Image-Based Face Recognition using Global Features

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Outline

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- Preprocessing
- Recognition technology:
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  - Feature-based matching
  - Holistic matching
    - Eigenfaces
    - Fisher’s Linear Discriminant (FLD)
    - Laplacianfaces
  - Hybrid method
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- Summary

Face recognition

- A formal method first proposed by Francis Galton in 1888
- A growing interest since 1990
- Research interest has grown:
  - Increasing commercial opportunities
  - Availability of better hardware, allowing real-time applications
  - The increasing importance of surveillance-related applications
  - Great improvements have been made in the design of classifiers

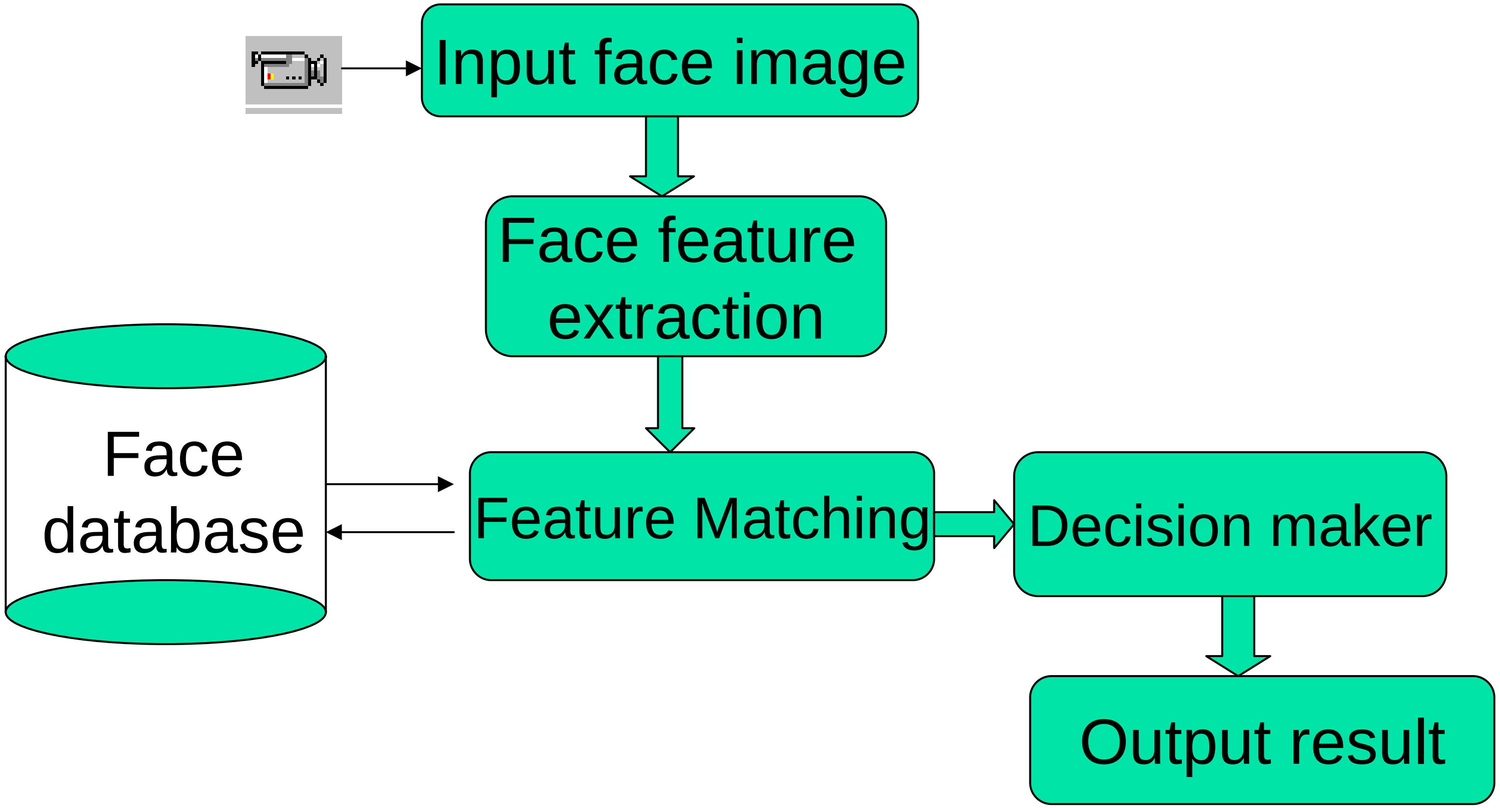
Face recognition

- Why face recognition?
  - Verification of credit card, personal ID, passport
  - Bank or store security
  - Crowd surveillance
  - Access control
  - Human-computer-interaction

Face recognition

- Evaluation of performance :
  - Precision of matching (Recognition rate)
  - Resistance against adverse factors (noise, facial expression…)
  - Computational complexity
  - Cost of the equipment

Face recognition: Procedure



Preprocessing

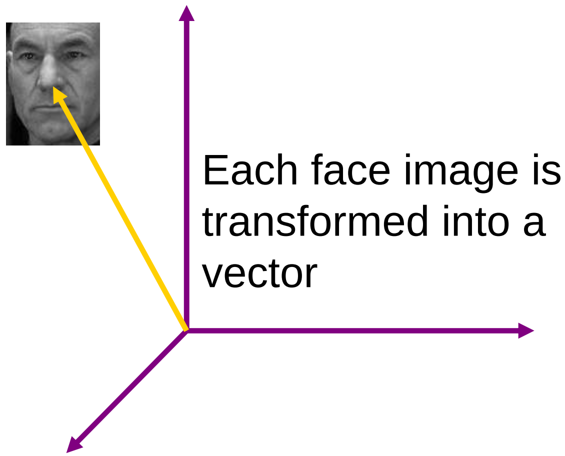
- Several preprocessing might be needed:
  - <u>Segmentation:</u>
    - Eliminate the background
  - <u>Scaling:</u>
    - Performance decreases quickly if the scale is misjudged
  - <u>Rotation:</u>
    - Symmetry operator to estimate head orientation

Recognition technology

- Three matching methods:
  - <u>Feature-based (structural) matching:</u> Local features such as the eyes, nose, and mouth

    ------> easily affected by irrelevant information

  - <u>Holistic matching:</u> Use the whole face region as the raw input (PCA, LDA, ICA…)



  - <u>Hybrid method:</u> Use both

Recognition technology
Feature-based VS. Holistic methods

Feature-based methods	Holistic methods
Local features	Global properties
Have more practical value and simpler	Complex algorithm, long training or special conditions
Accuracy problem	Storage problem
Allow perspective variation	Also allow perspective variation, better performance
Need accurate feature location	Accurate feature location improves the performance

Recognition technology: Feature-based matching

- Find the locations of eyes, nose and mouth, extract the feature points

- Use the width of head, the distances between eye corners, angles between eye corners, etc.

- Try to find invariant features

Recognition technology: Feature-based matching

- Algorithm:
  - Extracting feature points

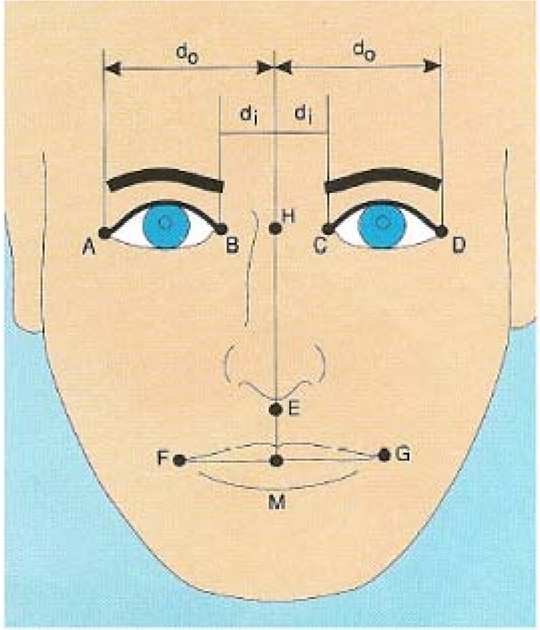
    ---->affected by head orientation
  - Define cross ratio of any four points on a line

    ----> Invariant distances
  - Correct the location of feature points

    ---->apply symmetry and cross ratio
  - The normalized feature vector:

$$N = \frac{F}{||F||}$$

  - Similarity measure: Euclidean distance



Recognition technology: Holistic matching

- One of the most successful and well-studied technique

  ------->holistic matching

- Represent an image x_i of N pixels by a vector N*1 in an N-dimensional space

  ------->too large for robust and fast FR

- Use dimensionality reduction techniques

Recognition technology: Holistic matching

- Find a set of transformation vectors (displayed as feature images), put them into W of size N*d

  ------>define the face subspace

- Project the face images onto the “face subspace”

  ------> $y_i = W^T x_i$, size of y_i is d*1

Holistic matching: Eigenfaces

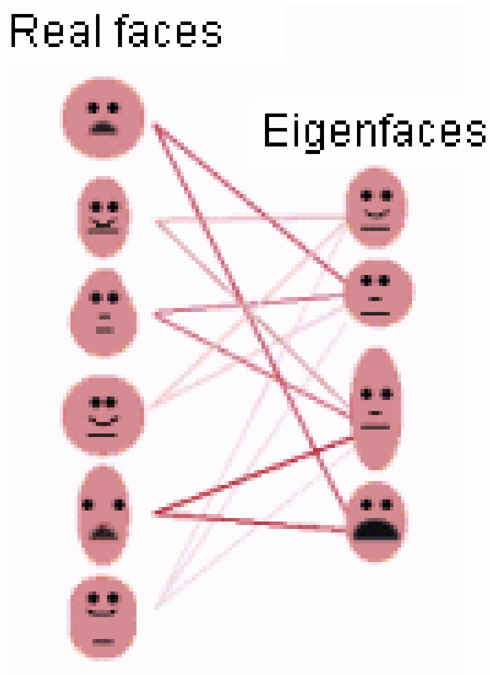
- One of the best global representation
- Central idea:

  Find a weighted combination of

  a small number of transformation vectors that can approximate any face in the face database → Eigenfaces
- An image can be reduced to

  a lower dimension →Projection
- Objective function, maximize the variation:

$$\max \sum_{i=1}^{n} (y - \bar{y})^2$$



Holistic matching: Eigenfaces

- Algorithm:
  - The covariance matrix: $\Omega = XX^T$
  - The principal components are the eigenvectors E of Ω

$$\Omega E = \Delta E$$

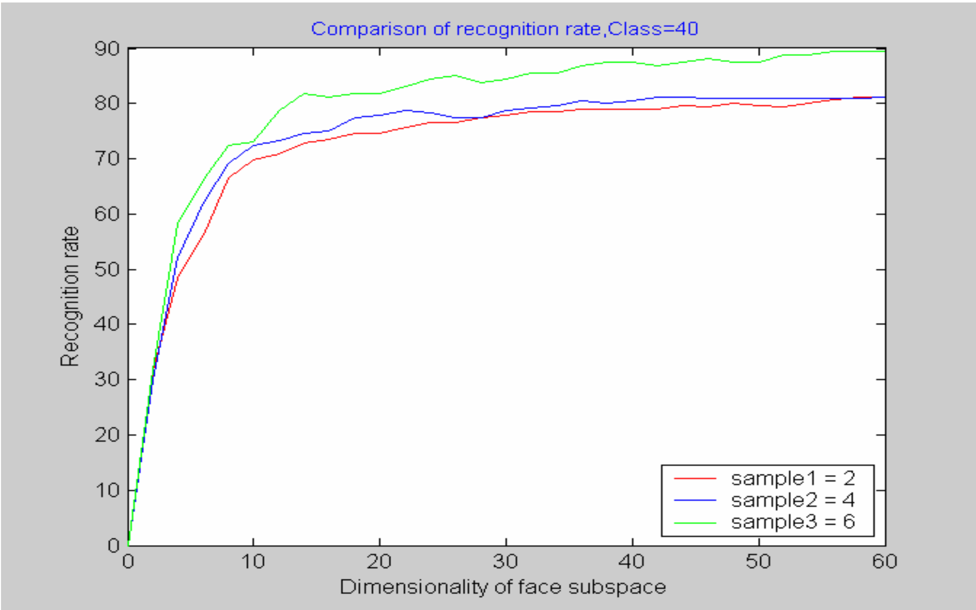
  - Truncate E → projection matrix E_d
  - The projection of an image:

$$y' = E_d \times (y - x_u)$$

  - A new image is recognized using a nearest neighbor classifier in a Eigenface subspace.

Holistic matching: Eigenfaces

- Classify a new face as the person with the closest distance
- Recognition accuracy increases with number of eigenfaces until 25
- Additional eigenfaces do not help much with recognition



<u>Best recognition rates</u>

Test set 90%

Holistic matching: Eigenfaces

- Run-time performance is very good
- Construction: computationally intense, but need to be done infrequently
- Fair robustness to facial distortions, pose and lighting conditions
- Need to rebuild the eigenspace if adding a new person
- Start to break down when there are too many classes
- Retains unwanted variations due to lighting and facial expression

Holistic matching: Fisher's Linear Discriminant (FLD)

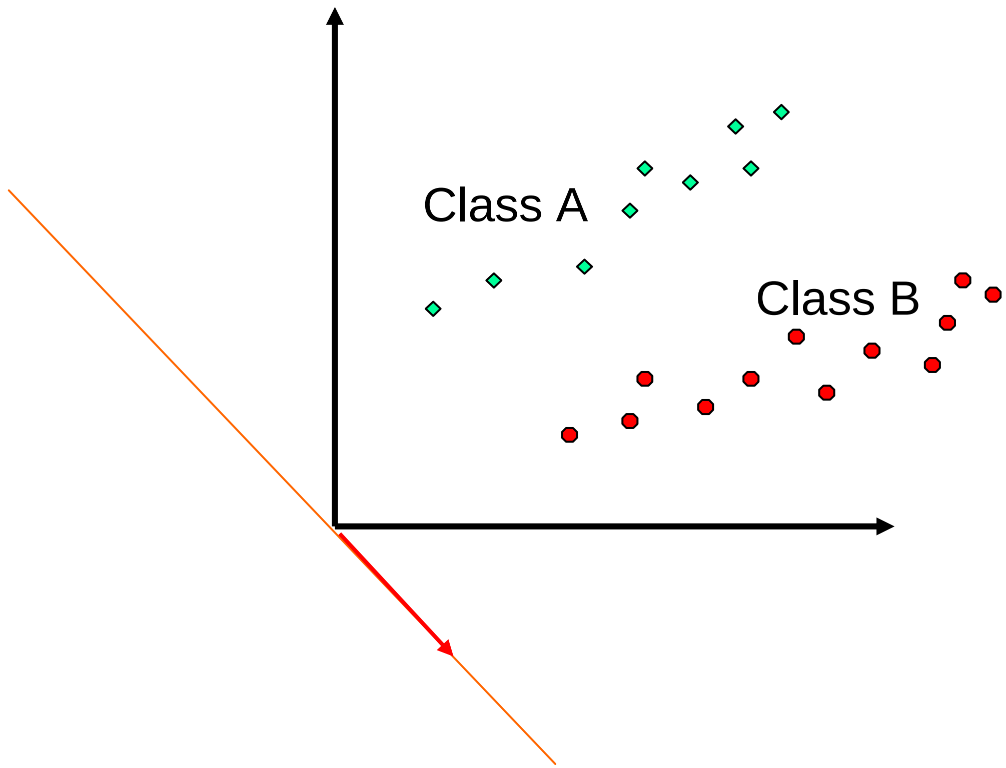
- Eigenfaces achieves larger total variance, FLD achieves greater between-class variance, and, consequently, classification is simplified.

- FLD tries to project away variations in lighting and facial expression while maintaining discriminability.

- It maximizes the ratio of between-class variance to that of within-class variance.

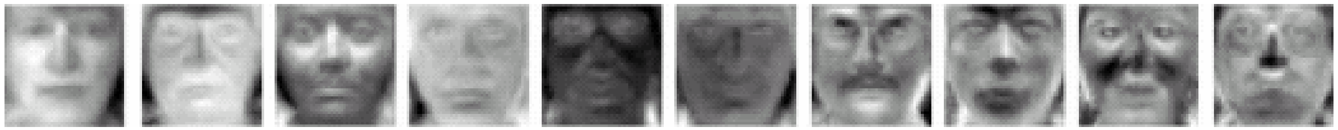
Holistic matching: Fisher's linear discriminant

- Fisherface seeks directions that are efficient for discrimination between the data.

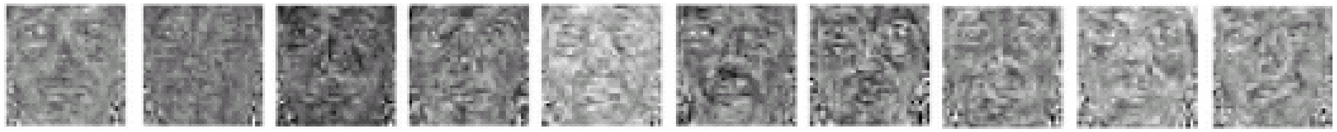


Holistic matching: Laplacianfaces

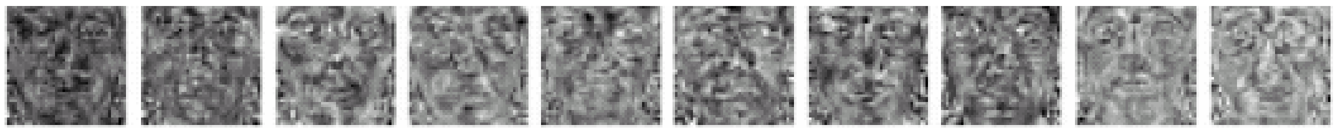
- Laplacianfaces method aims to preserve the local information.
- Unwanted variations can be eliminated or reduced.



Eigenfaces



Fisherfaces



Laplacianfaces

Holistic matching: Laplacianfaces

- Take advantage of more training samples, which is important to the real-world face recognition system

- More discriminating information in the low-dimensional face subspace

- Better and more sophisticated distance metric: variance-normalized distance

Recognition technology: Hybrid method

- Human perception system: use both local features and the whole face region to recognize a face
- The modular eigenfaces approach:
  - Global eigenfaces
  - Local eigenfeatures: eigeneyes, eigenmouth, etc.
- Useful when gross variations present
- Arbitrate the use of holistic and local features

Future work

- Implementation and detailed study of the novel algorithm→ <u>Laplacianfaces</u>
- Provide the system with an accurate feature-localization mechanism
- Try to combine the global feature with local feature
- Compare the performance of different classifiers, besides the nearest-neighbor classifier
- Evaluate the performance of the three systems on different face databases

Summary

- Face recognition:
  - How to model face variation under realistic settings
  - Without accurate location of important features, good performance can not be achieved
- Shortcomings of current algorithms:
  - Large amounts of storage needed
  - Good quality images needed
  - Sensitive to uneven illumination
  - Affected by pose and head orientation

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