Visual Recognition: Faces
Tuesday, January 23

Why faces?
- Natural applications in human-computer interfaces (teleconferencing, assistive technology), organizing personal photos, surveillance, etc.
- Well-studied category, special structure
- We'll touch on a only a few general approaches

Faces
- Detection: given an image, where is the face?
- Recognition: whose face is it?

Challenges
- Face pose
- Occlusions
- Illumination
- Variable components (glasses, mustache, etc.)
- Differences in expression

Approaches
- Subspaces
  - e.g. Turk and Pentland, Belhumeur and Kreigman
- Shape and appearance models
  - e.g. Cootes and Taylor, Blanz and Vetter
- Boosting
  - e.g. Viola and Jones
- Neural networks
  - e.g. Rowley et al.
- SVMs
  - e.g. Heisele et al., Guo et al.
- HMMs
  - e.g. Nefian et al.

Eigenpictures/Eigenfaces
- Sirovitch and Kirby 1987: PCA to compress face images
- Turk and Pentland 1991: PCA + nearest neighbors to classify face images
- **Main idea:** face images are highly correlated; low-d subspace captures most appearance variation
Images as high-dimensional points

- Around \( d = 80,000 \) pixels each
- To represent the space accurately, want num samples >> \( d \)
- But space of face images actually much smaller than space of all 80,000 dimensional images

PCA intuition

- Construct lower dimensional linear subspace that best explains variation of the training examples

PCA

- \( N \) data points: \( x_1, \ldots, x_N \) in \( \mathbb{R}^d \)
- Mean vector \( \mu \), covariance matrix \( \Sigma \)

What unit vector \( u \) in \( \mathbb{R}^d \) captures the most possible variance of the data?

PCA

\[
\text{var}(u) = \frac{1}{N} \sum_{i=1}^{N-1} u^T (x_i - \mu)(u^T (x_i - \mu))^T
\]

\[
= u^T \left( \sum_{i=1}^{N-1} (x_i - \mu)(x_i - \mu)^T \right) u
\]

\[
= u^T \Sigma u
\]

Maximizing this is an eigenvalue problem → use eigenvector(s) of \( \Sigma \) that correspond to the largest eigenvalue(s) as the new basis.

Eigenfaces

- Premise: Set of faces lie in a subspace of set of all images
- Use PCA to determine the \( k \) \((k < d)\) vectors \( u_1, \ldots, u_k \) that span that subspace:
  \[
x = \mu + w_1 u_1 + w_2 u_2 + \ldots + w_k u_k
\]
- Then essentially use nearest neighbors in "face space" coordinates \((w_1, \ldots, w_k)\) to do recognition

Eigenfaces

Training images:
\( x_1, \ldots, x_N \)
Eigenface recognition

- Process labeled training images:
  - Run PCA
  - Project each training image onto subspace
- Given novel image:
  - Project onto subspace
  - If reconstruction error too large
    - Not a face
  - Else if too far from any training face
    - Unknown face
  - Else
    - Classify as closest training face in k-dimensional subspace

Small demo

- Eigenfaces on the face images in the Caltech-4 database
- 435 images, same scale, aligned
Visualizing the primary modes of variation

Clustering in the face subspace

Limitations
- PCA useful to represent data, but directions of most variance not necessarily useful for classification (see work by Belhumeur & Kriegman using LDA)
- Not appropriate for all data: PCA is fitting hyperplane to data / Gaussian where $\Sigma$ is covariance matrix (see nonlinear techniques)
- In this application, assumptions about preprocessing applied to face images may be unrealistic
- Suited for what kinds of categories?
Fisherfaces

Belhumeur et al. PAMI 1997
Rather than maximize scatter of projected classes as in PCA, maximize ratio of between-class scatter to within-class scatter by using Fisher’s Linear Discriminant

Non-linear dimensionality reduction

- Locally Linear Embedding (LLE), Roweis and Saul
- Isomap, Tenenbaum et al.
- Kernel PCA, Scholkopf et al.
- Laplacian Eigenmaps, Belkin and Niyogi

Active appearance models

- Eigenfaces model appearance only, and so cannot be robust to shape, pose and expression changes
- Active appearance models (Cootes and Taylor) model shape and appearance

Active appearance models

Factor out the faces’ shape differences when comparing their texture / appearance

Coming up

- For Thursday: more on faces
  - Read Viola and Jones, and Sinha et al.
  - Review on Viola and Jones due
  - Zubair will present
- For Tuesday: part-based models
  - Read Felzenszwalb and Huttenlocher
  - Review due
  - Pushkala will present
  - Demo?