Data-driven Methods: Faces

15-463: Computational Photography
Alexei Efros, CMU, Fall 2011
The Power of Averaging
8-hour exposure

© Atta Kim
Fun with long exposures

Photos by Fredo Durand
More fun with exposures

http://vimeo.com/14958082
Figure-centric averages

Averages: Hundreds of images containing a person are averaged to reveal regularities in the intensity patterns across all the images.
More by Jason Salavon

<table>
<thead>
<tr>
<th>Homes for Sale</th>
<th>109 Homes for Sale, Seattle/Tacoma</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>117 Homes for Sale, Chicagoland</td>
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<tr>
<td></td>
<td>124 Homes for Sale, The 5 Boroughs</td>
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<td>121 Homes for Sale, LA/Orange County</td>
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<td></td>
<td>114 Homes for Sale, Dallas/Ft. Worth Metroplex</td>
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<tr>
<td></td>
<td>112 Homes for Sale, Miami-Dade County</td>
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“100 Special Moments” by Jason Salavon

Little Leaguer

Kids with Santa

The Graduate

Newlyweds

Why blurry?
Computing Means

Two Requirements:
• Alignment of objects
• Objects must span a subspace

Useful concepts:
• Subpopulation means
• Deviations from the mean
Images as Vectors

\[ n \times m = n^*m \]
Vector Mean: Importance of Alignment

\[ n \times m = \frac{1}{2} + \frac{1}{2} = \text{mean image} \]
How to align faces?

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

Provides alignment!
Average Face

1. Warp to mean shape
2. Average pixels

Objects must span a subspace
Example

Does not span a subspace
Subpopulation means

Examples:
- Happy faces
- Young faces
- Asian faces
- Etc.
- Sunny days
- Rainy days
- Etc.
- Etc.

Average female

Average male
Deviations from the mean

\[ \Delta X = X - X \]
Deviations from the mean

\[ \Delta X = X - \bar{X} \]

\[ X = \bar{X} + 1.7 \]
Manipulating Facial Appearance through Shape and Color

Duncan A. Rowland and David I. Perrett

*St Andrews University*

IEEE CG&A, September 1995
Face Modeling

Compute *average* faces
(color and shape)

Compute *deviations*
between male and female (vector and color differences)
Changing gender

Deform shape and/or color of an input face in the direction of “more female”
more same original androgynous more opposite
Changing age

Face becomes “rounder” and “more textured” and “grayer”
Back to the Subspace
Any new image $X$ can be obtained as weighted sum of stored "basis" images.

$$X = \sum_{i=1}^{m} a_i X_i$$

Our old friend, change of basis! What are the new coordinates of $X$?
The actual structure of a face is captured in the shape vector $\mathbf{S} = (x_1, y_1, x_2, \ldots, y_n)^T$, containing the $(x, y)$ coordinates of the $n$ vertices of a face, and the appearance (texture) vector $\mathbf{T} = (R_1, G_1, B_1, R_2, \ldots, G_n, B_n)^T$, containing the color values of the mean-warped face image.
The Morphable face model

Again, assuming that we have $m$ such vector pairs in full correspondence, we can form new shapes $S_{model}$ and new appearances $T_{model}$ as:

$$S_{model} = \sum_{i=1}^{m} a_i S_i \quad \text{and} \quad T_{model} = \sum_{i=1}^{m} b_i T_i$$

If number of basis faces $m$ is large enough to span the face subspace then:

Any new face can be represented as a pair of vectors $(\alpha_1, \alpha_2, \ldots, \alpha_m)^T$ and $(\beta_1, \beta_2, \ldots, \beta_m)^T$!
Issues:

1. How many basis images is enough?
2. Which ones should they be?
3. What if some variations are more important than others?
   - E.g. corners of mouth carry much more information than haircut

Need a way to obtain basis images automatically, in order of importance!

But what’s important?
Principal Component Analysis

Given a point set \( \{\mathbf{P}_j\}_{j=1}^P \), in an \( M \)-dim space, PCA finds a basis such that

- coefficients of the point set in that basis are uncorrelated
- first \( r < M \) basis vectors provide an approximate basis that minimizes the mean-squared-error (MSE) in the approximation (over all bases with dimension \( r \) )
PCA via Singular Value Decomposition

\[ [u, s, v] = \text{svd}(A); \]

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

First popular use of PCA on images was for modeling and recognition of faces [Kirby and Sirovich, 1990, Turk and Pentland, 1991]

- Collect a face ensemble
- Normalize for contrast, scale, & orientation.
- Remove backgrounds
- Apply PCA & choose the first $N$ eigen-images that account for most of the variance of the data.
First 3 Shape Basis

Mean appearance

Using 3D Geometry: Blinz & Vetter, 1999

show SIGGRAPH video