Data-driven Methods: Faces



CS194: Image Manipulation & Computational Photography Alexei Efros, UC Berkeley, Fall 2014

The Power of Averaging



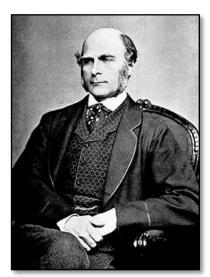


8-hour exposure



© Atta Kim

Image Composites



Sir Francis
Galton
1822-1911



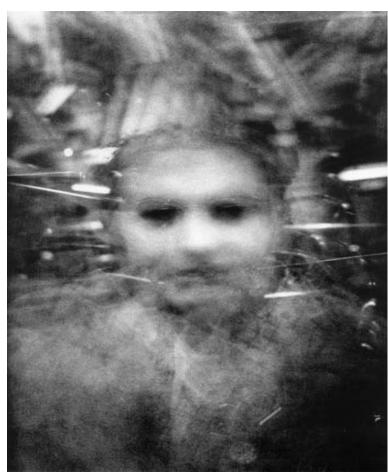
Multiple Individuals



Composite

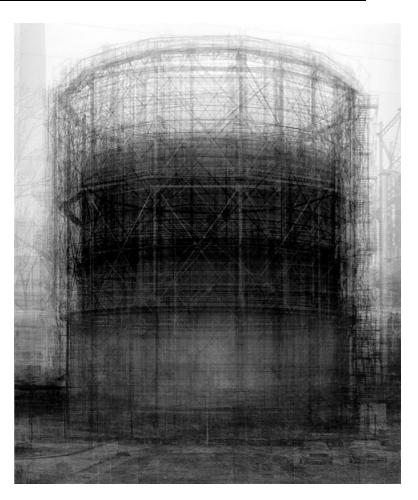
[Galton, "Composite Portraits", Nature, 1878]

Average Images in Art



"60 passagers de 2e classe du metro, entre 9h et 11h" (1985)

Krzysztof Pruszkowski



"Spherical type gasholders" (2004) Idris Khan

More by Jason Salavon



More at: http://www.salavon.com/

"100 Special Moments" by Jason Salavon



Object-Centric Averages by Torralba (2001)



Manual Annotation and Alignment



Average Image

Slide by Jun-Yan Zhu

Computing Means

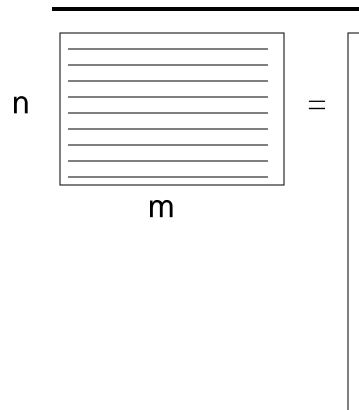
Two Requirements:

- Alignment of objects
- Objects must span a subspace

Useful concepts:

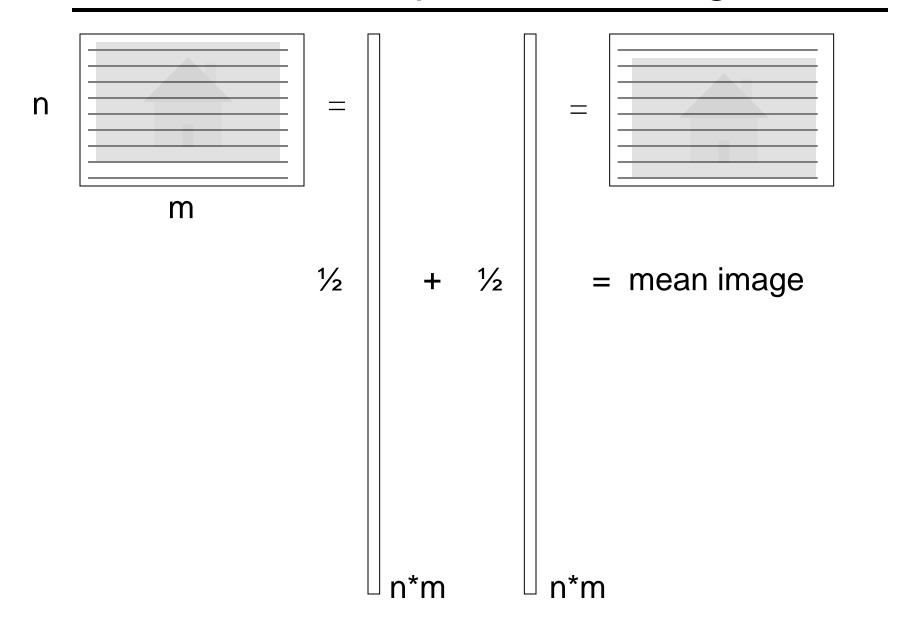
- Subpopulation means
- Deviations from the mean

Images as Vectors



n*m

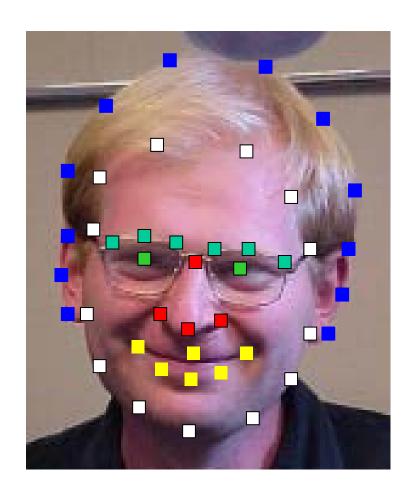
Vector Mean: Importance of Alignment



How to align faces?



Shape Vector



Provides alignment!

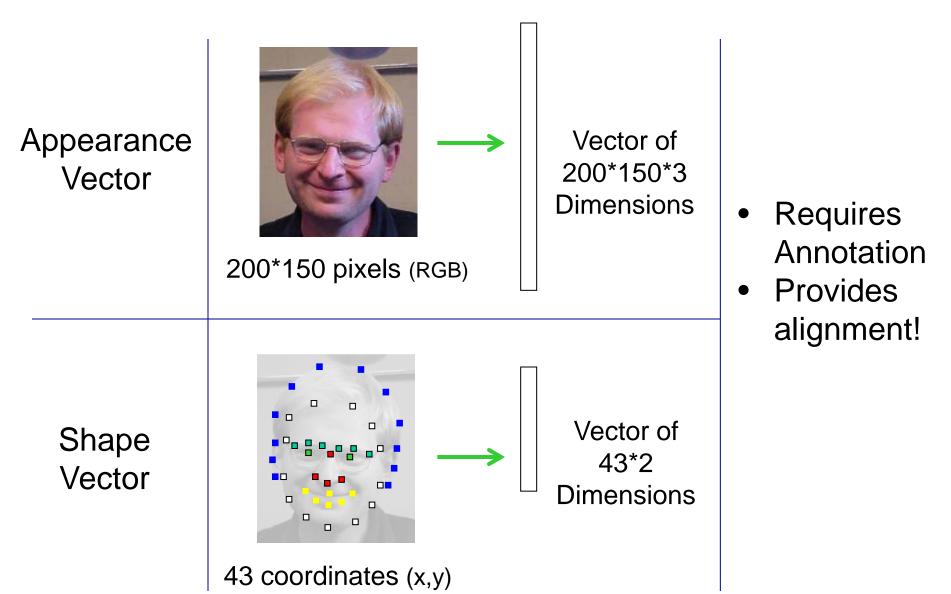
Average Face



- 1. Warp to mean shape
- 2. Average pixels

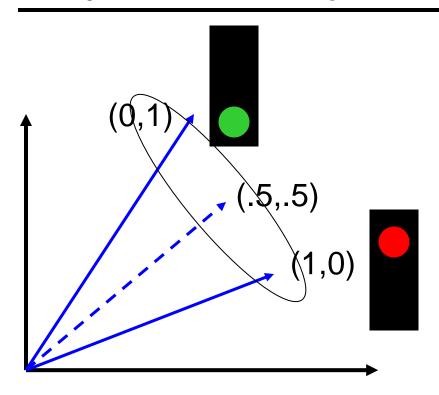


Appearance Vectors vs. Shape Vectors



Slide by Kevin Karsch

Objects must span a subspace



Example







mean

Does not span a subspace

Subpopulation means

Examples:

- Male vs. female
- Happy vs. said
- Average Kids
- Happy Males
- Etc.
- http://www.faceresearch.org



Average kid



Average happy male

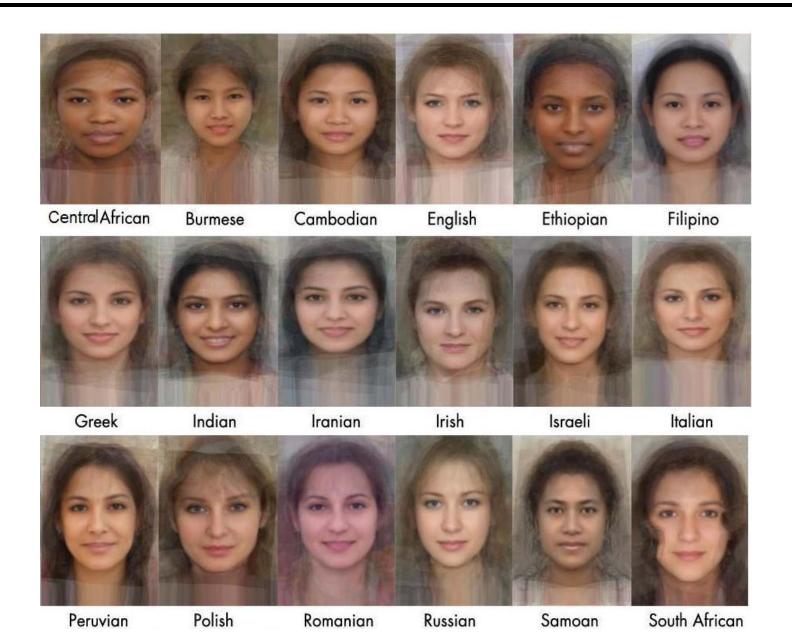


Average female

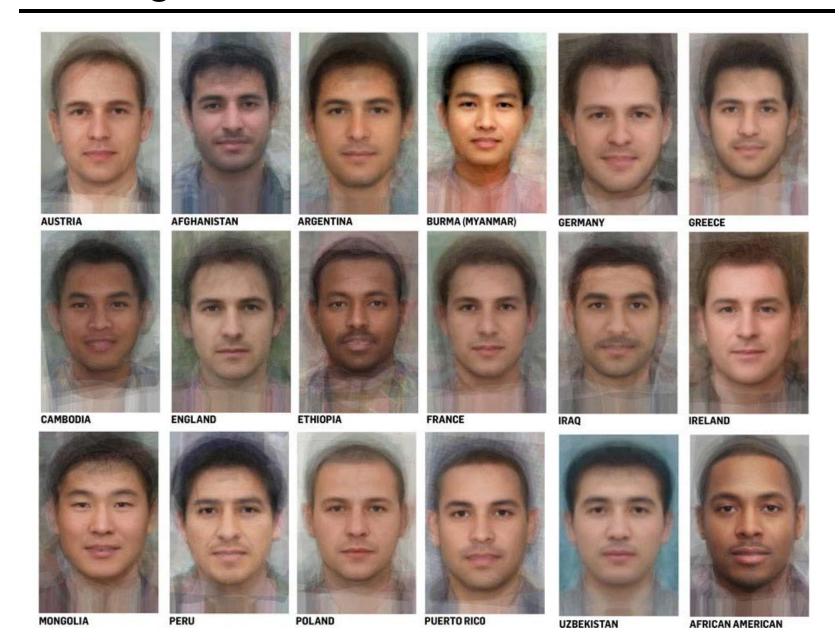


Average male

Average Women of the world



Average Men of the world



Deviations from the mean



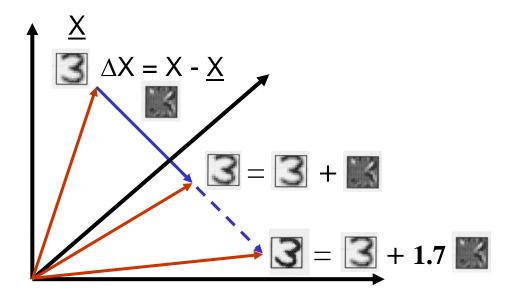


Image X Mean X



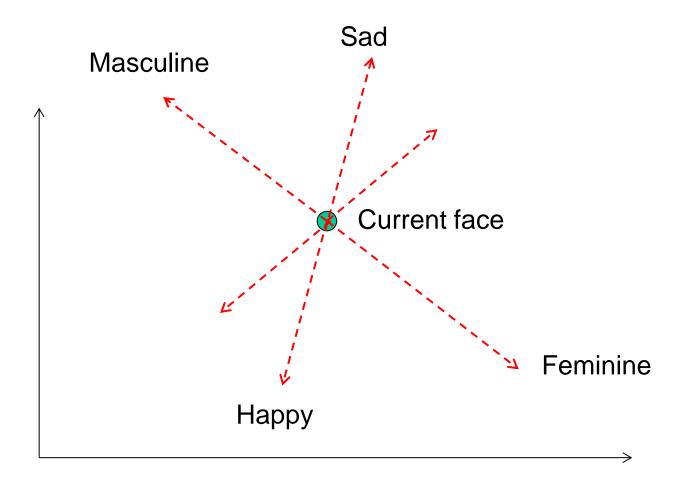
$$\Delta X = X - \underline{X}$$

Deviations from the mean



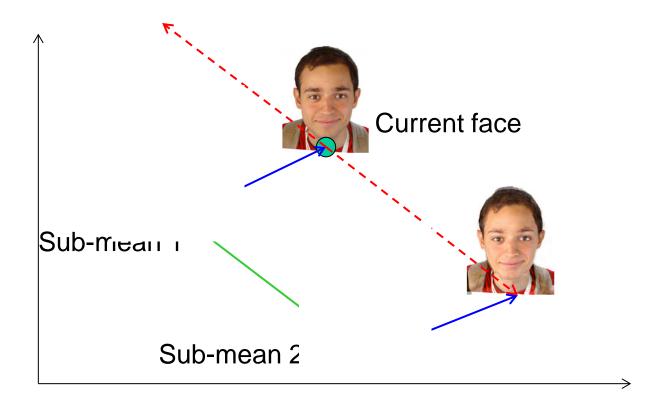
Extrapolating faces

We can imagine various meaningful <u>directions</u>.



Manipulating faces

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



Manipulating Facial Appearance through Shape and Color

Duncan A. Rowland and David I. Perrett

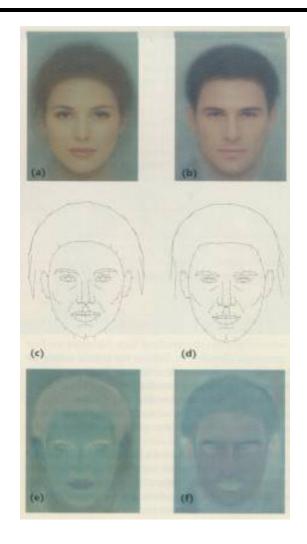
St Andrews University

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

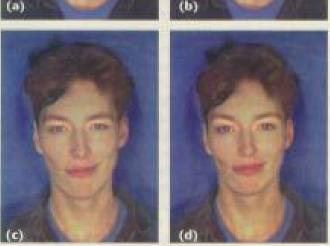
Deform shape and/or color of an input face in the direction of "more female"

original

(a) (b)

shape

color



both

Enhancing gender



more same original androgynous more opposite

Changing age

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

original

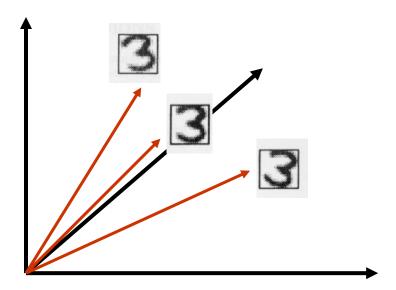
color



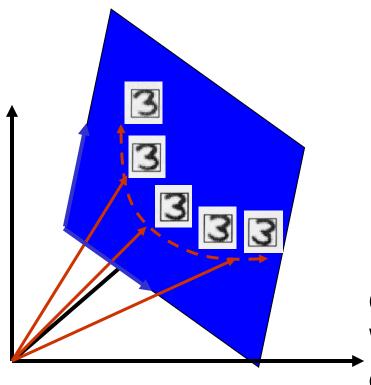
shape

both

Back to the Subspace



Linear Subspace: convex combinations



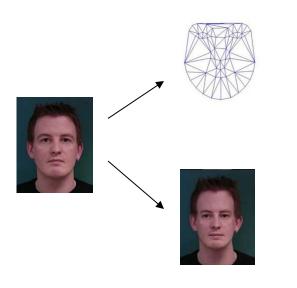
Any new image X can be obtained as weighted sum of stored "basis" images.

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

Our old friend, change of basis! What are the new coordinates of X?

The Morphable Face Model

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 \mathbf{S}_{model} and new appearances \mathbf{T}_{model} as:

$$\mathbf{S}_{model} = \sum_{i=1}^{m} a_i \mathbf{S}_i \qquad \mathbf{T}_{model} = \sum_{i=1}^{m} b_i \mathbf{T}_i$$

$$s = \alpha_1 \cdot \mathbf{O} + \alpha_2 \cdot \mathbf{O} + \alpha_3 \cdot \mathbf{O} + \alpha_4 \cdot \mathbf{O} + \dots = \mathbf{S} \cdot \mathbf{a}$$

$$t = \beta_1 \cdot \mathbf{O} + \beta_2 \cdot \mathbf{O} + \beta_3 \cdot \mathbf{O} + \beta_4 \cdot \mathbf{O} + \dots = \mathbf{T} \cdot \mathbf{B}$$



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

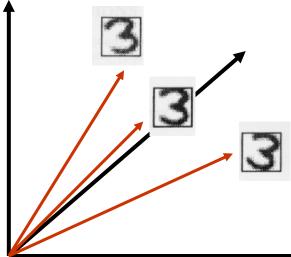
Issues:

- 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!

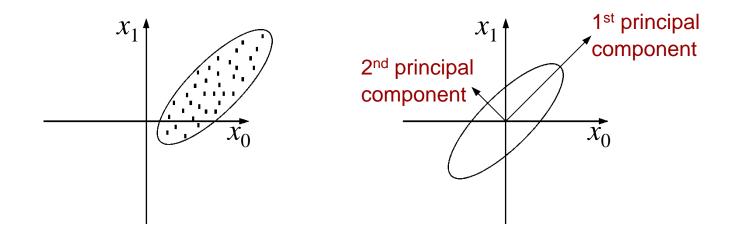
But what's important?



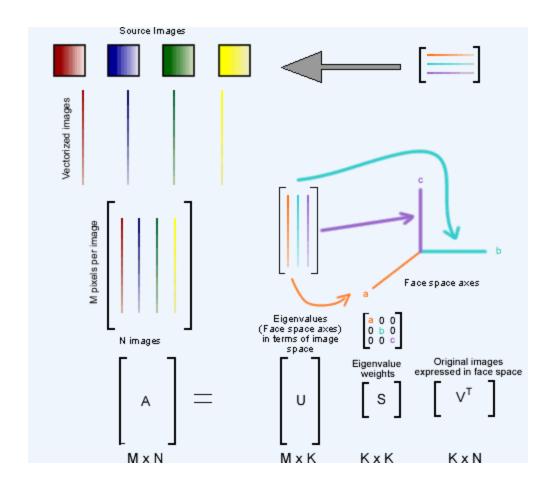
Principal Component Analysis

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

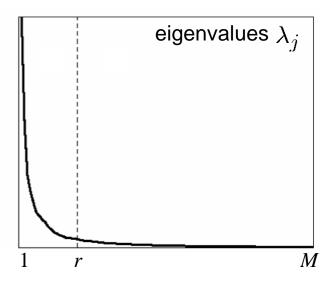


$$[u,s,v] = svd(A);$$

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



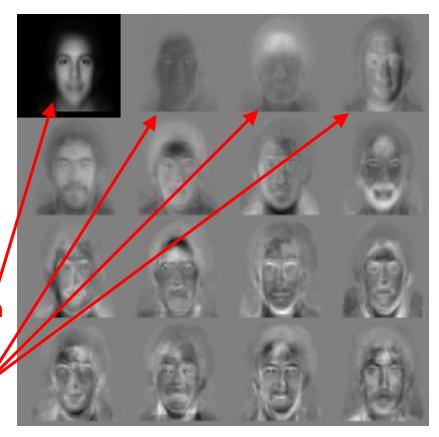
EigenFaces

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

- 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.
 mean

lighting variation

face



First 3 Shape Basis



Mean appearance

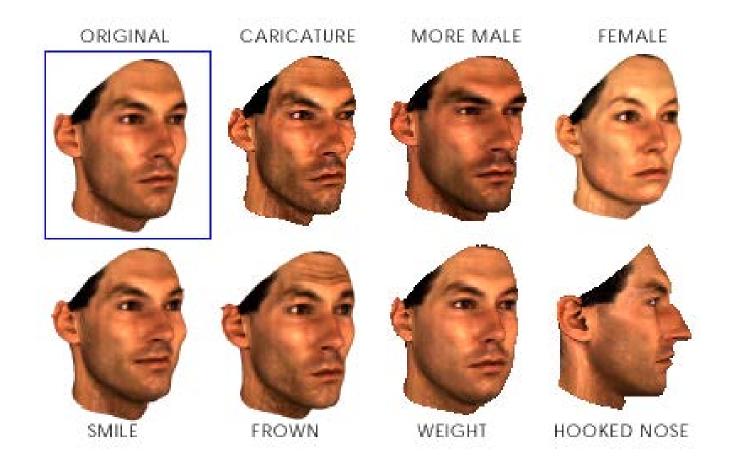






http://graphics.cs.cmu.edu/courses/15-463/2004_fall/www/handins/brh/final/

Using 3D Geometry: Blinz & Vetter, 1999



http://www.youtube.com/watch?v=jrutZaYoQJo

Walking in the Face-graph!



Source

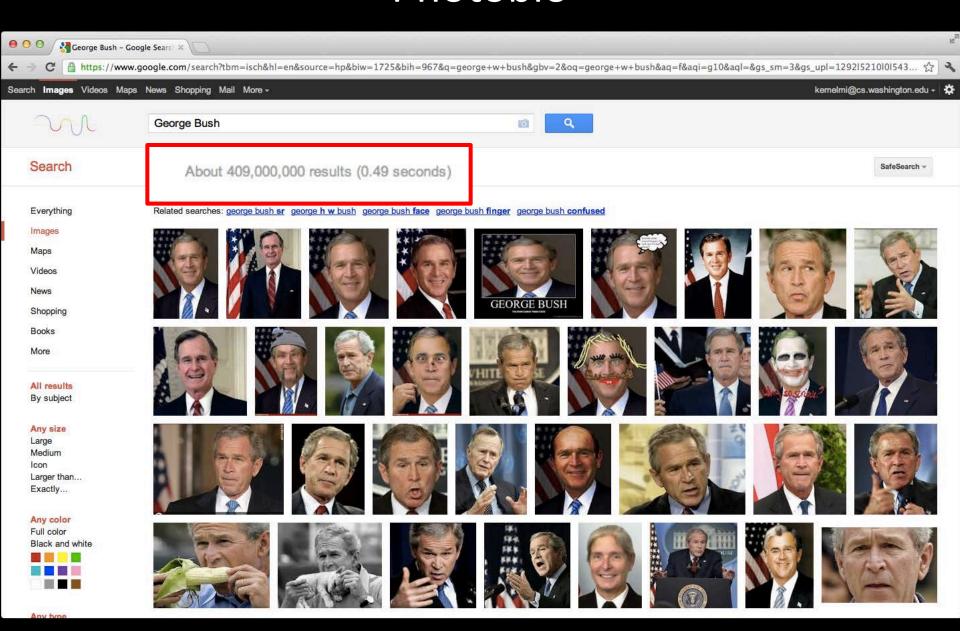
Automatically generated transition

Target

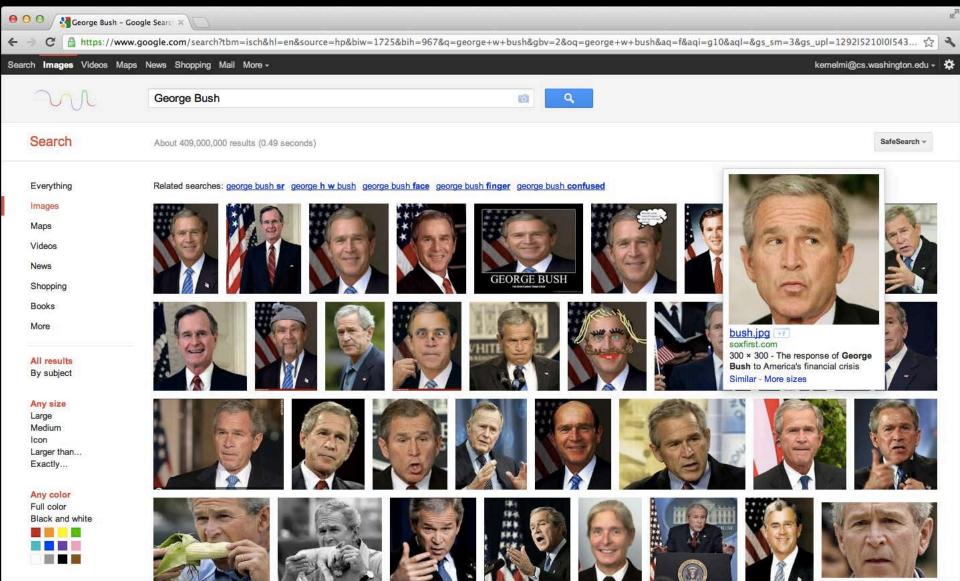
Ira Kemelmacher-Shlizerman, Eli Shechtman, Rahul Garg, Steven M. Seitz. "Exploring Photobios." ACM Transactions on Graphics 30(4) (SIGGRAPH), Aug 2011.

http://vimeo.com/23561002

Photobio



Photobio



Photobio



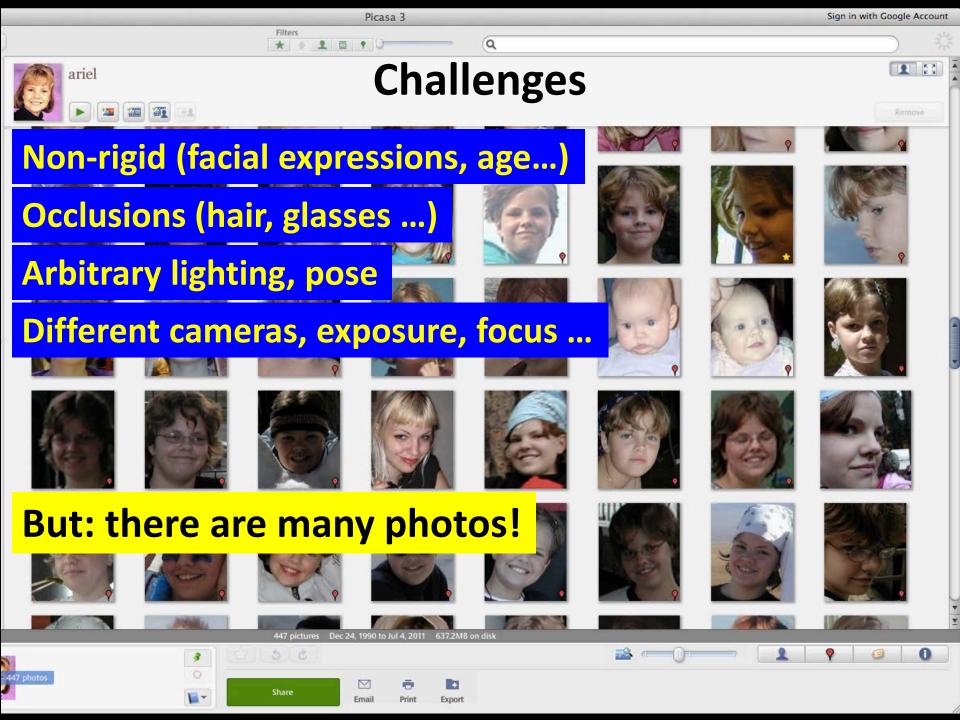


Image registration

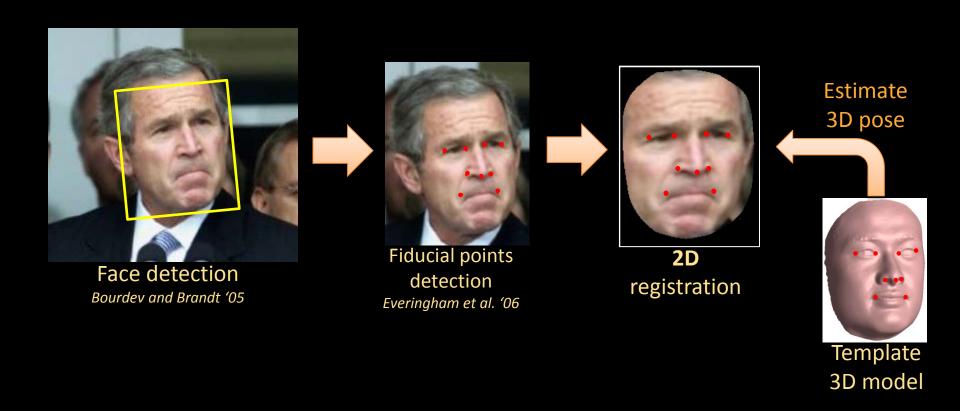


Image registration



3D transformed photos



Represent the photo collection as a graph



Similarity between 2 photos



3D Head Pose similarity

Facial Expression similarity

Time similarity

Represent the photo collection as a graph



Similarity between 2 photos



3D Head Pose similarity

Facial
Expression
similarity

Time similarity

Represent the photo collection as a graph



Similarity between 2 photos



3D Head Pose similarity Facial Expression similarity

Time similarity

Illumination-Aware Age Progression

CVPR 2014

<u>Ira Kemelmacher-Shlizerman</u>, <u>Supasorn Suwajanakorn</u>, <u>Steven M. Seitz</u>



http://www.youtube.com/watch?v=QuKluy7NAvE

Image-Based Shaving











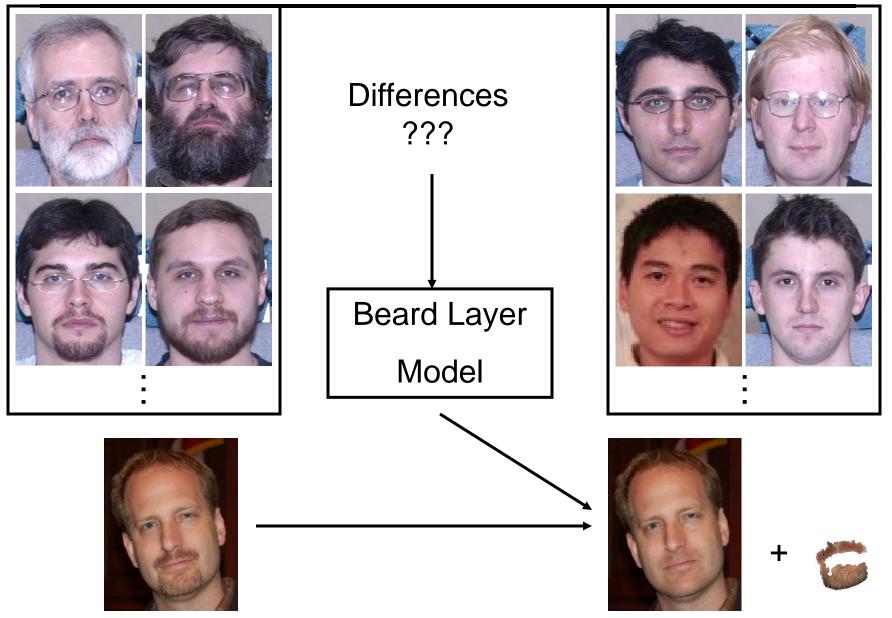






http://graphics.cs.cmu.edu/projects/imageshaving/

The idea

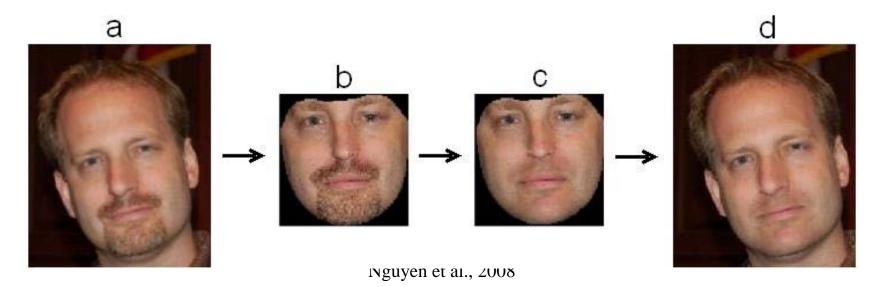


Nguyen et al., 2008

Processing steps



68 landmarks



Some results

