Data-driven Methods: Faces



Portrait of Piotr Gibas © Joaquin Rosales Gomez

15-463: Computational Photography Alexei Efros, CMU, Fall 2010

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



Antonio Torralba & Aude Oliva (2002)

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

More by Jason Salavon



Homes for Sale



More at: <u>http://www.salavon.com</u>/

"100 Special Moments" by Jason Salavon



The Graduate

Newlyweds

Why blurry? Two Requirements:

- Alignment of objects
- Objects must span a subspace

Useful concepts:

- Subpopulation means
- Deviations from the mean

Images as Vectors

n

	_		
	_		
 	_ =	=	
	_		
m			
			4
			n^m

Vector Mean: Importance of Alignment



How to align faces?



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

Shape Vector



Provides alignment!

Average Face



Warp to mean shape
Average pixels



http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/handins/brh/final/

Objects must span a subspace







mean

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











 $\Delta X = X - \underline{X}$

Deviations from the mean



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"

original

color



shape

both

Enhancing gender



more same original androgynous more opposite

Changing age

Face becomes "rounder" and "more textured" and "grayer"

original

color



shape

both

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 $\mathbf{S} = (x_1, y_1, x_2, ..., y_n)^T$, containing the (x, y)coordinates of the n vertices of a face, and the appearance (texture) vector $\mathbf{T} = (R_1, G_1, B_1, R_2, ..., G_n, B_n)^T$, containing the color values of the mean-warped face image.



Shape S

Appearance T

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:



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 $(\alpha_1, \alpha_2, ..., \alpha_m)^T$ and $(\beta_1, \beta_2, ..., \beta_m)^T$!

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 $\{\vec{\mathbf{p}}_j\}_{j=1...P}$, 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



http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/handins/brh/final/

Principal Component Analysis

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]

lighting variation

- 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. face



First 3 Shape Basis



Mean appearance







http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/handins/brh/final/

Using 3D Geometry: Blinz & Vetter, 1999



show SIGGRAPH video