

# Face Recognition in Unconstrained Environments: A Comparative Study

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# Motivation

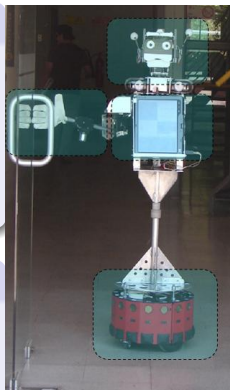
## Applications

- Human Robot Interfaces (HRI)
- Face recognition in large databases
  - ▶ Personal data collections
  - ▶ Web segments
  - ▶ News databases

## Requierements

Full online operation:

- Real world images: unconstrained environments.
- Incremental building of the database.
- Only one image per person in the database
- Fast processing (real time)



# Analysis

## We analyse/compare

- Variants of each methods
- Aligned (funneling) vs unaligned (output of the face detector)
- Amount of face/background
- Processing time

## LFW

The analysis is done using the image restricted setting of the LFW database

# Methods

## We consider four methods

Two local matching methods:

- Gabor Jet Descriptors + Borda Count [Zou et al. 2007]
- Local and global LBP histograms + distance between the histograms [Ahinene et al., 2004]

Two image matching methods:

- SIFT descriptors + matching and verification [Lowe 2004]
- ERCF of SIFT features + linear classifier (SVM) [Nowak et al. 2007]

# Methods

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Two image matching methods:

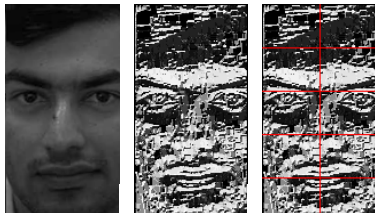
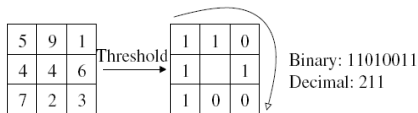
- SIFT descriptors + matching and verification [Lowe 2004]
- ERCF of SIFT features + linear classifier (SVM) [Nowak et al. 2007]

## Generalized PCA wasn't considered

- Requires very good alignment
- Low performance under occlusions and illumination changes
- Large processing time  
[Ruiz-del-Solar et al. 2008]

# Local Binary Pattern (LBP) Histograms

LBP represents the local image structure and is invariant to local contrast changes.



## Procedure

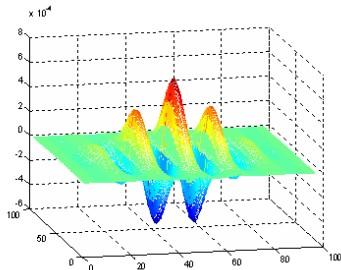
- Divided face area is into small regions:  
→ 10 (2x5), 40 (4x10) and 80 (4x20) regions.
- Calculate the LBP histogram for each region, and for the full region.
- Concatenate the histograms to obtain a feature vector.
- Compare the two faces using:  
→ euclidian distance (MSE) or chi square (XS).

# Gabor Jet Descriptor (GJD) and Borda Count

## GJD: Main Idea

A Gabor jet is the evaluation of a set gabor filters at a fixed scale ( $\lambda$ ) and position ( $x, y$ ), varying the orientation ( $\phi$ ).

- Gabor filters are applied different grid locations.
  - ▶ 8 orientations ( $\phi = \frac{n\pi}{8}$  with  $n = 0, \dots, 7$ ).
- A grid is defined for each scale
  - ▶ 5 scales ( $\lambda = 4, 4\sqrt{2}, 8, 8\sqrt{2}, 16$ ),



# Gabor Jet Descriptor (GJD) and Borda Count

## Borda Count: Main Idea

Voting system based on ranking

- Each voter ranks candidates in order preference.
- The accumulated inverse ranking is used to select the winner.

## Procedure

- Each Gabor Jets assigns a vote (rank) to each image in the database.
- The ranking is done comparing the corresponding Gabor Jets using the normalized inner product.
- The final vote is obtained by adding the reverse rankings.



# Gabor Jet Descriptor (GJD) and Borda Count

## GJD and Borda Count for pairs of images

- BD is a voting system based on ranking
- It does not work on pairs of images
- Solution: use randomly selected reference set to build a similarity measure

## Procedure to build a similarity measure $d(I_A, I_B)$

Take  $I_A$  and a reference set  $S = \{I_1, \dots, I_n\}$

- Rank  $S \cup I_B$  using  $I_A$
- Take position of  $I_B$  as a similarity measure  $d_A$

Take  $I_B$  and a reference set  $S = \{I_1, \dots, I_n\}$

- Rank  $S \cup I_A$  using  $I_B$ ,
- Take position of  $I_A$  as a similarity measure  $d_B$

return  $d(I_A, I_B) = d_A + d_B$

# SIFT

## Main Idea

- Local interest points are extracted independently from both images.
- Characterized both images using invariant descriptors.
- Match the descriptors.
- Obtained a consistent transformation between the two images.
- Distance:
  - ▶ Number of matches (MATCHES)
  - ▶ Number of votes (SIMPLE)



# ERCF

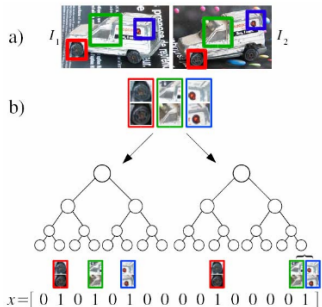
## Main Idea

Learn similarity measure for pairs of images.

- Makes use of ERCF and SIFT descriptors.
- The learning is done for specific object classes (e.g frontal faces, car view).

## Procedure

- Select pairs of similar patches using normalized cross-correlation.
- Code each pair of patches by means of an ERCF of SIFT descriptors.
- Obtain a similarity measure of the image pair using a SVM.



c) 
$$S_{lin}(I_1, I_2) = \omega^T x$$

[Image from Nowak et al.  
CVPR'07]

# Experiments: Cropped regions of size 100x185

## Funneling

We compare two cases:

- Aligned (funneled) faces
- Unaligned faces



## Cropping

- Regions are crop centered on the image
- Size: 100x185



## Experiments: Cropped regions of size 100x185

Method	Without alignment		With alignment	
	MCA	SME	MCA	SME
H-MSE-10	0.6375	0.0049	<b>0.6585</b>	0.0046
H-XS-10	0.6500	0.0043	<b>0.6668</b>	0.0044
H-MSE-40	0.6217	0.0055	<b>0.6527</b>	0.0057
H-XS-40	0.6383	0.0064	<b>0.6650</b>	0.0059
H-MSE-80	0.6527	0.0047	<b>0.6725</b>	0.0032
H-XS-80	0.6532	0.0053	<b>0.6785</b>	0.0055
GJD-EU	0.6410	0.0084	0.6375	0.0071
GJD-BC-10	0.6777	0.0080	0.6753	0.0082
GJD-BC-50	0.6770	0.0075	0.6742	0.0061
GJD-BC-100	0.6798	0.0065	0.6762	0.0069
SD-MATCHES	0.6015	0.0049	<b>0.6215</b>	0.0036
SD-SIMPLE	0.6295	0.0071	0.6288	0.0051
ERCF (250x250)	0.7245	0.0040	<b>0.7333</b>	0.0060

MCA: Mean classification accuracy. SME: Standard error of the mean.

# Experiments: region size

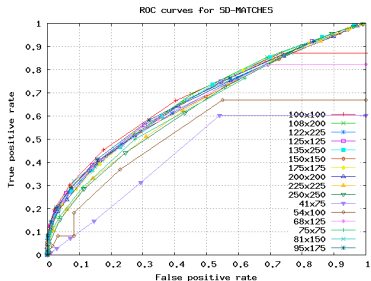
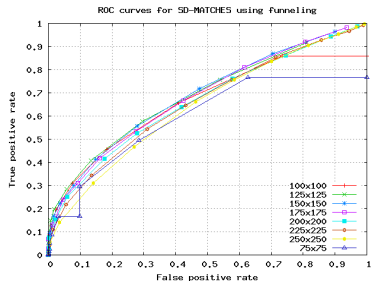
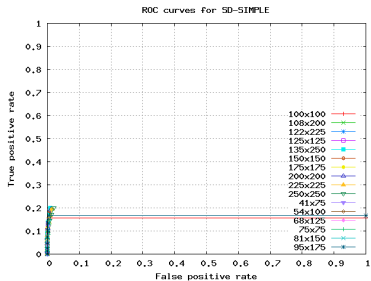
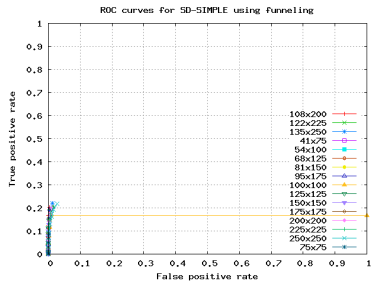
## Sizes

- Square image regions:  
50x50, 75x75, 100x100, ..., 250x250.
- Rectangular regions of ratio 1:1.85  
41x75, ..., 135x250.

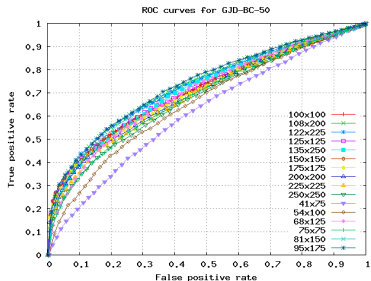
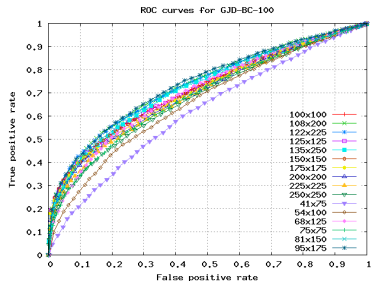
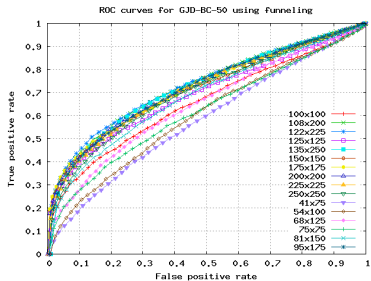
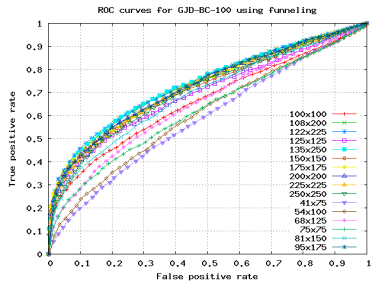
## Evaluation:

- Results are presented as ROC curves  
(True Positive rate vs False Positive rate).
- Processing time

# Experiments: SD

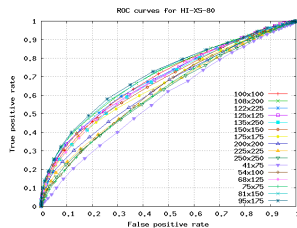
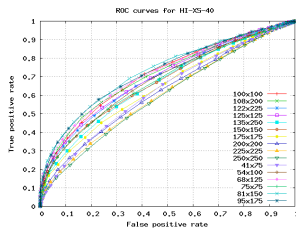
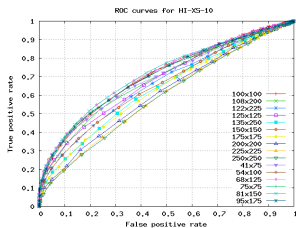
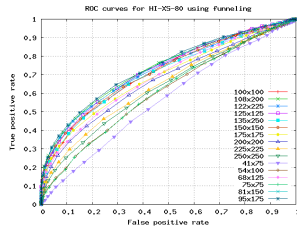
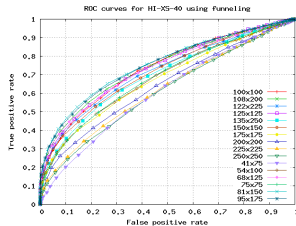
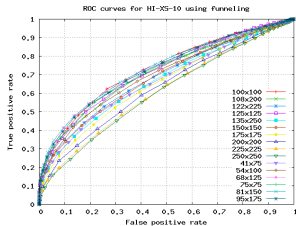


# Experiments: GJD

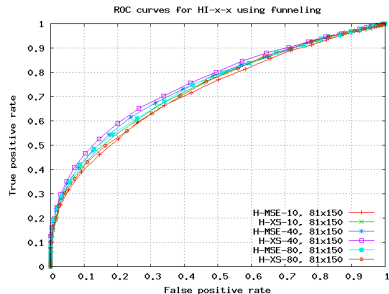
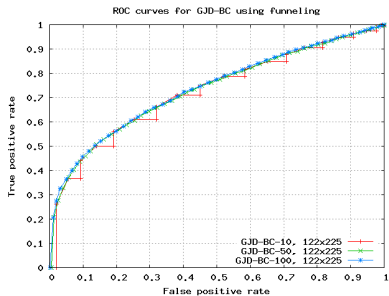
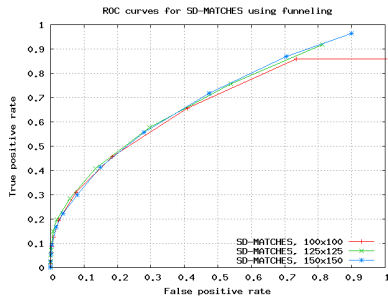




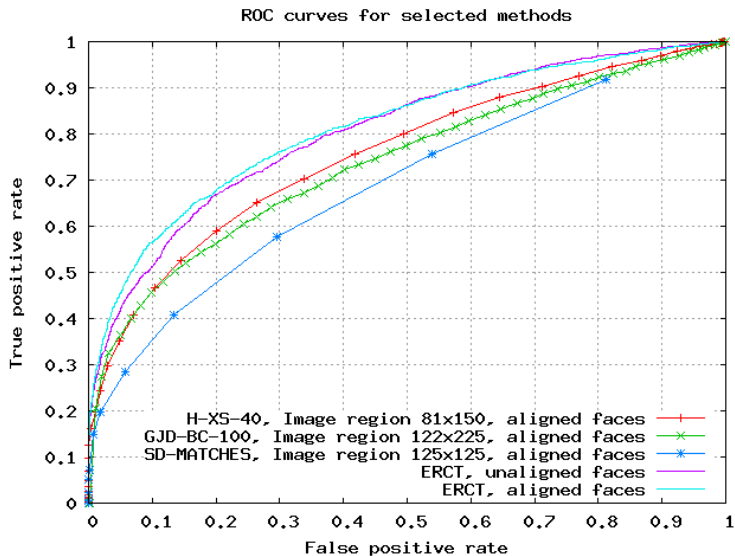
# Experiments: H (LBP)



# Experiments: Best for each method



# Experiments



## Experiments: Best size for each method



250x250	122x125	81x150	125x125
ERCF	GJD-BC	H-XS	SD

# Discussion

## Sizes

- In all cases (methods and parameters), small region sizes present the worst results, followed by the largest region sizes.

**Best results are obtained using medium-size regions.**

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- In all cases (methods and parameters), small region sizes present the worst results, followed by the largest region sizes.  
**Best results are obtained using medium-size regions.**

## Sizes: GJD-BC-X

- Aligned images: best results for size 122x225
- Unaligned images: best results for size 95x175
- In both cases, best results are obtained with 100 reference images.
- Aligned faces: reference image set size (10, 50 or 100) gives **very similar results for the optimal face size.**  
(68.38%, 68.38% and 68.47% respectively)
- Unaligned faces: slightly larger difference  
(67.52%, 67.8% and 68.08% respectively).

# Discussion

## Sizes: H-X-X

- Aligned images: best results for size 81x150.
- Unaligned images: best results for size 95x175.
- In both cases,
  - ▶ **best: 40 divisions**
  - ▶ worst: 80 divisions
- For a fixed number of divisions, **Chi-Square works better** than the euclidean distance.

# Discussion

## Sizes: H-X-X

- Aligned images: best results for size 81x150.
- Unaligned images: best results for size 95x175.
- In both cases,
  - ▶ **best: 40 divisions**
  - ▶ worst: 80 divisions
- For a fixed number of divisions, **Chi-Square works better** than the euclidean distance.

## Sizes: SD

- Aligned images: best results for size 125x125.
- Unaligned images: best results for size 100x100.
- **SD-Matches variant** gives best results in both cases.



## Discussion: Processing time

Table: Accuracy

Method	H-XS-40	GJD-BC-100	SD-Matches	ERCF
Size	81x150	122x225	125x125	250x250
MCA	0.6945	0.6847	0.6410	0.7333
SME	0.0048	0.0065	0.0062	0.0060

Table: Average processing time [millisec]

Method	H-X			GJD-BC			SD	ERCF
Size	81x150			122x225			125x125	250x250
Params	10	40	80	10	50	100	-	Nowak'08
<i>Time</i>	3.8	5.0	6.4	200	320	480	65	2000

Best LBP-based method (H-XS-40) is almost 3.9% below ERCF, and about 1% over GJDs best method (GJD-BC-100). In terms of the processing speed of the methods, the best variant of the LBP-based methods (H-XS-40), is at least 400 times faster than ERCF, and 96 times faster than the best Gabor-best method (GJD-BC-100).

# Conclusions

## Dependence on the region size

- Large dependence of the methods to the amount of face and background information that is included
- Region size is as important as alignment
- When the optimal size is used, other parameters become less relevant.
- Masking might further help.

# Conclusions

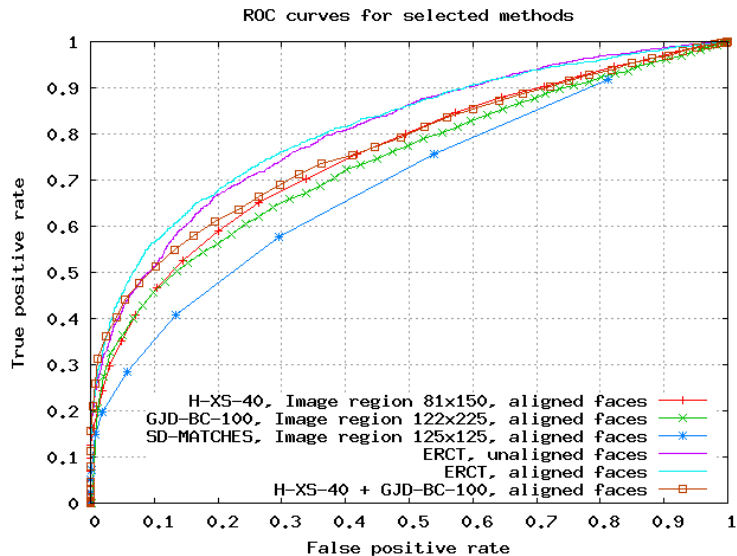
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## Summary

- LPB based method: Very fast, very simple and quite accurate.
- GJD based method: Relatively fast, simple and accurate.
- SIFT: not well fitted for face recognition.
- ERCF: Very slow, requires offline training, best performance on LFW. We have also evaluated ERCF in other databases: it seems to overfit and it has problems dealing with illumination changes.

# Combining methods



Thank you for your attention

- <http://rodrigo.verschae.org/about/> (presentation)
- <http://vision.die.uchile.cl> (UCH HRI Database)