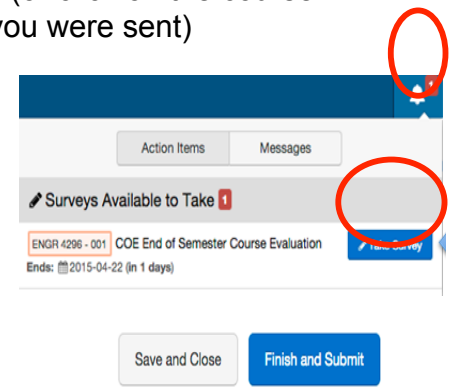
Course Evaluation: Log into aefis.wisc.edu using your netid (or click on the course link from the email you were sent)

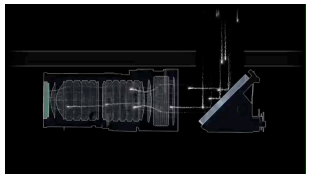
1. Go to the Notification Center and Dashboard, find course and click "Take Survey"
2. Answer questions
3. Once complete, choose "Finish and Submit"



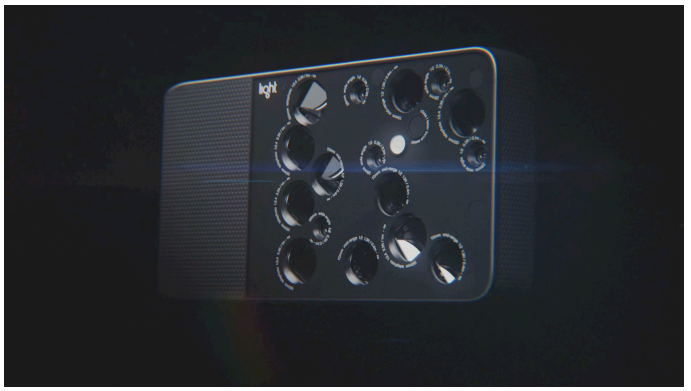
Nikon KeyMission 360

- Two back-to-back cameras, each with a 194° FOV, f2.0, 8.2mm lens (35mm equivalent). The camera can capture 3,840 x 2,160 video at 24 fps, with in-camera stitching
- Other similar 360° video cameras from Samsung, Kodak, Ricoh, Nokia, etc.

Light L16



- 16 cameras, 5 with f/2.0, 28mm lenses, 5 with f/2.0 70mm lenses, and 6 with f/2.4 150mm lenses
- Each scene is shot by up to 10 of 16 individual 28mm, 70mm, and 150mm camera modules firing simultaneously. The images are combined to create a high-resolution, up to 52 megapixel image
- Available mid 2017



3 Final Problems

- Photography in **low light**
- Photography in **bad weather**
- Detecting **fake** photos

Photography in Low Light

Using available ambient light:

+ natural lighting

- high noise
- color needs white balancing
- blur

Adding Lighting Shows Details

Using flash:

+ details
+ color
+ low noise

- flat/artificial
- flash shadows
- red eye

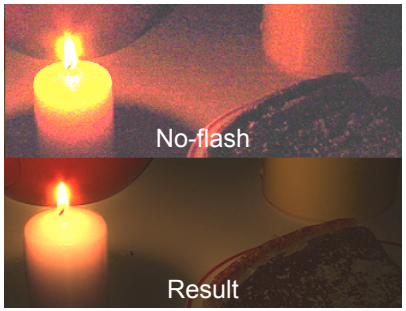
Flash + No-Flash Photography

Take 2 photos and combine best aspects of each

Flash + No-Flash Approach

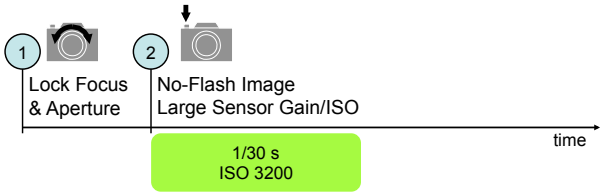
Either use the no-flash image to relight the flash image, or use the flash image to relight the no-flash image

+ original lighting
+ details/sharpness
+ noise removal
+ color

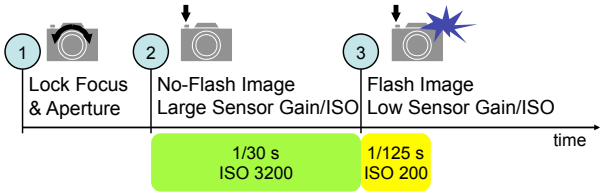


Acquisition Process

Acquisition Process

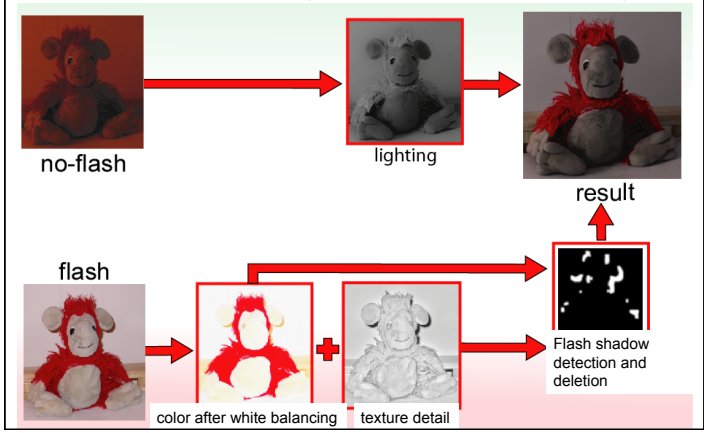


Acquisition Process

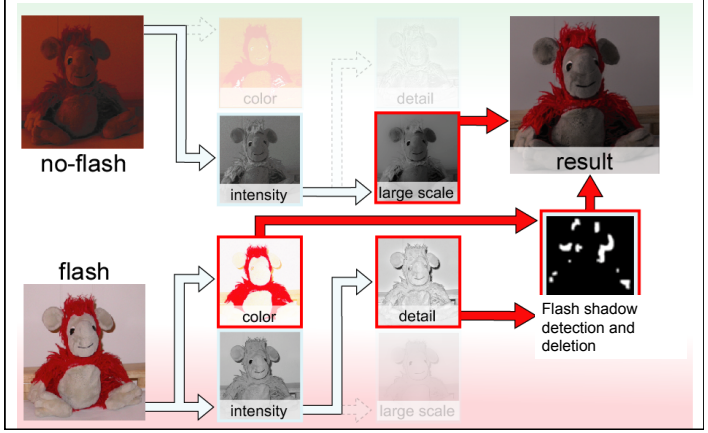


Eisemann and Durand Algorithm

Use color from flash image after inverse white balancing



Eisemann and Durand Algorithm



Decomposition

Color + Intensity Representation:

$$I = \frac{R}{R+G+B}R + \frac{G}{R+G+B}G + \frac{B}{R+G+B}B$$

$$R = \frac{R}{I}, G = \frac{G}{I}, B = \frac{B}{I}$$

Decoupling

- **Lighting = Coarse-scale variation**
- **Detail / Texture = Fine-scale variation**
- Implemented using a **bilateral filter**, which is a weighted average of the pixels in a neighborhood, and the weight is a product of a Gaussian and the pixel intensity difference

Lighting

Detail / Texture

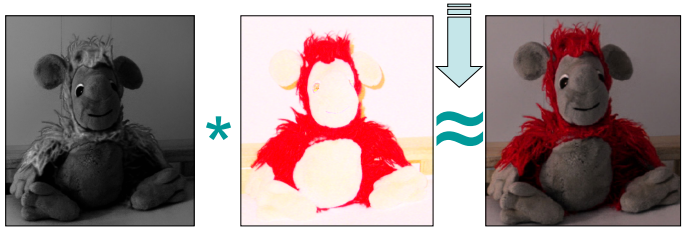
Recombination

Coarse-scale No-flash | Fine-scale Flash | Intensity Result

Recombination: Large scale * Detail = Intensity

Recombination

shadow removal



Intensity Result | Color Flash | Result

Recombination: Intensity * Color = Original

Results

No-flash

Flash

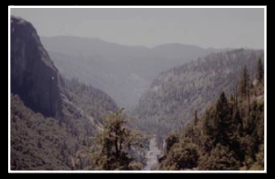
Results

No-flash

Flash

Poor Result

Haze Removal from a Single Image


Haze

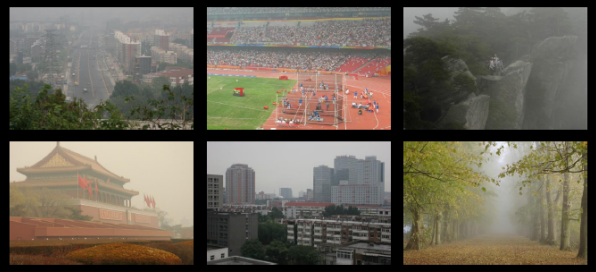

Mist


Fog


Rain

Images Courtesy : Steve and Carol Sheldon

Hazy Images



- Low visibility
- Faint colors
- Low contrast

Aerial Perspective

- aka Atmospheric Perspective
- Objects farther away appear less saturated (whiter) and less sharp (blurrier) than those nearby
- The more atmospheric particles between the viewer and a distant object, the more light is scattered

Distant Objects are Desaturated

Aerial Perspective

Leonardo, *Virgin and St. Anne*, 1510

Color Perspective

Distant objects tend toward blue, near objects toward red

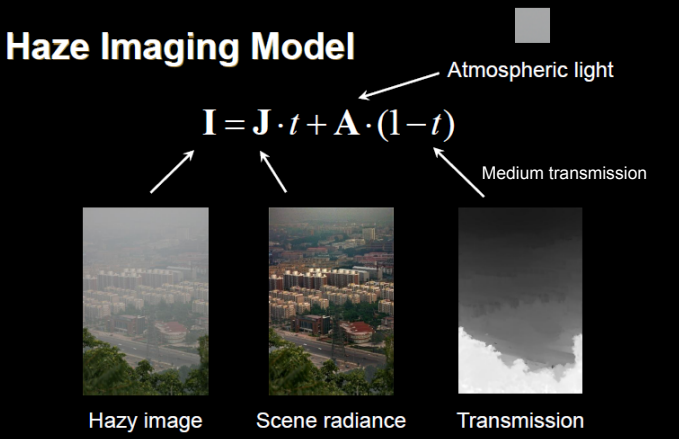
Goals of Haze Removal

depth

- Scene restoration
- Depth estimation

"Single image haze removal using dark channel prior," K. He *et al.*, CVPR, 2009

Haze Imaging Model

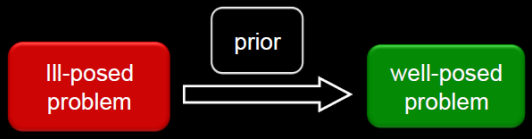


Heuristic: Haze-free images have higher contrast than hazy images

Ambiguity in Haze Removal

When the atmosphere is homogeneous, scene radiance is attenuated exponentially with scene depth, *d*, but we don't know *d*

Priors in Computer Vision



- Smoothness prior
- Sparseness prior
- Exemplar-based prior

Dark Channel Prior

Heuristic: Most local patches in haze-free outdoor images that do not contain sky contain *some* pixels that have very low intensity values in at least one color channel

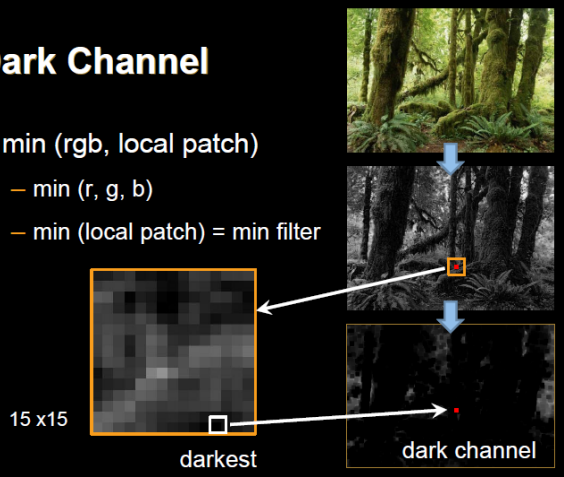
Dark Channel

- min (rgb, local patch)
  - min (r, g, b)

min (r, g, b)

Dark Channel

- min (rgb, local patch)
  - min (r, g, b)
  - min (local patch) = min filter

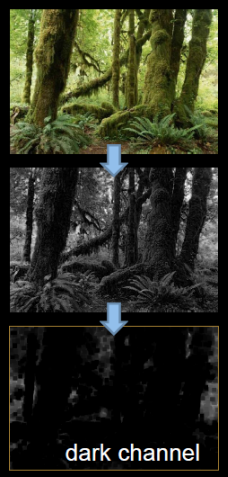


Dark Channel

- min (rgb, local patch)
  - min (r, g, b)
  - min (local patch) = min filter

$$J^{dark}(\mathbf{x}) = \min_{\mathbf{y}\in\Omega(\mathbf{x})} \left(\min_{c\in\{r,g,b\}} J^c(\mathbf{y}) \right)$$

  - J^c: color channel of $\mathbf{J}$
  - J^{dark}: dark channel of $\mathbf{J}$



A Surprising Observation

Haze-free

A Surprising Observation

Haze-free

Haze-free images have ***most*** pixels in the dark channel near 0

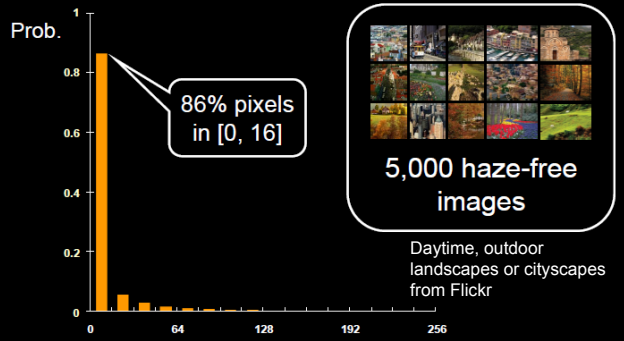
A Surprising Observation

Haze-free

A Surprising Observation

Haze-free

A Surprising Observation



5,000 haze-free images

Daytime, outdoor landscapes or cityscapes from Flickr

What makes it dark?

- Shadow
- Colorful object
- Black object

Dark Channel of Hazy Image

hazy image dark channel

- The dark channel is no longer dark.
- The intensity of the dark channel is an approximation of the thickness of the haze – use it to estimate **J**, **A**, and *t*

Results

input

Results

recovered image

Results

depth

Results

input

Results

recovered image

Results

depth

Results

input

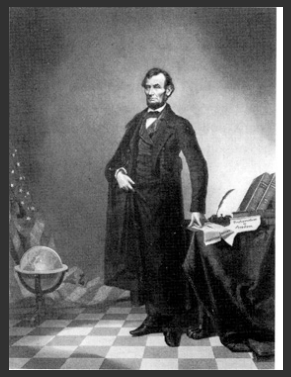
recovered image

Digital Image Forensics:

Detecting Faked/Manipulated Images

A Long History of Photo Manipulation

Examples collected by Hany Farid: http://www.cs.dartmouth.edu/farid/research/tampering.html



Iconic Portrait of Lincoln (1860)

Photo Manipulation as Art

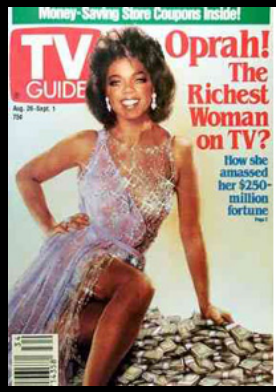
Sarolta Ban

Photo Manipulation for Aesthetics

Airbrushing and retouching to enhance appearance

Retouching is “completely in line with industry standards”

Before and After Retouching Examples



1989 composite of Oprah and Ann-Margret (without either's permission)

Photo Manipulation for Government Campaigns

NYC poster shows man who supposedly lost his leg to diabetes, though original image is on right. Source: New York Times, 1/25/2012

Photo Manipulation in Journalism

2000: black student's face inserted into UW magazine

http://www.cs.dartmouth.edu/farid/research/digitaltampering/

Pulitzer Prize winning photograph of Kent State killing (1970)

2003: Long-time staff photographer for LA Times was fired for this one

Fake Photos in Politics

1930s: Stalin had disgraced comrades removed from photos

http://www.newseum.org/berlinwall/commissar_vanishes/index.htm

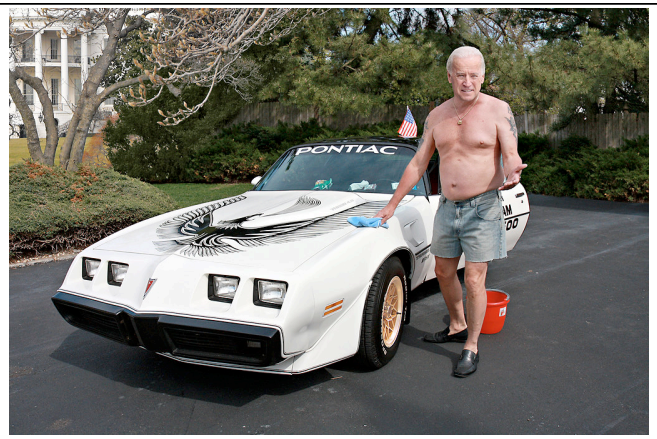
http://www.cs.dartmouth.edu/farid/research/digitaltampering/

Mussolini in a Heroic Pose (1942)

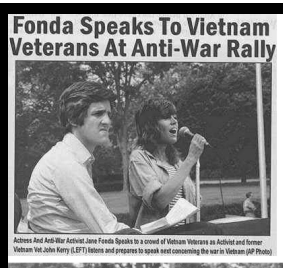
Fake Photos in Politics

2008

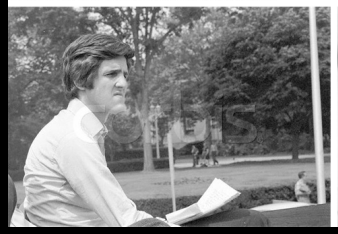
"Talking to a Trump volunteer who says this picture of Clinton and Bin Laden is real and she saw it on TV in the 70s." -- Ben Jacobs, *The Guardian*



"Shirtless Biden Washes Trans Am In White House Driveway," *The Onion*, May 5, 2009



Caption: "Actress and Anti-war activist Jane Fonda speaks to a crowd of Vietnam veterans, as activist and former Vietnam vet John Kerry listens and prepares to speak next concerning the war in Vietnam." (AP Photo)



Kerry at Rally for Peace 1971

Fonda at rally in 1972

"Ape Appointed Banana Czar," *The Onion*, March 19, 1997

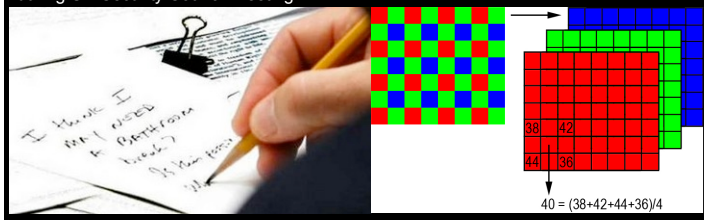
Detecting Forgery: Cloning

- **Exposing Digital Forgeries by Detecting Duplicated Image Regions**
  - A.C. Popescu and H. Farid
  - Technical Report, TR2004-515, Dartmouth College, Computer Science

Detecting Forgery: Retouching

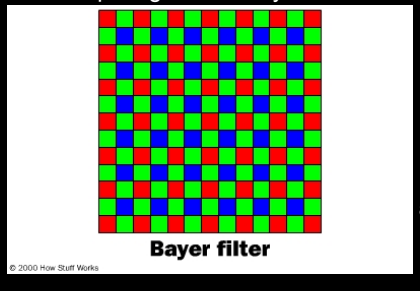
- **Exposing Digital Forgeries in Color Filter Array Interpolated Images**
  - A.C. Popescu and H. Farid
  - IEEE Transactions on Signal Processing, 53(10):3948-3959, 2005

2005: Pres Bush scribbles a note to C. Rice during UN Security Council Meeting



Demosaicing Prediction

- In demosaicing, RGB values are filled in based on surrounding measured values
- Filled in values will be correlated in a particular way for each camera
- Local tampering will destroy these correlations



Farid: "Photo Fakery and Forensics" 2009

Detecting Forgery: Lighting/Shadows

- **Exposing Digital Forgeries by Detecting Inconsistencies in Lighting**
  - M.K. Johnson and H. Farid
  - ACM Multimedia and Security Workshop, New York, NY, 2005

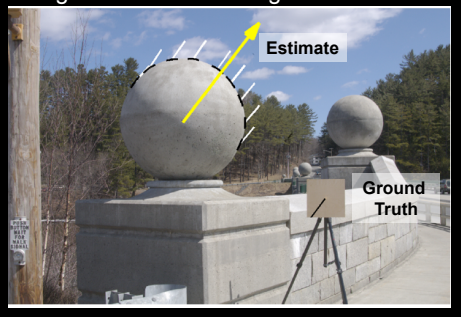
Detecting Forgery: Lighting/Shadows

- **Exposing Digital Forgeries by Detecting Inconsistencies in Lighting**
  - M.K. Johnson and H. Farid
  - ACM Multin York, NY, 2005

Estimating Lighting Direction

1 Method: 2D direction from occluding contour

- Provide at least 3 points on occluding contour (surface has 0 angle in Z direction)
- Estimate light direction from brightness



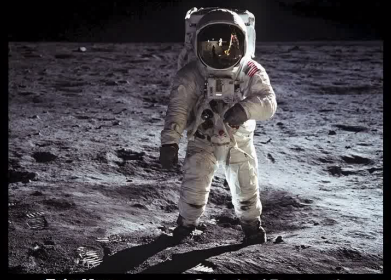
Detecting Inconsistencies in Lighting

Fake photo

Real photo

Detecting Forgery: Lighting/Shadows

Exposing Photo Manipulation with Inconsistent Shadows



Eric Kee Columbia / Dartmouth
James O'Brien Berkeley
Hany Farid Dartmouth

Lighting: Specular Highlights in the Eye

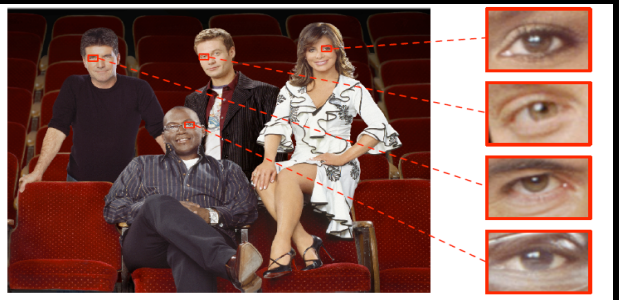


Fig. 1. This photograph of the *American Idol* host and judges is a digital composite of multiple photographs. The inconsistencies in the shape and position of the specular highlight on the eyes suggest that these people were originally photographed under different lighting conditions. Photo courtesy of Fox News and the Associated Press.

M.K. Johnson and H. Farid,
"Exposing Digital Forgeries Through Specular Highlights on the Eye,"
2007

Estimating Lighting from Eyes

Summary

- Digital forgeries are a major problem as it is easy to fake images
- A variety of automatic and semi-automatic methods are available for detection forgeries
  - Checking lighting consistency
  - Checking demosaicing consistency
  - Checking JPEG compression level consistency
- But more methods are needed!