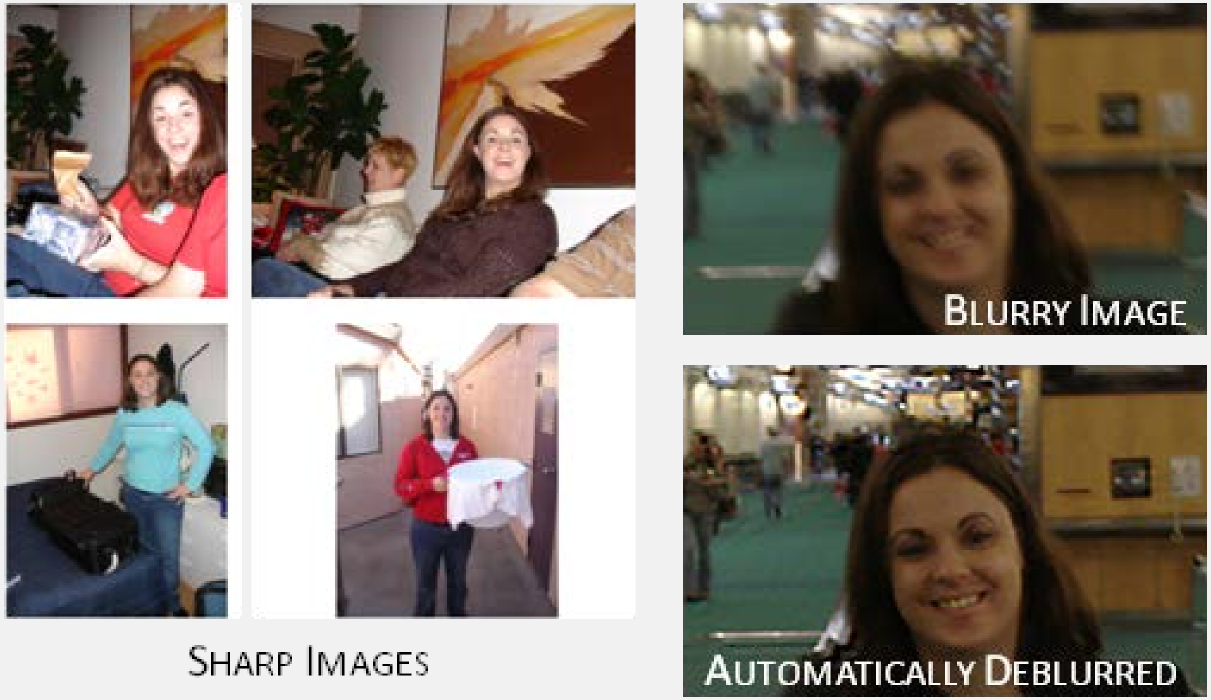
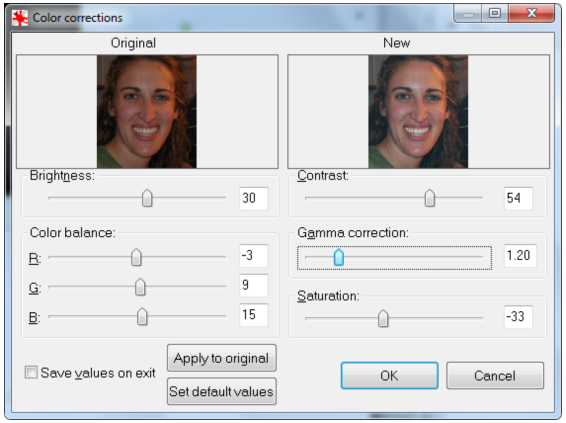


Personal Photo Enhancement using Example Images

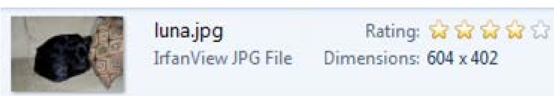
Neel Joshi
Wojciech Matusik, Edward H. Adelson, and David J. Kriegman

Microsoft Research, Disney Research, Adobe Research, MERL, MIT CSAIL, and UCSD

Motivation and Approach



- It is difficult for most users to fix their images



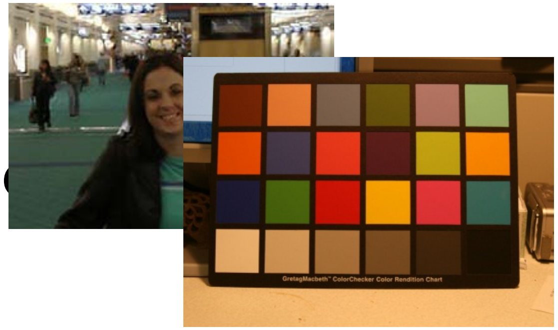
- It’s easier for users to rate their good photos

- Use examples of a persons **good photos to fix the bad ones** automatically

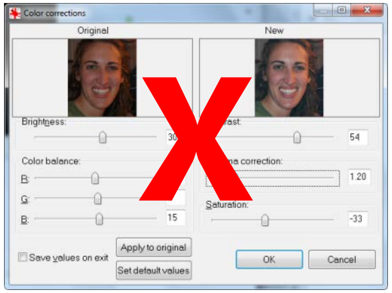
Our Approach

- Focus on images with faces

- Use a **known face** as a calibration obje



- Users provide good examples, instead performing manual edits

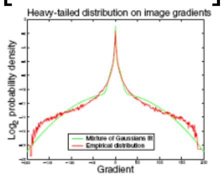


Previous Work

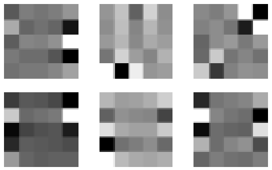
- Deblurring and Upsampling/Super-Resolution
  - Poisson image/noise models [Richardson 1972; Lucy 1974]; Sparse gradient priors [Fergus et al. 2006; Levin 2006; Levin 2007]; Sparse wavelet coefficients [de Rivaz 2001]; Spatially Varying [Whyte et al. 2010; Gupta et al. 2010]; Baker and Kanade 2000; Freeman et al. 2000; Freeman et al. 2002; Liu et al. 2007; Dai et al. 2007; Fattal 2007
- Denoising
  - Sparse wavelet coefficients [Simoncelli and Adelson 1996; Portilla et al. 2003], Anisotropic diffusion [Perona and Malik 1990], Field of Experts [Roth and Black 2005];, Baker and Kanade 2000; Freeman et al. 2000; Freeman et al. 2002; Liu et al. 2007; Dai et al. 2007; Fattal 2007
- White-Balancing/Color Correction
  - Finlayson et al. 2004, 2005; Weijer et al. 2007
- Using photo collections
  - Baker and Kanade 2000, Liu et al. 2007 , Dale et al. 2009
- Hardware Methods
  - Joshi et al. 2010, Raskar et al. 2008, Levin et al. 2008, Veeraraghavan et al. 2007, Levin et al. 2007, Raskar et al. 2006, Ben-Ezra et al. 2005, Ben-Ezra and Nayar 2004

Specific vs. General Priors

Sparse Prior
[Levin et al.]



Field of Experts
[Roth and Black]



Example Based
[Freeman et al.]

Photo Collections
[Dale et al.]

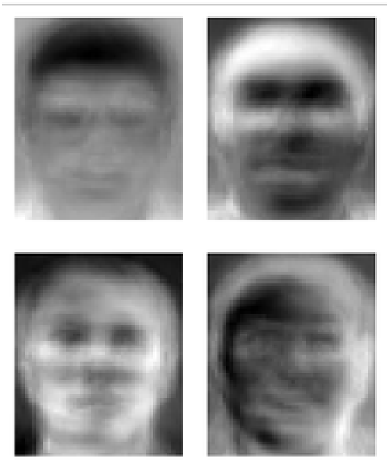
Our Approach

Generic Image Prior

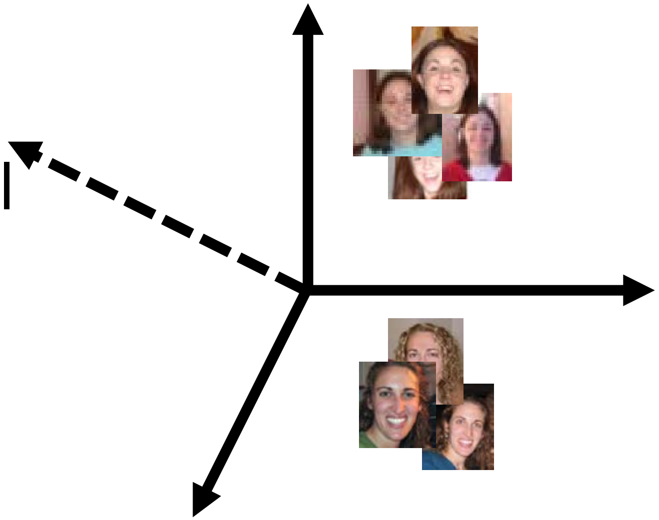
Multi-Image

- We use an **identity specific** prior

Facespace

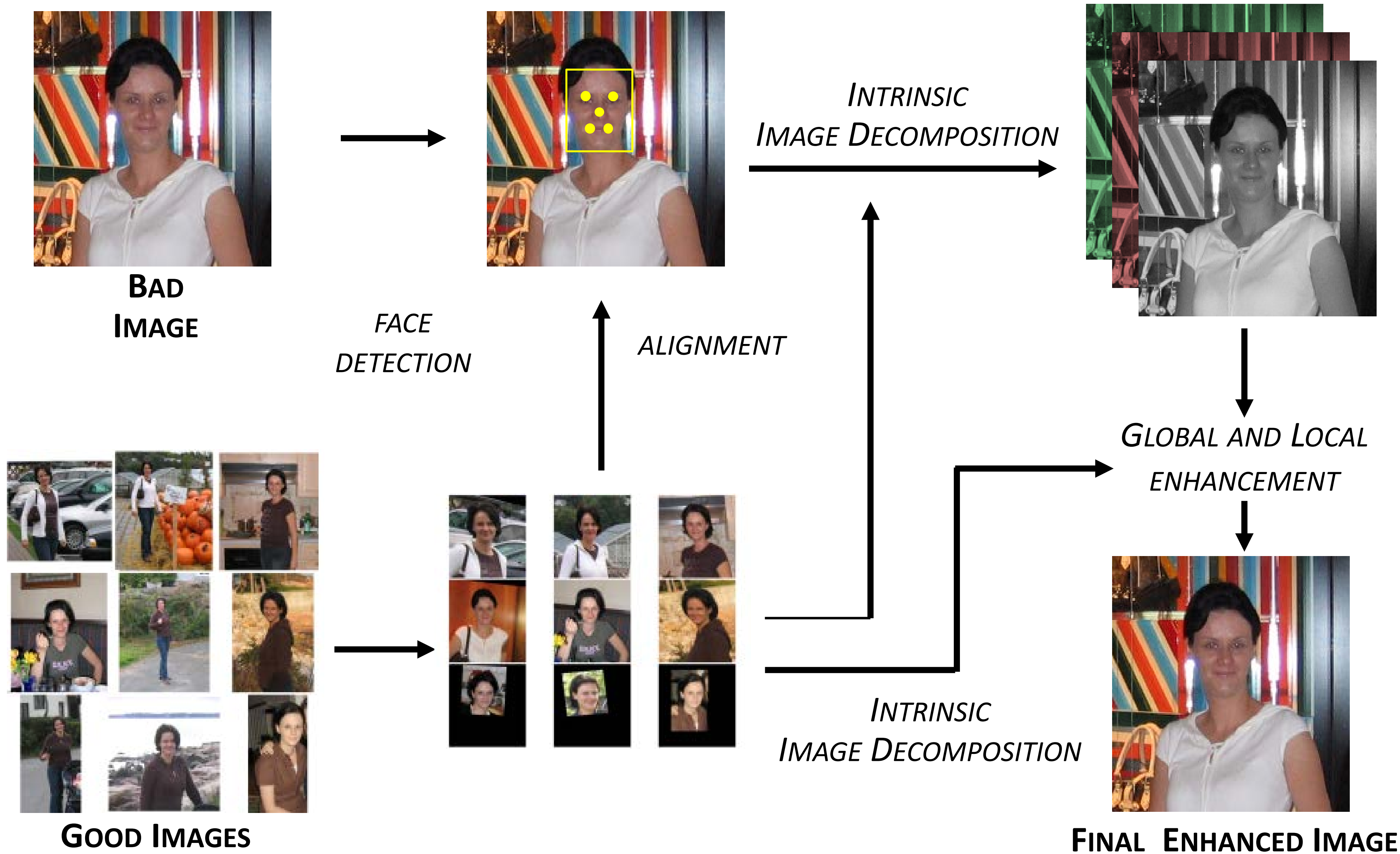


- Faces are a subspace of all images
  - Eigenfaces -- Turk and Petland 1987



- Person-specific space is relatively small
- The range of images can be captured with a few good examples

Personal Image Enhancement Pipeline



Intrinsic Images [Land and McCann 1971,Barrow and Tenenbaum 1978]

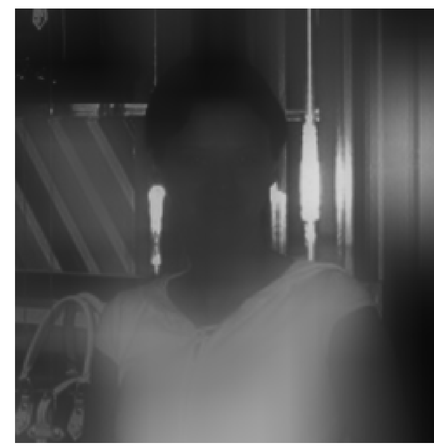
Input Image

Chroma R

Detail/Texture

Chroma G

Lighting



- Separation into Lighting, Texture, Color Layers
- Use base/detail decomposition of Eisemann and Durand 2004

Image Enhancements

- Blur (Global)

- Color/Exposure Balance (Global)

- Super-Resolution/Up-sampling

Image Enhancements

- Blur

- Color/Exposure Balance

- Super-Resolution/Up-sampling

Blur Formation

Blurry image

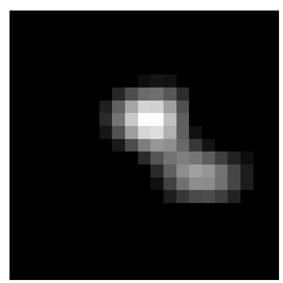
$=$

Sharp image

$\otimes$

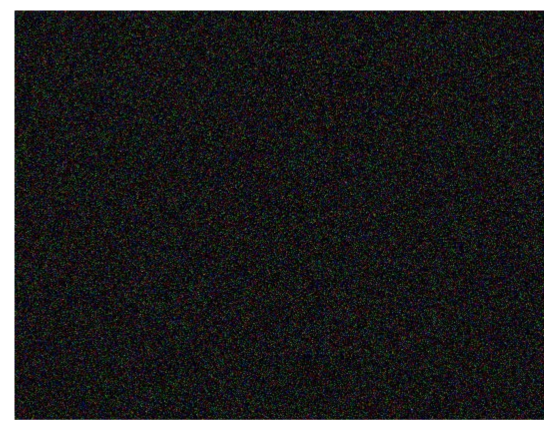
Convolution

Blur kernel (Point-Spread Function)



$+$

Zero Mean Gaussian Noise



Blur Estimation Goal

Blurry image

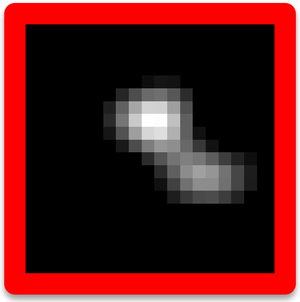
=

Known

Sharp image

$\otimes$

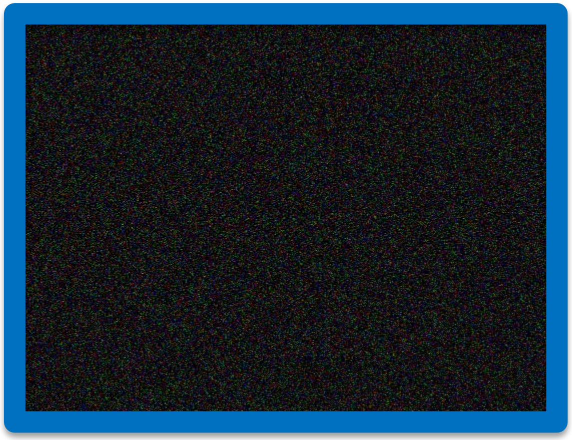
Blur kernel



+

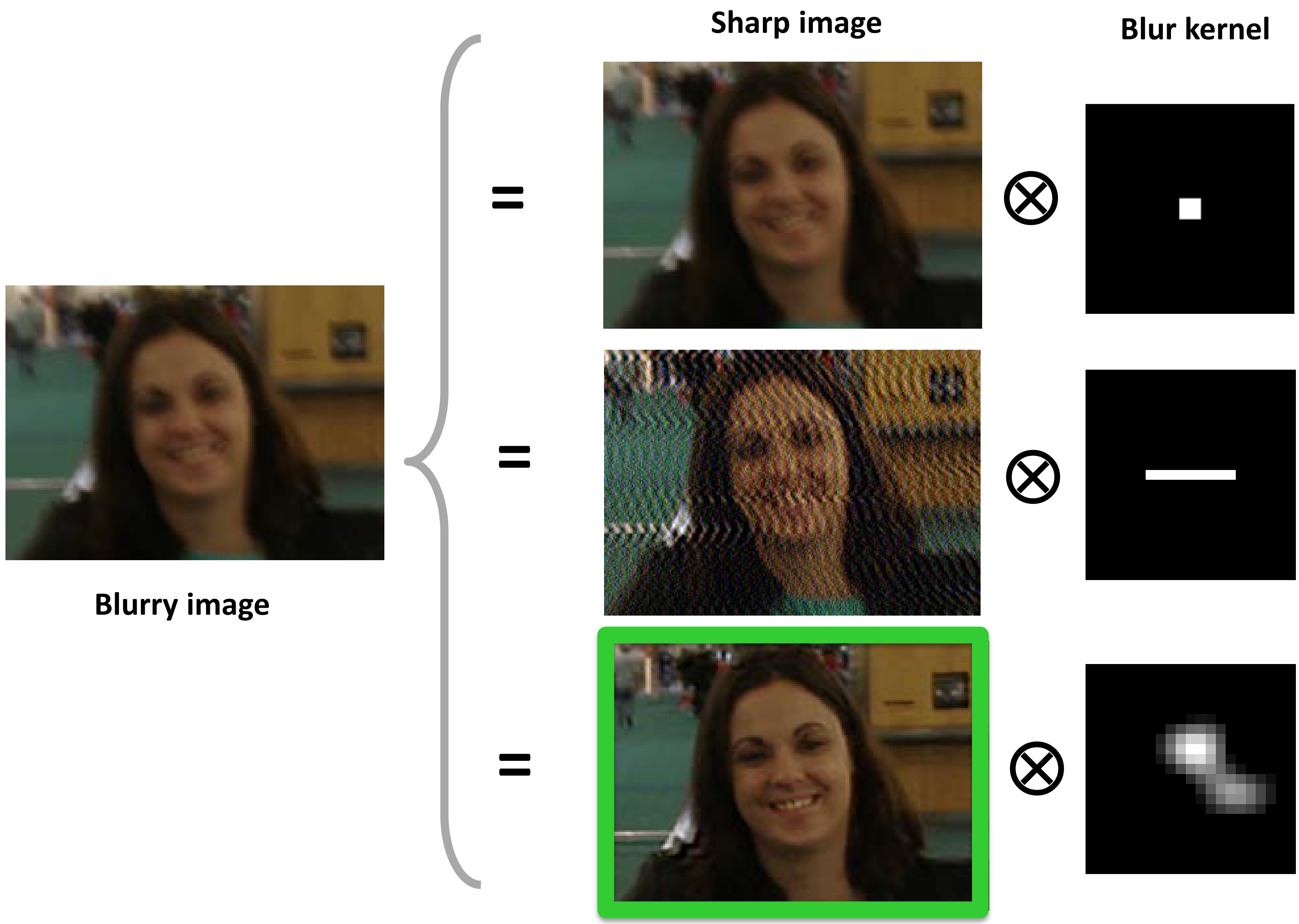
Known σ

Zero Mean Gaussian Noise



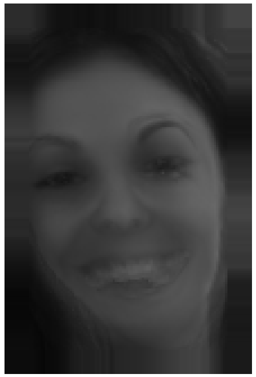
Unknown

Deblurring: Multiple Possible Solutions



Eigenspace

Mean Face



Eigenvectors * 3 *σ + Mean Face

Eigenvectors * -3 *σ + Mean Face

- Identity Specific Images are used to build an aligned eigenspace

Eigenspace used for Blind Deconvolution

$$I,K = \underset{I,K}{\operatorname{argmin}} \underbrace{\boxed{\rho(B - I \otimes K)}}_{\text{Data Term}} \big/ \sigma^2 + \underbrace{\boxed{\lambda_1 \left|\nabla I\right|^{0.8}}}_{\text{Sparse Prior}}$$

$$+ \lambda_2 \boxed{\rho\left(\left(\Lambda^T \Lambda (I - \mu) + \mu\right) - I\right)}$$

$$+ \boxed{\lambda_3 \left\|K\right\|^p + \lambda_4 \left\|\nabla K\right\|^2}$$

B = Blurry Image
I = Sharp Prediction
Λ = Eigenbasis vectors
μ = Mean Vector
ρ(.) = Robust Norm
σ = Noise standard deviation
λ = Regularization parameter
$p < 1$

- Eigenspace used as a linear constraint
- Robust norm
- Sparsity and smoothness priors on the Kernel
- Solved using an Multi-Scale EM style algorithm

Image Enhancements

- Blur

- Color/Exposure Balance

- Super-Resolution/Up-sampling

Image Enhancements

- Blur

- Color/Exposure Balance

- Super-Resolution/Up-sampling

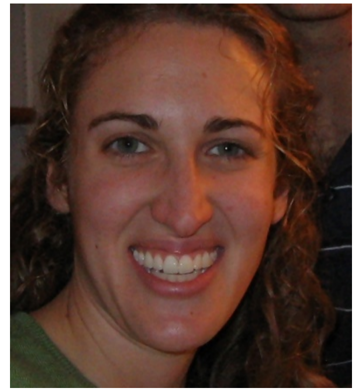
Color Correction: Multiple Possible Solutions

Observed image

White-balanced Image

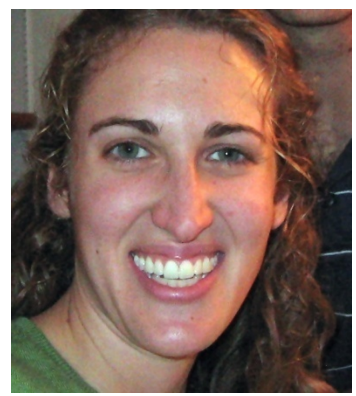
Lighting Color

=

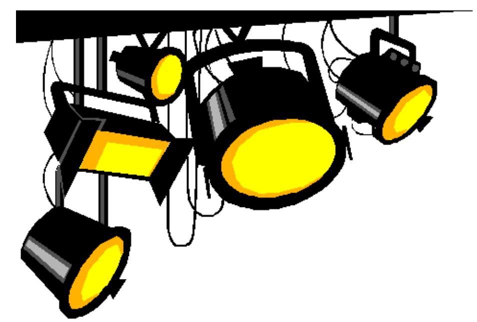


X

=



X



White Balance and Exposure Correction

$$C_r = \underset{C_r}{\operatorname{argmin}}\, \rho(\mu_r - C_r r)$$

$$C_g = \underset{C_g}{\operatorname{argmin}}\, \rho(\mu_g - C_g g)$$

$$C_L = \underset{C_L}{\operatorname{argmin}}\, \rho(\mu_L - C_L L)$$

C_r = r scale
C_g = g scale
C_L = L scale

μ_r = Mean r Vector
μ_g = Mean g Vector
μ_L = Mean L Vector

$\rho(.)$ = Robust Norm

- Diagonal white balancing matrix (scales r and g independently)
- Exposure adjustment scales lighting layer

Image Enhancements

- Blur

- Color/Exposure Balance

- Super-Resolution/Up-sampling

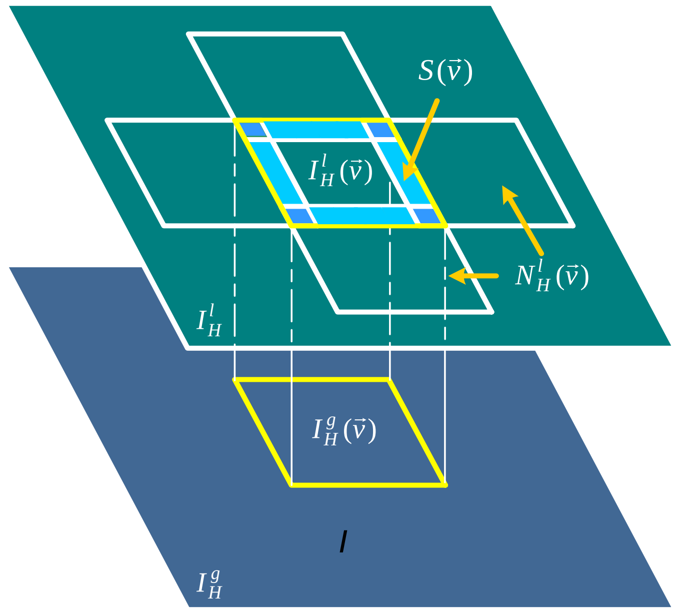
Image Enhancements

- Blur

- Color/Exposure Balance

- Super-Resolution/Up-sampling

Face Correction: Patch Based [Freeman et al. 2000, Liu et al. 2007]

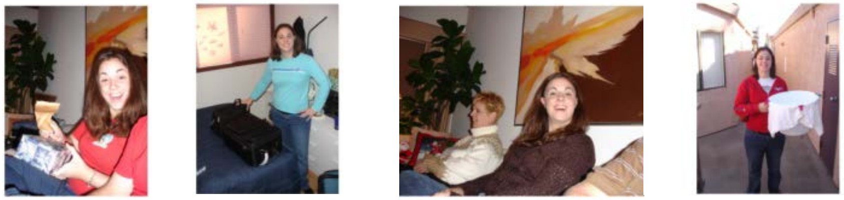


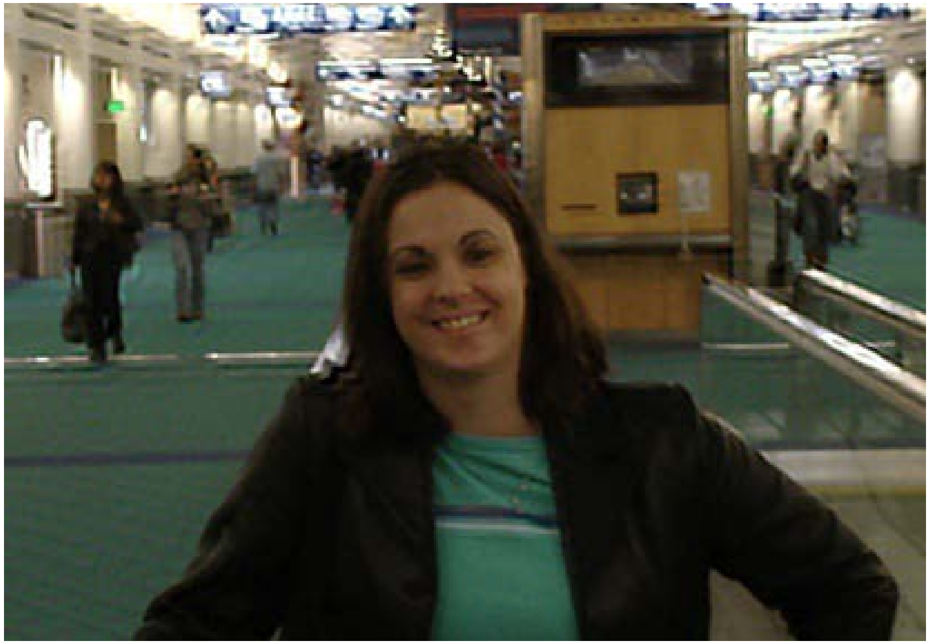
- High-frequencies hallucinated by minimizing the energy of patch-based Markov network
- Two types of energies:
  - *external potential* — to model the connective statistics between two linked patches in I_H^l and I_H^G.
  - *internal potential* — to make adjacent patches in I_H^L smooth.
- Energy minimization by raster scan [Freeman et al. 2000]

Results

Camera Motion Blur (Global Correction)

Good Example Images



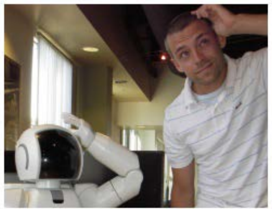


Exposure Correction and White-Balancing

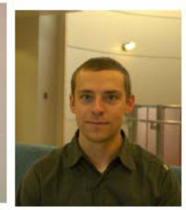
Good Example Images

Defocus Blur (Local Correction)

Good Example Images







Upsampling (Local Correction)

Good Example Images

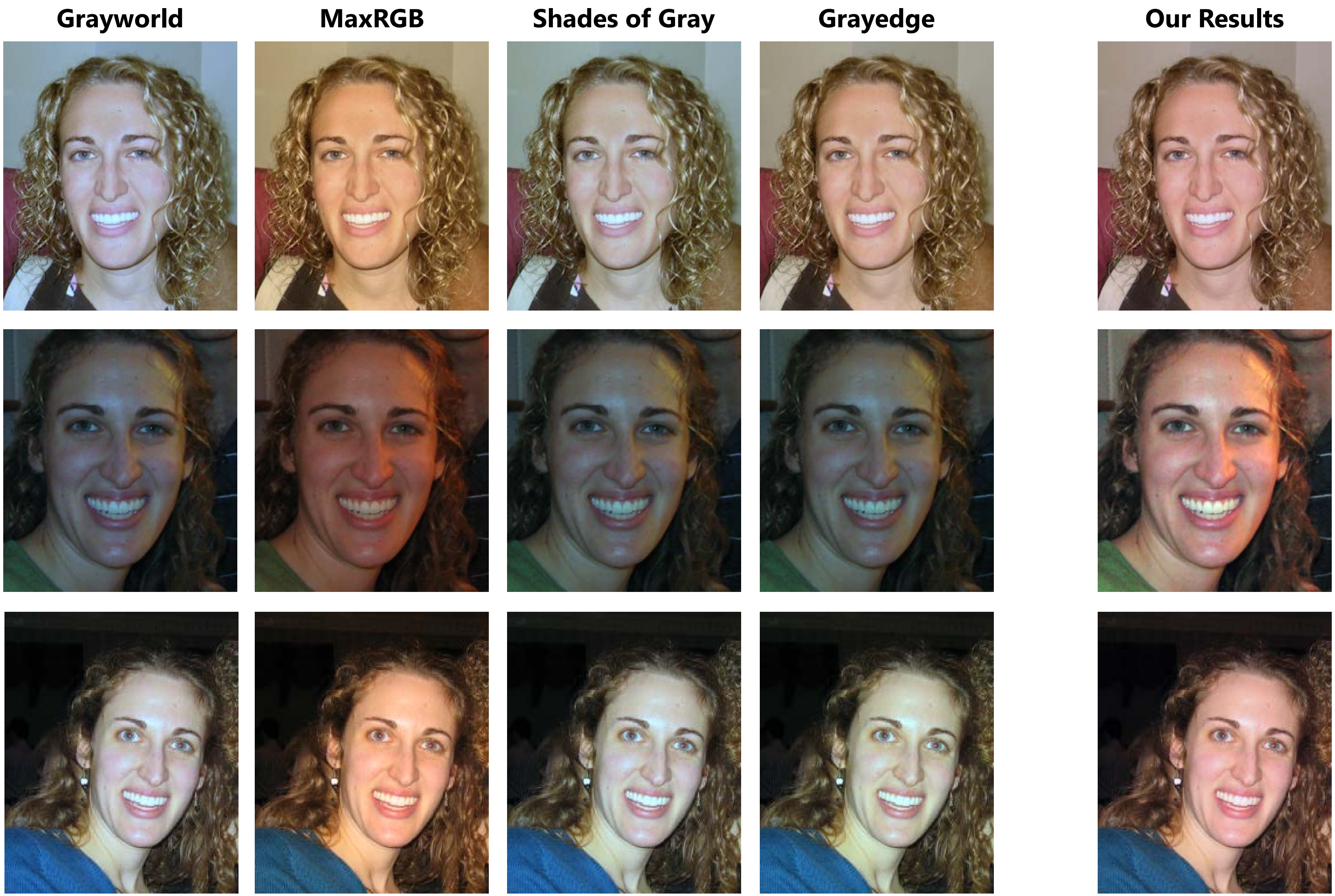
Comparisons

Comparisons to Previous Work

Fergus et al. 2006

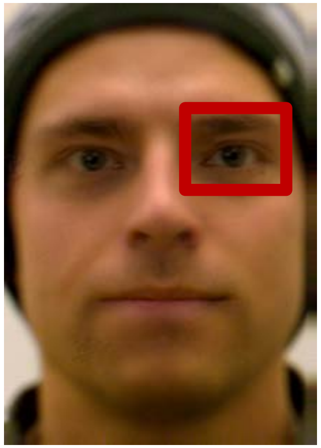
Our Result

Comparisons to Color Constancy [Weijer et al. 2007]



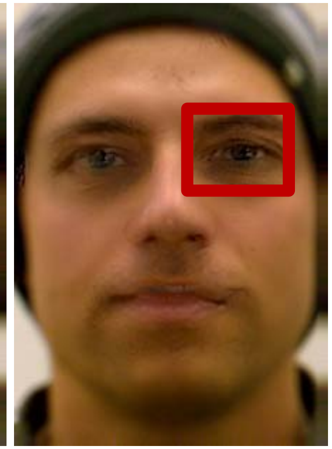
Using Generic Faces

Our Result



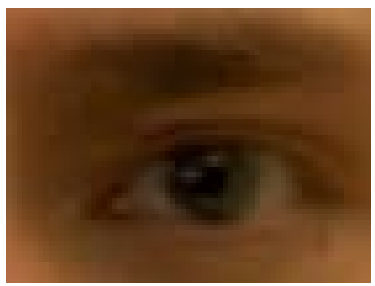
Liu et al. 2007

Generic Faces (10)



Generic Faces (50)

Our Result



Generic (10)

Liu et al.

Generic (50)

Using Generic Faces

Input

Our Result

Liu et al. 2007

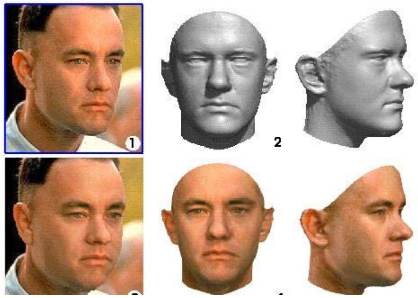
Generic Faces (10)

Generic Faces (50)

Discussion/Future Work

- Latent photo may not be well modeled by the Eigenspace
- All parts of the Eigenspace may not be equally likely

- A prior on the distribution within the Eigenspace
- Better non rigid alignment/morphable model



- Personalized Enhancement on camera/phone

Contributions

- We use good examples of known face images for corrections

- Faces are used as calibration objects for global corrections

- We can further improve the faces in images

- Identity-specific priors out-perform generic priors

Thank You!




http://research.microsoft.com/en-us/um/people/neel/personal_photos/