Understanding Faces

Computational Photography
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Lecture by Amin Sadeghi

Some slides from Lana Lazebnik, Silvio Savarese, Fei-Fei Li
Face detection and recognition

Detection

Recognition

“Sally”
Applications of Face Recognition

Album organization

Digital photography
Face Detection
How to find faces anywhere in an image?

• Filter Image with a face?
Train a Filter

Positive Training Images

Negative Training Images

SVM
Face detection: sliding windows

Filter/Template

Multiple scales
What features?

- Exemplars (Sung Poggio 1994)
- Edge (Wavelet) Pyramids (Schneiderman Kanade 1998)
- Intensity Patterns (with NNs) (Rowely Baluja Kanade 1996)
- Haar Filters (Viola Jones 2000)
How to classify?

• Many ways
  – Neural networks
  – Adaboost
  – SVMs
  – Nearest neighbor
What makes face detection hard?

Expression
What makes face detection hard?

Viewpoint
What makes face detection hard?

Occlusion
Consumer application: iPhoto 2009

http://www.apple.com/ilife/iphoto/
Consumer application: iPhoto 2009

• **Things iPhoto thinks are faces**
Face Recognition
Face recognition

1. Detect
2. Align
3. Represent
4. Classify
Simple technique

1. Treat pixels as a vector

\[ \mathbf{x} \]

2. Recognize face by nearest neighbor

\[ k = \arg\min_k \| \mathbf{y}_k^T - \mathbf{x} \| \]
DeepFace

• 3D Alignment

• Deep Learning
Morphing and Alignment
Figure-centric averages

- Need to Align
  - Position
  - Scale
  - Orientation

Averages: Hundreds of images containing a person are averaged to reveal regularities in the intensity patterns across all the images.
How do we average faces?

http://www2.imm.dtu.dk/~aam/datasets/datasets.html
Morphing

image #1

warp

morphing

image #2

warp
Cross-Dissolve vs. Morphing

Average of Appearance Vectors

Average of Shape Vectors

http://www.faceresearch.org/demos/vector

Images from James Hays
Aligning Faces

- Need to Align
  - Position
  - Scale
  - Orientation
  - Key-points
- The more key-points the finer alignment

Images from Alyosha Efros
Average of two Faces

1. Input face key-points
2. Pairwise Average key-point co-ordinates
3. Triangulate the faces
4. Warp: Transform every face triangle
5. Average The pixels
Average of multiple Face

1. Warp to mean shape
2. Average pixels

http://www.faceresearch.org/demos/average

Appearance Vectors vs. Shape Vectors

Appearance Vector

- Vector of 200*150*3 Dimensions
- Requires Annotation
- Provides alignment!

Shape Vector

- Vector of 43*2 Dimensions

Complements

- 200*150 pixels (RGB)
- 43 coordinates (x,y)
Average Men of the world
Average Women of the world

Central African  Burmese  Cambodian  English  Ethiopian  Filipino

Greek  Indian  Iranian  Irish  Israeli  Italian

Peruvian  Polish  Romanian  Russian  Samoan  South African
Subpopulation means

- Other Examples:
  - Average Kids
  - Happy Males
  - Etc.
  - http://www.faceresearch.org

Average kid

Average happy male

Average female

Average male
Eigen-face
Eigenfaces example

- Training images
- $x_1, \ldots, x_N$
PCA

• General dimensionality reduction technique

• Preserves most of variance with a much more compact representation
  – Lower storage requirements (eigenvectors + a few numbers per face)
  – Faster matching

• What are the problems for face recognition?
Principal Component Analysis

• Given a point set \( \{ \vec{p}_j \}_{j=1}^P \), in an \( M \)-dim space, PCA finds a basis such that
  – coefficients of the point set in that basis are uncorrelated
  – The most variation is in the first basis vector, then second, ...
PCA in MATLAB

- \(x = \text{rand}(3,10);\) % 10 3D examples
- 
- \(M = \text{mean}(x,2);\)
- \(x2 = x - \text{repmat}(M, [1 \ n]);\)
- \(\text{covariance} = x2 \ast x2';\)
- \([U \ E] = \text{eig} (\text{covariance})\)

\[
U = \\
\begin{bmatrix}
0.74 & 0.07 & -0.66 \\
0.65 & 0.10 & 0.74 \\
-0.12 & 0.99 & -0.02 \\
\end{bmatrix}
\]

\[
E = \\
\begin{bmatrix}
0.27 & 0 & 0 \\
0 & 0.63 & 0 \\
0 & 0 & 0.94 \\
\end{bmatrix}
\]
Principal Component Analysis

• Continued...
  – first $r < M$ basis vectors provide an approximate basis that minimizes the mean-squared-error (MSE) in the approximation (over all bases with dimension $r$)

Choosing subspace dimension $r$:
• look at decay of the eigenvalues as a function of $r$
• Larger $r$ means lower expected error in the subspace data approximation
Eigenfaces example

Top eigenvectors: $u_1, \ldots, u_k$
Face Space

- How to find a set of directions to cover all space?

  - We call these directions **Basis**
  - If number of basis faces is large enough to span the face subspace:
  - Any new face can be represented as a linear combination of basis vectors.

\[ s = \alpha_1 \cdot \text{face} + \alpha_2 \cdot \text{face} + \alpha_3 \cdot \text{face} + \alpha_4 \cdot \text{face} + \cdots = S \cdot a \]
Limitations

Global appearance method: not robust to misalignment, background variation
Use Shape information

Appearance Vector

200*150 pixels (RGB)

Shape Vector

43 coordinates (x,y)
First 3 Shape Basis

Mean appearance

Manipulating faces

• How can we make a face look more female/male, young/old, happy/sad, etc.?
• http://www.face research.org/demos/transform
Manipulating faces

- We can imagine various meaningful directions.
Psychological Attributes

Unreliable → Trustworthy
Incompetent → Competent
Introverted → Extroverted
Human Perception
Result 1

- Humans can recognize faces in extremely low resolution images.
Result 3

- High-frequency information by itself does not lead to good face recognition performance
Eyebrows are among the most important for recognition.
Result 8

- Vertical inversion dramatically reduces recognition performance
Result 20

- Human memory for briefly seen faces is rather poor
Which face is more attractive?

beautified

original
System Overview

Original Facial Data
- Feature points
- Distances vector

Training Set

Beautification engine

Modified distances vector

Result image

Input image

Image warp
Things to remember

• Face Detection
• Face Recognition
• Appearance Vector
• Shape Vector
• Face Transformation
• Principal Component Analysis