



Face Recognition

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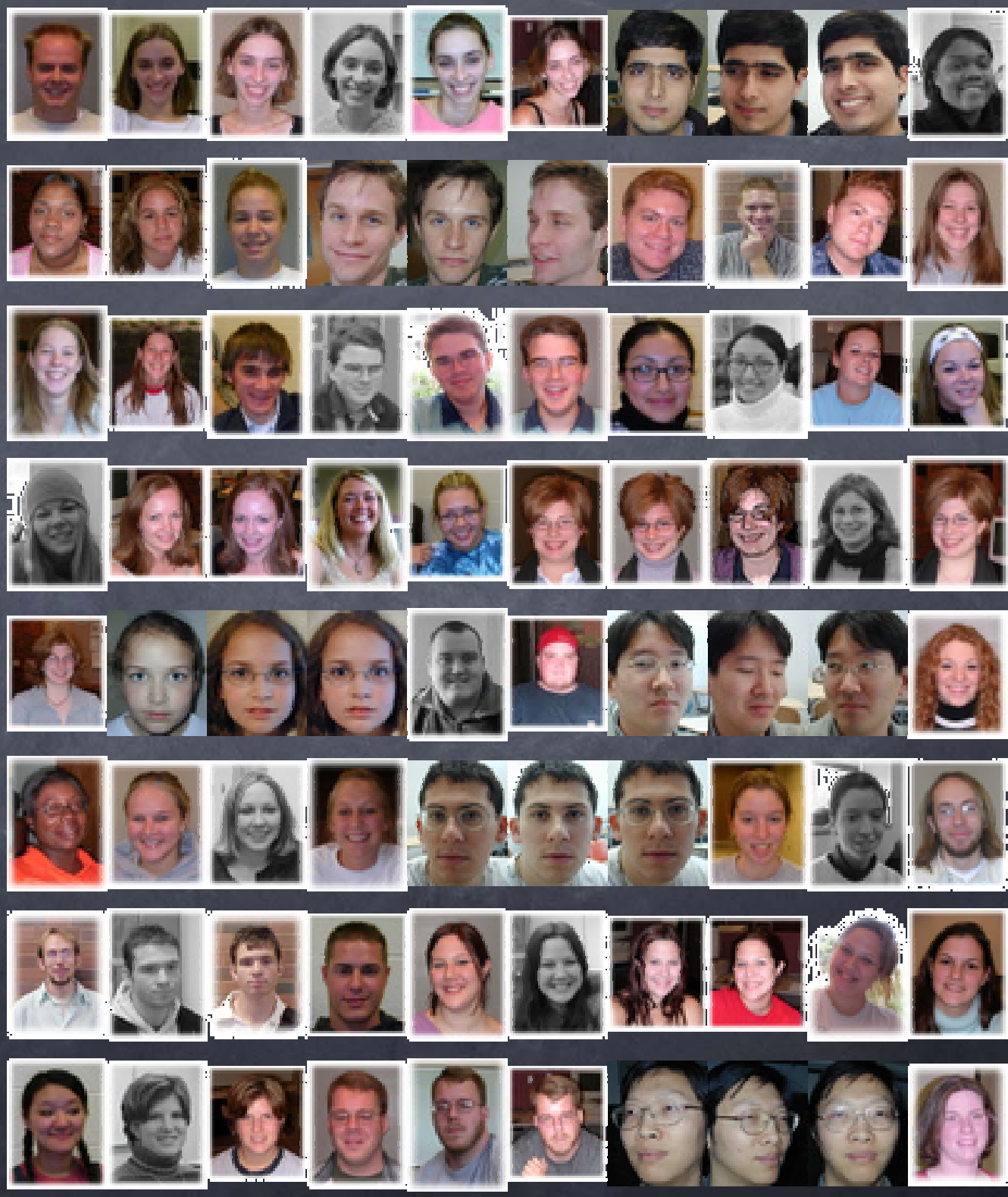
June 2, 2004

Outline

- Problem & History
- Mathematics
- Results
 - UMIST (controlled lighting)
 - ALAN (typical face snapshots)
- Ideas for Further Work

Problem Definition

Who is this?



Assumptions

- Face detection is done, so we know:
 - scale,
 - rotation,
 - and alignment



CMU's face detection online demo

<http://www.vasc.ri.cmu.edu/cgi-bin/demos/findface.cgi>

detected 77/80 faces with defaults. See results here:

<http://vasc.ri.cmu.edu/demos/faceindex/05312004/users/4333.html>.

History: Influential Contributions

- 1964, 1970, 1977: Facial feature-based recognition (Bledsoe, Kelly Kanade)
- 1984: WIZARD neural net approach (Stonham)
- 1991, 1994: Eigenface PCA (Pentland & Turk)
- 1997: Fisherface FLD + PCA (Belheumeur)
- 2000: FERET standard testing method & database
- 2002: Indep Component Analysis (ICA) captures higher-order statistics (Bartlett)
- 2003: Kernel, SVM, RBF, combos (Liu, Er)
- 2004: Plenoptic light-fields (Gross), 2D-PCA (Yang)

our
focus

Mathematics: Eigenface

Given:

training
images

#1



N

...

#M



recognition
images

#1



N

...

#c



M_p = desired #
of principal
components

Feature Extraction:

$$X = [x_1 \ x_2 \ \dots \ x_m]$$

column vector for
each train face

$$me = \text{mean}(X, 2)$$

average face



$$A = X - [me \ me \ \dots \ me]$$

$$[U, E, V] = \text{svd}(A, 0)$$

avoids $N^2 \times N^2$ matrix computation of $[V, D] = \text{eig}(A^* A')$
only computes M columns of U : $A = U * E * V'$

$$\text{eigVals} = \text{diag}(E)$$

$$lmda = \text{eigVals}(1:M_p)$$

$$P = U(:, 1:M_p)$$

pick face-space principal
components (eigenfaces)

$$\text{train_wt} = P' * A$$

store weights of training data
projected into eigenspace

Nearest-Neighbor Classification:

$$\text{recog_wt} = P' * A_2$$

A_2 created from
the recog data

$$\text{euDis}(i, j) = \text{sqrt}((\text{recog_wt}(:, j) - \text{train_wt}(:, i))^2)$$

i^{th} recog face,
 j^{th} train face

Mathematics: Fisherface

Given:



P_1 = eigenface
result (used
by fisherface)

Feature Extraction:

$$A = X - [\text{me me} \dots \text{me}]$$

same as eigenface

for $i=1:c$

$$S_b = S_b + \text{clsMean}_i * \text{clsMean}_i'$$

computes $N^2 \times N^2$ **between**-class scatter matrix

for $i=1:c, j=1:c_i$

$$S_w = S_w + (X(j) - \text{clsMean}_i) * (X(j) - \text{clsMean}_i)'$$

computes $N^2 \times N^2$ **within**-class scatter matrix

$$S_{bb} = P_1' * S_b * P_1$$

$$S_{ww} = P_1' * S_w * P_1$$

PCA project into $(N-c) \times (N-c)$ subspace

$$[V, D] = \text{eig}(S_{bb}, S_{ww})$$

generalized eigenvalue decomposition
solves $S_{bb} * V = S_{ww} * V * D$

$$\text{eigVals} = \text{diag}(D)$$

$$\text{lmda} = \text{eigVals}(1:M_p)$$

$$P = P_1 * V(:, 1:M_p)$$

$$\text{train_wt} = P' * A$$

store training
weights

Databases

UMIST

- By Daniel B Graham
- <http://images.ee.umist.ac.uk/danny/database.html>
- 20 people, 565 images
(avg of 28 images per person)
- Constructed under controlled lighting & background conditions, with a purpose of being used for facial recognition algorithm testing.
- Varied pose uniformly from frontal to side view.

ALAN

- By Alan Brooks
- <http://pubweb.northwestern.edu/~acb206/ece432/tmbwClassOval40x60.zip>
- 14 people, 47 images
(avg of 3 images per person)
- Gathered from collections of snapshots taken at different times. No controlled lighting or backgrounds.
- Pre-processed by hand to align, normalize, and remove background.

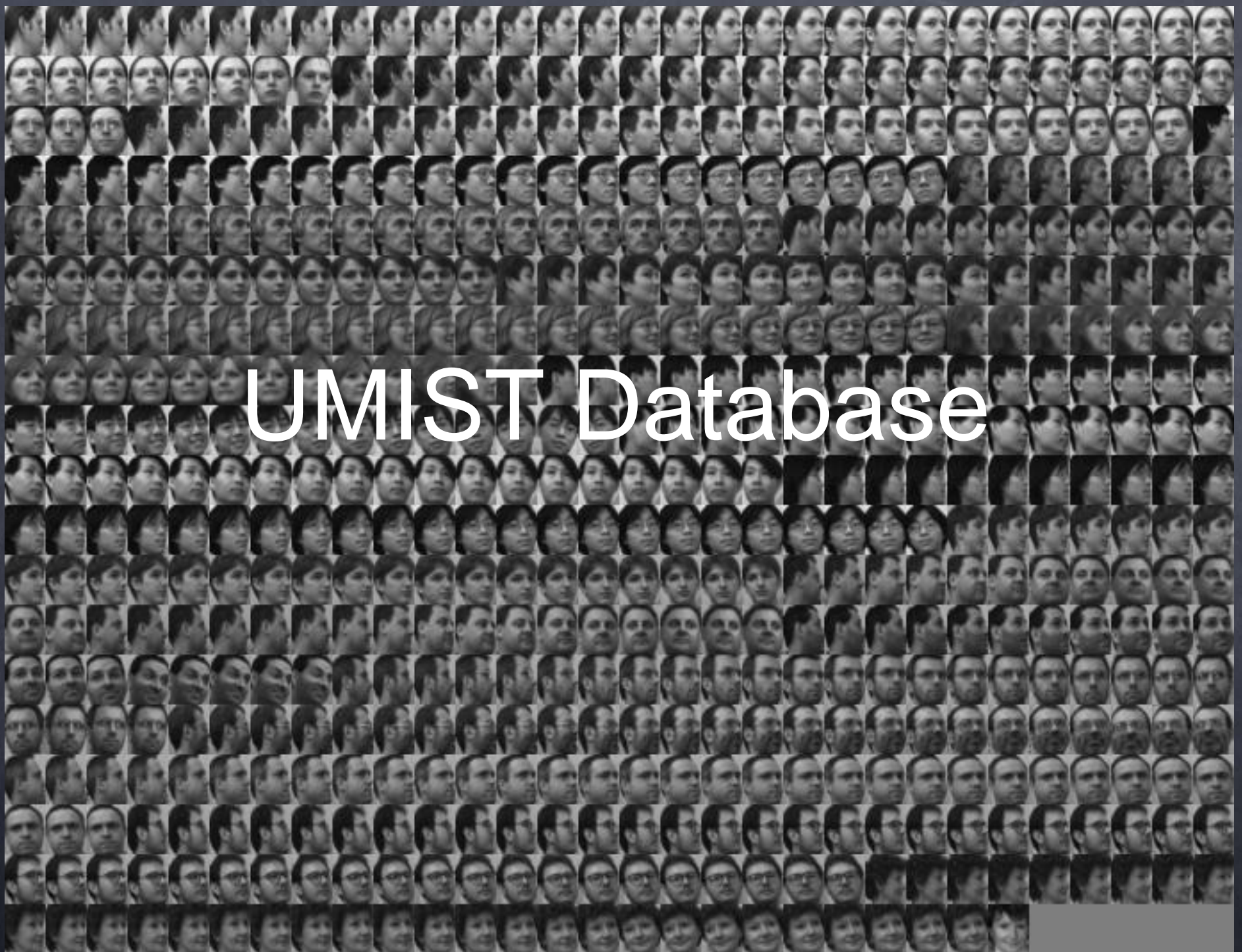


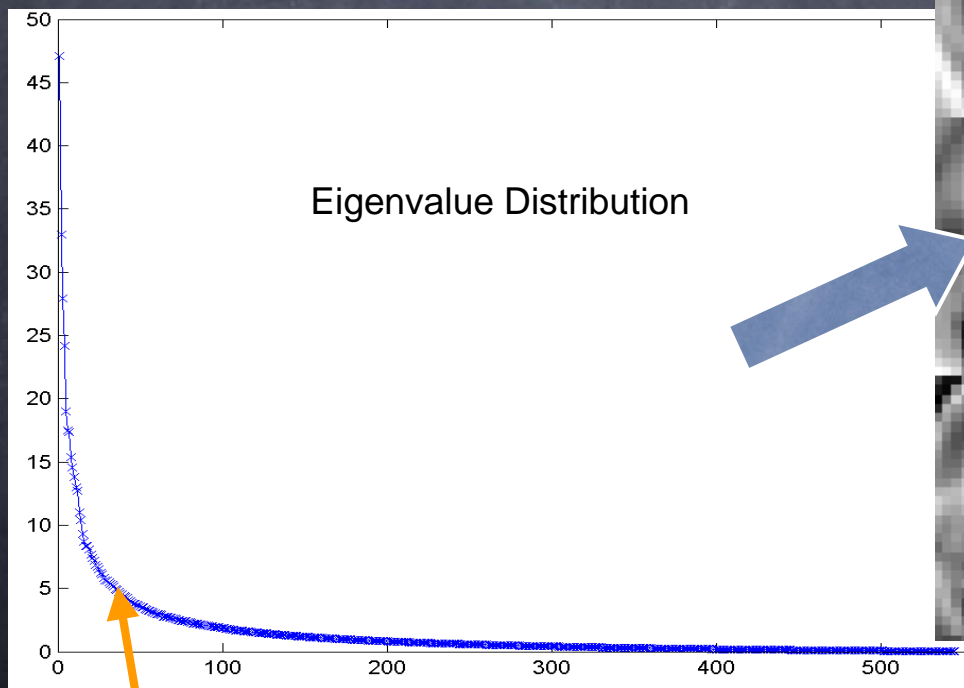
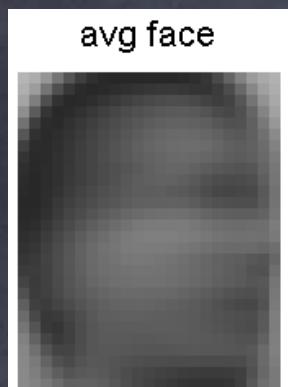
Image produced using ImageMagick's "montage" command like this:

```
$ montage +frame +shadow +label -tile 30x20 -geometry 23x28+0+0 -background gray *.* joined.jpg
```

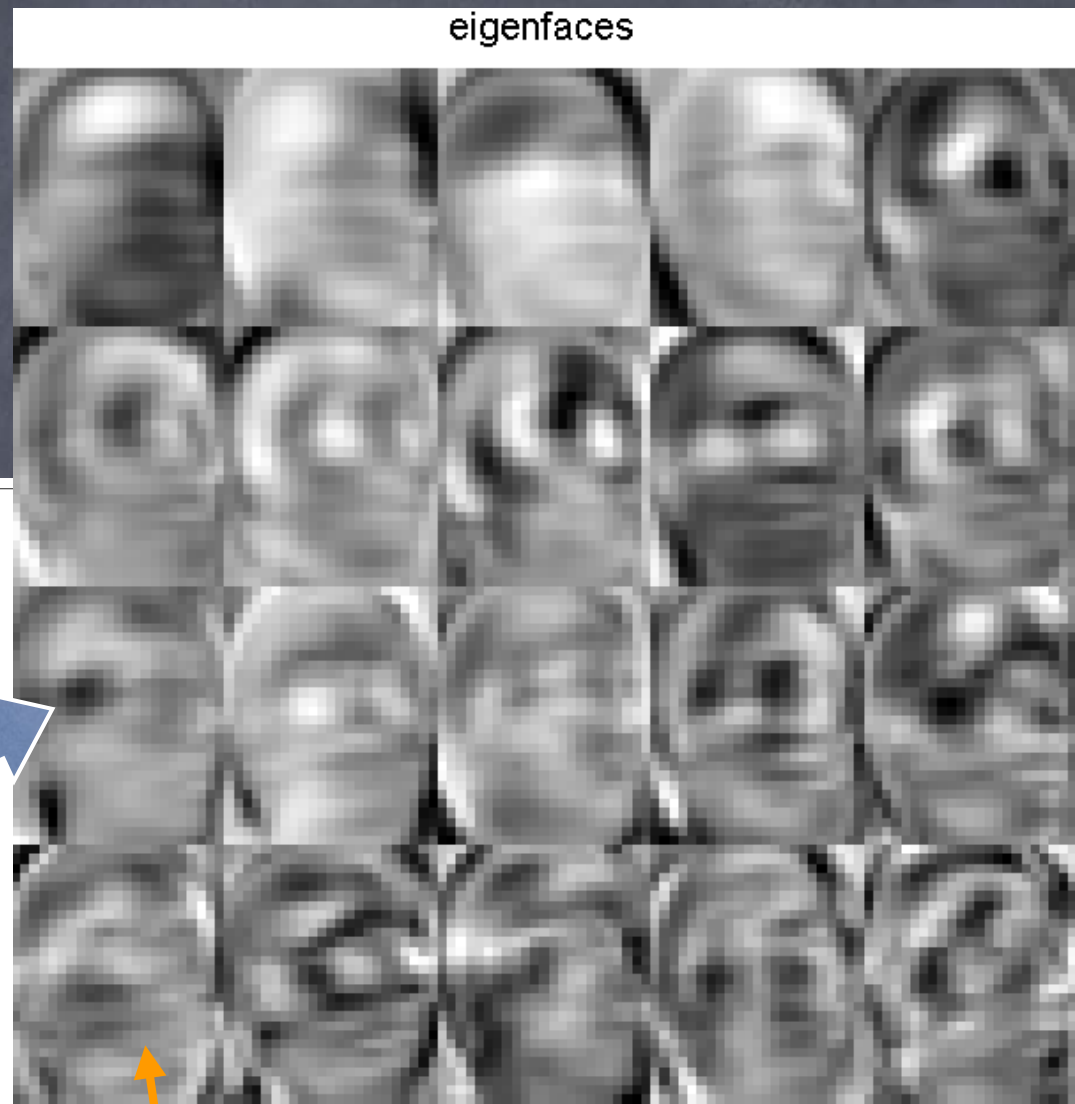
UMIST Results Using Eigenface Approach

- 545 training faces from 20 people
- 20 recognition faces (randomly picked from database)

Feature Extraction



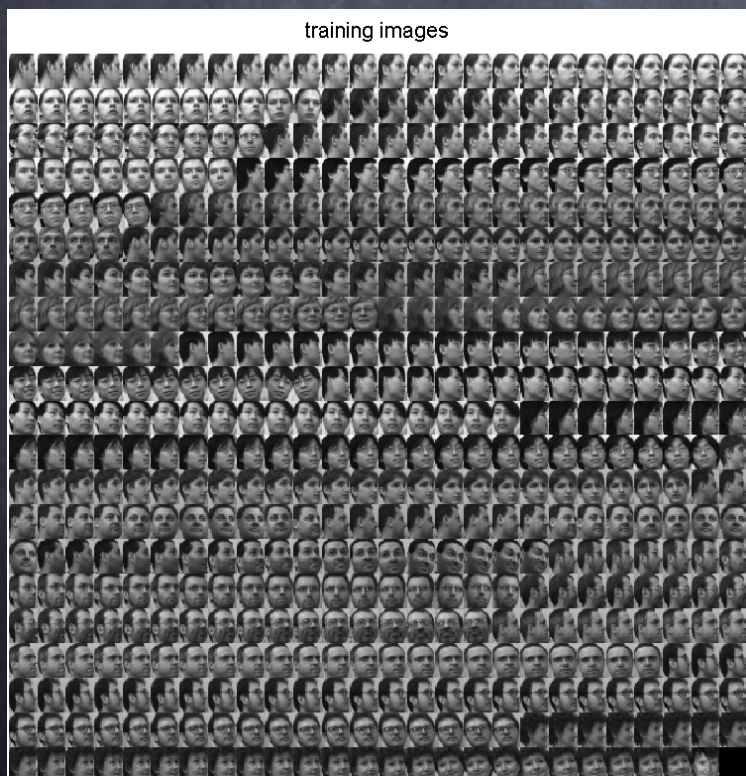
20 largest eigenvalues



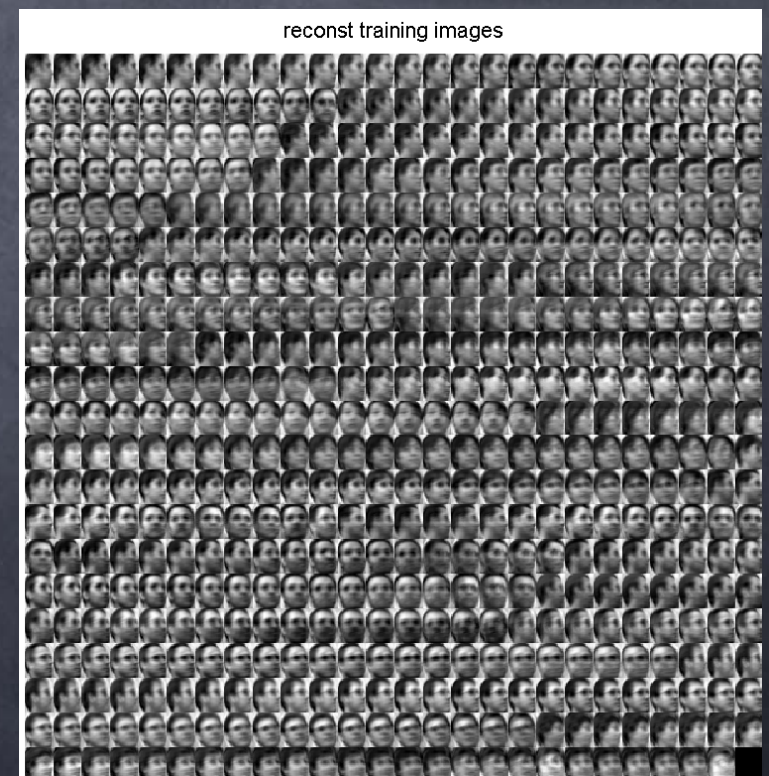
20 corresponding
eigenfaces (eigenvectors)

Training

- Keeping M_p (20) principal components, project all training data into subspace and store projection weights.
- Weights can be used to reconstruct faces.

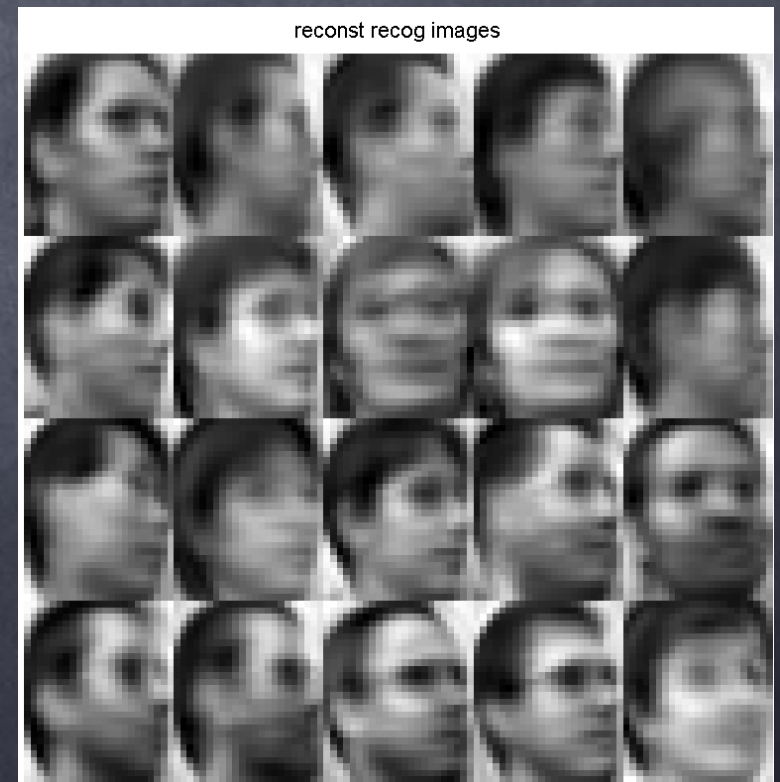
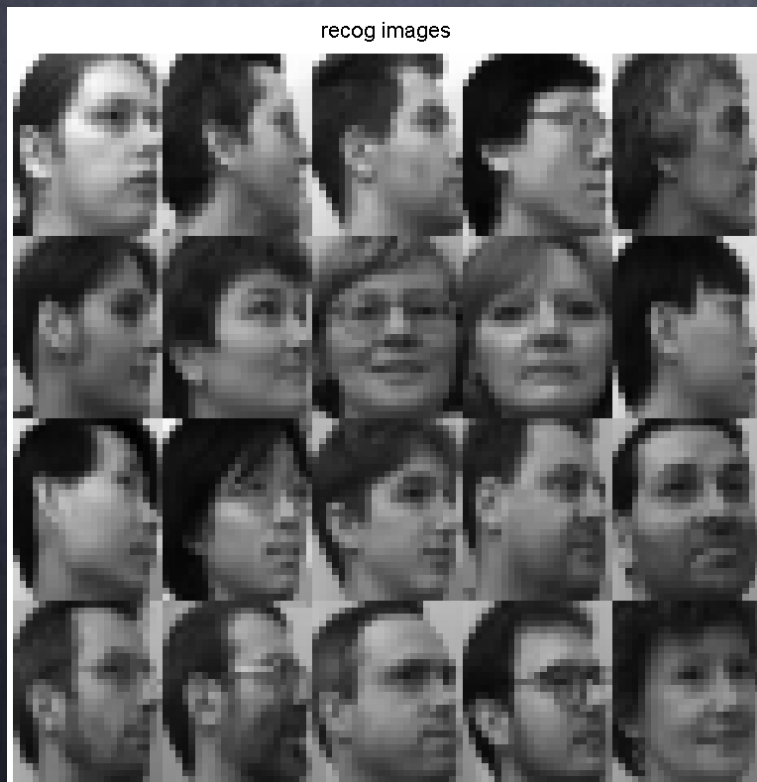


Store
weights
as
training
data

A diagram showing the flow from training images to reconstructed training images. It consists of two blue arrows pointing from the 'training images' grid to the 'reconst training images' grid, with the text 'Store weights as training data' centered between them.

Projection

- Project new faces into eigenface-space.



Classification

- Classify by comparing projection weights of new faces to known face weights.
- 20 of 20 (100%) faces correctly classified.

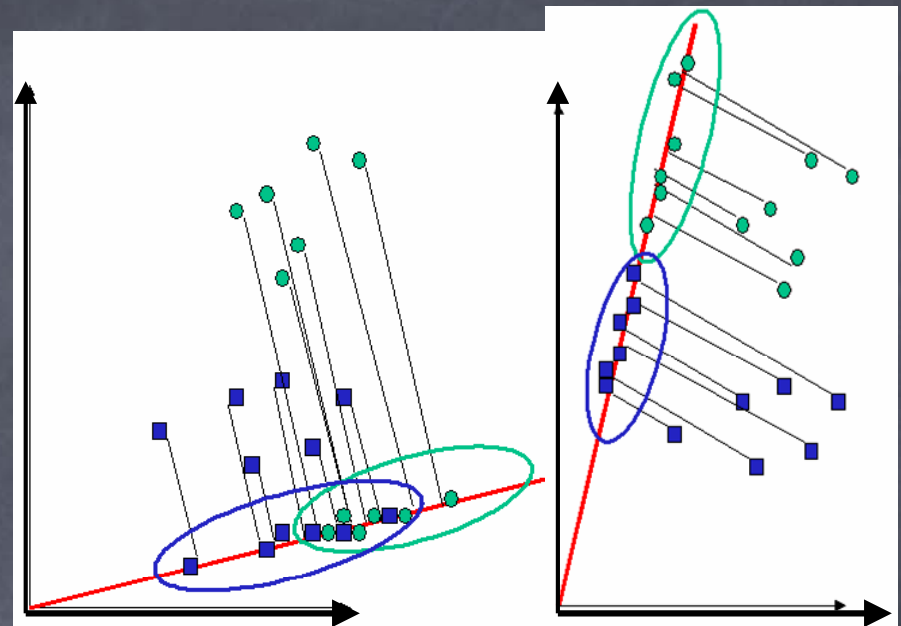
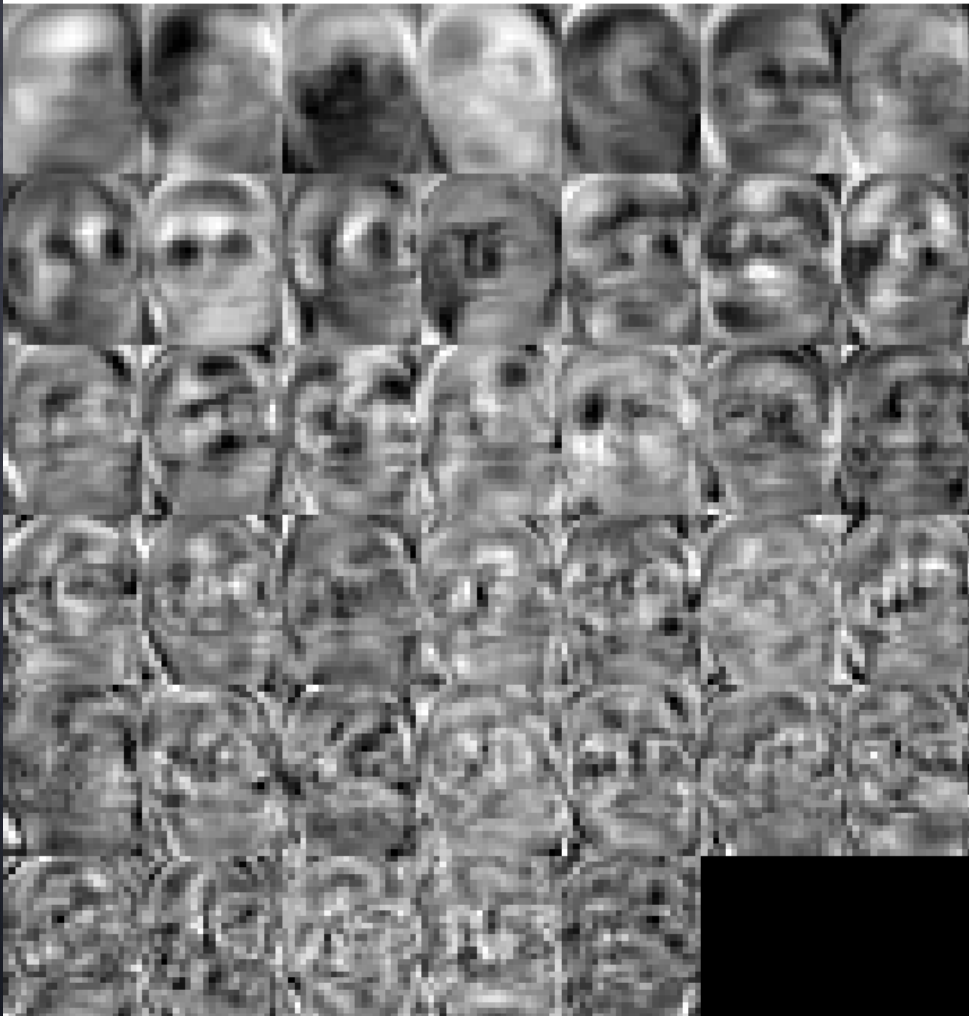


UMIST Results Using Fisherface Approach

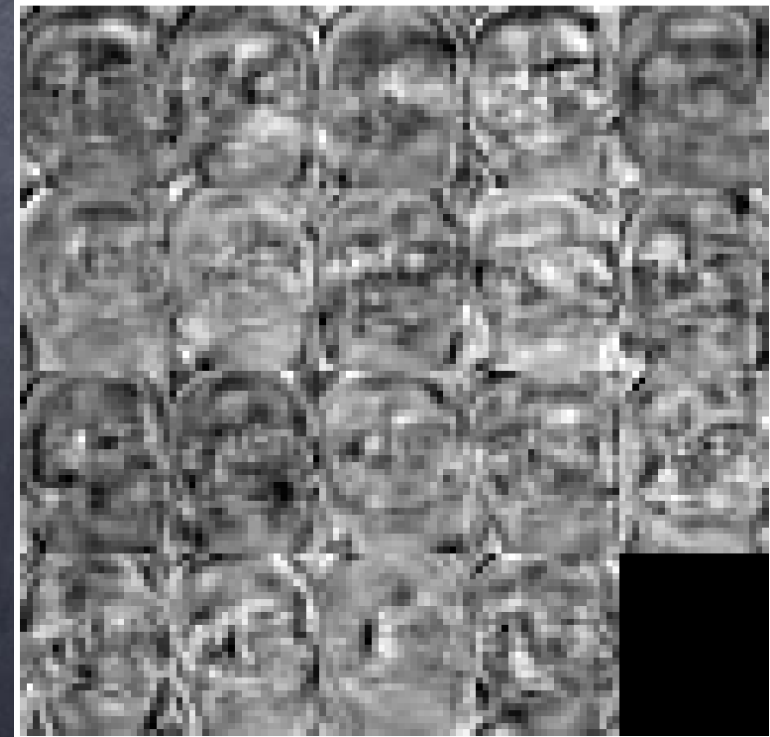
- Subset of UMIST data
- 60 training faces from 20 people (front, angled, profile pose)
- 20 recognition faces (randomly picked from database)

Feature Extraction

eigenfaces

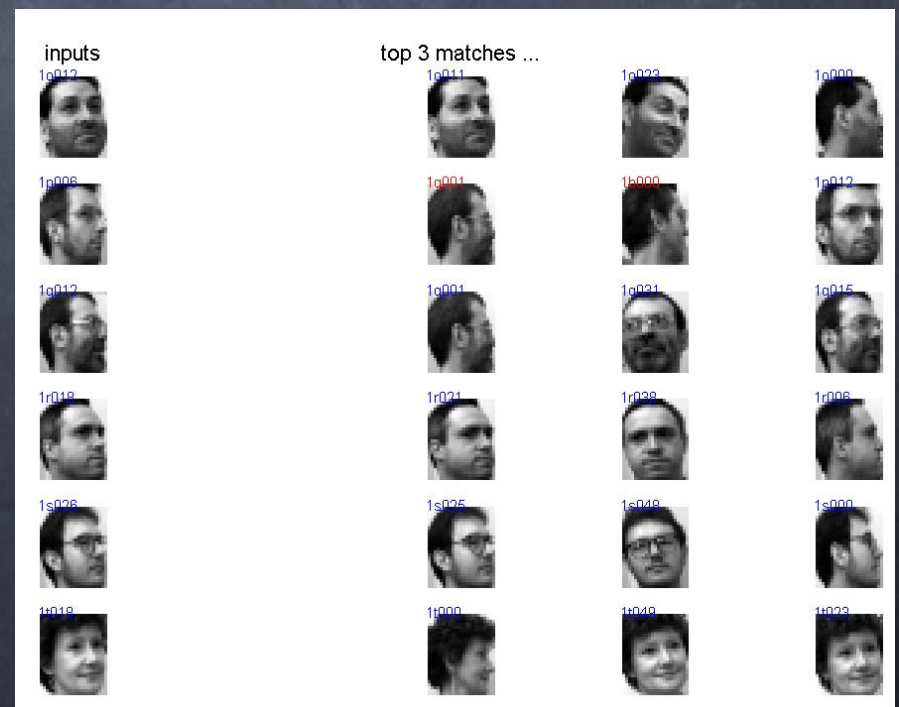


fisherfaces



Classification

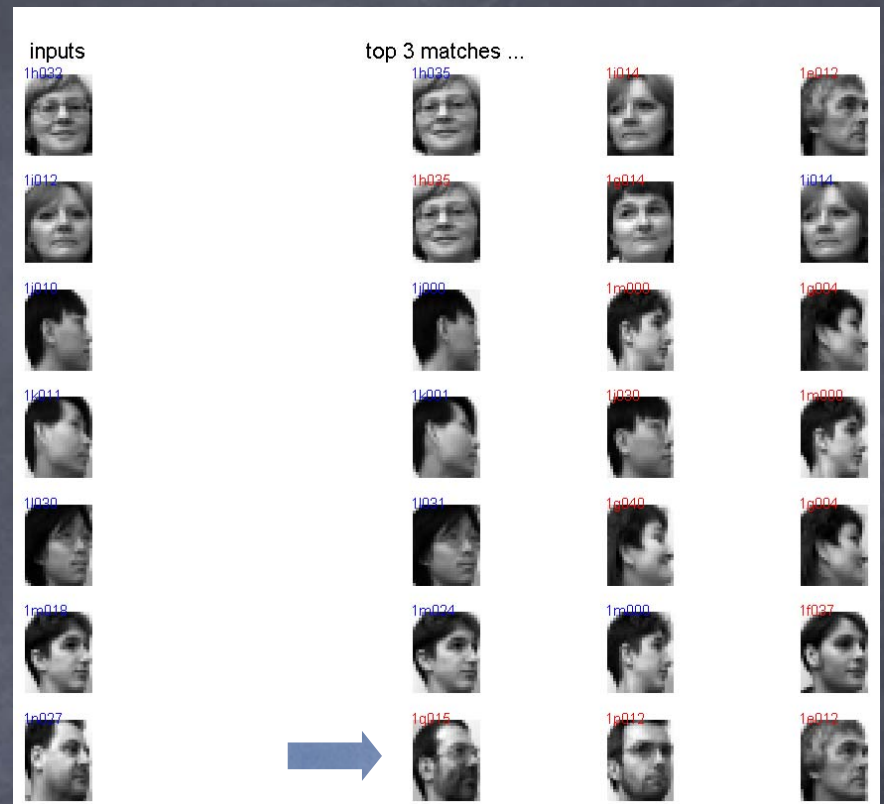
- Fisherface: 16 of 20 (80%) faces correctly classified.
- Pose invariant in top 3: often (13 times) picks all 3 correct database images.



Classification

For comparison:

- Eigenface (with the same data): only 14 of 20 (70%) were correctly classified.
- Picks same pose, wrong people in top 3. Never gets all 3 correct poses.



Fisherface (FLD) vs. Eigenface (PCA)

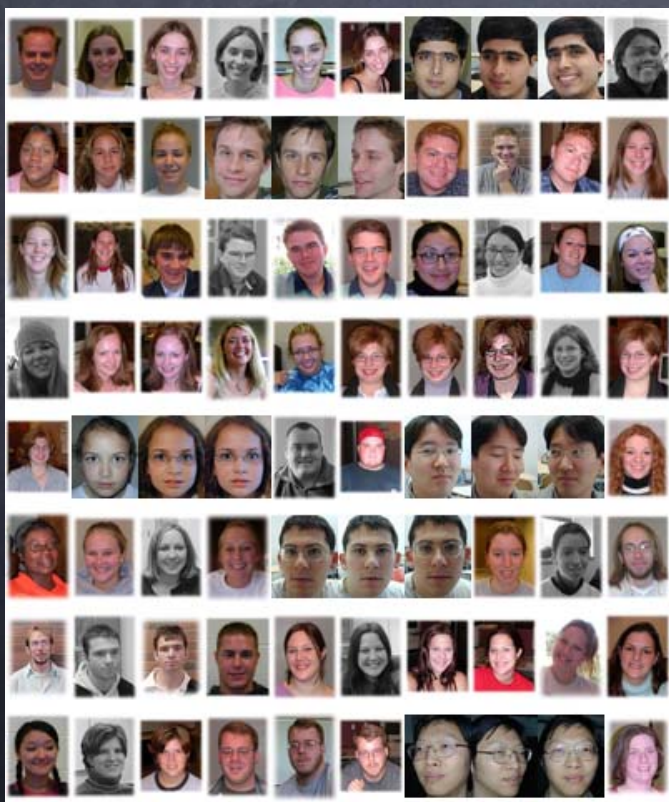
	Fisherface	Eigenface
Computational Complexity	slightly more complex	simple
Effectiveness across Pose	good, even with limited data	some, with enough data
Sensitivity to Lighting	little	very

ALAN Database Results

- 26 training faces from 11 people
- 11 recognition faces (randomly picked)

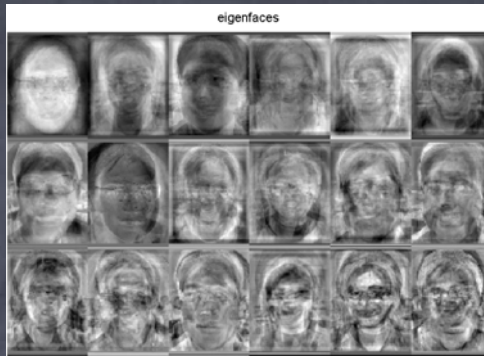
Preprocessing Important

- Lighting, scale, alignment, background

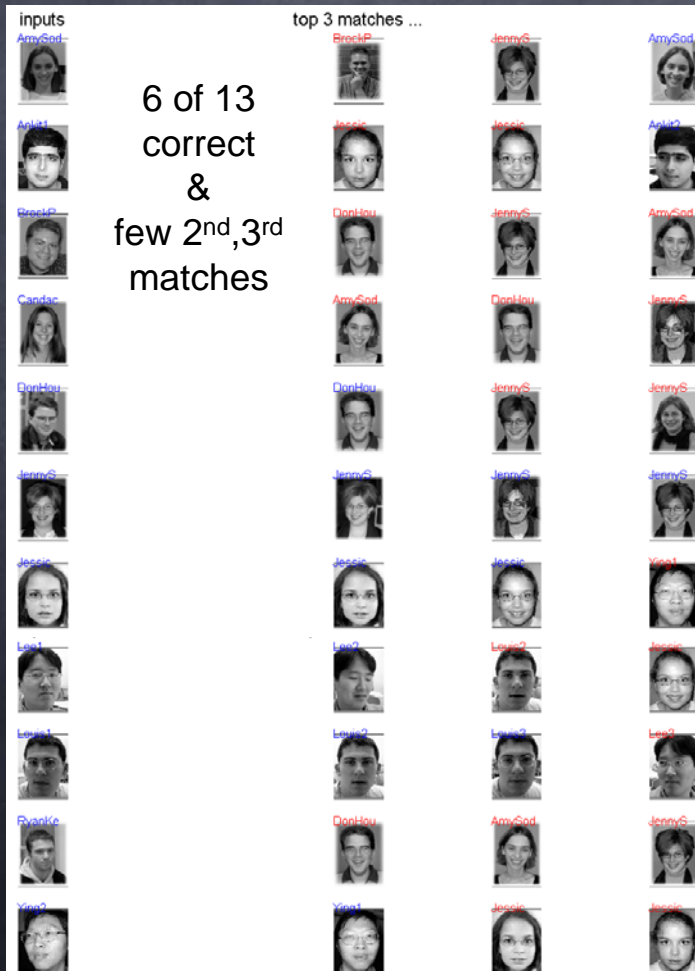
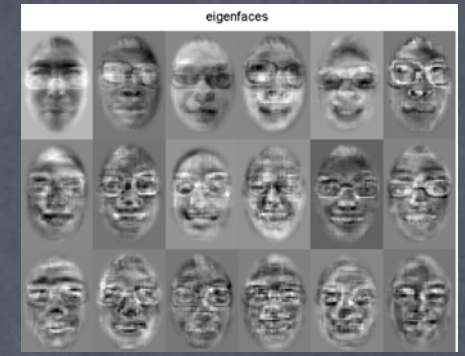


Performance Improvement

Before Pre-Processing

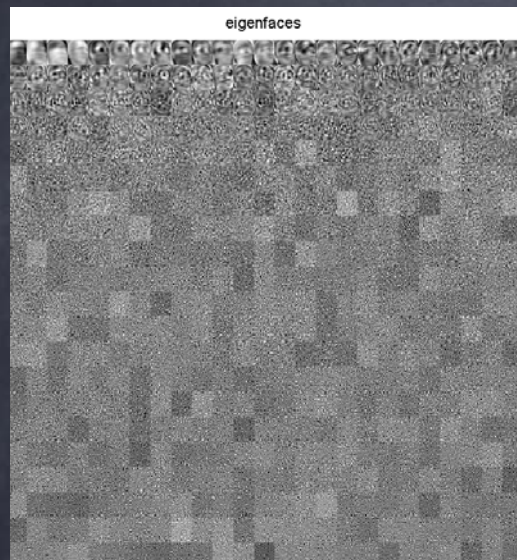


After Pre-Processing

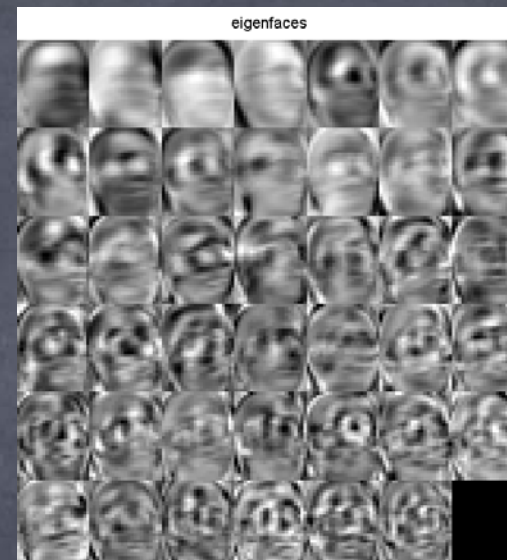
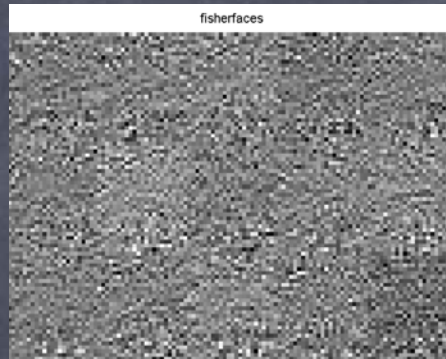


Fisherface Modification

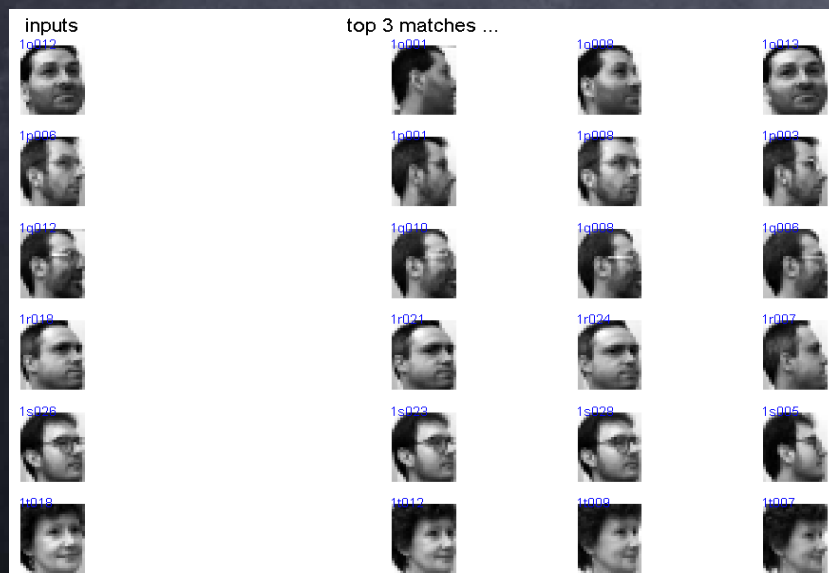
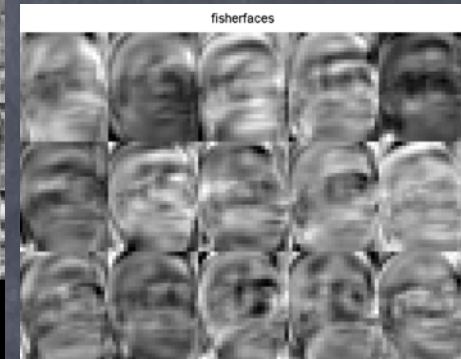
- Impose a maximum on the number of PCA components to use in dimension reduction. Rationale: “face-space” doesn’t need more than M_p eigenvectors to be well-represented.



eigenface dimension
= $n-c$



eigenface dimension
= 41



Further Work

- Integrate with face detector.
- Incorporate time info in classifier.
- Try SVM, kernel, ICA, wavelet, plenoptic (light-field) approaches.
- Acquire & use CMU PIE and FERET databases and formal evaluation techniques.

References

- M. Turk and A. Pentland, "Eigenfaces for recognition," *J. Cognitive Neuroscience*, vol. 3, no. 1, 1991.
- M. Turk and A. Pentland, "Face recognition using eigenfaces," *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, 1991, pp. 586-591.
- P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. fisherfaces: recognition using class specific linear projection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, pp. 711-720, July 1997.