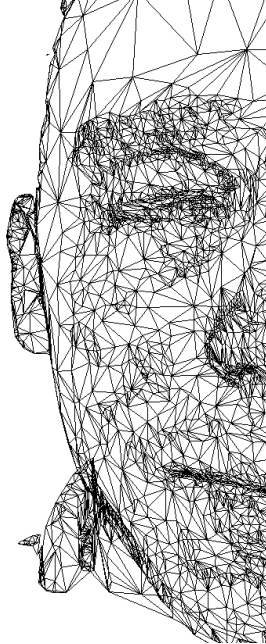


# Occlusions in 3D Face Recognition

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Lyon, 28 January 2011



# Outline

- ▶ Preliminaries
- ▶ Detection of occluded 3D faces
- ▶ Recognizing occluded 3D faces: a restoration approach
- ▶ Experimental Results on artificial and real occlusions
- ▶ Future Directions

# Why occlusions?



Authentication

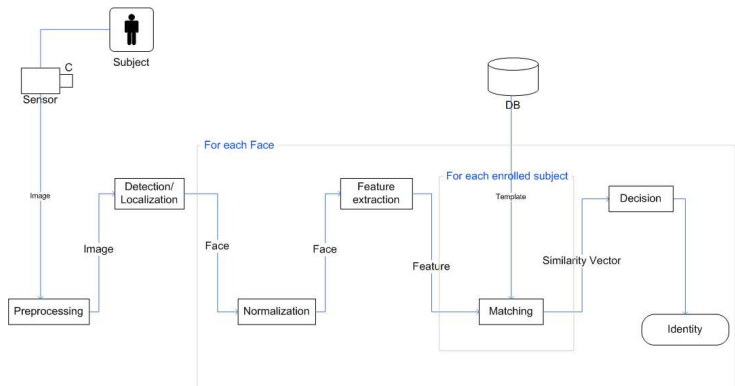


Identification

## Occlusions in 3D

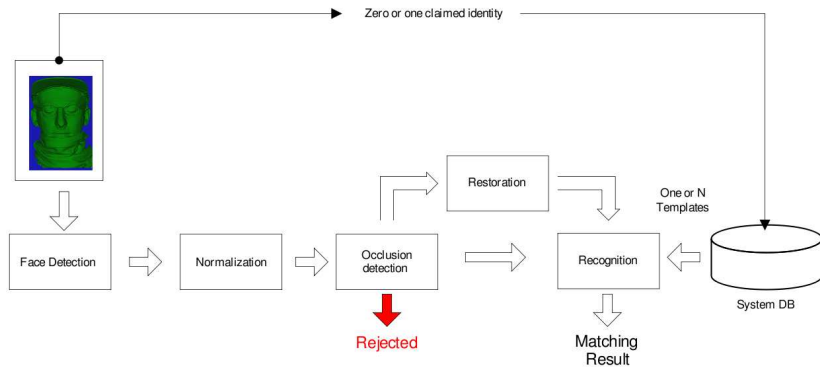


# Requirements



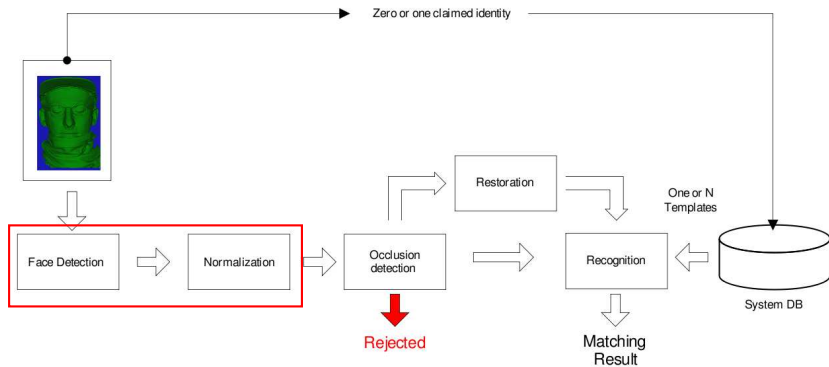
- ▶ Fully automatic
- ▶ Scalable
- ▶ *Is an holistic approach possible?*

# System design choices



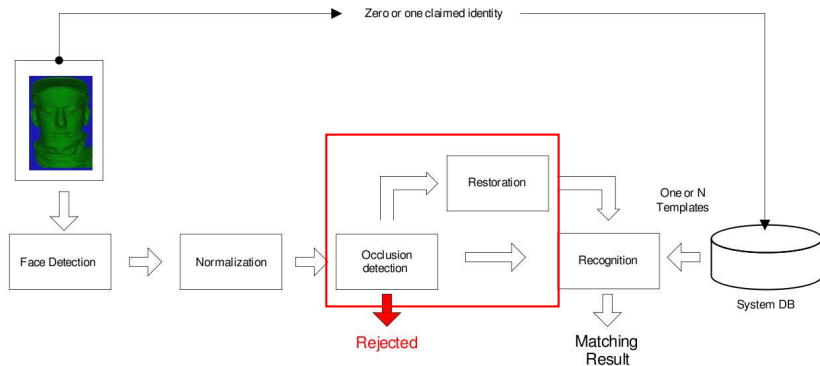
- Occlusion detection and restoration based pipeline.

# System design choices



- Occlusion tolerant detection and *pre*-matching normalization.

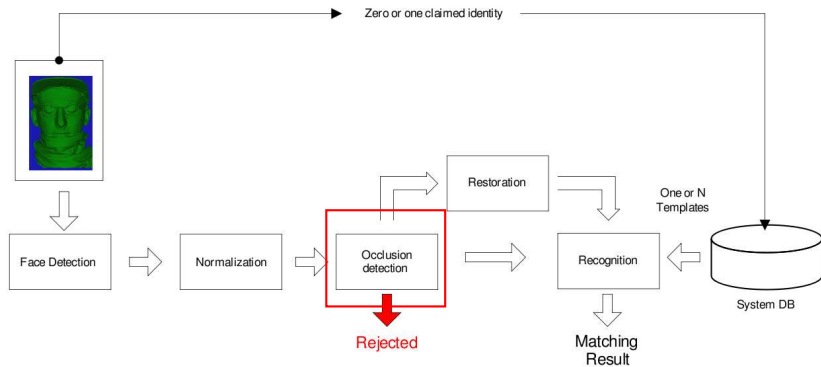
# System design choices



- ▶ Holistic approach through occlusion detection and restoration.

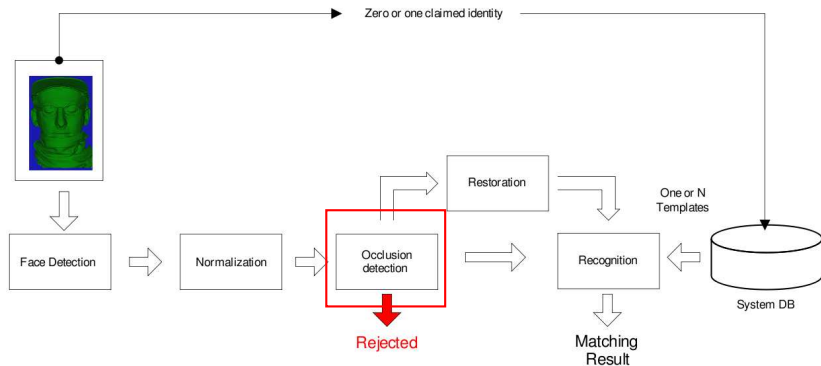


# System design choices



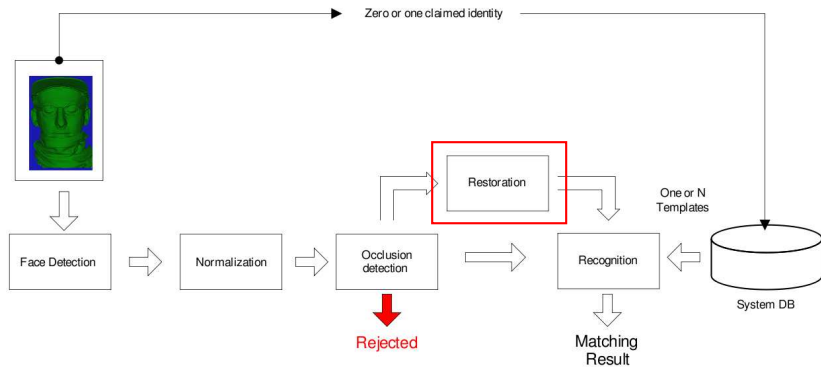
- Faces are analyzed in order to detect occlusions.

# System design choices



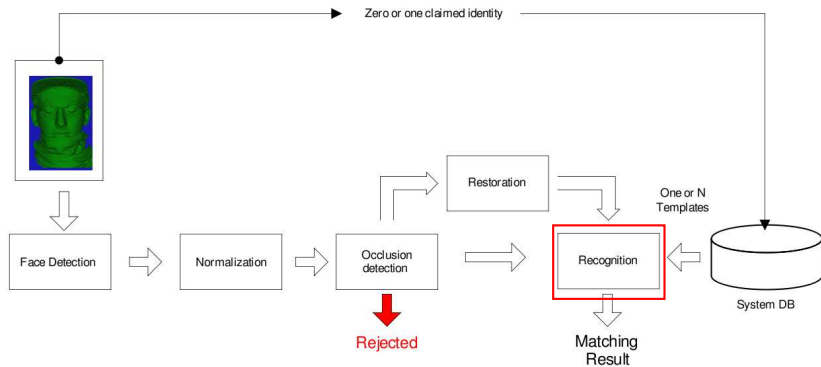
- If occlusions are too large the acquisition may be eventually rejected.

# System design choices



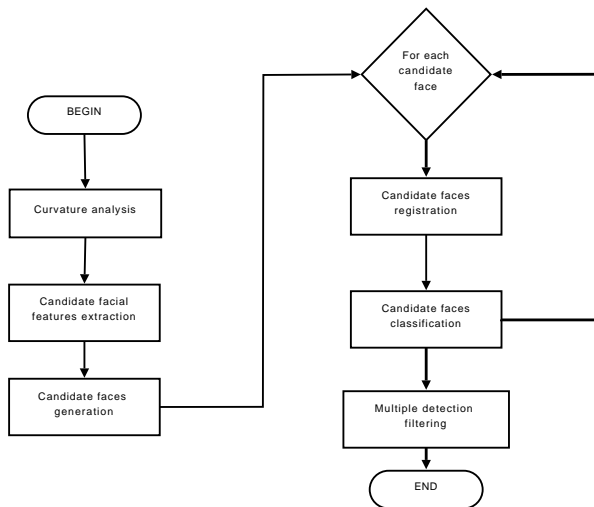
- ▶ Occlusions are cleared and the missing facial surface is reconstructed.

# System design choices



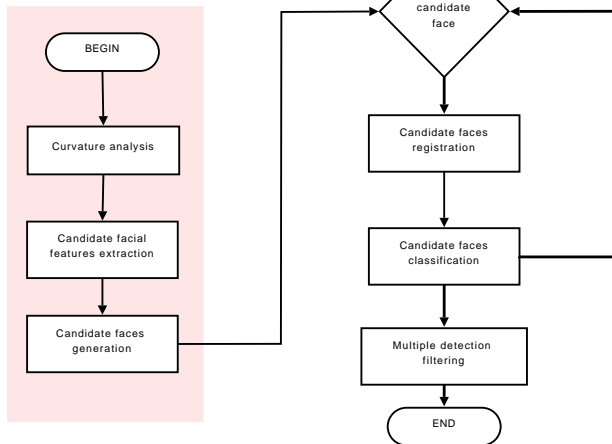
- ▶ *Any state* of the art recognition strategy may be applied.

# Occlusion Tolerant 3D Face Detector



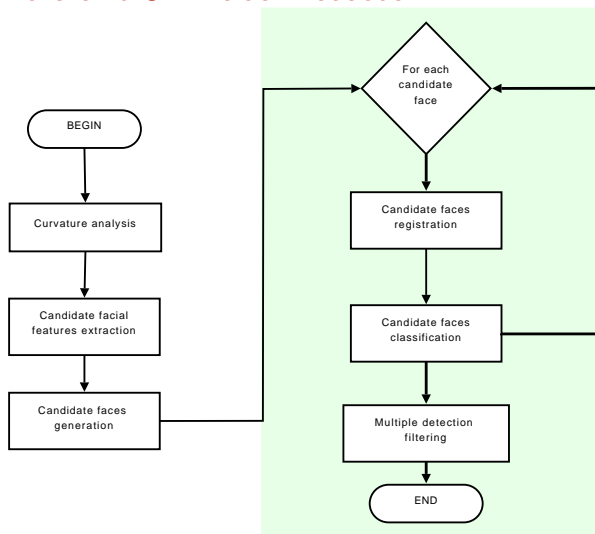
- Hypothesis generation and test structure.

# Occlusion Tolerant 3D Face Detector



► Hypothesis generation.

# Occlusion Tolerant 3D Face Detector



► Hypothesis test.

## Curvature Analysis







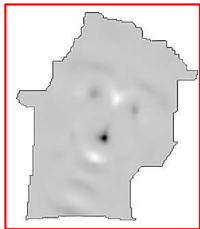
## Curvature Analysis



Mean Curvature



$$H(x_0, y_0) = \frac{(1+f_y^2)f_{xx} - 2f_x f_y f_{xy} + (1+f_x^2)f_{yy}}{2(1+f_x^2+f_y^2)^{\frac{3}{2}}}$$



Gaussian Curvature



$$K(x_0, y_0) = \frac{f_{xx}f_{yy} - f_{xy}^2}{(1 + f_x^2 + f_y^2)^2}$$



## Curvature Analysis

### HK Classification



	$K < 0$	$K = 0$	$K > 0$
$H < 0$	<i>Hyperbolic concave</i>	Cylindrical concave	<i>Elliptical concave</i>
$H = 0$	Hyperbolic symmetric	Planar	Impossible
$H > 0$	<i>Hyperbolic convex</i>	Cylindrical convex	<i>Elliptical convex</i>

## Candidate Features Extraction





## Candidate Features Extraction

Candidate Noses



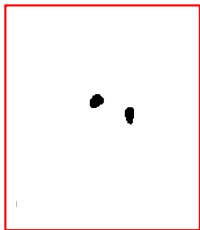
Positive Mean regions;

$$H(u, v) > T_h$$



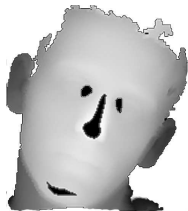


## Candidate Features Extraction



Candidate Eyes

Elliptical concave regions;  
 $|K(u, v)| > T_k$

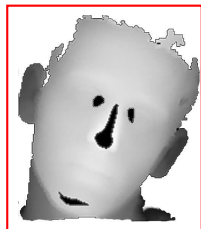


## Candidate Features Extraction

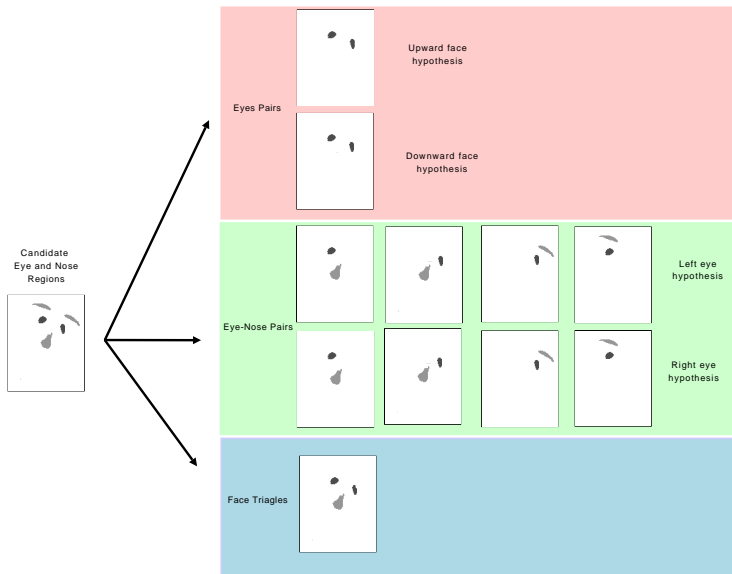


Final candidate filtering

Region size, shape, average curvature etc.

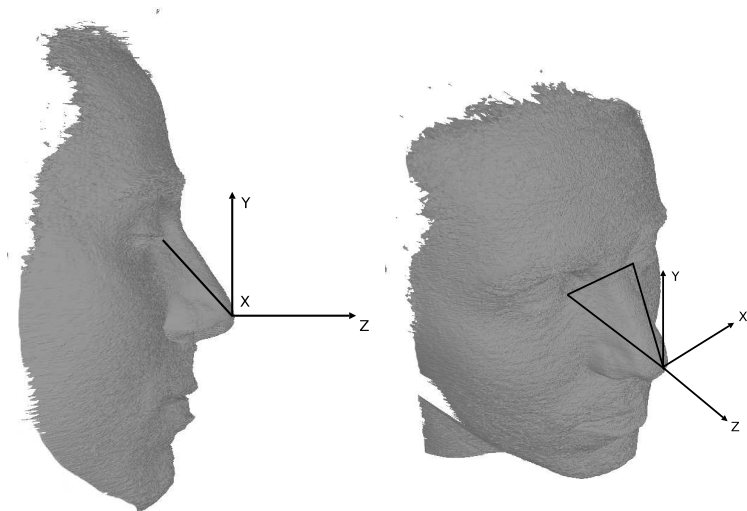


# Candidate faces generation



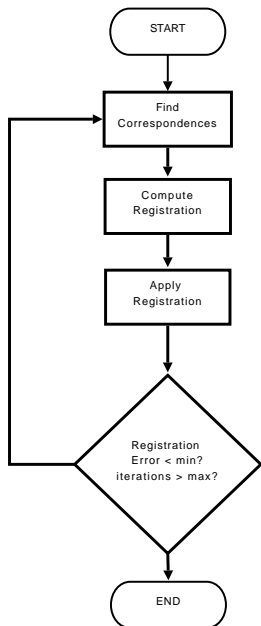
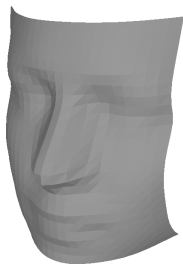


## Candidate faces rough registration



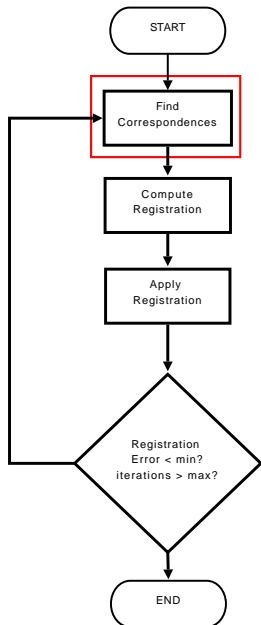
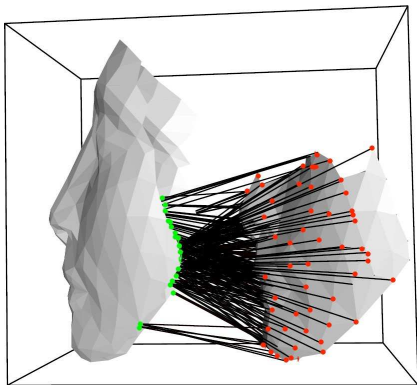
## Candidate faces fine registration

- ▶ Global registration through ICP with a mean reference face



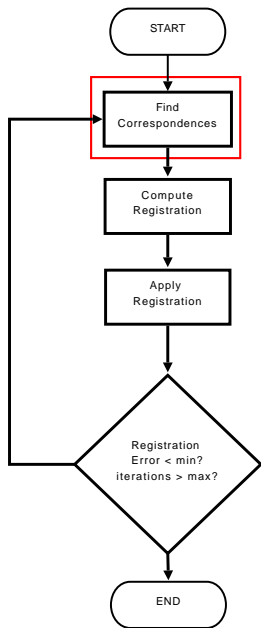
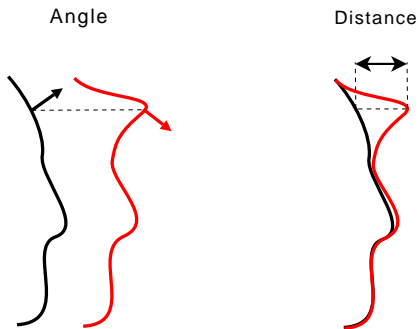
## Candidate faces fine registration

- ▶ Global registration through ICP with a mean reference face
- ▶ Projective matcher



## Candidate faces fine registration

- ▶ Global registration through ICP with a mean reference face
- ▶ Projective matcher
- ▶ Geometric correspondences rejector



# Candidate faces classification

Standard PCA classification



# Candidate faces classification

Standard PCA classification

$$\text{Image} \approx \text{Mean Image} + y_1 \times \text{PCA Component 1} + y_2 \times \text{PCA Component 2} + \dots + y_n \times \text{PCA Component n}$$

# Candidate faces classification

Standard PCA classification

$$\text{Image} \approx \text{Mean Image} + y_1 \times \text{Eigenface 1} + y_2 \times \text{Eigenface 2} + \dots + y_n \times \text{Eigenface } n = \text{Reconstructed Image}$$

# Candidate faces classification

## Standard PCA classification

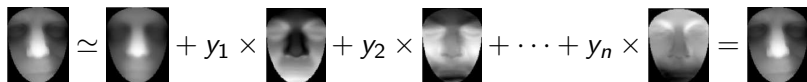
$$\text{Image} \approx \text{Mean} + y_1 \times \text{Component}_1 + y_2 \times \text{Component}_2 + \dots + y_n \times \text{Component}_n = \text{Reconstructed Image}$$

$$D.F.F.S. = \left\| \text{Image} - \text{Reconstructed Image} \right\|$$



# Candidate faces classification

## Standard PCA classification

$$\text{Target Face} \approx \text{Mean Face} + y_1 \times \text{Basis 1} + y_2 \times \text{Basis 2} + \dots + y_n \times \text{Basis n} = \text{Reconstructed Face}$$


$$D.F.F.S. = \|\text{Target Face} - \text{Reconstructed Face}\| \ll \|\text{Target Face} - \text{Candidate Face}\|$$


# Candidate faces classification

## Standard PCA classification

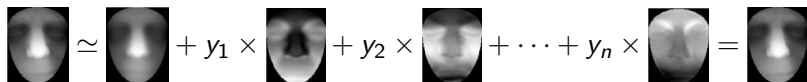
$$\text{Target Face} \approx \text{Mean Face} + y_1 \times \text{Basis 1} + y_2 \times \text{Basis 2} + \dots + y_n \times \text{Basis n} = \text{Reconstructed Face}$$

$$D.F.F.S. = \|\text{Target Face} - \text{Reconstructed Face}\| \ll \|\text{Target Face} - \text{Candidate Face}\|$$

- ▶ Missing data?

# Candidate faces classification

## Standard PCA classification

$$\text{Target Face} \simeq \text{Mean Face} + y_1 \times \text{PCA Component 1} + y_2 \times \text{PCA Component 2} + \dots + y_n \times \text{PCA Component n} = \text{Reconstructed Face}$$


$$D.F.F.S. = \|\text{Target Face} - \text{Reconstructed Face}\| \ll \|\text{Target Face} - \text{Candidate Face}\|$$


- ▶ Missing data?
- ▶ Occlusions?

# Candidate faces classification

Gappy PCA



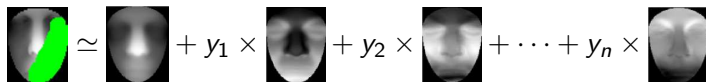
# Candidate faces classification

Gappy PCA



# Candidate faces classification

Gappy PCA


$$\text{Target Face} \approx \text{Mean Face} + y_1 \times \text{PC}_1 + y_2 \times \text{PC}_2 + \dots + y_n \times \text{PC}_n$$

# Candidate faces classification

Gappy PCA

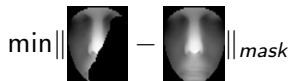

$$\text{Target Face} \approx \text{Mean Face} + y_1 \times \text{Basis 1} + y_2 \times \text{Basis 2} + \dots + y_n \times \text{Basis n} = \text{Reconstructed Face}$$

The diagram shows a sequence of grayscale face images. The first image is a target face with a green mask covering the right side. This is followed by an approximation symbol (≈), then a mean face image, a plus sign, a coefficient  $y_1$ , a multiplication sign, a basis face image, a plus sign, a coefficient  $y_2$ , a multiplication sign, another basis face image, a plus sign, an ellipsis, a plus sign, a coefficient  $y_n$ , a multiplication sign, a final basis face image, and an equals sign (=). The final image is the reconstructed face, which is a smooth grayscale representation of the target face.

# Candidate faces classification

Gappy PCA

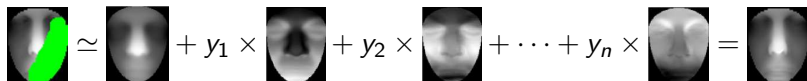

$$\text{Masked Face} \approx \text{Base Face} + y_1 \times \text{Basis}_1 + y_2 \times \text{Basis}_2 + \dots + y_n \times \text{Basis}_n = \text{Unmasked Face}$$


$$\min \| \text{Masked Face} - \text{Unmasked Face} \|_{\text{mask}}$$



# Candidate faces classification

## Gappy PCA


$$\text{Masked Face} \approx \text{Base Face} + y_1 \times \text{Feature 1} + y_2 \times \text{Feature 2} + \dots + y_n \times \text{Feature n} = \text{Unmasked Face}$$

$$\min \| \text{Masked Face} - \text{Unmasked Face} \|_{\text{mask}} = D.F.F.S.$$

# Candidate faces classification

## Gappy PCA

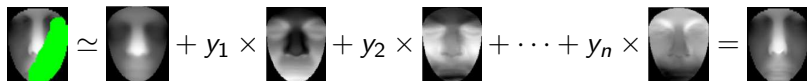

$$\text{Masked Face} \approx \text{Mean Face} + y_1 \times \text{Basis}_1 + y_2 \times \text{Basis}_2 + \dots + y_n \times \text{Basis}_n = \text{Reconstructed Face}$$

$$\min \| \text{Masked Face} - \text{Reconstructed Face} \|_{\text{mask}} = D.F.F.S.$$

- ▶ Closed form for GPCA projection; *really fast*.

# Candidate faces classification

## Gappy PCA

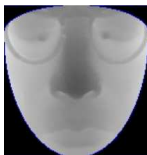

$$\text{Face with mask} \simeq \text{Mean face} + y_1 \times \text{Basis 1} + y_2 \times \text{Basis 2} + \dots + y_n \times \text{Basis n} = \text{Original face}$$

$$\min \| \text{Face with mask} - \text{Reconstructed face} \|_{\text{mask}} = D.F.F.S.$$

- ▶ Closed form for GPCA projection; *really fast*.
- ▶ Occlusions?

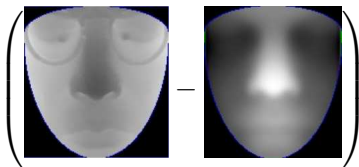
# Candidate faces classification

Rough occlusion detection



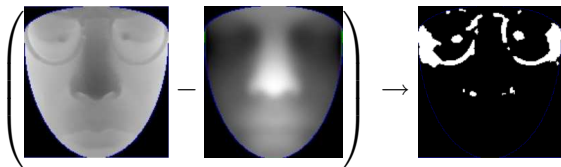
# Candidate faces classification

Rough occlusion detection



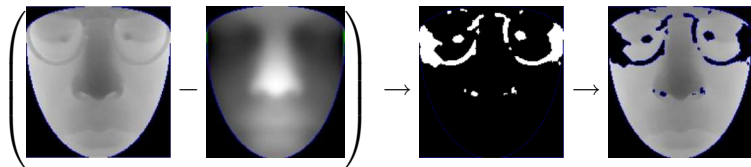
# Candidate faces classification

## Rough occlusion detection



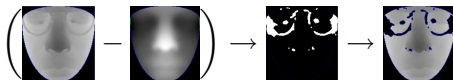
# Candidate faces classification

Rough occlusion detection



# Candidate faces classification

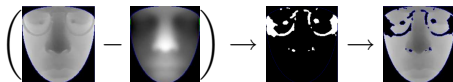
## Summary





# Candidate faces classification

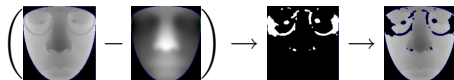
## Summary



$$\begin{matrix} \text{Glasses mask} \\ \text{Candidate face with glasses} \end{matrix} \approx \begin{matrix} \text{Base face} \\ \text{Candidate face} \end{matrix} + y_1 \times \begin{matrix} \text{Glasses mask} \\ \text{Candidate face} \end{matrix} + y_2 \times \begin{matrix} \text{Glasses mask} \\ \text{Candidate face} \end{matrix} + \dots + y_n \times \begin{matrix} \text{Glasses mask} \\ \text{Candidate face} \end{matrix} = \begin{matrix} \text{Base face} \\ \text{Candidate face} \end{matrix}$$

# Candidate faces classification

## Summary

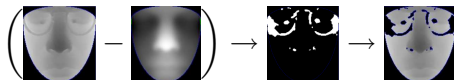


$$\begin{matrix} \text{[Glasses Mask]} \\ \approx \\ \text{[Face Mask]} + y_1 \times \text{[Nose Mask]} + y_2 \times \text{[Mouth Mask]} + \dots + y_n \times \text{[Eye Mask]} = \text{[Target Face Mask]} \end{matrix}$$

$$D.F.F.S. = \left\| \begin{matrix} \text{[Glasses Mask]} \\ - \\ \text{[Face Mask]} \end{matrix} \right\|_{mask}$$

# Candidate faces classification

## Summary



$$\text{Refined Face} \approx \text{Mask} + y_1 \times \text{Feature 1} + y_2 \times \text{Feature 2} + \dots + y_n \times \text{Feature n} = \text{Candidate Face}$$

The equation shows the reconstruction of a refined face image from a mask and a set of features. The refined face image is approximately equal to the mask plus a linear combination of features, which is equal to the candidate face image.

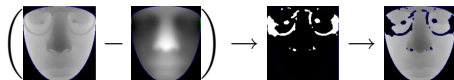
$$D.F.F.S. = \left\| \begin{array}{c} \text{Refined Face} \\ \text{Mask} \end{array} \right\|_{mask}$$

The equation defines the Distance from Face to Face Set (D.F.F.S.) as the norm of the difference between the refined face image and the mask, measured using the mask norm.

► if  $D.F.F.S. < \tau \rightarrow$  candidate is a face

# Candidate faces classification

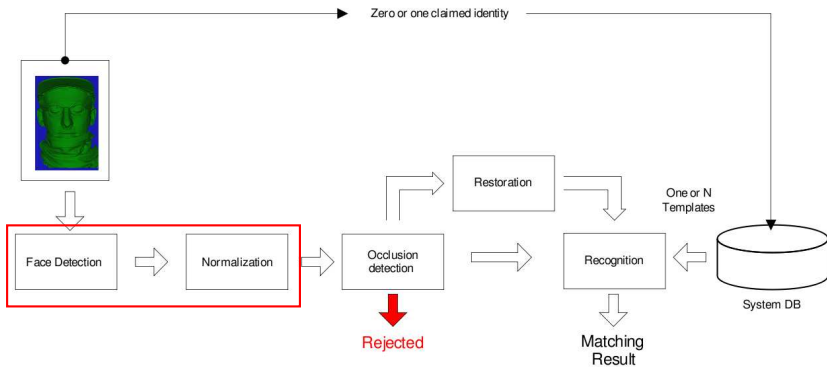
## Summary

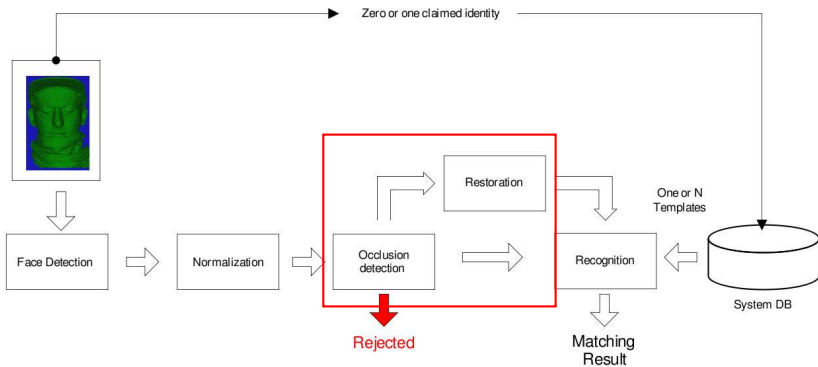


$$\text{Face Mask} \approx \text{Mask} + y_1 \times \text{Feature 1} + y_2 \times \text{Feature 2} + \dots + y_n \times \text{Feature n} = \text{Target Face}$$

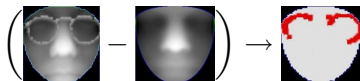
$$D.F.F.S. = \left\| \begin{array}{c} \text{Face Mask} \\ \text{Mask} \end{array} \right\|_{mask}$$

- ▶ if  $D.F.F.S. < \tau \rightarrow$  candidate is a face
- ▶ If the occluded area is large the candidate may be rejected



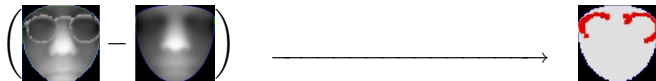


# Occlusion Detection and Face Restoration



- ▶ Need a more precise detection of occluded pixels and reconstruction of the face for maximizing recognition performances

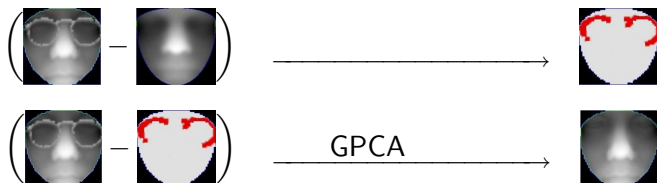
# Occlusion Detection and Face Restoration



- ▶ a “large” threshold  $\tau$  is used to discriminate occluded pixels

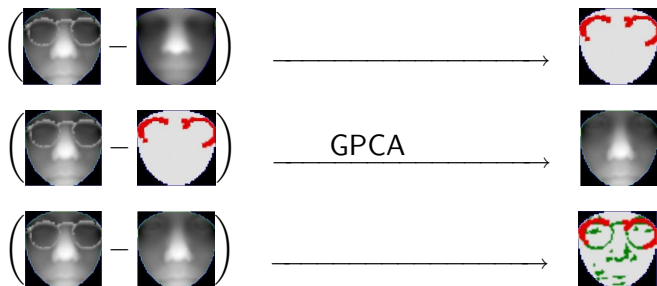


# Occlusion Detection and Face Restoration



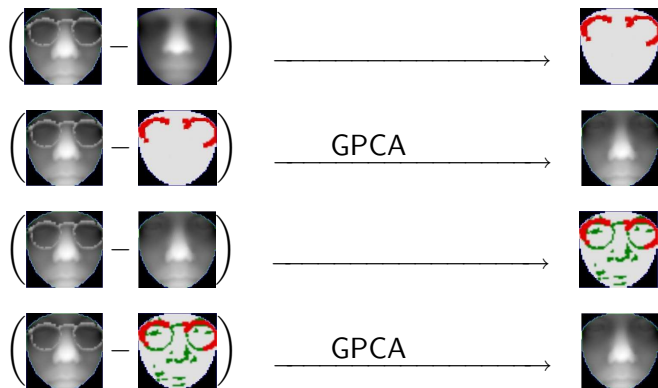
- ▶ a first reconstruction is generated through GPCA projection

# Occlusion Detection and Face Restoration



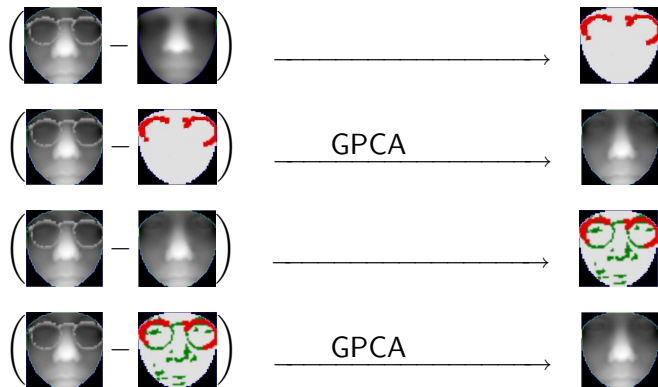
- ▶ a smaller threshold  $\tau_2$  is used. Morphological operators are also applied

# Occlusion Detection and Face Restoration



- ▶ a new projection with the refined mask is generated

# Occlusion Detection and Face Restoration



- ▶ If the occluded area is large the face may be rejected

# Experimental Results

## Dataset Requirements:

- ▶ large number of subjects
- ▶ different occlusion types (object type, location, size of occluded area)

## Ground truth needed for an in-depth analysis:

- ▶ occluded/non-occluded regions, *pixel precision*
- ▶ landmarks, *even if occluded*
- ▶ original, *non-occluded surface*

# Experimental Results

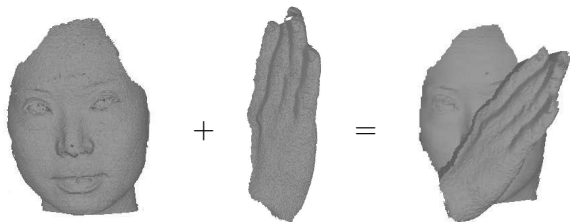
## Dataset Requirements:

- ▶ large number of subjects
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- ▶ occluded/non-occluded regions, *pixel precision*
- ▶ landmarks, *even if occluded*
- ▶ original, *non-occluded surface*

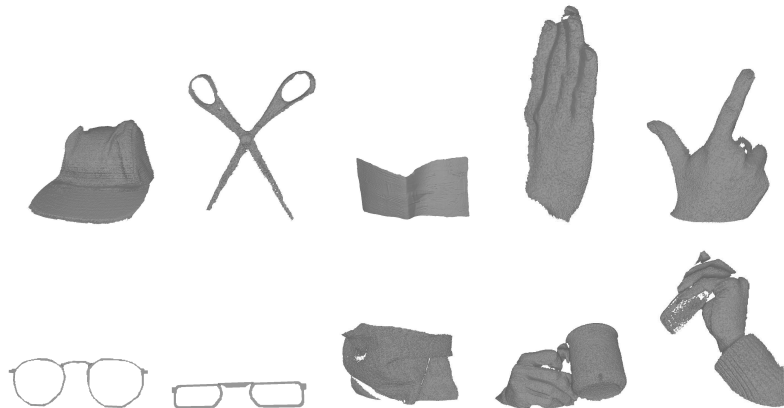
## Artificial Occlusions Generation



- ▶ Random or semi-random position and orientation of the object

# Artificial Occlusions Generation

Occluding objects



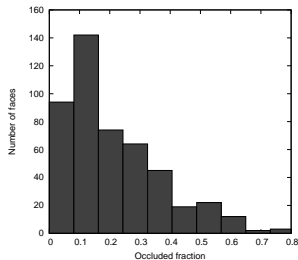


# Artificial Occlusions Generation

## The Artificially Occluded UND Dataset

### UND Dataset:

- ▶ 277 subjects (male/female, different races)
- ▶ 953 acquisitions (frontal, neutral expression, 2D+3D)
- ▶ facial features annotation



# Face Detection Results

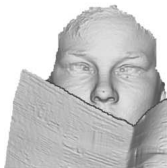
## Artificially occluded UND Dataset

Test Set	Classifier	Total Faces	False Positives	False Negatives	Detected Faces
UND (non-occluded)	PCA	951	3	1	950 (99.9%)
	GPCA	951	18	0	951 (100%)
UND (artificially occluded)	PCA	951	165	483	468 (49.2%)
	GPCA	951	135	104	847 (89.8%)

Object Type	Total Faces	False Positives	False Negatives	Detected Faces
hand with cup	91	5	3	88 (96.7%)
eyeglasses	184	4	0	184 (100.0%)
free hands	181	46	41	140 (77.3%)
newspaper	77	20	18	59 (76.6%)
hand with phone	97	1	0	97 (100.0%)
scarf	123	42	29	94 (76.4%)
scissors	109	9	7	102 (93.6%)
hat	89	8	6	83 (93.6%)
all	951	135	104	847 (89.8%)

# Face Detection Results

## Successes



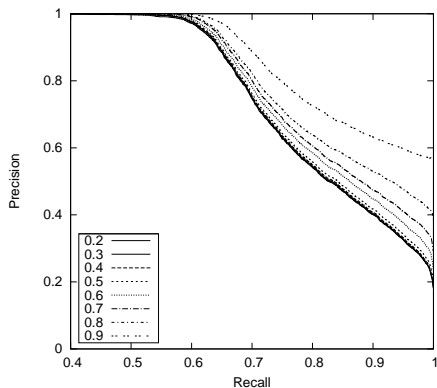
# Face Detection Results

## Failures



# Face Detection Results

## Detector Precision vs Recall



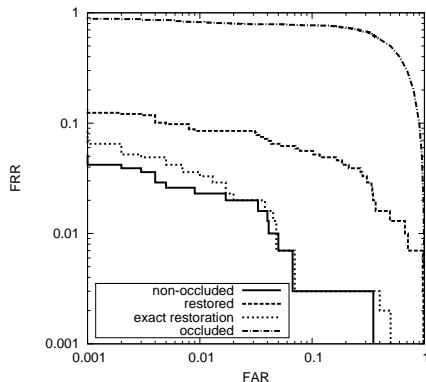
- Precision vs Recall varying the minimum valid area fraction threshold

# Face Recognition Results

## Artificially occluded UND Dataset

- ▶ Fisherfaces recognition approach; Manual normalization
- ▶ Training: 474 images; 3 x subject (*non-occluded*)
- ▶ Test: 477 remaining images (*occluded*)

Set	EER	IR
non occluded	0.020	99.35%
occluded	0.488	27.45%
restored	0.062	96.08%
exact restoration	0.022	99.35%

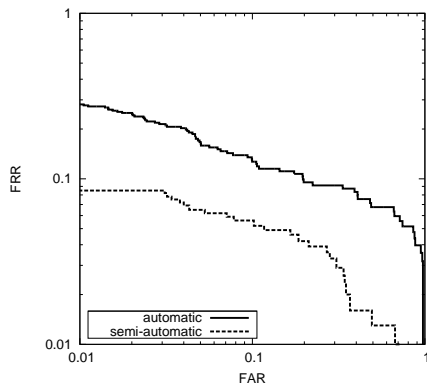


# Face Recognition Results

## Artificially occluded UND Dataset

- ▶ Full Automatic Pipeline: face detection, occlusion detection and restoration
  - ▶ Fisherfaces recognition approach;
  - ▶ Same training and test sets
- 
- ▶ EER drops from 0.062 to 0.115
  - ▶ IR drops from 96.08% to 81%

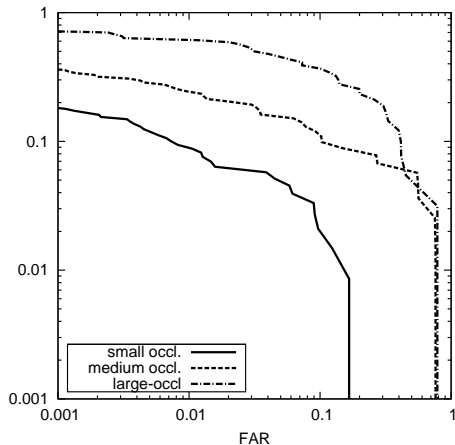
Occlusion type	Manual normalization	Automatic normalization
Cup	100%	81%
Scissors	100%	100%
Eyeglasses	100%	100%
Hat	100%	63.16%
Hand	97.18%	96.49%
Phone	100%	93.75%
Newspaper	92%	87.5%
Scarf	95.92%	46.34%



# Face Recognition Results

Artificially occluded UND Dataset

subset	from %	to %
small	0%	20%
medium	20%	40%
large	40%	82%

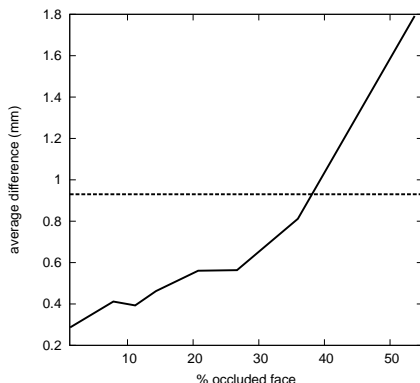




# Restoration Accuracy

## Artificially occluded UND Dataset

- ▶ Average absolute difference between depth of corresponding points for each pair of restored and original faces.



- ▶ Average absolute z difference between the pixels of pairs of non-occluded acquisitions of the same subject: 0.93 mm.
- ▶ GPCA is able to precisely reconstruct faces even if occluded up to 40%.

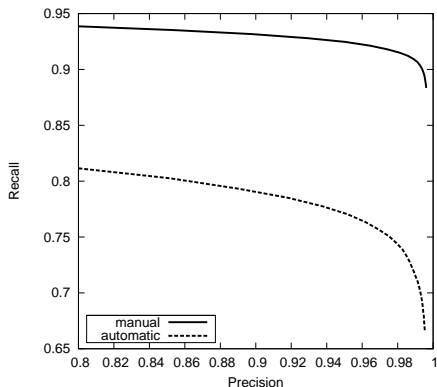
# Occlusion Detection Accuracy

Artificially occluded UND Dataset

- Occlusion detection performances evaluated at the pixel level

$$precision = \frac{tp}{tp + fp}$$

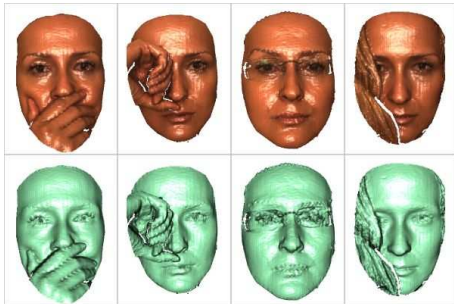
$$recall = \frac{tp}{tp + fn}$$



# Face Recognition Results

## Bosphorus Database

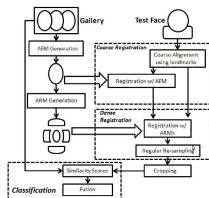
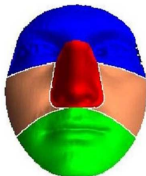
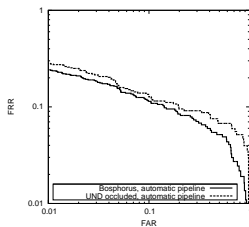
- ▶ 105 subjects; 4652 acquisitions, 381 occluded.
- ▶ Occluding objects:
  - ▶ mouth with hand
  - ▶ one eye with hand
  - ▶ eyeglasses (not sunglasses, normal eyeglasses)
  - ▶ hair



# Face Recognition Results

## Bosphorus Database

Method	Occlusion Type			
	Eye	Mouth	Eyeglasses	Hair
Alyuz et al.[1] (semi-auto)	93.62%	93.62%	97.87%	89.66%
Proposed approach (auto)	91.18%	74.75%	94.23%	90.47%



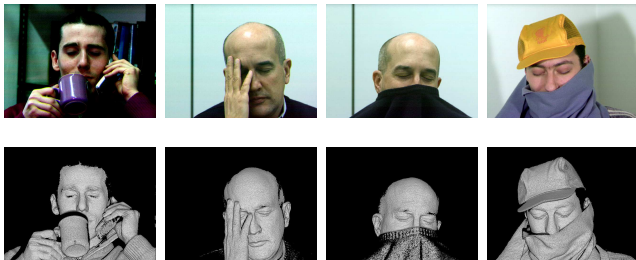
1

<sup>1</sup>N. Alyuz, B. Gokberk, L. Akarun, 3D Face Recognition System for Expression and Occlusion Invariance, IEEE 2nd International Conference on Biometrics: Theory, Applications, and Systems (IEEE BTAS), Washington, DC, USA, September 2008.

# UMB-DB Database

The University of Milano-Bicocca 3D face Database

- ▶ 143 subjects
- ▶ 1461 acquisitions; 9 - 12 per subject
- ▶ 4 facial expressions
- ▶ 578 occluded acquisitions
- ▶ 6+ occluding objects



# UMB-DB Database

## Face Detection Preliminary Results

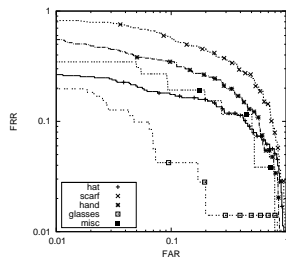
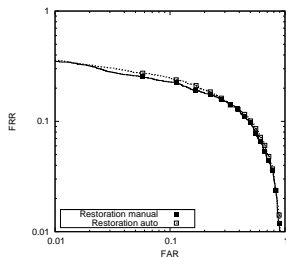
Total Faces	False Positives	False Negatives	Detected Faces
1473	56	52	1421 (96.5%)

Acquisition type	Number of faces	Detected Faces
Neutrals	441	437 (99.1%)
Non-neutral	442	431 (97.5%)
Occluded	578	553 (95.7%)
Scarf	151	141 (93.4%)
Glasses	75	71 (94.7%)
Hair	33	30 (90.9%)
Hand	165	150 (90.9%)
Hat	183	179 (97.8%)
Misc	28	26 (92.85%)

# UMB-DB Database

## Face Recognition Preliminary Results

Normalization	Test set	EER	IR
Manual	All cases	0.186	71.0%
Automatic	All cases	0.195	69.6%
Automatic	Neutral	0.019	98.0%
Automatic	Occlusions	0.238	56.5%



# Conclusions

- ▶ Main contributions:
  - ▶ a fully automatic occlusion tolerant 3D face recognition pipeline
  - ▶ occlusion tolerant face detector
  - ▶ occlusion detector
  - ▶ face restoration module



# Conclusions

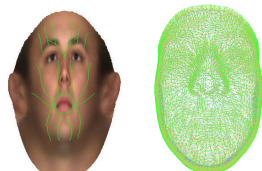
- ▶ Main contributions:
  - ▶ a fully automatic occlusion tolerant 3D face recognition pipeline
  - ▶ occlusion tolerant face detector
  - ▶ occlusion detector
  - ▶ face restoration module
- ▶ Considerations:
  - ▶ there is enough information to recognize faces even with 40% of the occluded area
  - ▶ face detection and normalization is *crucial*

# Conclusions

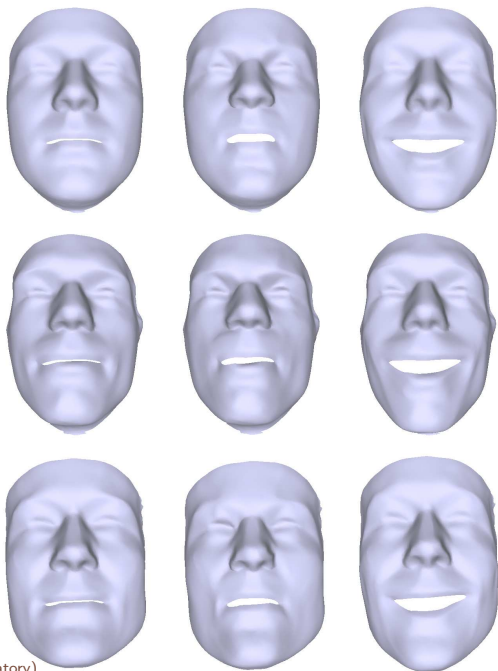
- ▶ Main contributions:
  - ▶ a fully automatic occlusion tolerant 3D face recognition pipeline
  - ▶ occlusion tolerant face detector
  - ▶ occlusion detector
  - ▶ face restoration module
- ▶ Considerations:
  - ▶ there is enough information to recognize faces even with 40% of the occluded area
  - ▶ face detection and normalization is *crucial*
- ▶ Work in progress & Future work
  - ▶ use of other surface features and 2D data in order to improve occlusion detection, normalization and restoration
  - ▶ embed face detection, normalization, occlusion detection and face restoration in an iterative schema
  - ▶ explore facial expressions
  - ▶ artificial generation of datasets with facial expressions and occlusions

# Facile

A system for artificial face datasets generation



- ▶ Given a face 3D textured model with neutral facial expression, the current version of facile is able to:
  - ▶ simulate facial expressions through a physical simulator based on a mass-spring system and synthetic muscles.
  - ▶ render images of the morphed faces from different viewpoints and with different lighting conditions
- ▶ Features:
  - ▶ facial expressions are defined by the user on a mean face specifying muscle contractions
  - ▶ facial expressions are **automatically** transferred on novel faces
  - ▶ a dense annotation of facial feature points is **automatically** generated
  - ▶ ready to be used with synthetic faces generated through morphable models or morphing techniques





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# Thresholds

- ▶ Histogram of the distribution of the pixel by pixel difference between training faces and the mean face

