Robust Face Recognition based on Feature Points Matching

Laboratoire d'InfoRmatique en Image et Systèmes d'information

LIRIS UMR 5205 CNRS/INSA de Lyon/Université Claude Bernard Lyon 1/Université Lumière Lyon 2/Ecole Centrale de Lyon

Université Claude Bernard Lyon 1, bâtiment Nautibus

43, boulevard du 11 novembre 1918 — F-69622 Villeurbanne cedex

http://liris.cnrs.fr

Focus

Effective facial description methods and robust matching schemes in different recognition scenarios:

- Only 3D Shape based Face Recognition
- Textured 3D Face Recognition
- Asymmetric Face Recognition

2D Probes Gallery Set 3D Probes

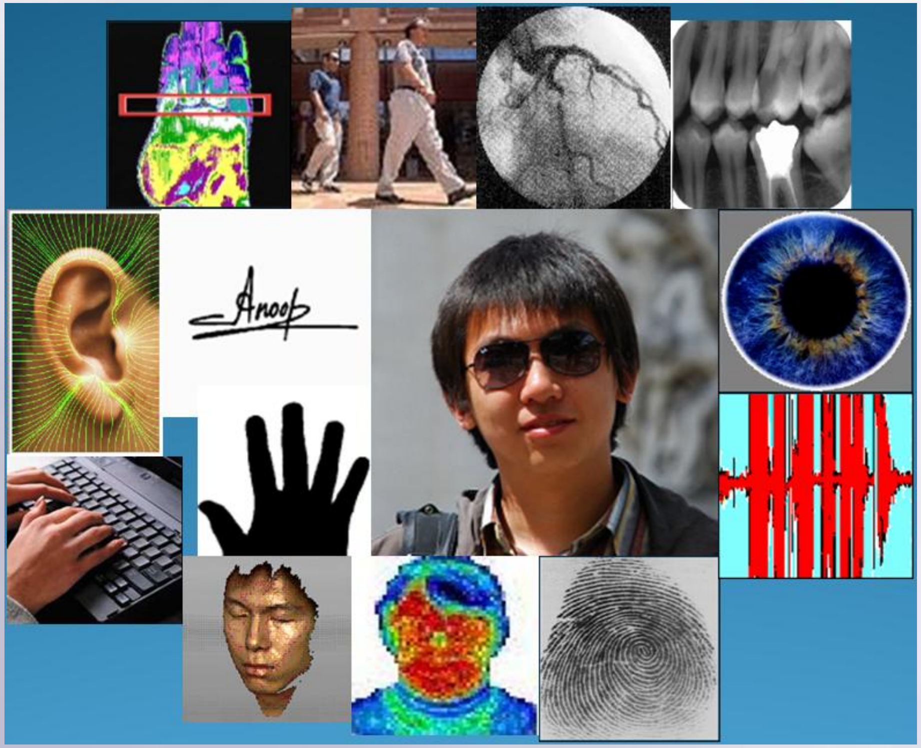
Outline

- Background
- Only 3D Shape based Face Recognition
- Textured 3D Face Recognition
- Asymmetric Face Recognition

Background

Advantages of Face Recognition

- Universal
- Facile
- Acceptable
- Contactless

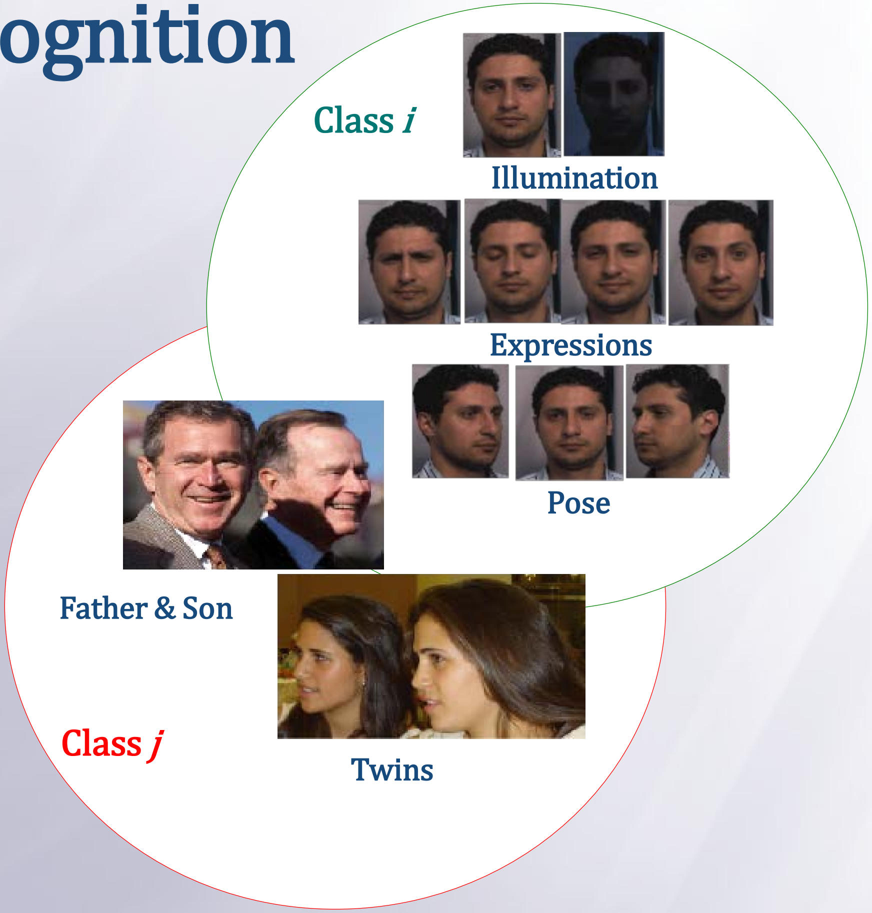


Background

Challenges in Face Recognition

- **Inter-Class Similarities**
  - All faces are similar !
- **Intra-class Variations**
  - Illumination
  - Facial Expressions
  - Pose
  - Aging
  - Occlusion
  - Make-up
  - ...

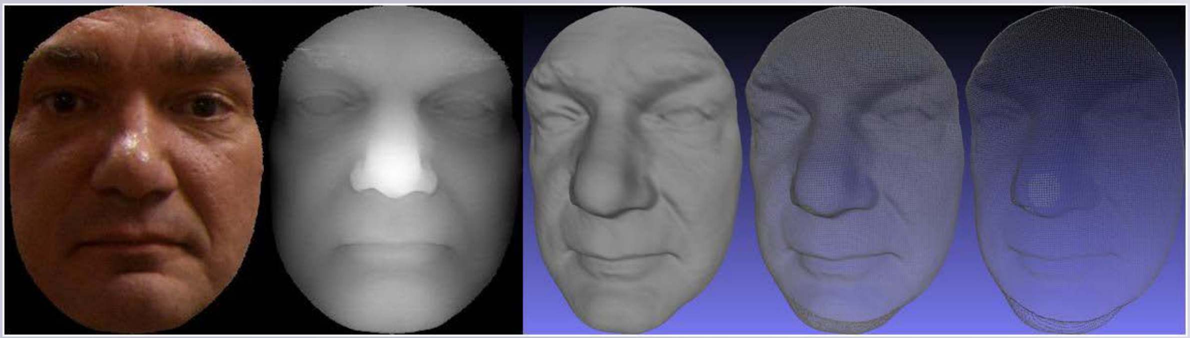
(A) Intra-Class Variations



(B) Inter-Class Similarities

Background

- 3D face models capture exact geometric shapes of facial surfaces (along with their texture maps):
  - Main merits
    - Illumination variation invariance
    - Convenient pose correction
    - Cosmetic use tolerance
  - Main limitations
    - Facial expression changes
    - Data acquisition and computation cost



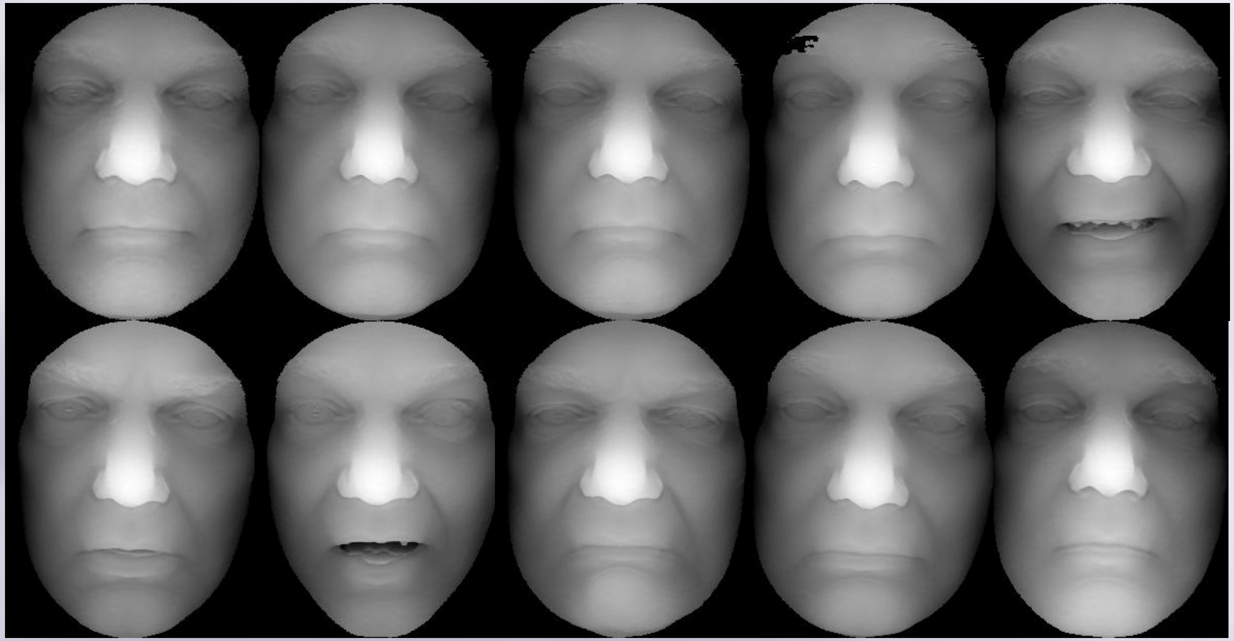
Outline

- Background
- Only 3D Shape based Face Recognition
- Texture 3D Face Recognition
- Asymmetric Face Recognition

Problem Statement

Key Issues:

- How to represent 3D facial surfaces
- How to achieve robust matching across expression variations



Literature Review

3D Facial Representation Taxonomy

- **Original Feature:**
  - Uses the entire face area as the input to compute similarities

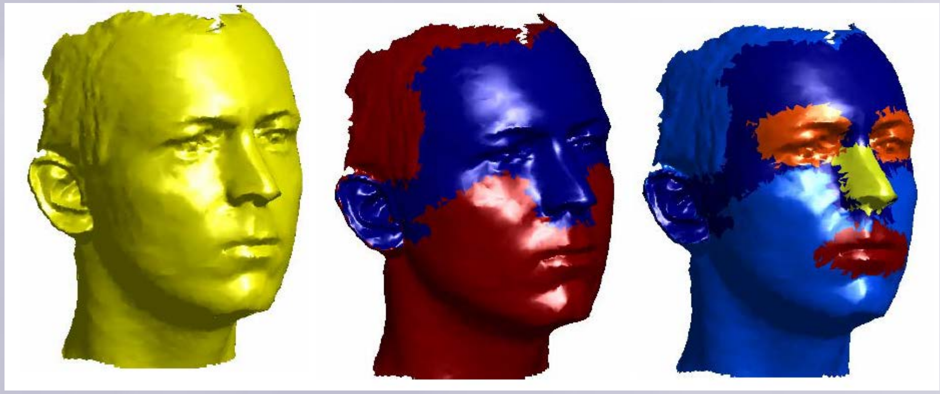
  Ref. PCA on facial range images [2003 Bronstein et al. AVBPA]

  ICP-based matching using 3D point-clouds [2006 Lu et al. TPAMI]…

- **Region or Point Feature:**
  - Detects representative facial areas or points to construct feature spaces

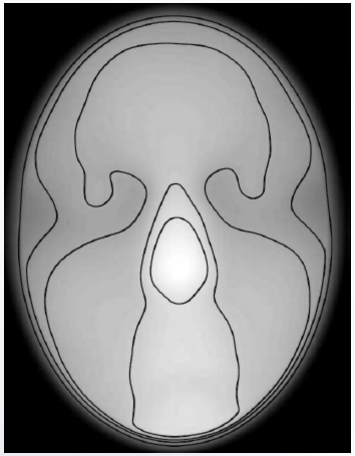
  Ref. Eye and nose regions [1992 Gordon et al. CVPR]

  Segmented facial regions [2003 Moreno et al. IMVIP] …



Literature Review

3D Facial Representation Taxonomy



- **Curve Feature:**
  - Extracts discriminative facial curves

  Ref. Three main curves [1992 Nagamine et al. ICPR]

  A union of the level curves[2006 Samir et al. TPAMI] ...

- **Shape Feature:**
  - Focuses on the attributes of local surfaces

  Ref. Curvatures [1992 Gordon et al. CVPR]

  Point signature [2000 Chua et al. FG]

  ...

  Signed Shape Difference Map (SSDM) [2010 Wang

Literature Review

3D Face Matching Taxonomy

- **Holistic Matching:**
  - It requires accurate normalization with respect to pose and scale changes, and proves sensitive to facial expression changes and partial occlusion.

  Ref. Subspace based [2003 Bronstein et al. AVBPA]

  Isometry Invariant [2005 Bronstein et al. IJCV]

  ICP based [2006 Lu et al. TPAMI]...

- **Local Matching:**
  - It is robust to expression, pose variations, and even to partial occlusions. But it is difficult to extract sufficient informative features from similar or smooth 3D facial surfaces.

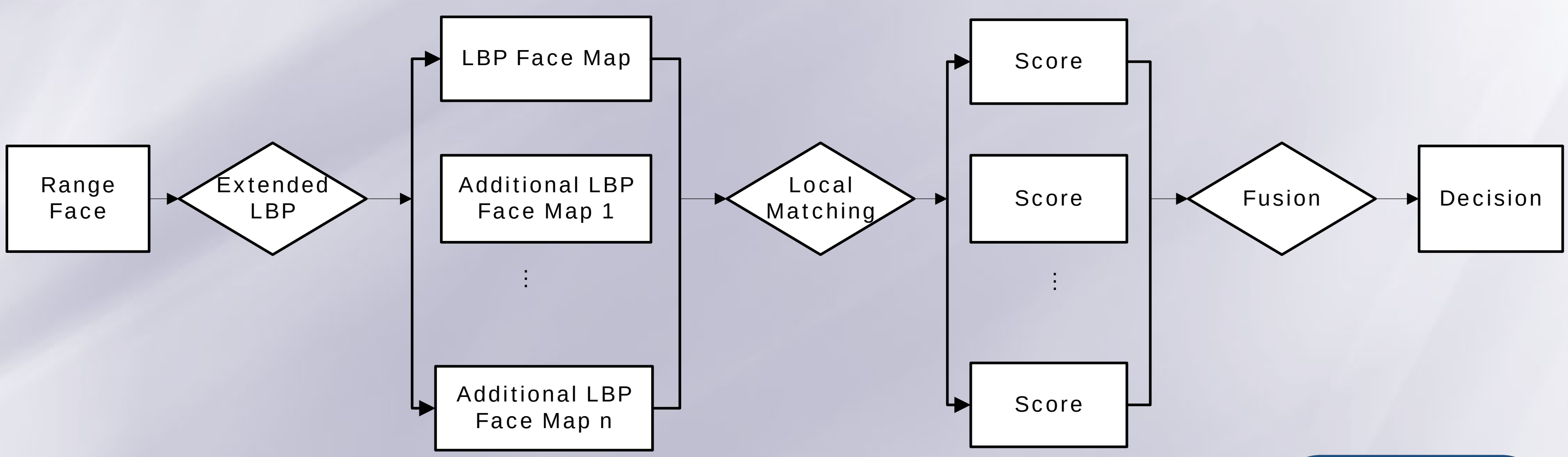
  Ref. Point signature [2000 Chua et al. FG]

  Region ICP [2009 Ouji et al. MMM]

  Signed Shape Difference Map (SSDM) [2010 Wang et al. TPAMI]...

Motivation

- 3D face recognition approach using Multi-scale-extended LBP (MS-eLBP) facial Representation and SIFT based local matching
  - ◆Why we eLBP to describe 3D facial surfaces? (Shape Feature based)
    - Accurate description and excellent performance in 2D face recognition
    - LBP is not powerful enough for 3D face recognition
  - ◆Why we apply local Matching? (Local Matching)
    - Registration tuning free for nearly frontal faces

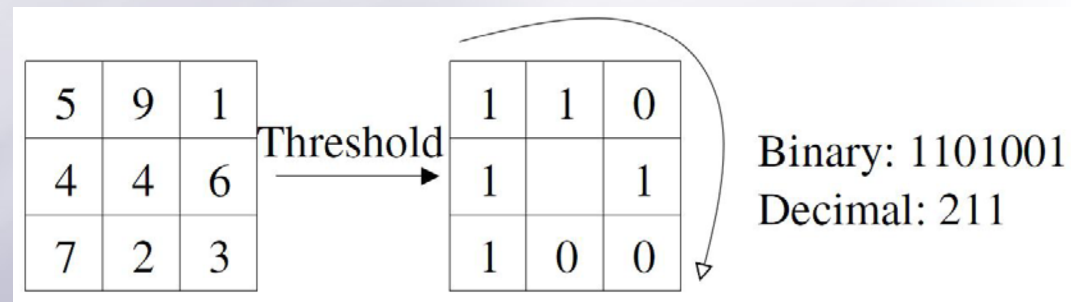


MS-Extended LBP Maps

Local Binary Patterns (LBP)

$$LBP(x_c, y_c) = \sum_{n=0}^{P} s(i_n - i_c)2^n$$

$$s(x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases}$$

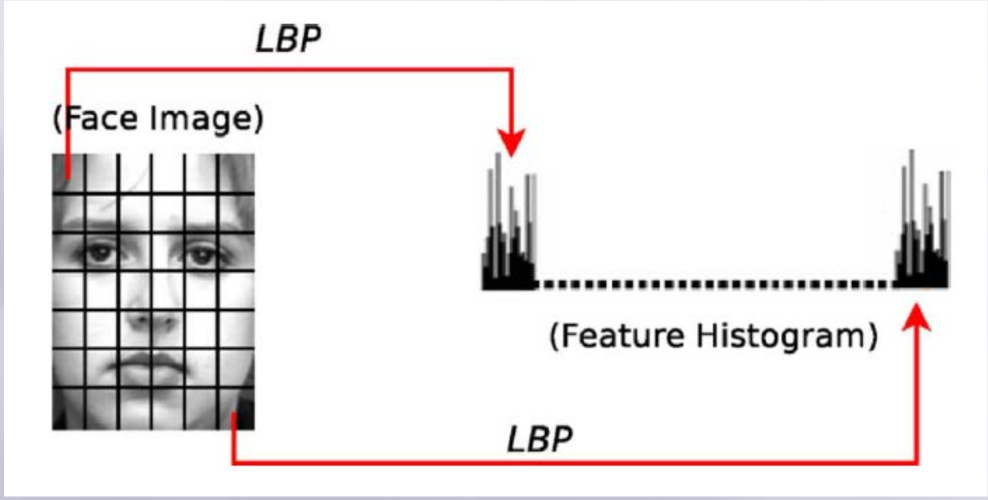


- i_c : Central pixel
- i_n : Neighboring pixel

MS-Extended LBP Maps

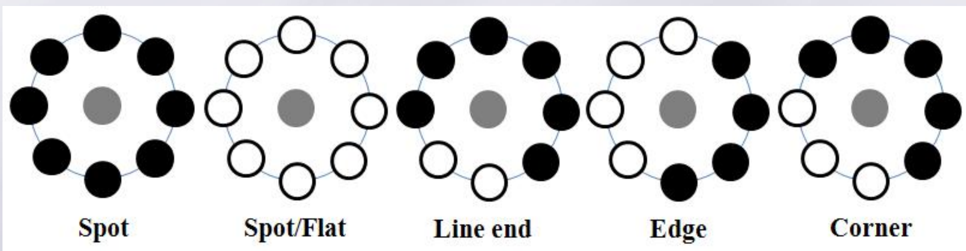
- LBP based facial representation
  - Histogram Based
  - Image Based

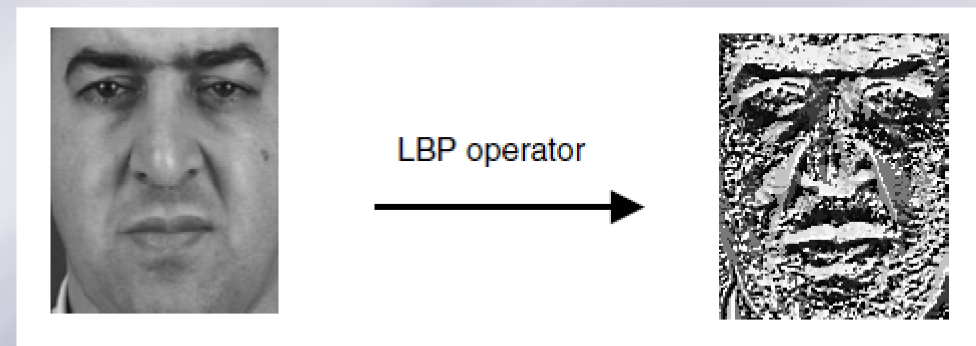
    Reserve all 2D spatial information



MS-Extended LBP Maps

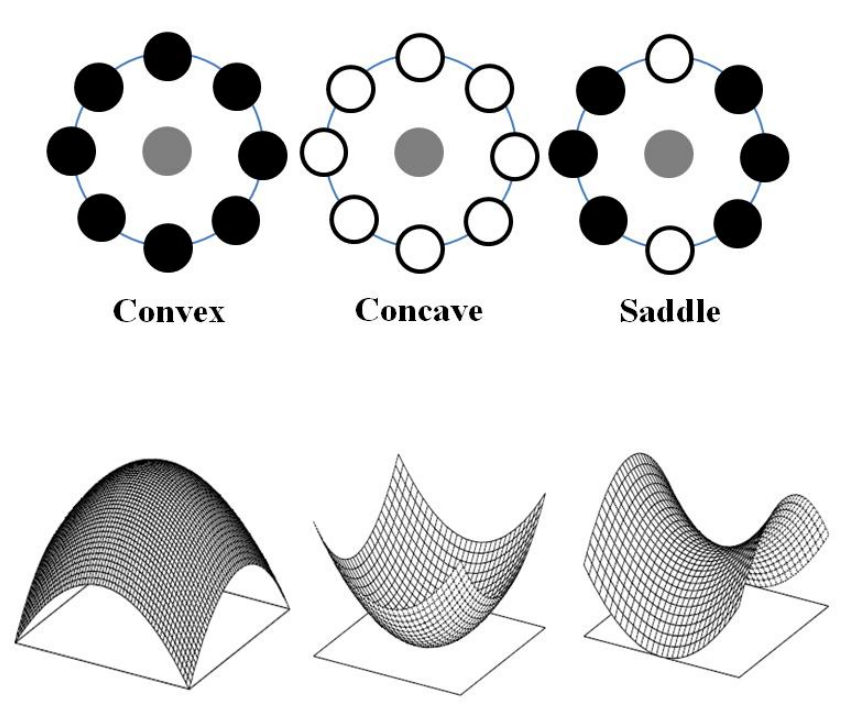
- LBP describes texture in 2D facial images

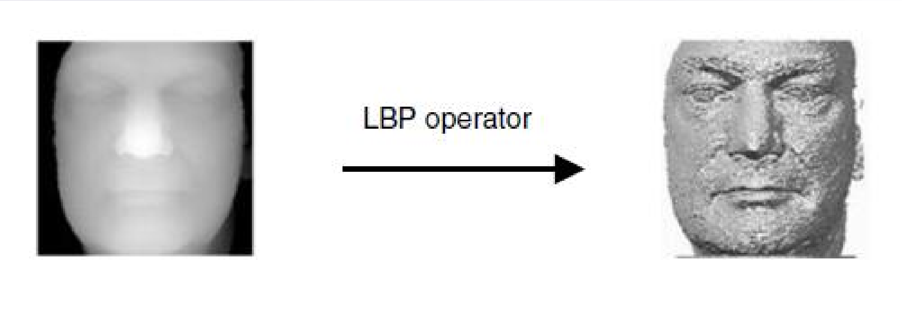




MS-Extended LBP Maps

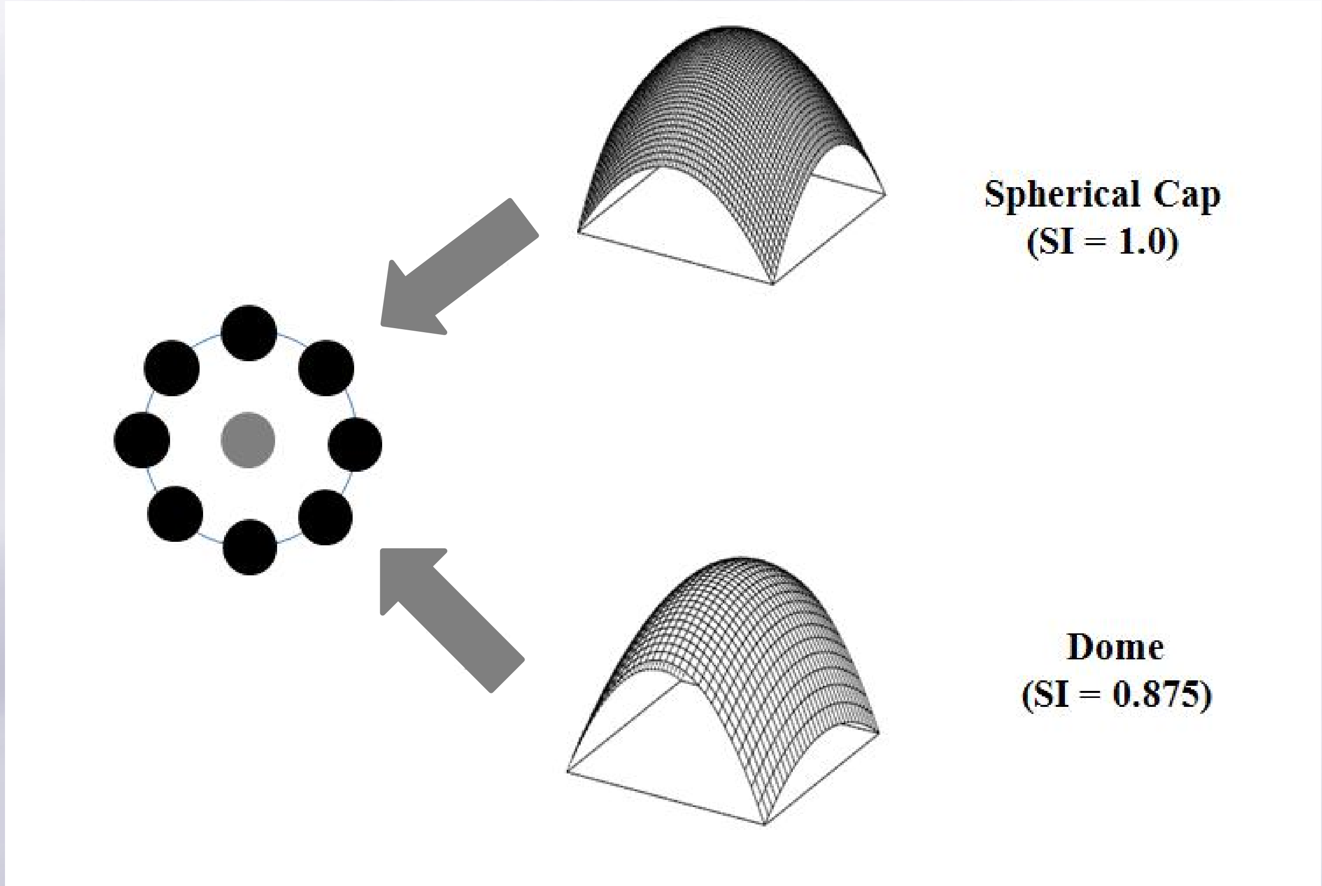
- LBP describes shape in 3D facial surfaces (range images)





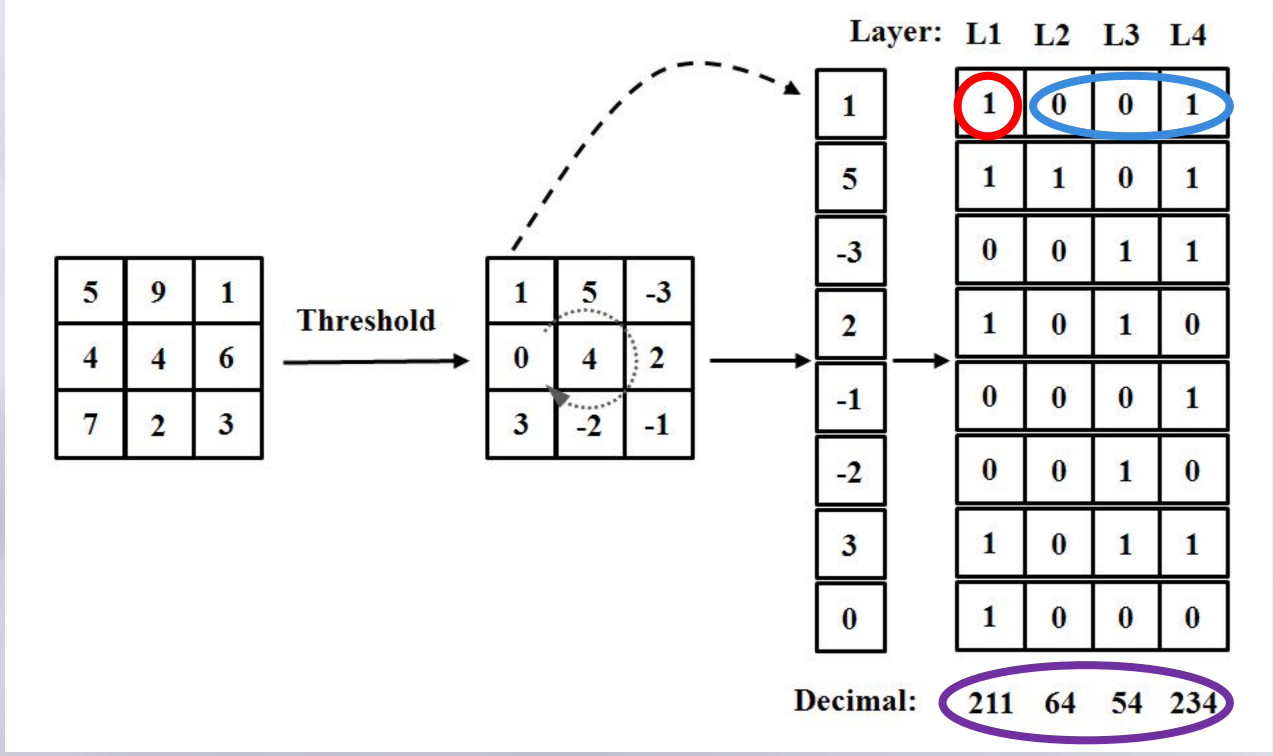
MS-Extended LBP Maps

- Problem!!!



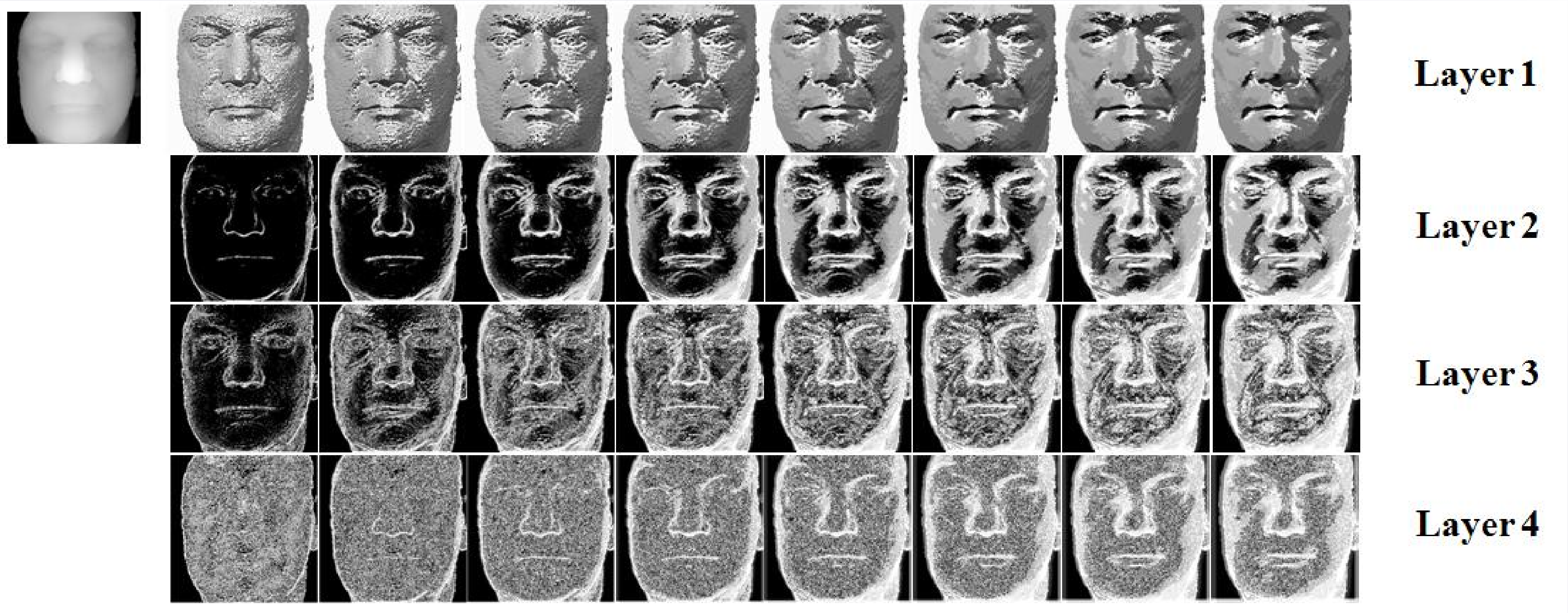
MS-Extended LBP Maps

- Solutions:
  - Extended LBP
  - Multi-Scale Strategy



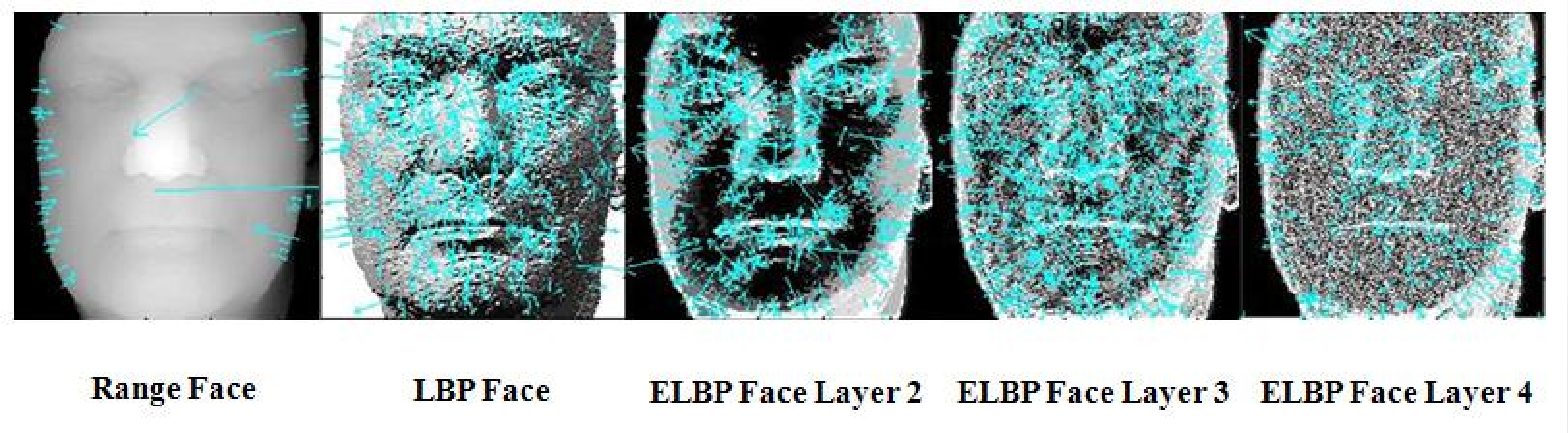
MS-Extended LBP Maps

- Solutions:
  - Extended LBP
  - Multi-Scale Strategy



SIFT based Local Matching

- Local Feature Extraction
  - SIFT Keypoint Detection
  - SIFT Feature Descriptor



SIFT based Local Matching

Matching Strategy

- **SIFT Feature Matching**
  - N_{ELRi} denotes the number of the matched keypoints respectively in the i^{th} layer of MS-eLBP Face Map pair generated using the ELBP operator from facial range images with the neighborhood of R_i.
- **Facial Component Constraint**
- **Facial Configuration Constraint**

SIFT based Local Matching

Matching Strategy

- SIFT Feature Matching
- Facial Component Constraint
  - Emphasizes matching between points within corresponding components in gallery and probe face respectively.
- Facial Configuration Constraint

Divide the entire face region roughly into 3×3 components

$$I = (f_1^1, \cdots f_1^{m_1}, f_2^1, \cdots f_2^{m_2}, \cdots, f_k^1, \cdots f_k^{m_k})$$

$$C(I_p, I_g) = \frac{1}{k}\sum_{i=1}^{k}(\max(d(f_{p_i}^x, f_{g_i}^y)) \times w_i)$$

SIFT based Local Matching

$$d_e = \frac{1}{n_e}\sum_{i=1}^{n_e}\left|d_{pi} - d_{gi}\right|$$

$$d_n = \frac{1}{n_n}\sum_{i=1}^{n_n}\left|n_{pi} - n_{gi}\right|$$

$$D = w_e * d_e + w_n * d_n$$

Matching Strategy

- Feature-based Matching
- Facial Component Constraint
- Facial Configuration Constraint
  - Computes errors between corresponding vertices and edges

SIFT based Local Matching

Similarity Fusion

- All the fusion weights are computed dynamically during the online step

$$S = w_N * S_N + w_C * S_C + w_D * (1 - S_D)$$

$$w_{S_i} = \frac{mean(S_i) - \min_1(S_i)}{mean(S_i) - \min_2(S_i)}$$

where *i* corresponds to the three similarity measurements: *N*, *C*, and *D*, and operators $\min_1(S_i)$ and $\min_2(S_i)$ produce the first and second minimum value of the vector S_i.

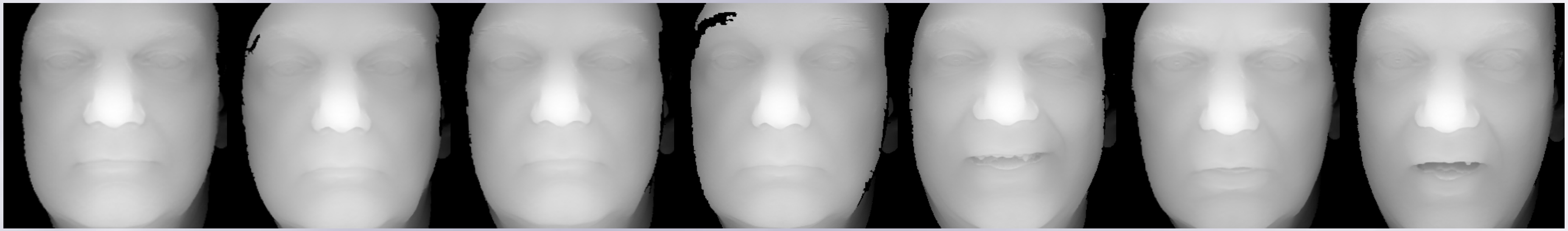
Experimental Results

Database: FRGC v2.0

- 4007 3D models of 466 subjects;
- Median filter is utilized for removing spikes;
- Cubic interpolation is adopted for filling holes;
- Costly registration step is not necessary.

Protocol Settings: FRGC v2.0

- The first facial scan with a neutral expression of each subject makes up of a gallery set; and the remaining faces(4007-466=3541) are treated as probes.



Experimental Results

Parameter Evaluation

Rank-one recognition rates based on different eLBP depth maps of single scale with various parameter settings on the FRGC v2.0 dataset.

P=4	*R=2*	*R=3*	*R=4*	*R=5*	*R=6*	*R=7*	*R=8*
LBP	81.6%	84.8%	86.9%	87.7%	87.6%	86.2%	85.9%
eLBP L2	75.2%	83.3%	85.7%	87.1%	87.6%	87.3%	87.0%
eLBP L3	76.9%	74.7%	71.6%	68.8%	67.4%	63.7%	61.9%
eLBP L4	4.5%	8.0%	12.7%	16.0%	25.9%	33.2%	40.6%
eLBP	**90.0%**	**90.9%**	**92.0%**	**92.6%**	**92.4%**	**92.3%**	**92.3%**

P=8	*R=2*	*R=3*	*R=4*	*R=5*	*R=6*	*R=7*	*R=8*
LBP	86.1%	87.8%	88.5%	88.3%	87.7%	86.6%	86.0%
eLBP L2	73.6%	84.6%	88.6%	89.2%	89.2%	89.3%	89.9%
eLBP L3	80.1%	78.3%	76.4%	76.3%	75.6%	76.6%	76.3%
eLBP L4	6.6%	11.1%	17.8%	29.8%	40.3%	50.8%	55.6%
eLBP	**91.3%**	**92.5%**	**93.5%**	**93.4%**	**93.0%**	**92.7%**	**92.6%**

Experimental Results

Parameter Evaluation

Rank-one recognition rates based on different eLBP depth maps of single scale with various parameter settings on the FRGC v2.0 dataset.

P=12	*R=2*	*R=3*	*R=4*	*R=5*	*R=6*	*R=7*	*R=8*
LBP	85.3%	86.1%	86.2%	87.2%	85.8%	85.4%	84.6%
eLBP L2	71.7%	84.4%	87.3%	88.6%	89.3%	88.9%	88.4%
eLBP L3	81.9%	78.7%	78.1%	76.6%	78.5%	78.9%	79.6%
eLBP L4	6.2%	12.3%	22.1%	35.6%	48.7%	57.4%	63.2%
eLBP	**90.9%**	**92.1%**	**92.9%**	**93.3%**	**92.3%**	**92.3%**	**91.5%**

P=16	*R=2*	*R=3*	*R=4*	*R=5*	*R=6*	*R=7*	*R=8*
LBP	82.1%	82.9%	85.3%	84.2%	84.3%	83.5%	82.7%
eLBP L2	73.7%	86.1%	87.9%	88.6%	88.2%	87.5%	87.7%
eLBP L3	81.6%	80.0%	78.7%	78.4%	79.4%	79.1%	79.7%
eLBP L4	7.2%	11.8%	27.7%	42.3%	52.3%	60.0%	66.1%
eLBP	**90.6%**	**91.9%**	**92.4%**	**92.4%**	**91.8%**	**91.6%**	**91.6%**

Experimental Results

Face Recognition

Rank-one recognition rates on the FRGC v2.0 dataset.

	Rank-one recognition rate
(1) ICP	72.2%
(2) SI Faces	91.8%
(3) MS-LBP-DFs	93.8%
(4) [2005 Chang FRGC Workshop]	91.9%
(5) [2006 Cook BMVC]	94.6%
(6) [2007 Wang CVPR]	87.7%
(7) [2007 Mian TPAMI]	96.2%
(8) [2007 Kakadiaris TPAMI]	97.0%
(9) [2008 Mian IJCV]	93.5%
(10) [2008 Faltemier TIFS]	**98.1%**
(11) [2010 Huang BTAS]	96.1%
(12) [2010 Wang TPAMI]	**98.4%**
(13) MS-eLBP-DFs	**97.6%**

Experimental Results

Expression Validation in Face Recognition

Rank-one face recognition rates using the expression protocol on the FRGC v2.0 dataset.

	Subset I	Subset II	Degradation
SI Faces	97.2%	84.1%	13.1%
MS-LBP-DFs	97.7%	88.9%	8.8%
MS-eLBP-DFs	99.0%	**94.9%**	**4.1%**
SI and MS-LBP [2010 Huang BTAS]	99.1%	92.5%	6.6%
3D [2008 Mian IJCV]	99.0%	86.7%	12.3%
2D+3D [2008 Mian IJCV]	**99.4%**	92.1%	7.3%

Subset I: Neutral vs. Neutral ;

Subset II: Neutral vs. Non-Neutral;

Experimental Results

Expression Validation in Face Verification

Face verification rates at FAR = 0.001 using the expression protocol on the FRGC v2.0 dataset.

	VR I	VR II	VR III
SI Faces	94.4%	98.9%	87.5%
MS-LBP-DFs	96.1%	99.1%	91.9%
MS-eLBP-DFs	**98.4%**	99.6%	**97.2%**
[2005 Maurer FRGC Workshop]	92%	97.8%	NA
[2005 Passalis FRGC Workshop]	85.1%	94.9%	79.4%
[2005 Husken FRGC Workshop]	89.5%	NA	NA
[2006 Cook BMVC]	95.8%	NA	NA
[2007 Mian TPAMI]	**98.5%**	NA	NA
[2008 Mian IJCV]	97.4%	**99.9%**	92.7%
[2010 Wang TPAMI]	**98.6%**	NA	NA

I: Neutral vs. All; II: Neutral vs. Neutral; III: Neutral vs. Non-Neutral

Experimental Results

Aging Validation in Face Verification

Comparisons of verification rates at 0.001 FAR using ROC I, ROC II, ROC III and All vs. All protocol on the FRGC v2.0 dataset.

	Roc I	Roc II	Roc III	All vs. All
[2005 Maurer FRGC Workshop]	NA	NA	92.0%	87.0%
[2005 Husken FRGC Workshop]	NA	NA	89.5%	NA
[2006 Cook BMVC]	93.7%	92.9%	92.0%	92.3%
[2007 Mian TPAMI]	NA	NA	NA	86.6%
[2007 Kakadiaris TPAMI]	**97.3%**	**97.2%**	**97.0%**	NA
[2008 Faltemier TIFS]	NA	NA	94.8%	93.2%
[2010 Wang TPAMI]	**98.0%**	**98.0%**	**98.0%**	**98.1%**
MS-eLBP-DFs	95.1%	95.1%	95.0%	94.2%

Experimental Results

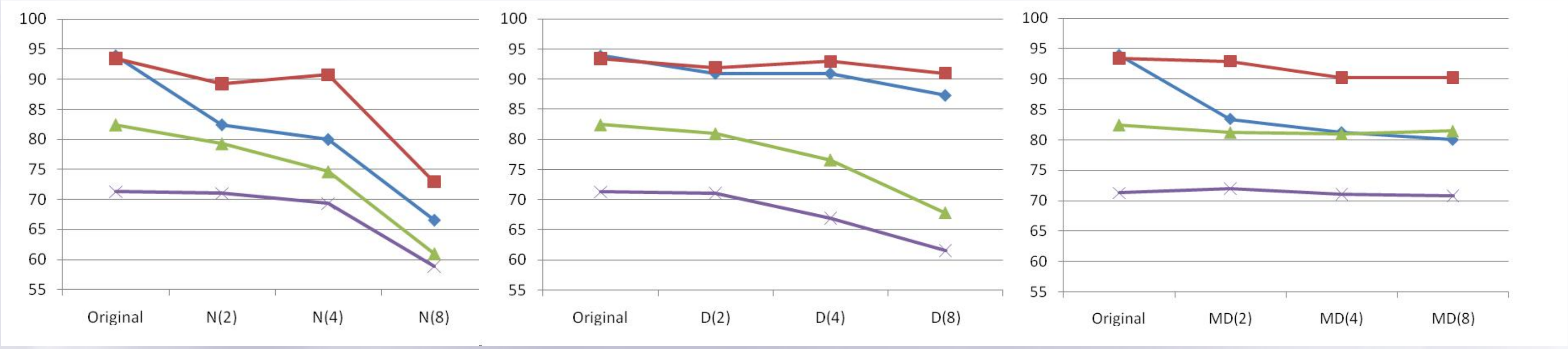
Degradation Validation

- Noisy data correspond to error injection by a Gaussian distribution on Z coordinates in depth facial images. This tends to simulate the behavior of electronic noise of acquisition devices in a simplistic manner. We set the RMS value of the error respectively to 0.2mm, 0.4mm and 0.8mm.
- Decimation aims at removing a certain number of vertices from original surfaces. Vertices are picked up randomly and removed respectively from a ratio of 2, 4 and 8.
- Missing data (holes) are generated at random locations on 3D surfaces. A random vertex is selected and the hole is cropped according to a sphere with a radius value of 10mm centered at the given vertex. For each level, 1, 2, 3 holes are produced on the entire face respectively.

Experimental Results

Degradation Validation

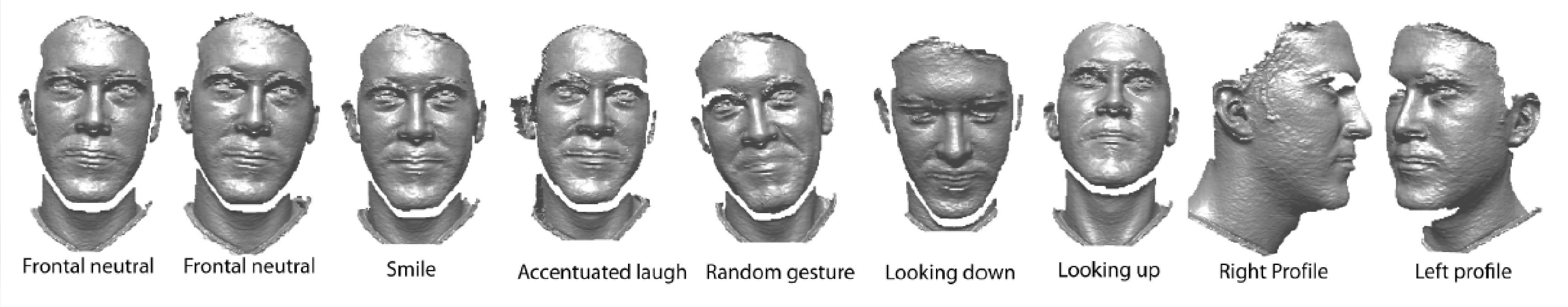
Performance comparison with Iterative Closest Point (ICP, violet), Thin-Plate Spline (TPS, green), as well as the Elastic Radial Curve Matching [2010 Drira BMVC] (blue). The proposed method is marked in red.



Gaussian noise | Decimation | Random holes

Experimental Results

- Database: Gavab DB (Occlusion Validation)
  - 549 3D models of 61subjects;
  - Median filter is utilized for removing spikes;
  - Cubic interpolation is adopted for filling holes;
  - Costly registration step is not necessary.
- Experiment Settings: Face Recognition in Gavab DB
  - The first 3D facial scan with a neutral expression of each subject makes up of a gallery set; and the remaining models (488) are treated as probes.



Experimental Results

Face Recognition

Comparisons of rank-one recognition rates on the Gavab DB dataset: (A) without pose variations; (B) only with pose variations

	I. Neutral	II. Expressive	I + II
[2005 Moreno ISPA]	90.16%	77.90%	NA
[2006 Berretti AMR]	94.00%	81.00%	84.25%
[2008 Mousavi ICCIS]	NA	NA	91.00%
[2009 Li CVPR]	96.67%	93.33%	94.68%
[2009 Mahoor PR]	95.00%	72.00%	78.00%
[2010 Drira BMVC]	100.00%	NA	94.67%
MS-eLBP-DFs	**100.00%**	**93.99%**	**95.49%**

(A)

Experimental Results

Face Recognition

Comparisons of rank-one recognition rates on the Gavab DB dataset: (A) without pose variations; (B) only with pose variations

	(a)	(b)	(c)	(d)	(e)
[2006 Berretti AMR]	85.30%	88.60%	NA	NA	NA
[2009 Mahoor PR]	80.00%	79.00%	NA	NA	NA
[2010 Drira BMVC]	**100.00%**	**98.36%**	70.49%	86.89%	88.94%
MS-eLBP-DFs	96.72%	96.72%	**78.69%**	**93.44%**	**91.39%**

(a): Looking down

(b): Looking up

(c): Right Profile

(d): Left profile

(e): Overall

(B)

Summary

Only 3D Shape based Face Recognition

- We propose to exploit LBP Depth Faces to represent 3D facial surfaces and introduce eLBP and Multi-Scale strategy to improve its discriminative power for distinguishing similar shapes;
- We design a SIFT based local matching scheme that combines feature based matching, facial component and configuration constraints;
- The final performance is comparable to the best ones in the literature on the FRGC v2.0 and Gavab DB datasets, showing the effectiveness and robustness of the entire system;
- The proposed method requires no training samples, and can perform without surface registration on nearly frontal faces.

Outline

- Background
- Only 3D Shape based Face Recognition
- Texture 3D Face Recognition
- Asymmetric Face Recognition

Problem Statement

Important Factors:

- How to describe both types of face data, i.e. texture and shape
- How to fuse complementary information from both modalities

Literature Review

Multi-modal Systems

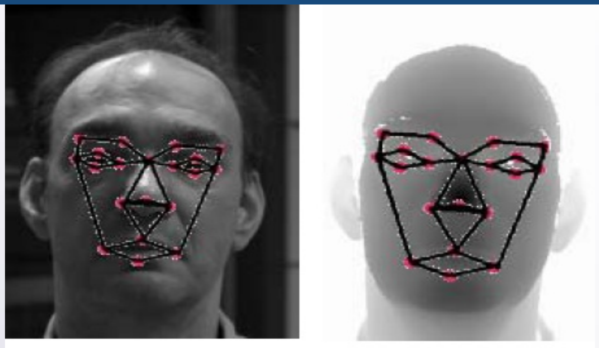
- **Sensor Fusion:**
  - considers both texture and shape as an entire input of the system

  Ref. 4D ICP [2004 Papatheodorou et al. FG]

  Texture and shape image combination [2008 Kusuma et al. ICIAR]…
- **Feature Fusion:**
  - extracts features from multiple data sources and builds a final feature set to represent faces

  Ref. 2D Gabor and 3D profile[2007 Arca et al. KES]…

Literature Review



Multi-modal Systems

- **Matching Score/Rank/Decision Fusion:**
  - outputs a set of matching scores by various classifiers which are fused to generate a single scalar score , or own class label.

  Ref. [2005 Chang et al. TPAMI]
  [2007 Husken et al. CVPR]
  [2008 Gökberk et al., TSMC-C]…

- **Multi-level Fusion:**
  - applies fusion at different levels

  Ref. Feature and decision level [2005 Li et al. AMFG]
  Feature and score level [2010 Ben Soltana et al. ICPR].

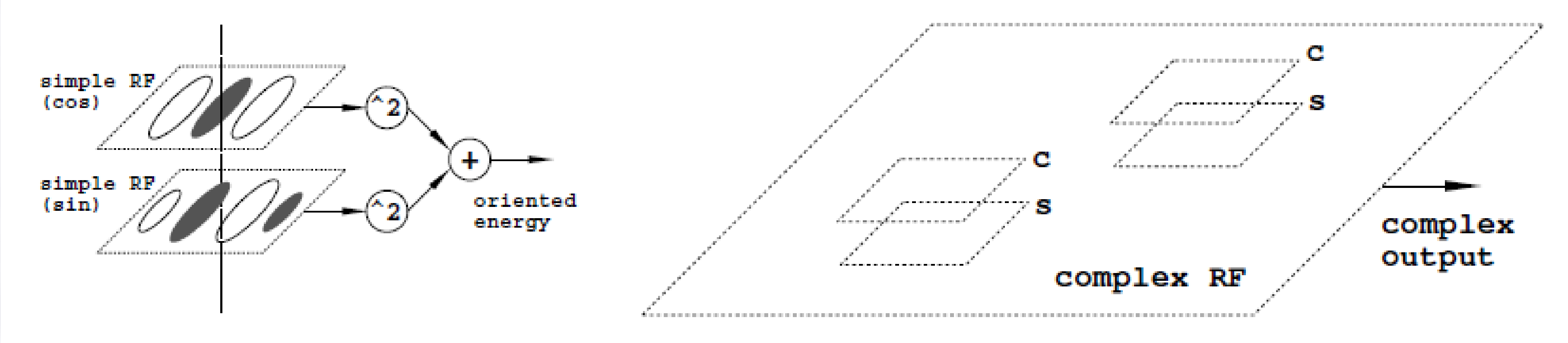
Motivation

- Oriented Gradient Maps and GA based optimized weighted score sum fusion for textured 3D face recognition.
  - Why Oriented Gradient Maps (OGMs)?
    - Biological vision based description on both range and texture faces
    - Highly distinctive
    - Robust to affine lighting and geometric transformations
  - Why learning based score level fusion?
    - Late (score) fusion generally provides better results
    - With a learning process, the method can find an optimal set of weights to combine matching scores (GA, SA...)

Oriented Gradient Maps

Complex Neuron Response

- Complex cells and Object Recognition (1997 Edelman et al. Unpublished documents)
  - Complex neurons combine the responses of different orientations of simiple neurons
  - Complex neurons prove more insensitive to positions of receptive fields (RF)



Oriented Gradient Maps

- A Biological vision based facial representation Oriented Gradient Maps (OGMs)
  - Each gradient map describes gradient norms of the input original image in an orientation *o* at every pixel.

$$L_o = \left(\frac{\partial I}{\partial o} \right)^+$$

    - I: input image
    - $L_1, L_2, \ldots, L_o$: gradient maps for each quantized direction o

  - Each gradient map is convolved with a Gaussian kernel G, and the standard deviation of G is proportional to the radius value of the given neighborhood area, R, as :

$$\rho_o^R = G_R * L_o$$

Oriented Gradient Maps

- A Biological vision based facial representation Oriented Gradient Maps (OGMs)
  - At a pixel location (x, y), we collect all the values of the convolved gradient maps at that location and form the vector, $\rho^R(x, y)$ and it has a response value of complex neurons for each orientation o.

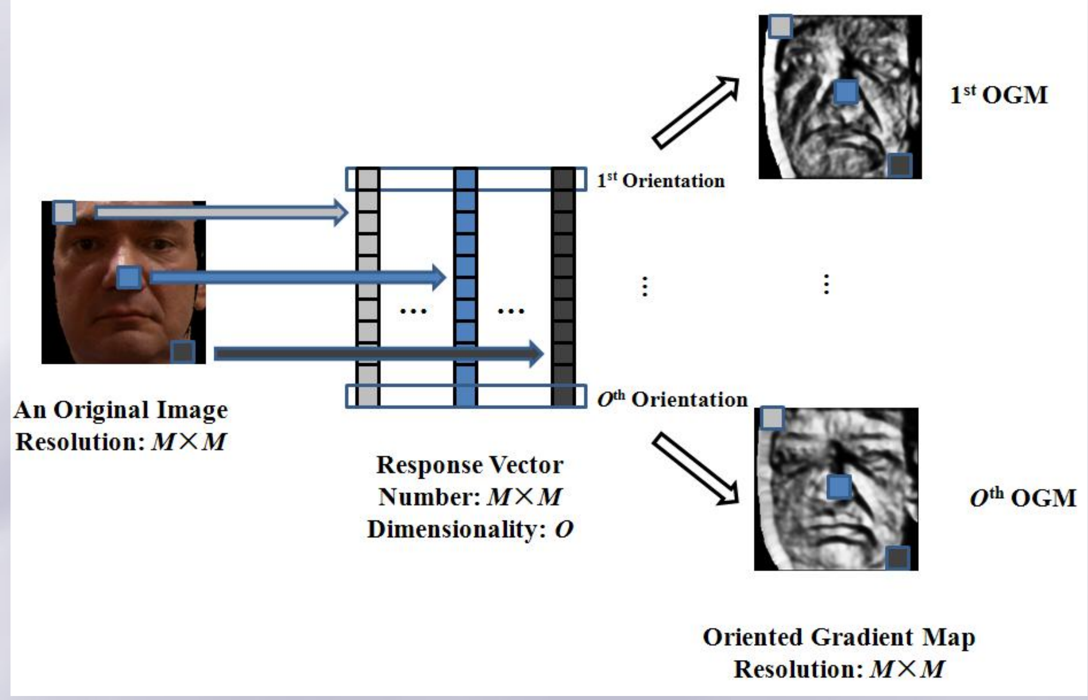
$$\rho^R(x,y) = \left[\rho_1^R(x,y), \cdots, \rho_O^R(x,y)\right]^t$$

  - The vector $\rho^R(x, y)$ is further normalized to an unit norm vector to produce the complex neuron response vector $\underline{\rho^R}$

Oriented Gradient Maps

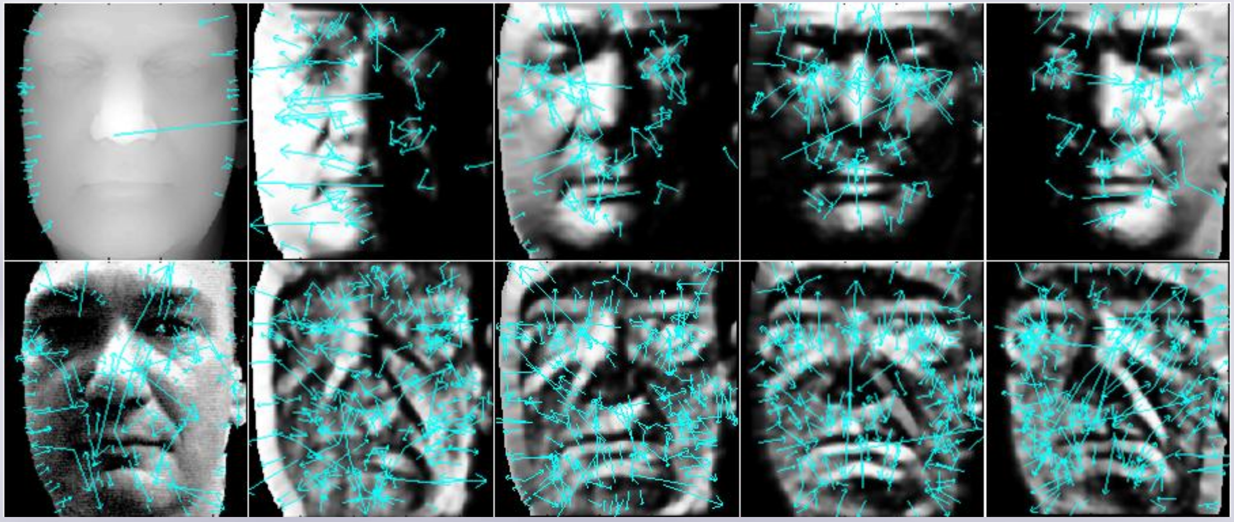
- A Biological vision based facial representation Oriented Gradient Maps (OGMs)
  - The facial representation, OGM J_o, is achieved by response vectors for each orientation o defined as:

$$J_o(x, y) = \underline{\rho}_o^R(x, y)$$



Local Feature Matching

- Local Feature Extraction
  - SIFT Keypoint Detection
  - SIFT Feature Descriptor
- SIFT Feature based Matching
  - The similarity measurement is the number of matched keypoints in corresponding facial representation pairs.



Optimized Weighted Score Sum Fusion

- A weighted sum rule is used:
  - Widely adopted for its performance and simplicity

$$S = \sum_{i=1}^{N} w_i * S_i$$

  - S_i is a similarity score; w_i is its corresponding weight;
  - N is the number of generated similarity scores.
- The proposed weighting scheme
  - Learning-based

Experimental Results

Database and Settings

- FRGC v1.0
  - 943 3D models of 275 subjects for training optimized weights;
- FRGC v2.0
  - 4007 3D models of 466 subjects for evaluation;

    (The first scan with a neutral expression of each subject makes up of a gallery set; and the remaining are treated as probes)
  - Median filter is utilized for removing spikes;
  - Cubic interpolation is adopted for filling holes;
  - Histogram equalization (2D facial texture images)
  - Costly registration step is not necessary.

Experimental Results

2D Feature Evaluation in Face Recognition

Comparisons with the state-of-the-art using only 2D face data.

2D Approaches	Rank-one RR
Eigenface	49.8%
LBP Histogram	71.8%
Gabor	77.9%
Original Texture + SIFT	**79.3%**
Texture LBP Face + SIFT	44.8%
Texture OGMs + SIFT	**95.9%**

Experimental Results

3D Feature Evaluation in Face Recognition

Comparisons with the state-of-the-art using only 3D face data.

3D Approaches	Rank-one RR
[2005 Chang et al. FRGC Workshop]	91.9%
[2007 Kakadiaris et al. TPAMI]	97.0%
[2007 Mian et al. TPAMI]	96.2%
[2008 Mian et al. IJCV]	93.5%
[2010 Huang et al. BTAS]	93.8%
[2011 Huang et al. FG]	97.2%
Original Range + SIFT	NA
Range LBP Face + SIFT	80.1%
Range OGMs + SIFT	95.5%

Experimental Results

Face Recognition and Verification

Comparisons with the state-of-the-art using textured 3D face data.

Systems	Rank-one RR	VR@FAR=0.1%
[2005 Maurer et al. FRGC Workshop]	NA	95.8%
[2005 Husken et al. FRGC Workshop]	NA	97.3%
[2007 Mian et al. TPAMI]	97.4%	**99.3%**
[2008 Mian et al. IJCV]	96.1%	98.6%
[2008 Gokberk et al. TSMC-B]	95.5%	NA
[2009 Xu et al. PR]	NA	97.5%
[2010 Ben Soltana et al. 3DPVT]	95.5%	97.0%
Texture OGMs + SIFT	95.9%	97.3%
Range OGMs + SIFT	95.5%	97.1%
Multi-Modal OGMs +SIFT	**98.0%**	**98.9%**

Experimental Results

Neighborhood Size Analysis

Rank-one results using different neighborhood size on texture faces.

Texture	R = 1.0	R = 1.5	R = 2.0	R = 2.5	R = 3.0	R = 3.5
OGM_1	78.00%	81.42%	82.60%	83.23%	83.56%	83.20%
OGM_2	83.08%	84.69%	86.19%	85.31%	84.61%	83.51%
OGM_3	85.17%	87.18%	87.49%	87.97%	87.63%	87.09%
OGM_4	86.22%	87.49%	88.62%	87.77%	87.49%	86.33%
OGM_5	80.06%	81.90%	83.65%	82.43%	82.15%	80.66%
OGM_6	80.74%	82.97%	84.89%	86.02%	85.77%	85.03%
OGM_7	84.44%	86.02%	85.26%	85.63%	84.67%	82.01%
OGM_8	84.19%	85.63%	86.39%	87.46%	86.64%	85.99%
Fusion I	**95.31%**	**95.74%**	**95.51%**	**95.51%**	**95.54%**	**94.38%**
Fusion II	**95.45%**	**95.85%**	**95.54%**	**95.71%**	**95.76%**	**94.78%**

Fusion I: Fusion method used in [2008 Mian et al. IJCV]

Fusion II: The GA based fusion approach

Experimental Results

Neighborhood Size Analysis

Rank-one results using different neighborhood size on range faces.

Range	*R* = 1.0	*R* = 1.5	*R* = 2.0	*R* = 2.5	*R* = 3.0	*R* = 3.5
OGM_1	79.95%	80.54%	80.68%	78.96%	76.76%	74.10%
OGM_2	84.33%	83.95%	82.91%	81.30%	78.68%	76.67%
OGM_3	89.04%	88.84%	87.97%	87.01%	85.37%	84.16%
OGM_4	85.09%	85.43%	83.71%	82.10%	79.70%	78.17%
OGM_5	82.91%	83.39%	82.58%	81.05%	78.62%	76.28%
OGM_6	89.24%	88.93%	87.18%	85.43%	83.96%	82.15%
OGM_7	84.75%	84.24%	82.01%	79.53%	76.73%	72.83%
OGM_8	88.20%	88.68%	86.90%	85.65%	84.07%	81.73%
Fusion I	**95.14%**	**94.55%**	**93.67%**	**92.26%**	**91.10%**	**90.06%**
Fusion II	**95.48%**	**94.94%**	**94.07%**	**92.54%**	**91.67%**	**90.43%**

Fusion I: Fusion method used in [2008 Mian et al. IJCV]

Fusion II: The GA based fusion approach

Experimental Results

Expression Validation in Face Recognition

Rank-one results using expression protocol on the FRGC v2.0 dataset.

	Subset I	Subset II	Degradation
[2008 Mian et al. IJCV]	99.4%	92.1%	7.3%
[2010 Ben Soltana et al. 3DPVT]	98.6%	90.7%	7.9%
Texture OGMs + SIFT	98.8%	92.1%	6.7%
Range OGMs + SIFT	98.5%	91.7%	6.8%
Multi-Modal OGMs +SIFT	**99.6%**	**96.0%**	**3.6%**

Subset I: Neutral vs. Neutral ; Subset II: Neutral vs. Non-Neutral;

Experimental Results

Expression Validation in Face Verification

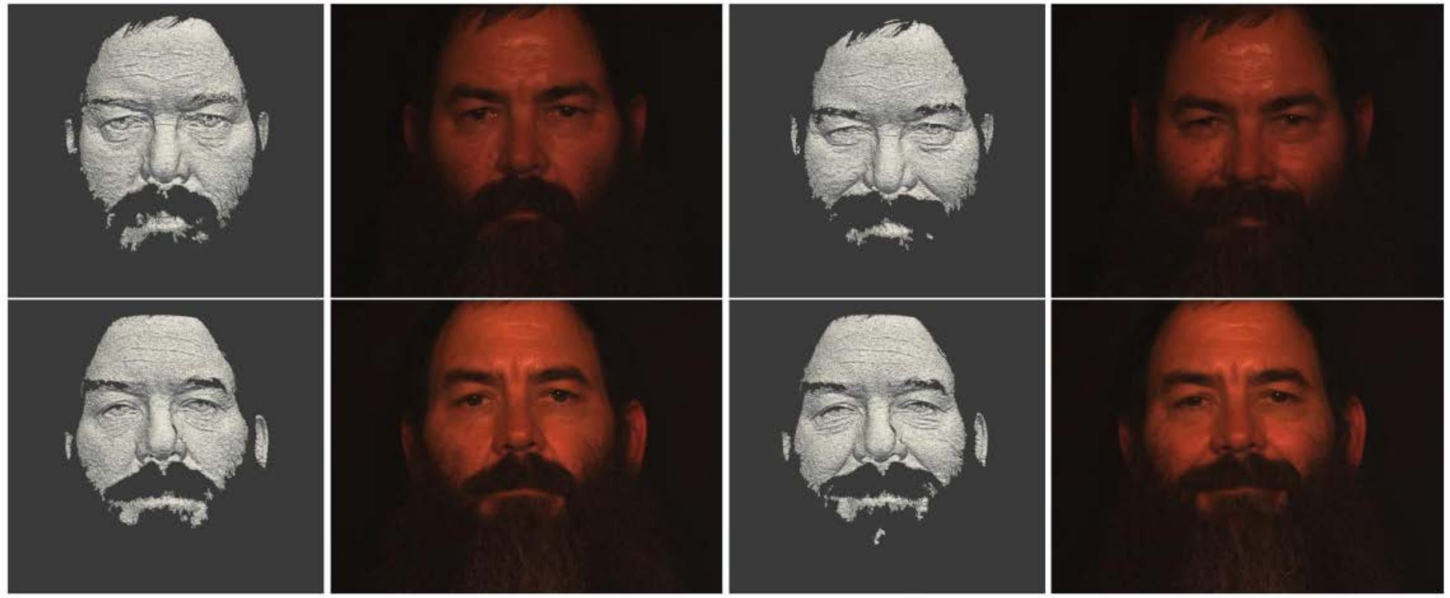
Comparison of verification rates at 0.001 FAR using the expression protocol on the FRGC v2.0 dataset.

	VR I	VR II	VR III
Mian et al. [IJCV, 08]	97.4%	99.9%	92.7%
Texture PFI + SIFT	97.3%	99.7%	93.7%
Range PFI + SIFT	97.1%	99.4%	93.5%
Multi-Modal PFI +SIFT	**98.9%**	**99.9%**	**97.1%**

I: Neutral vs. All; II: Neutral vs. Neutral; III: Neutral vs. Non-Neutral

Experimental Results

- Evaluation on distinguishing twins
  - Dataset: 3DTEC
    - 107 Pairs of identical twins;
    - Each subject has two 3D face models: one is neutral, and the other is with a smile expression



Experimental Results

- Evaluation on distinguishing twins
  - Experimental Settings
    - One model as gallery and the other as probe
  - Experiment Design
    - Four experimental protocols
    - Face Recognition
    - Face Verification

Experiment No.	Gallery	Probe
Exp.I	A Smile, B Smile	A Neutral , B Neutral
Exp.II	A Neutral , B Neutral	A Smile, B Smile
Exp.III	A Smile, B Neutral	A Neutral , B Smile
Exp.IV	A Neutral , B Smile	A Smile, B Neutral

Experimental Results

Face recognition and verification

Rank-one recognition rates of four experiments on the 3DTEC dataset

Rank-one RR	RR I	RR II	RR III	RR IV
Texture OGMs + SIFT	95.8%	96.3%	92.1%	92.5%
Range OGMs + SIFT	91.6%	93.9%	69.2%	71.0%
Multi-modal OGMs + SIFT	96.3%	96.3%	88.8%	88.8%

Verification rates of four experiments at 0.1% FAR on the 3DTEC dataset

Rank-one RR	RR I	RR II	RR III	RR IV
Texture OGMs + SIFT	96.7%	96.7%	93.0%	93.5%
Range OGMs + SIFT	94.9%	94.4%	68.7%	69.2%
Multi-modal OGMs + SIFT	96.7%	96.7%	88.3%	89.7%

Summary

Textured 3D Face Recognition

- Biological vision-inspired facial representation, namely Oriented Gradient Maps (OGMs) and apply it to both facial texture and range images for the issue of textured 3D face recognition;
- The designed score level fusion scheme further improves final performance when combining the results of OGMs at different orientations and fusing the accuracies of range and texture faces;
- The final rank-one recognition and verification rates at 0.1% FAR are 98.0% and 98.9% on the FRGC v2.0 dataset, respectively.

Outline

- Background
- Only 3D Shape based Face Recognition
- Texture 3D Face Recognition
- Asymmetric Face Recognition

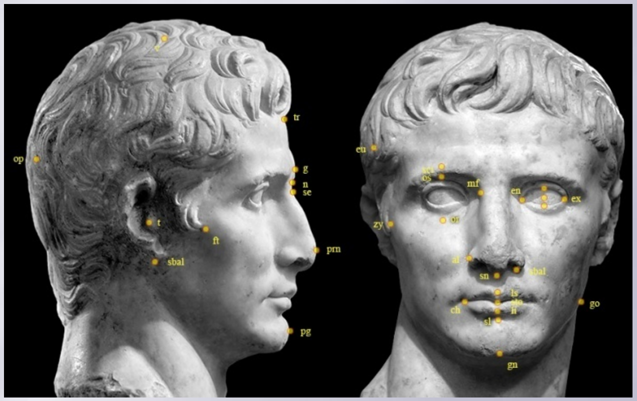
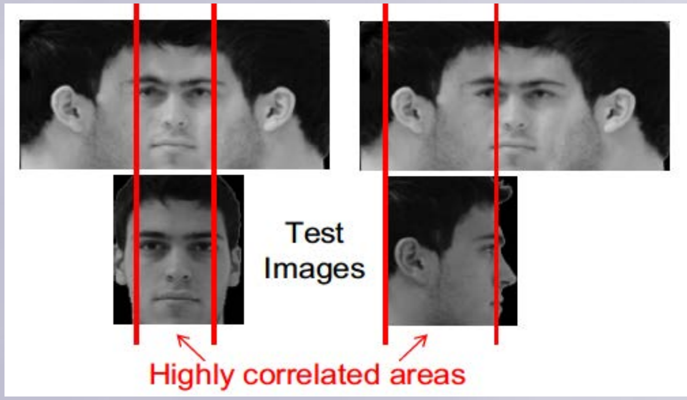
Problem Statement

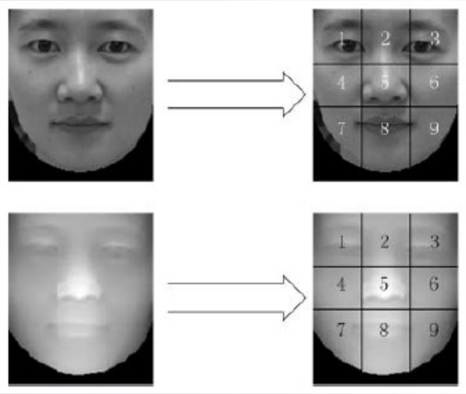
- Comparison of 2D & 3D Face Recognition
  - 3D data has more information for face representation
  - 3D face recognition is robust to illumination and pose
  - 2D data is easier for acquisition
  - 2D face recognition needs less computation cost

- Goal: Combining advantages of 2D and 3D data for robust face recognition; and limiting the use of 3D data to where it really helps to improve performance.
  - Accuracy: better than 2D-2D, comparable to 3D-3D
  - Time-Consuming: under control, much less than 3D-3D

Background

- Geometrical Invariants
  - [2005 Riccio and Dugelay ICIAP]
- Partial Principle Component Analysis (P^2CA)
  - [2006 Rama et al. ICASSP]
- Patch based Kernel Canonical Correlation Analysis
  - [2008 Yang et al. FG]

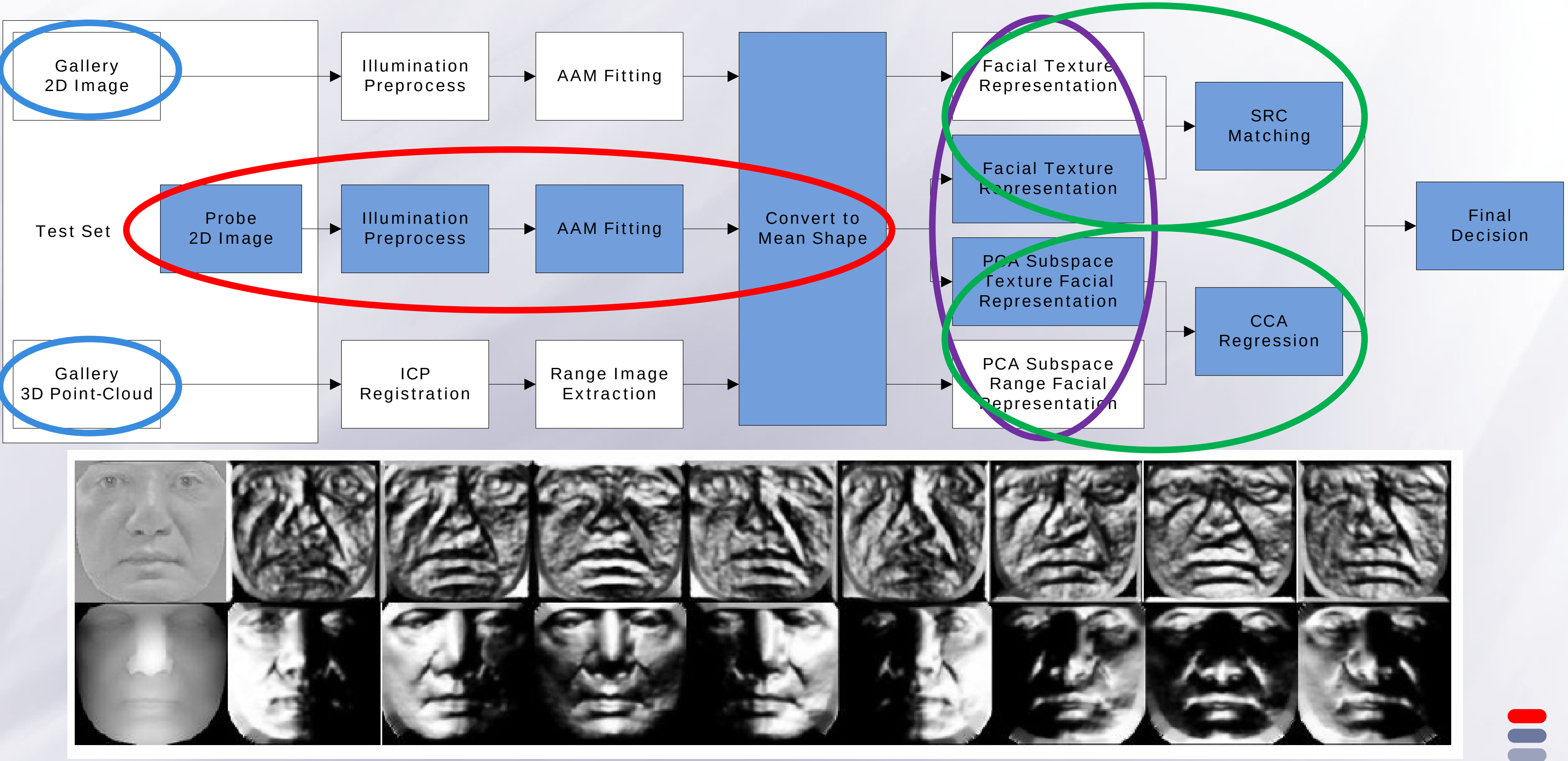


Canonical Correlation Analysis

- What's new?
  - More information
    - Gallery Set: Textured 3D facial models (3D point-clouds and their 2D texture counterparts)
    - Probe Set: Facial texture images
  - Illumination normalization and pose correction
  - Distinctiveness enhanced facial representations
    - Multi-Scale LBP Maps
    - Oriented Gradient Maps

Overview

The Proposed Method Overview



Asymmetric 3D-2D Face Recognition

Score Fusion

Finally, by the Min-Max normalization, the two matching scores from 2D-2D and 3D-2D are normalized to [0, 1], and a weighted sum rule is used for fusion.

$$F = w_S * S_S + w_R * (1 - S_R)$$

Their weights w_S and w_R are calculated dynamically during the online step using:

$$w_{S_i} = \frac{mean(S_i) - \min_1(S_i)}{mean(S_i) - \min_2(S_i)}$$

where i corresponds to the two similarity measures: S, and R, and operators $\min_1(S_i)$ and $\min_2(S_i)$ produce the first and second minimum value of the vector S_i.

Experimental Results

Database and Settings

- FRGC v2.0
  - 4007 3D models of 466 subjects for evaluation;

    (The first scan with a neutral expression of each subject makes up of a gallery set; and the remaining are treated as probes)

Experiment Design: FRGC v2.0

- The Effectiveness of the Preprocessing Pipeline
- The Performance of Individual Matching steps
- Radius Analysis of OGM Neighborhood
- Identification of Asymmetric Face Recognition

Experimental Results

The Effectiveness of the Preprocessing Pipeline

2D-2D Face Matching (SRC)

2D-2D Face Matching	PCA	LBP Histogram
Original Faces	46.68%	75.74%
Preprocessed Faces	78.54%	79.95%

3D-2D Face Matching (CCA)

2D-2D Face Matching	PCA	LBP Histogram
Original Faces	36.18%	42.42%
Preprocessed Faces	81.70%	76.36%

Experimental Results

The Performance of Individual Matching Steps

◆ 2D-2D Face Matching (SRC)

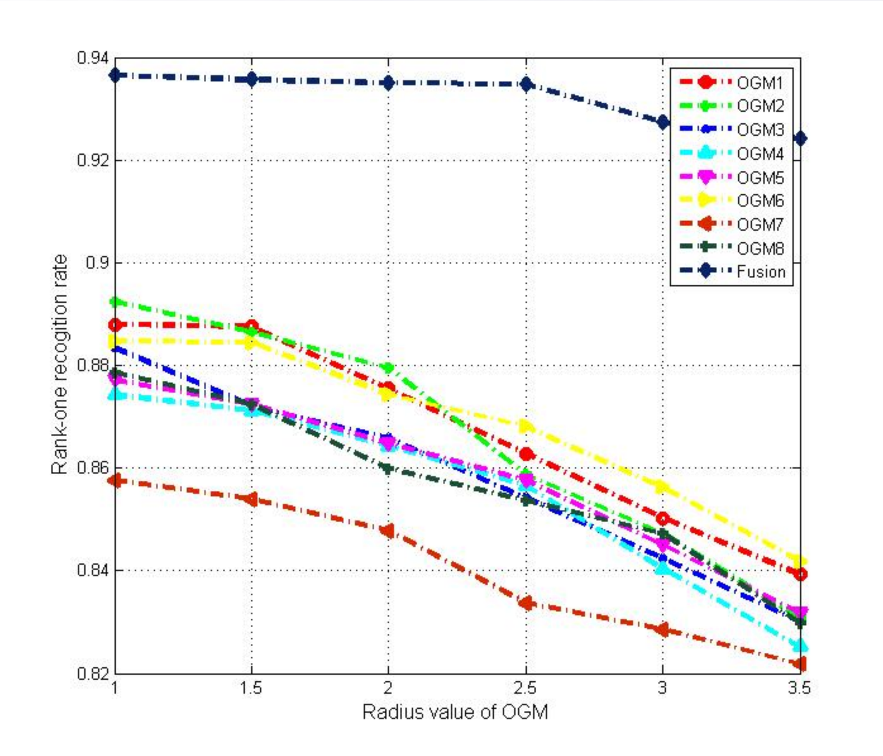
2D-2D Face Matching	Accuracy
(S1): OGMs + LBP Histogram	**93.90%**
(S2): OGMs + PCA	93.65%
(S3): Original Faces + MS-LBP	**89.18%**
(S4): Original Faces + PCA	78.54%

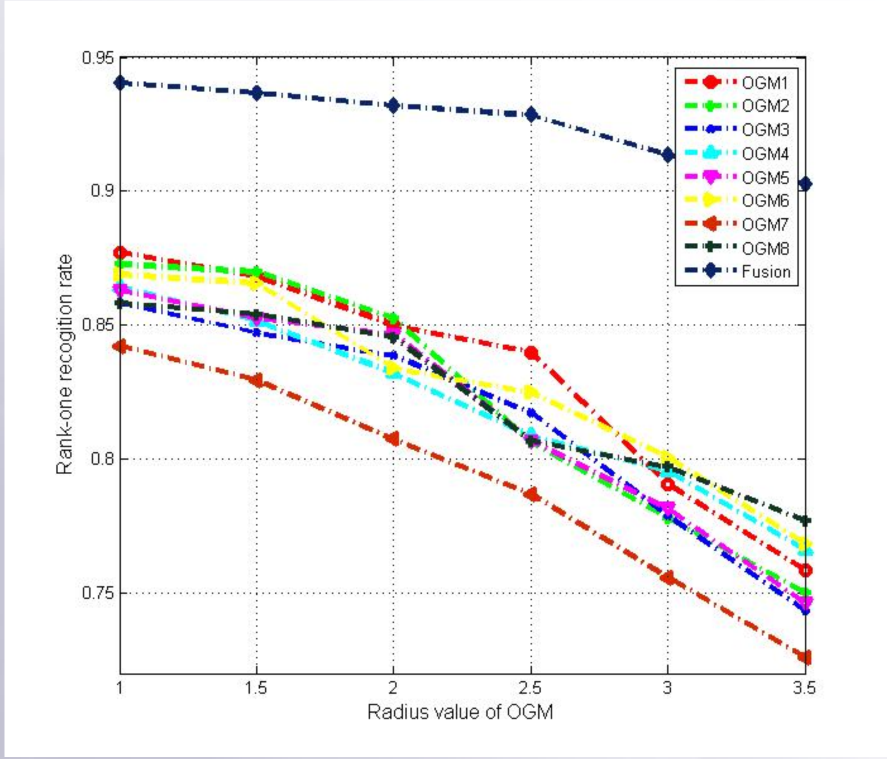
◆ 3D-2D Face Matching (CCA)

3D-2D Face Matching	Accuracy
(A1): OGMs	**94.04%**
(A2): MS-LBP	**87.00%**
(A3): PCA	81.70%

Experimental Results

Radius Analysis of OGM Neighborhood





2D-2D face matching

3D-2D face matching

Experimental Results

Identification of Asymmetric Face Recognition

Different Fusion	Accuracy
(S4) + (A3) PCA	89.01%
(S3) + (A2) MS-LBP	91.27%
(S1) + (A1) OGM	95.37%

Summary

Asymmetric Face Recognition

- We propose a new framework, asymmetric 3D-2D face recognition, enrolling in textured 3D while performing identification using 2D images;
- We design an effective preprocessing pipeline for illumination reduction and pose correction;
- MS-LBP and OGM Maps improve the distinctiveness of original facial texture and range images, and OGMs perform better than MS-LBP;
- The proposed asymmetric 3D-2D face recognition achieves satisfying results on the entire FRGC v2.0 dataset, which is better than 2D-2D, since it uses 3D information, while it also avoids the high online cost of data acquisition and registration in 3D-3D.

Outline

- Background
- Only 3D Shape based Face Recognition
- Textured 3D Face Recognition
- Asymmetric Face Recognition

Publications

International Journal:

- **D. Huang**, C. Shan, M. Ardabilian, Y. Wang, and L. Chen: Local binary patterns and its application to facial image analysis: a survey, IEEE Transactions on Systems, Man, and Cybernetics, Part C (TSMC-C): Applications and Reviews, 2011.

International Conference:

- **D. Huang,** M. Ardabilian, Y. Wang, and L. Chen: Asymmetric 3D/2D face recognition based on LBP facial representation and canonical correlation analysis, IEEE International Conference on Image Processing (ICIP), Cairo, Egypt, 2009;
- W. Ben Soltana, **D. Huang**, M. Ardabilian, L. Chen, and C. Ben Amar: Comparison of 2D/3D features and their adaptive score level Fusion for 3D Face Recognition, International Symposium on 3D Data Processing, Visualization, and Transmission (3DPVT), Paris, France, 2010;
- **D. Huang**, M. Ardabilian, Y. Wang, and L. Chen: Automatic asymmetric 3D-2D face recognition, IAPR International Conference on Pattern Recognition (ICPR), Istanbul, Turkey, 2010;
- X. Zhao, **D. Huang**, E. Dellandréa, and L. Chen: Automatic 3D facial expression recognition based on a bayesian belief net and a statistical facial feature model, International Conference on Pattern Recognition (ICPR), Istanbul, Turkey, 2010;
- **D. Huang**, G. Zhang, M. Ardabilian, Y. Wang, and L. Chen: 3D face recognition using distinctiveness enhanced facial representation and local feature hybrid matching, IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS), Washington DC, USA, 2010;
- **D. Huang**, K. Ouji, M. Ardabilian, Y. Wang, and L. Chen: 3D face recognition based on local shape patterns and sparse representation classier, International Conference on MultiMedia Modeling (MMM), Taipei, Taiwan, 2011;
- **D. Huang,** M. Ardabilian, Y. Wang, and L. Chen: A novel geometric facial representation based on multi-scale extended local binary patterns, IEEE International Conference on Automatic Face and Gesture Recognition (FG), Santa Barbara, USA, 2011;
- **D. Huang,** W. Ben Soltana, M. Ardabilian, Y. Wang, and L. Chen: Textured 3D face recognition using biological vision-based facial representation and optimized weighted sum fusion, IEEE Conference on Computer Vision and Pattern Recognition Workshop (CVPRW) on Biometrics Colorado Spring, USA, 2011;
- W. Ben Soltana, **D. Huang**, M. Ardabilian, L. Chen, and C. Ben Amar: A mixture of gated experts optimized using simulated annealing for 3D face recognition, IEEE International Conference on Image Processing (ICIP), Brussels, Belgium, 2011;

Publications

- H. Li, **D. Huang**, P. Lemaire, J.-M. Morvan, L. Chen: Expression robust 3D face recognition via mesh-based histograms of multiple order surface differential quantities, IEEE International Conference on Image Processing (ICIP), Brussels, Belgium, 2011;
- H. Li, **D. Huang**, J.-M. Morvan, L. Chen: Learning Weighted Sparse Representation of Encoded Facial Normal Information for Expression-Robust 3D Face Recognition, IEEE International Joint Conference on Biometrics (IJCB), Washington DC, USA, 2011;
- V. Vijayan, K. Bowyer, P. Flynn, **D. Huang**, L. Chen, M. Hansen, S. Shah, Omar Ocegueda, and I. Kakadiaris: Twins 3D Face Recognition Challenge, IEEE International Joint Conference on Biometrics (IJCB), Washington DC, USA, 2011.

International Journal under Review:

- **D. Huang**, M. Ardabilian, Y. Wang, and L. Chen: 3D Face Recognition using eLBP-based Facial Description and Local Feature Hybrid Matching, Submitted to IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI);
- **D. Huang**, M. Ardabilian, Y. Wang, and L. Chen: Automatic Asymmetric 3D-2D Face Recognition, IEEE Transactions on Information Forensics and Security (TIFS).

International Journal to be Finalized:

- **D. Huang**, M. Ardabilian, Y. Wang, and L. Chen: Textured 3D Face Recognition based on Oriented Gradient Maps and optimized weighted sum fusion.

French Patent

- L. Chen and **D. Huang**: Oriented Gradient Maps (OGM) and SIFT-based Matching for Biometric Applications, B20230.