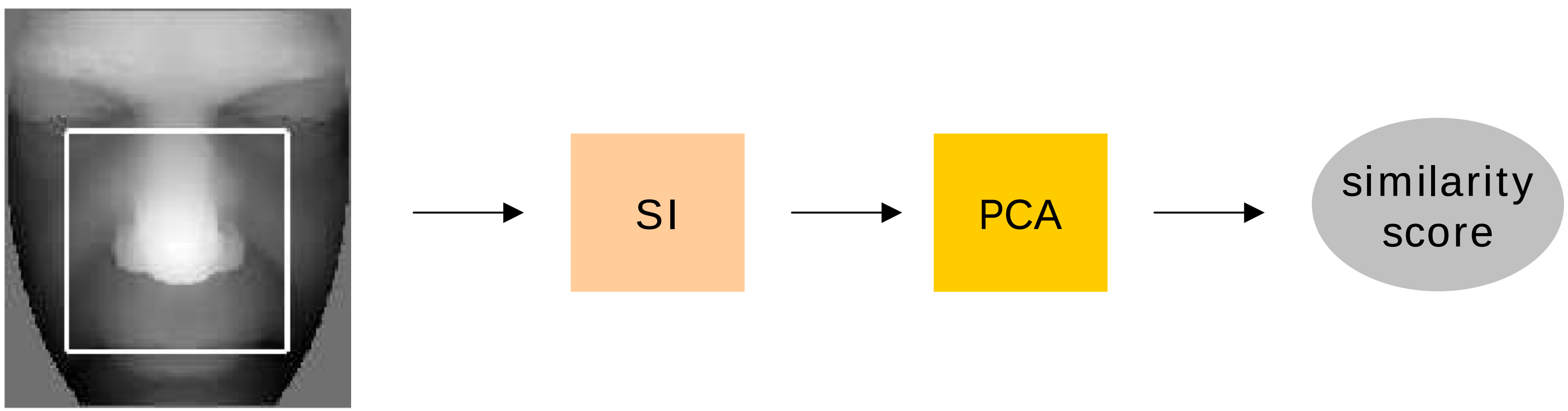
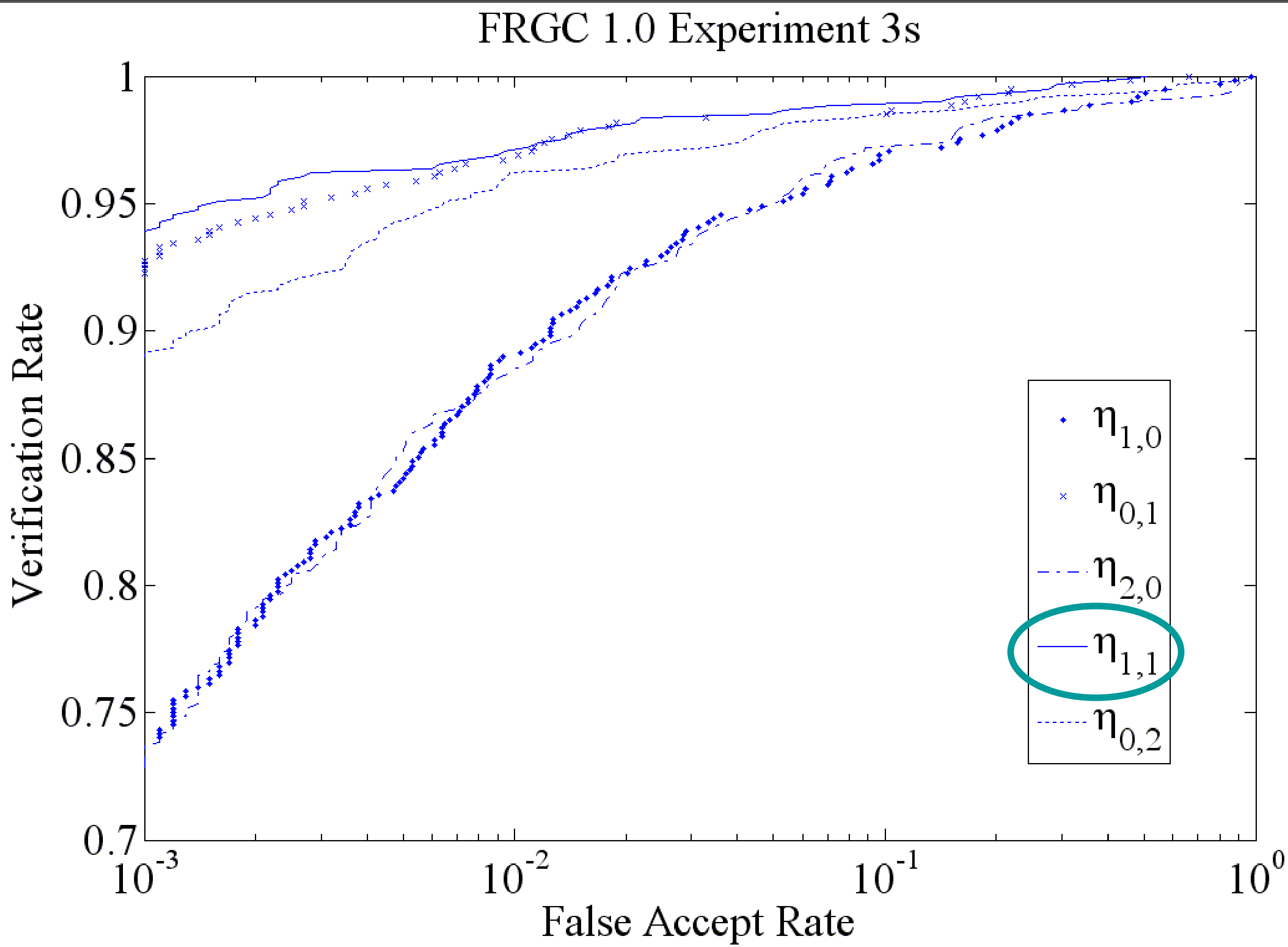
Block diagram



Single Region Algorithm



Lin *et. al.*,“Fusion of Summation Invariants in 3D Human Face Recognition”, accepted to appear in CVPR’06


FRGC 1.0 Experiment 3s
Verification Rate
False Accept Rate
1
0.95
0.9
0.85
0.8
0.75
0.7
10^{-3}
10^{-2}
10^{-1}
10^{0}
$\eta_{1,0}$
$\eta_{0,1}$
$\eta_{2,0}$
$\eta_{1,1}$
$\eta_{0,2}$

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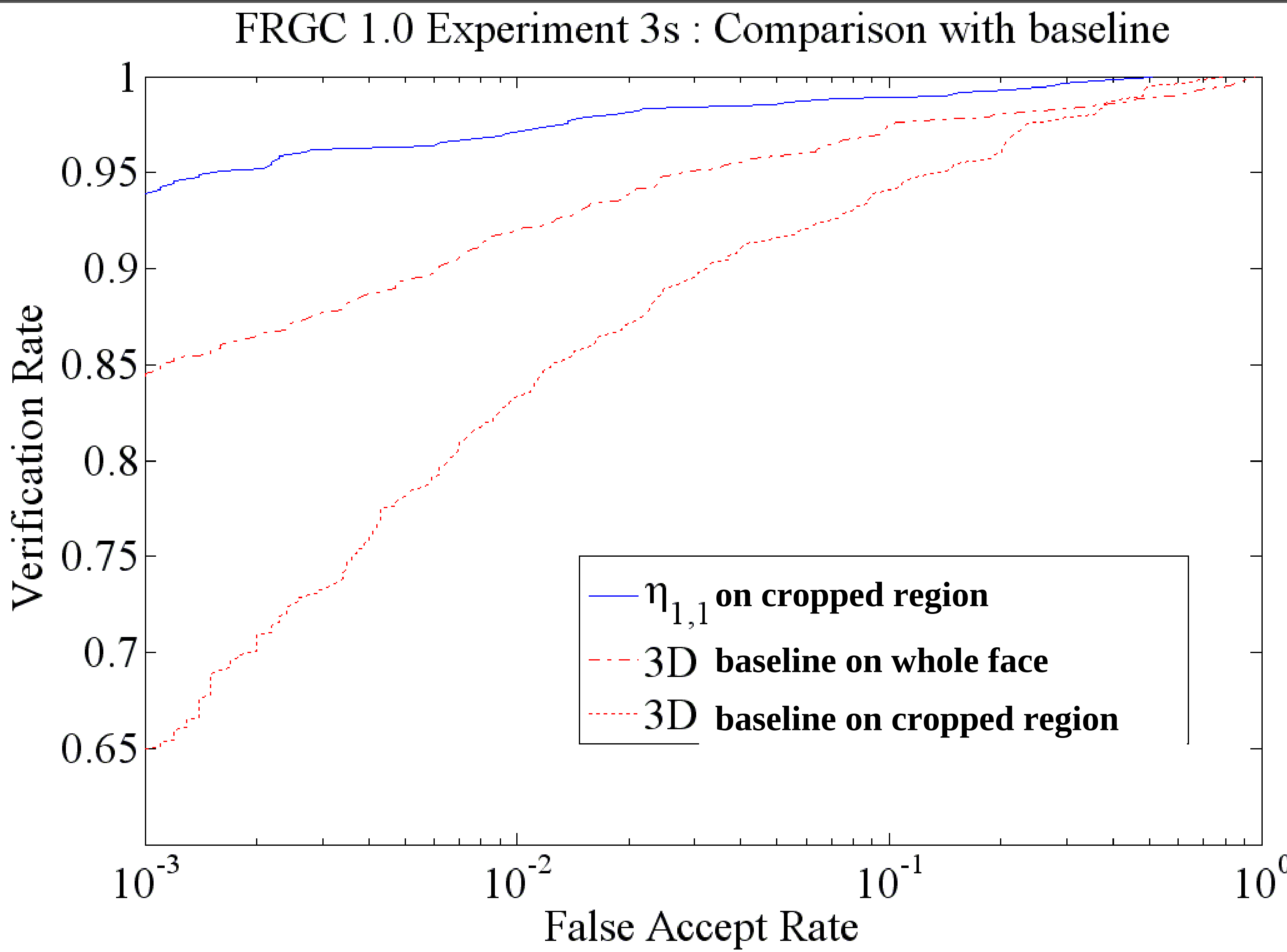
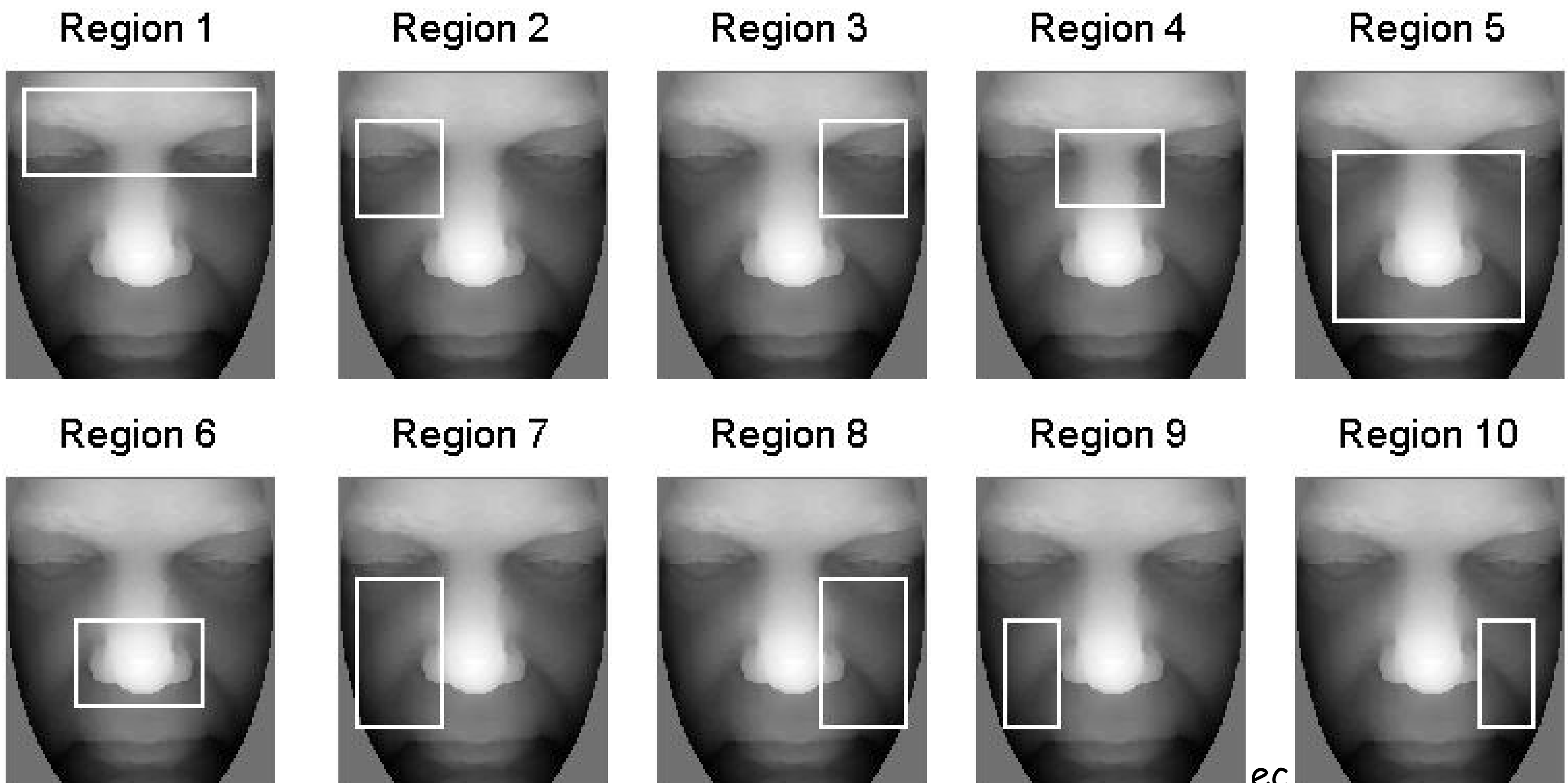
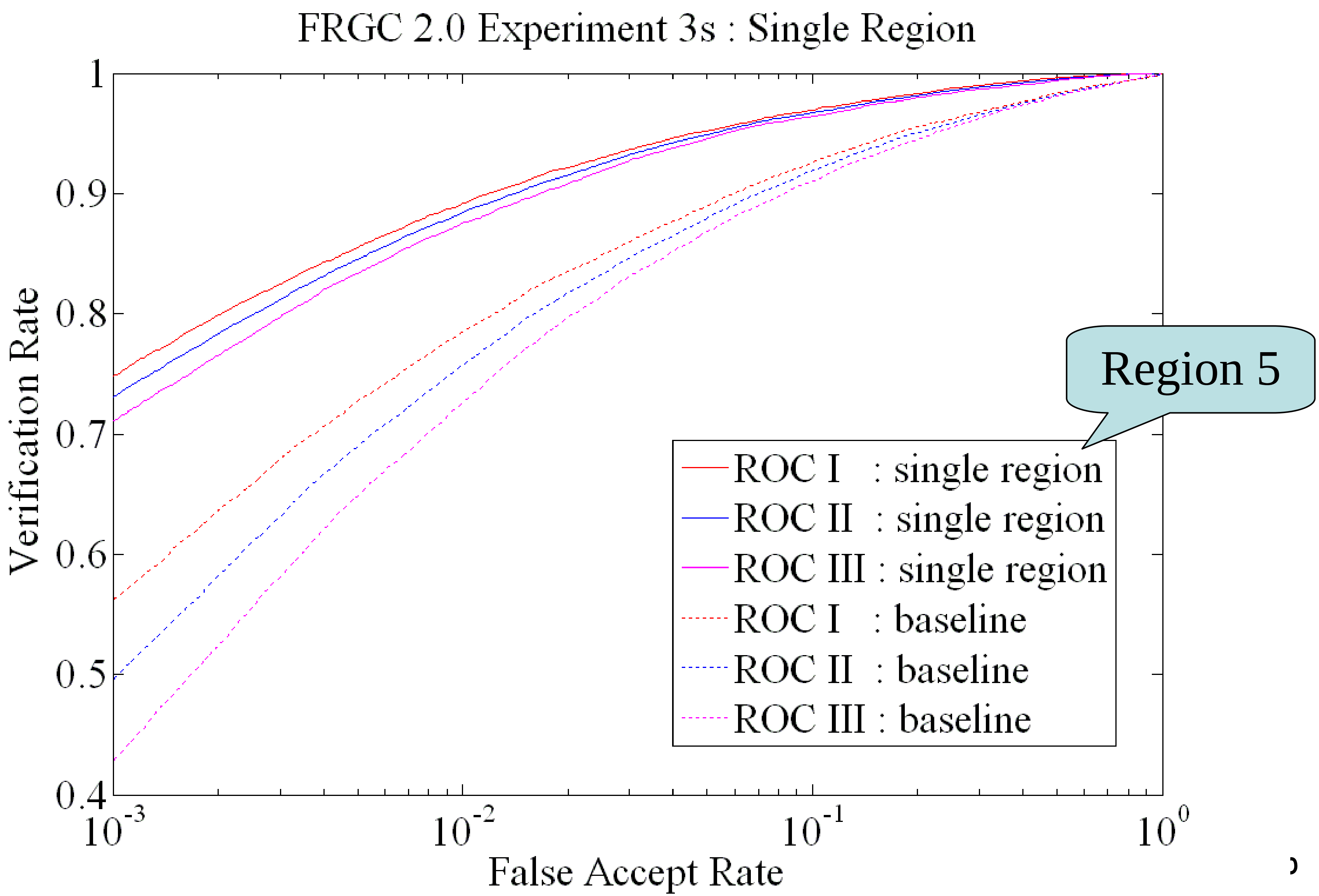


Multi-Region Summation Invariants (MSI) Algorithm




FRGC 2.0 Experiment 3s : Single Region
Verification Rate
False Accept Rate
0.4
0.5
0.6
0.7
0.8
0.9
1
10^{-3}
10^{-2}
10^{-1}
10^{0}
Region 5
ROC I : single region
ROC II : single region
ROC III : single region
ROC I : baseline
ROC II : baseline
ROC III : baseline

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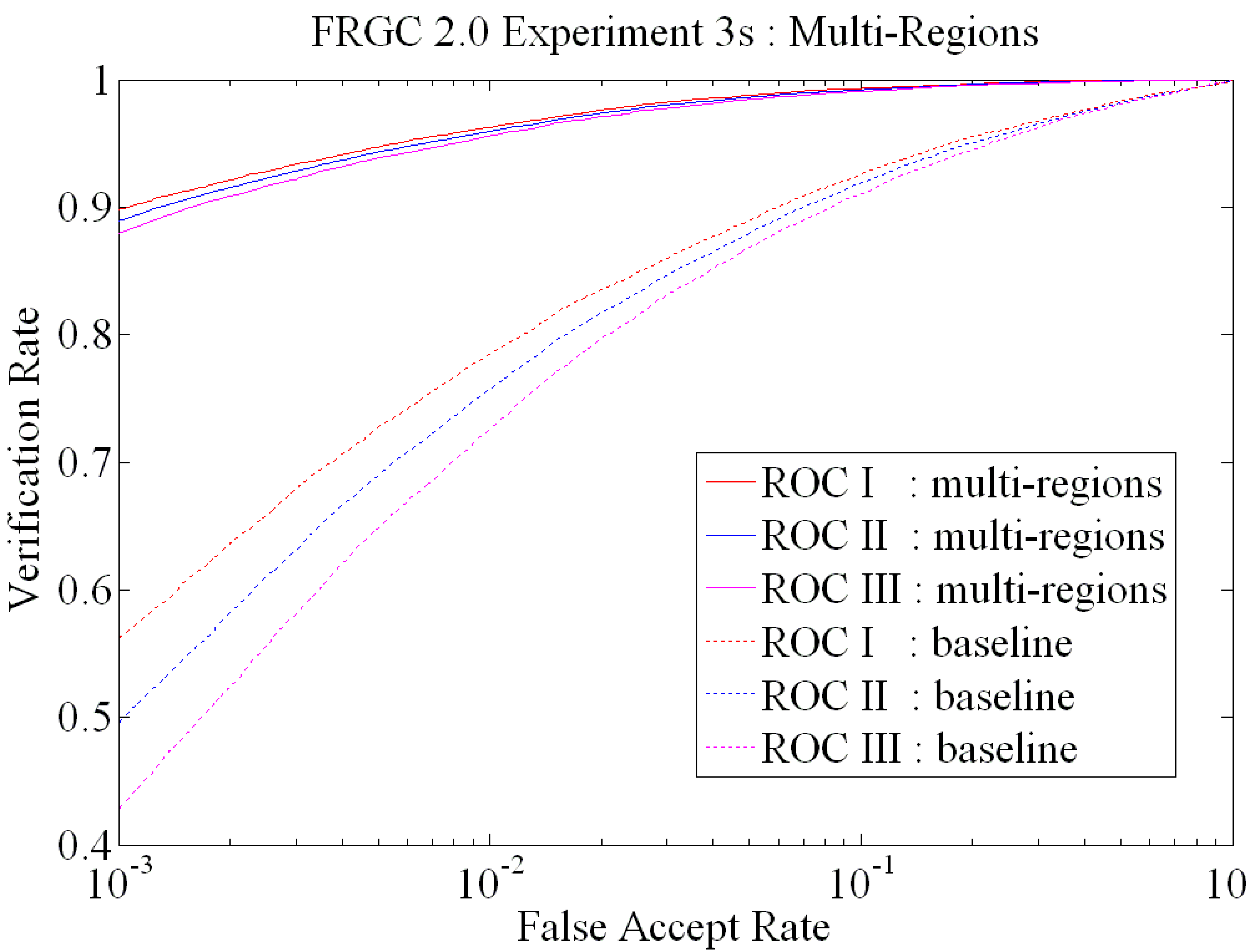
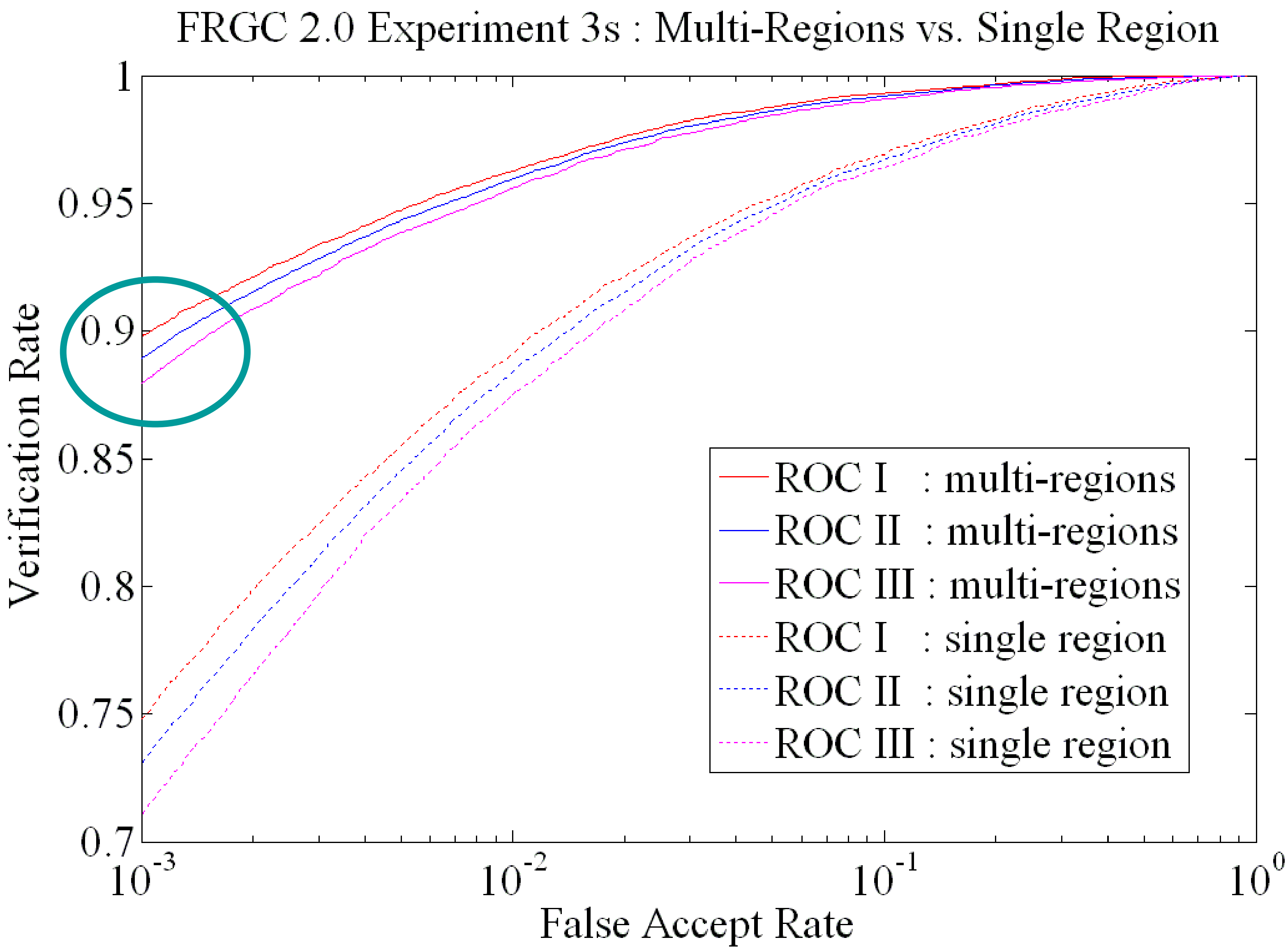
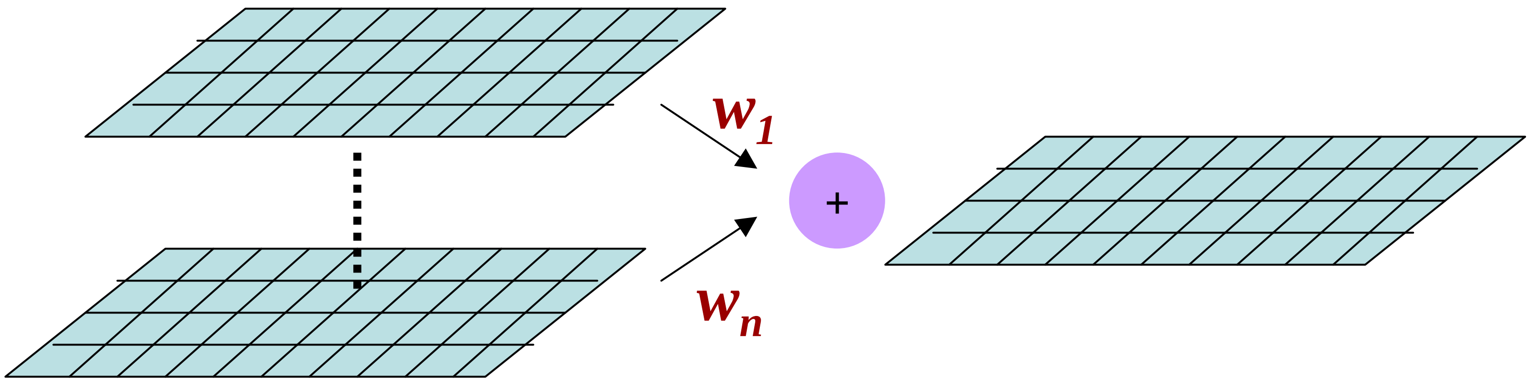



FRGC 2.0 Experiment 3s : Multi-Regions vs. Single Region
Verification Rate
False Accept Rate
1
0.95
0.9
0.85
0.8
0.75
0.7
10^{-3}
10^{-2}
10^{-1}
10^{0}
ROC I : multi-regions
ROC II : multi-regions
ROC III : multi-regions
ROC I : single region
ROC II : single region
ROC III : single region

Optimal Fusion with LDA

$$\mathbf{W} = \mathbf{S}^{-1} (\mathbf{m}_2 - \mathbf{m}_1)$$



Similarity matrices from 10 regions

Final similarity matrix

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LDA Fusion Results and Feature Selection

# of regions	Weight on each region										V.R. @ FAR = .001		
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	ROC I	ROC II	ROC III
9 regions	.3586	.3222	.2665	.3661	.4849	.4008	.2396	.2749	.1831		**.9185**	**.9120**	**.9045**
8 regions	.3630	.3162	.2675	.3784	.4958	.4067	.2564	.2763			.9065	.8992	.8910
7 regions	.3708	.3125	.2709	.3759	.6225		.2881	.2819			.8867	.8751	.8614
6 regions	.3922	.2400		.3906	.6289		.2994	.3044			.9046	.8984	.8918
5 regions	.3980	.3736		.3923	.6679			.3192			.9086	.9034	.8983
4 regions	.4052	.3754		.3950	.7339						.8863	.8771	.8663
3 regions	.4692			.4374	.7671						.8450	.8302	.8133
2 regions	.5367				.8437						.8630	.8536	.8414
1 regions	1.0										.7591	.7429	.7242

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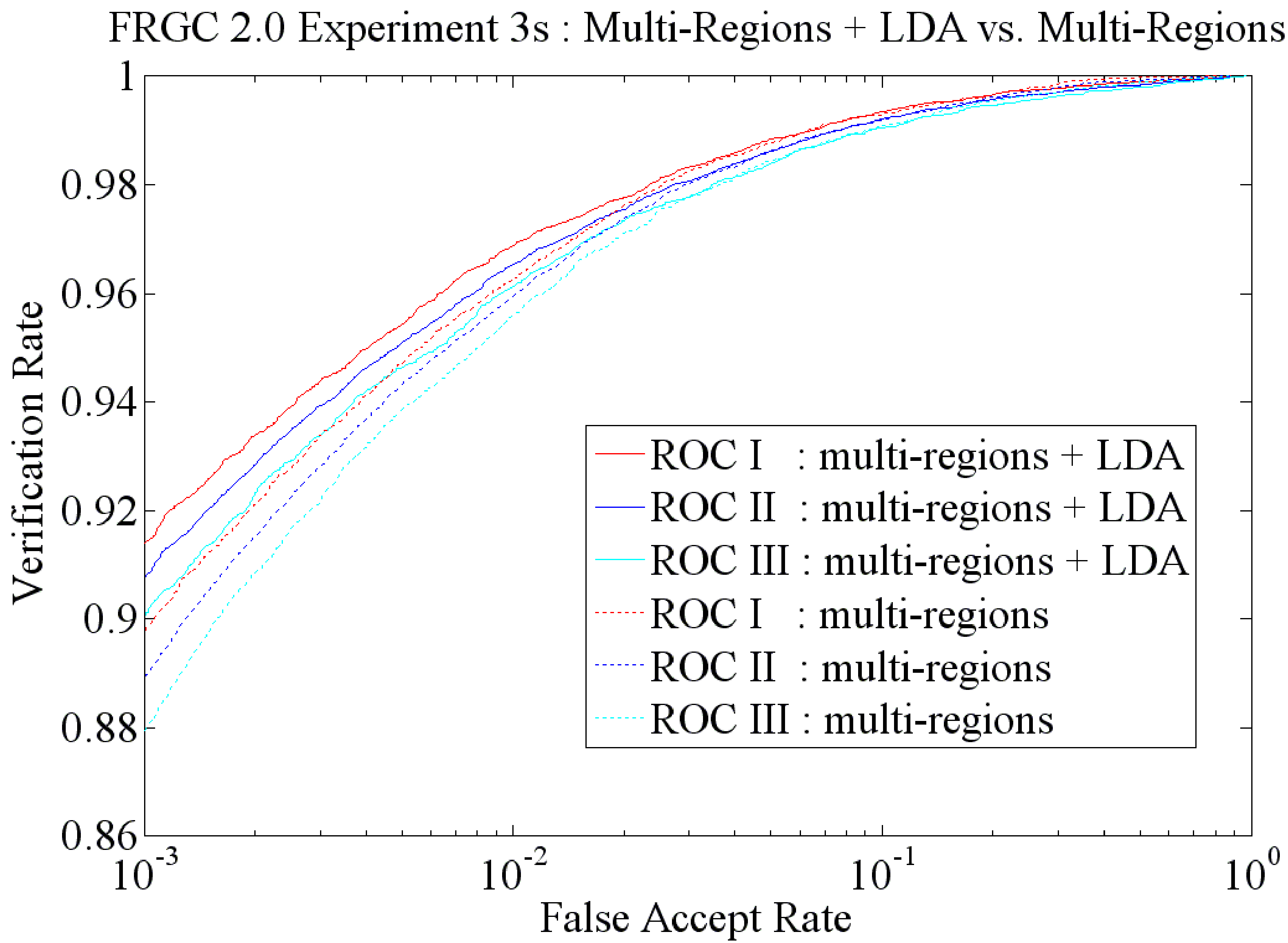

Conclusion and Future Works

- Summation invariants
  - A systematical way to derive geometric invariants for pattern recognition
  - extract useful shape information
- Fusion of multiple regions
  - LDA can improve performance
- Future work
  - Apply SI on non-normalized shapes

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