

MAIA - MedicAl Imaging and Applications
Advanced Image Analysis

Lectures on Advanced Color Image Processing

B6 – Image Dehazing

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Image Dehazing

The Problem of Image Dehazing



HAZE ~ MIST, FOG, SMOG =
DEGRADATION DUE TO BAD WEATHER

The Problem of Image Dehazing

Particularity of haze degradation: it is **depth-dependent**.

A good dehazing method will increase more contrast in regions far-away from the observer, while increasing less contrast on nearby regions.



Hazy image

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Histogram Equalization

The Problem of Image Dehazing

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Dehazed image

Image Dehazing

Key Ingredient

A physical model of the degradation: $I(x) = J(x)t(x) + A(1 - t(x))$

H. Kochsmieder, Theorie der horizontalen Sichtweite: Kontrast und Sichtweite, 1925

- $I(x)$ is the acquired pixel intensities – Input Image
- $J(x)$ is the degraded intensities – Haze-Free Image
- $t(x)$ is transmission – Inverse of 3D depth $t(x) = e^{-\beta d(x)}$
- A is the airlight – Color of Fog

Image Dehazing

Physical Model - Intuition

$$I(x) = J(x)t(x) + A(1 - t(x))$$

$$t(x) = e^{-\beta d(x)}$$

$J(x)$, the haze-free image, is what we want to retrieve. According to the model, it undergoes a **multiplicative** degradation depending on depth, and an **additive** degradation depending on depth and haze color.

As distance goes to 0, $t(x) \rightarrow 1$. Near the observer, haze has no effect and we have:

$$\lim_{t(x) \rightarrow 1} I(x) = J(x)$$

As distance increases, haze takes over the scene, and we have:

$$\lim_{t(x) \rightarrow 0} I(x) = A$$

The Dark Channel Method

- Outdoor haze-free images contain shadows and colorful texture everywhere.
- Thus, locally at least some color channel will have low values.
- This is encoded in the so-called Dark Channel Prior:

$$J^{\text{dark}}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R, G, B\}} J^c(y) \right)$$

- For haze-free images,

$$J^{\text{dark}}(x) \rightarrow 0$$



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$$t(x) = e^{-\beta d(x)}$$

$$J^{\text{dark}}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R, G, B\}} J^c(y) \right) \sim 0$$

**Dark-Channel
Prior**

Taking minima on the model, the first term on the rhs vanishes, and we can estimate $t(x)$ from the hazy input.

$$\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left(\min_c \left(\frac{I^c(x)}{A^c} \right) \right)$$

This assumes locally constant depth in the scene.
It results in block artifacts in the depth map.

Image Dehazing

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Depth Map Refinement



Image Dehazing

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Depth Map Refinement



The Dark Channel Method - Model Inversion

$$I(x) = J(x)t(x) + A(1 - t(x))$$

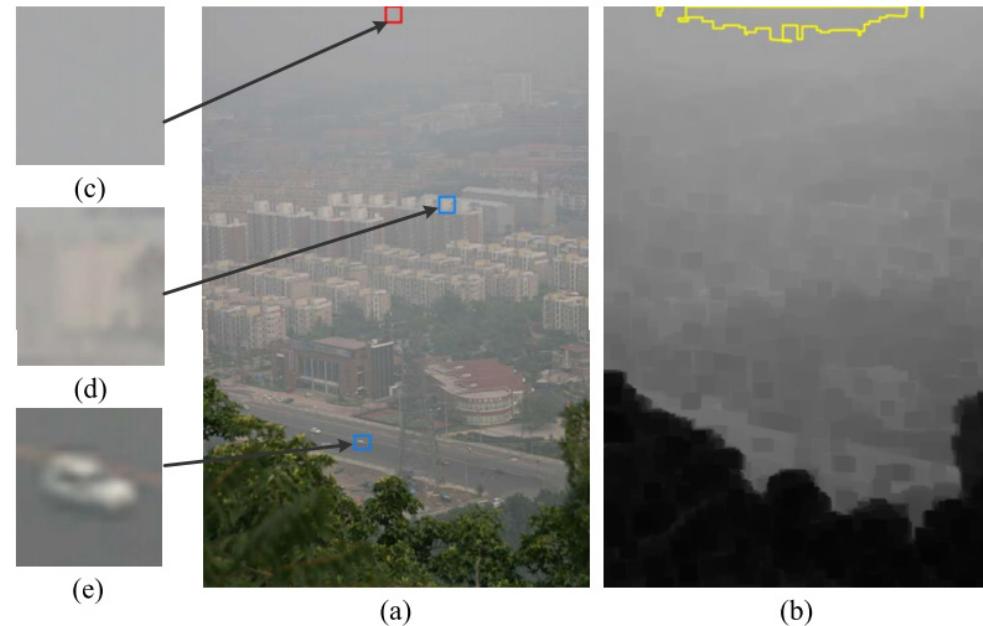


$$J(x) = \frac{(I(x) - A)t(x) + A}{\max(t(x), 0.1)} + A$$

- After depth has been estimated, we simply invert the degradation model.
- But we have assumed all the time we knew A!

Airlight Estimation

- Once the dark channel image has been built, select from it the brightest pixels (1%).
- Those should correspond to the furthest pixels in the RGB image. Select the corresponding brightest RGB pixel as A.



The Dark Channel Method – Pseudo-code

1.- Compute: $J^{\text{dark}}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R,G,B\}} J^c(y) \right)$

2.- Estimate A from I as the brightest pixel in the Dark Channel

3.- Compute transmission map: $\tilde{t}(x) = 1 - \min_{y \in \Omega(x)} \left(\min_c \left(\frac{I^c(x)}{A^c} \right) \right)$

4.- Refine the transmission map (guided filtering).

5.- Invert the model: $J(x) = \frac{(I(x) - A)t(x) + A}{\max(t(x), 0.1)} + A$

The Dark Channel Method - Results



Hazy image

The Dark Channel Method - Results



Dehazed image

The Dark Channel Method - Results



Hazy image

The Dark Channel Method - Results



Dehazed image

The Dark Channel Method - Results



Hazy image

Image Dehazing

The Dark Channel Method - Results



Dehazed image

The Dark Channel Method - Results



Hazy image

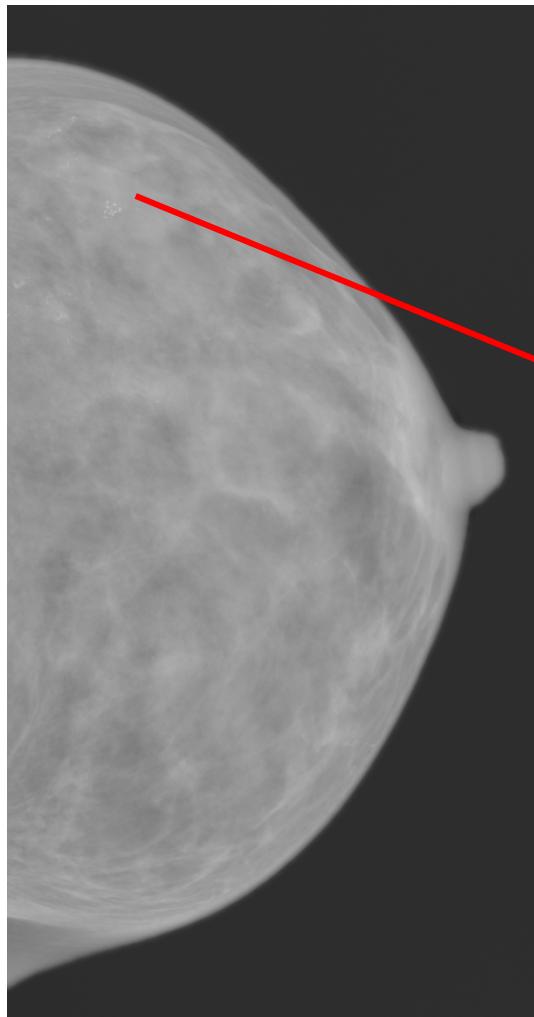
The Dark Channel Method - Results



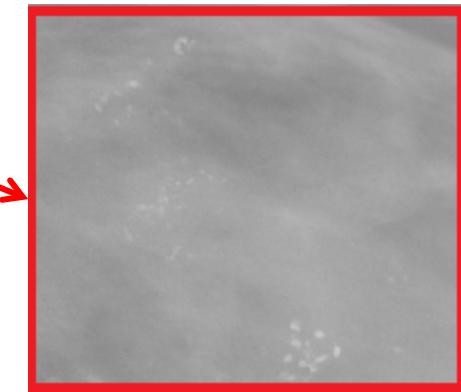
Dehazed image

Image Dehazing

The Dark Channel Method - Results



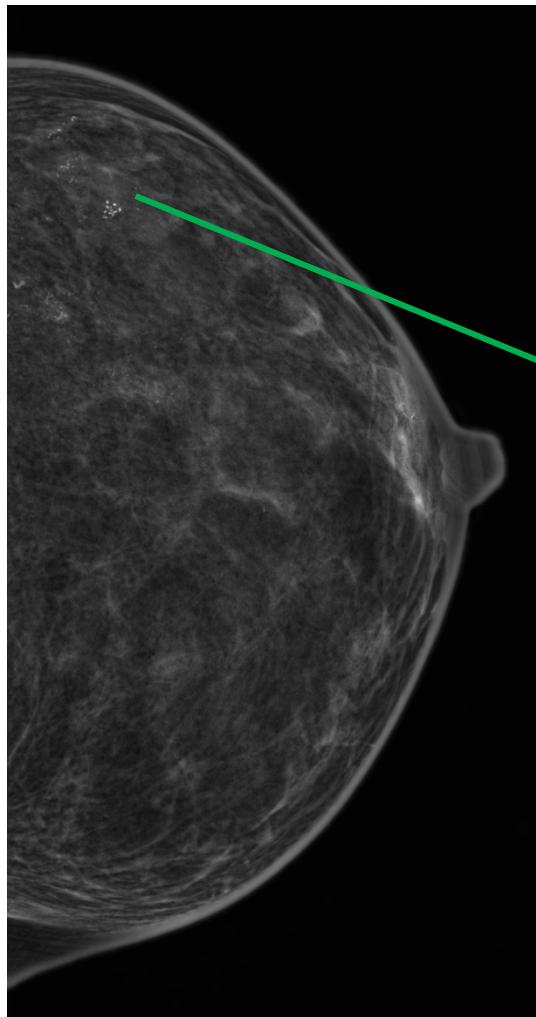
Digital Mammogram



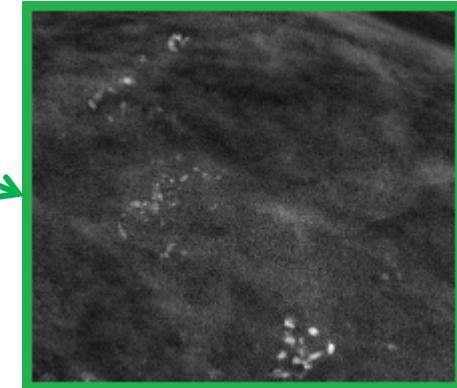
Micro-calcification Cluster

Image Dehazing

The Dark Channel Method - Results



Digital Mammogram



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Image Dehazing

Inverted Dark Channel

- Think of shadows as the inverse of fog.
- They drive intensities towards white instead of towards dark.

$$\text{Shadow Removal}(I(x,y)) \rightsquigarrow 1 - \text{Dehazing}(1 - I(x,y))$$



Fog Map Estimate

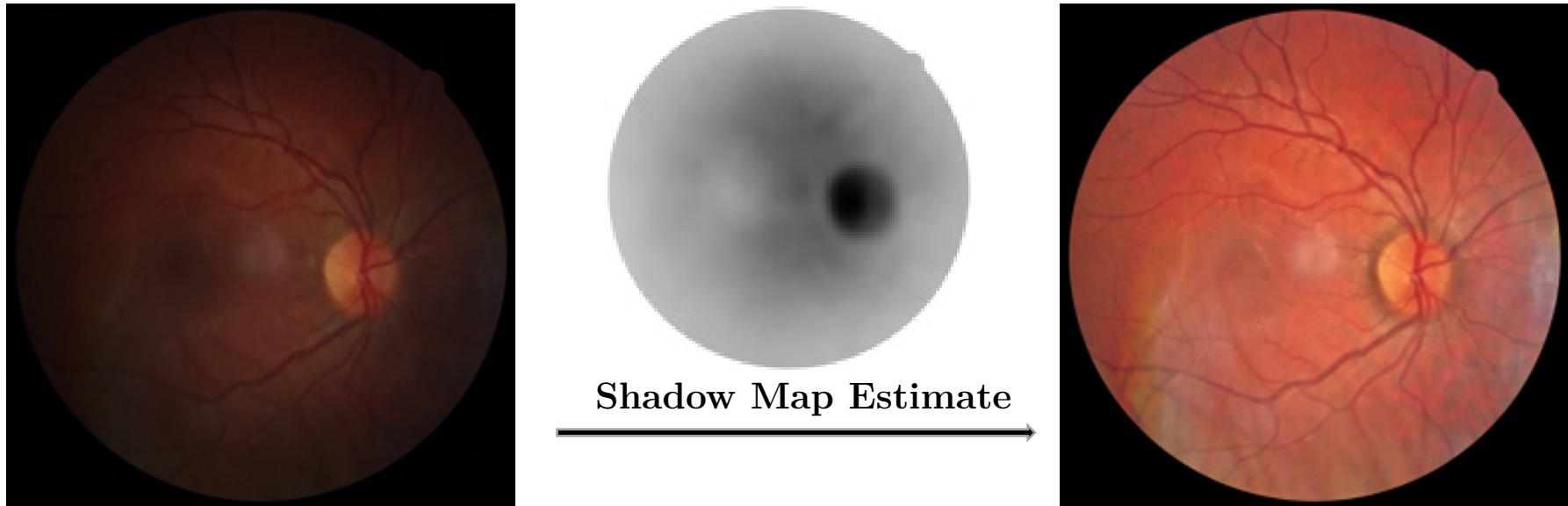


Image Dehazing

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