The Role of Face Parts in Gender Recognition

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Motivation

Our goal is to evaluate the discriminant capabilities of the face parts in gender recognition

Why could it be interesting to evaluate the effectiveness of face parts?

- To use them in the presence of partial occlusions
  - The effectiveness of a face part can be taken as the reliability of the decision
- To evaluate the joint efficacy of several visible face parts

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Outline

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Related papers (I)

A comparison of the gender differentiation capability between facial parts[1]

- Face parts studied: jaw, mouth, nose, eyes and full face
- Images from a database of expressionless frontal Asian faces
- Regions manually clipped and represented by an appearance-based method
- Classified using linear discriminant analysis

The best recognition rate was 89.8% by the jaw; whereas the worst were achieved by the nose and the eyes and were lower than 80%

[1] Kawano,T., *et al.*

Related papers (II)

Gender classification of faces images: The role of global and feature-based information[2]

- Face parts studied: eyes, mouth and full face
- Images selected from three databases: FERET, AR and BioID
- PCA, CCA and SOM were applied to reduce the dimensionality feature space
- SVM with RBF kernel was used

The best recognition rate was 85.5% for the eyes and was dimensionality reduced using PCA. The worst rates were those achieved when SOM was applied.

[2] Buchala, S., *et al.*

Outline

Contribution

- Study of several classifiers
- Usage images from 2 databases
  - Selection of images of frontal faces without glasses
- Portraits of people of different races, ages and facial expressions
- Evaluation of a higher number of face parts

$$\Downarrow$$

More robust and general conclusion can be extracted from our results

Outline

Locating the interesting face parts (I)

- It is necessary to know where are located the face parts of interest
- The coordinates of the eyes are used to semi-automatically locate the face parts

Eight images containing the eyes, the nose, the mouth, the chin, the right eye, the internal face, the external face and the full face are extracted

Locating the interesting face parts (II)

- Steps of the process:
  1. Conversion into grey scale format
  2. Coordinates of the eyes are the start point
  3. Estimation of the grid using the eyes coordinates
  4. Histogram equalization of the area of the image inside the grid
  5. Selection of the regions which enclose the interesting face parts

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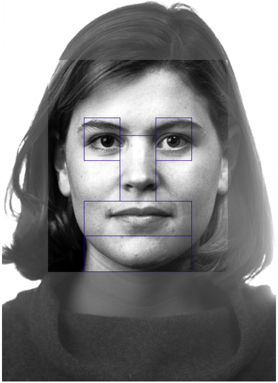
Locating the interesting face parts (II)



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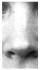
Extracting the face parts features (I)

- Local face parts:

Eyes

Right eye

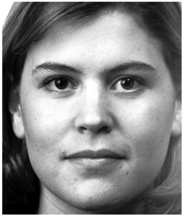


Nose

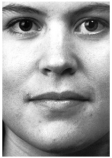
Mouth

Chin

- Global face parts:



Full face



Internal face

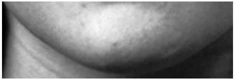
External face

Extracting the face parts features (II)

Feature extraction process

1. The images are scaled down to low resolution → the new pixels are computed by averaging the original ones
2. The new images are transformed into linear vectors
3. PCA is applied to the vectors to reduce dimensionality and to boost data information

Example of scaling chin's image down:

 →  → 

Outline

Overview

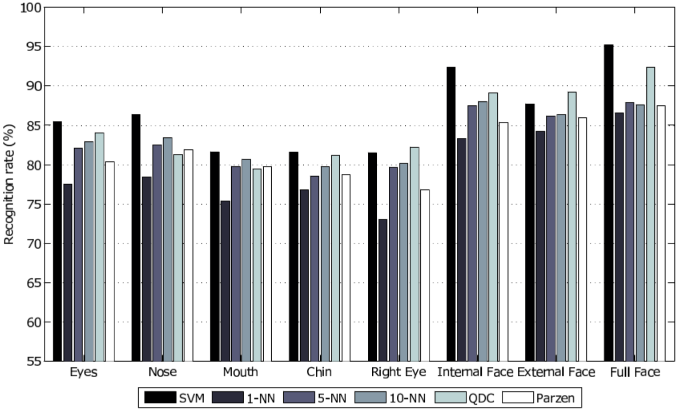
Databases details

- FERET: 2147 images → 842 female & 1305 male face images
- XM2VTS: 1378 images → 732 female & 646 male face images

Classification details

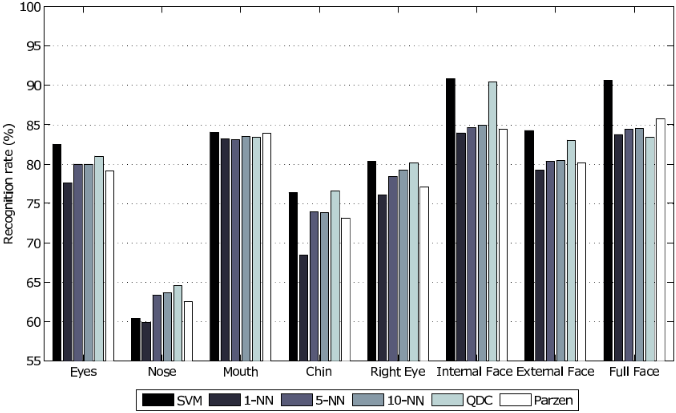
- Several learning algorithms:
  - SVM with a linear polynomial kernel,
  - {1,5,10}-Nearest Neighbour,
  - Quadratic Bayes Normal &
  - Parzen classifier
- 5-fold crossvalidation technique
  - All the face images of the same person are in the same subset

On FERET database



- Nose was the most relevant part (except using QDC)
- Nose and eyes were more discriminant than mouth and chin
- External face was almost as discriminant as internal face
- Global parts were more accurate in the recognition

On XM2VTS database



- Mouth and eyes were the most relevant parts
- Nose was surprisingly ineffective
- Mouth was as effective as global parts with several classifiers
- Internal face appeared to be as discriminant as full face

Discussion of results

- Eyes gave rise to good classification in both databases and mouth and chin were also effective
- Nose produced conflicting results → high exposure to changes in illumination and descriptions more unstable
- Poorer results in XM2VTS
  - Differences between databases: number of subjects is 4 times greater in FERET and it has twice as many images per subject
- External face was capable enough to distinguish between genders → relation between gender and traditional cultural patterns
- There was a high correlation among classifiers

Evaluation of complementarity of face parts

Successful cases (%)					**Error cases (%)**			
		eyes	nose	mouth	chin	internal face	external face	full face
	eyes	-	8.8	13.97	14.01	3.35	8.01	2.46
	nose	9.68	-	11.73	12.90	3.07	7.49	1.63
	mouth	10.10	6.98	-	8.57	2.65	6.28	1.76
	chin	10.10	8.10	8.52	-	3.16	6.42	1.95
	internal	10.24	9.08	13.41	13.97	-	9.08	2.14
	external	10.24	8.84	12.38	12.57	4.42	-	1.02
	full	12.20	10.47	15.37	15.60	4.98	8.52	-

- Performance of the eyes-based SVM could be improved → 10% of the errors could be corrected
- Recognition rate of SVM trained from full faces could reach 97% using the information of the eyes

Significant complementarities between pairs of face parts exist, so effective and robust ensembles of classifiers can be proposed

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Conclusions

- Two databases, several classifiers and eight face parts → more general and robust conclusions
- Local face parts have succeed with rates above 80% and global parts with rates over 95%
- Experiments have evaluated the dependence of the results on the database and the classifier → they are strongly dependent on the database
- There is a complementary relation between pairs of face parts → ensembles more effective than the plain classifiers studied could be proposed

Future work

- This effort is part of a project in which gender recognition is investigated under partial occlusions of the face
- Ensembles of classifiers are being evaluated to take advantage of the complementarity relation between face parts
  - The first results have been accepted in the *13th Iberoamerican Congress on Pattern Recognition*
- Our plan includes the tasks of recognizing race and age from portraits with occlusions

Thank you for your attention

For further information...

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