Reflection Removal Using Ghosting Cues

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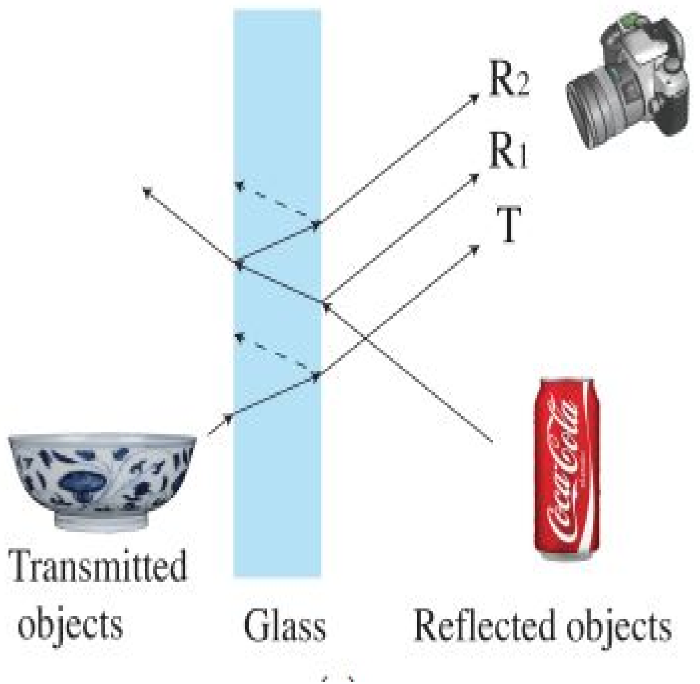
Implementation of paper

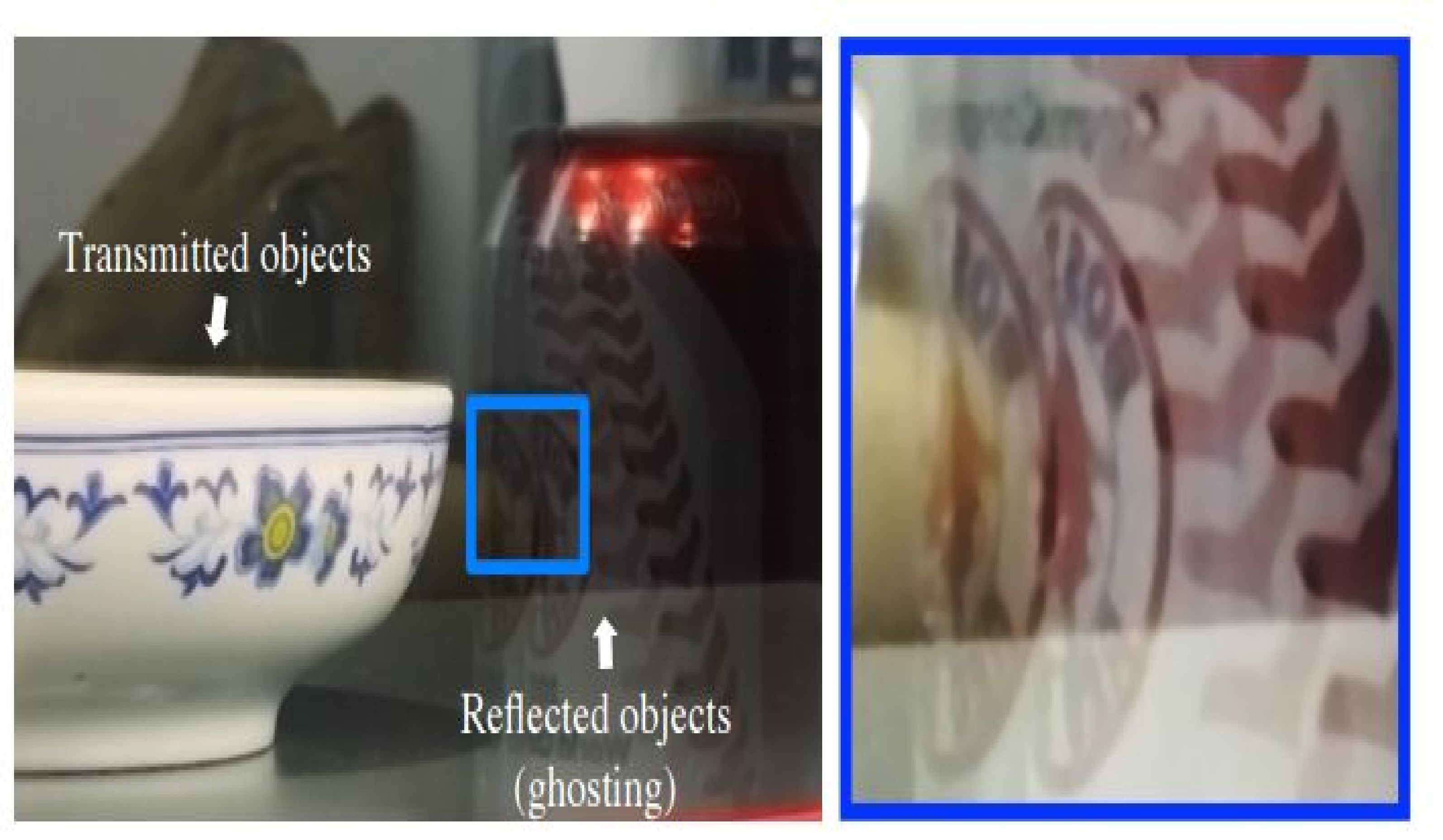
Reflection removal using Ghosting cues

http://ieeexplore.ieee.org/document/7298939/?reload=true&arnumber=7298939

Introduction

When taking a picture through a window pane, reflections of objects are often captured.




Transmitted objects
Reflected objects
(ghosting)

Challenge

Traditional imaging model:

$$I=T+R$$

As both T and R are natural, separating them is ill-posed since both T and R are natural images and appear the same statistical properties.

What paper accomplishes..

Separate the reflection layer using

- the double reflection imaging model
- with patch-based image prior

How can we do this?

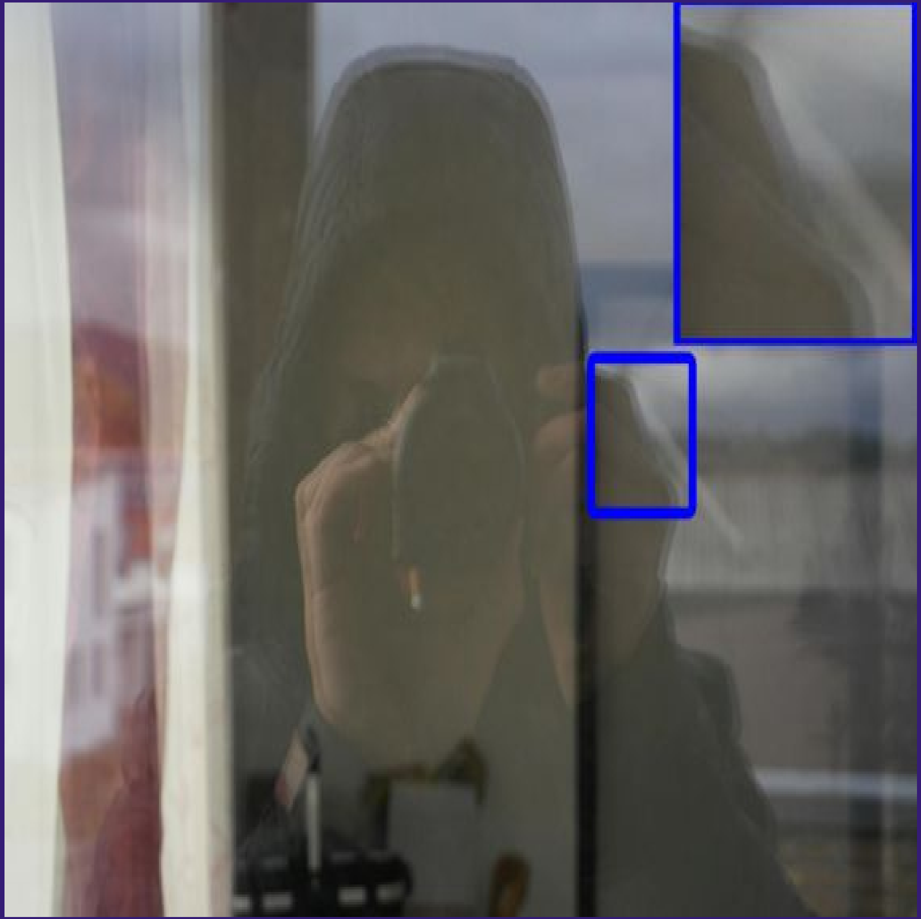
Key idea..

Break the symmetry of T and R using Ghosting

What's Ghosting ? Appearance of secondary image on the main display.

Observation: Window reflection often appear multiple times.

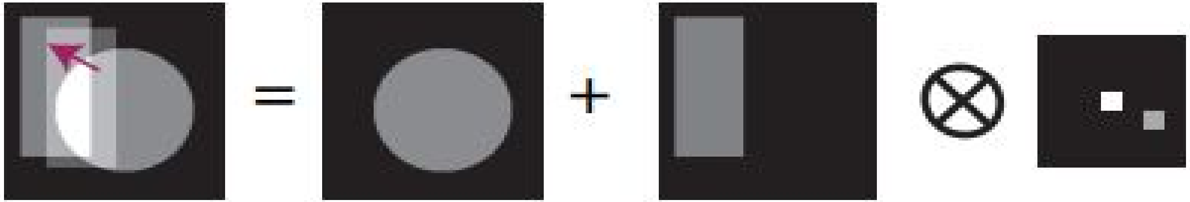

TOWN OF
WEST
HARTFORD



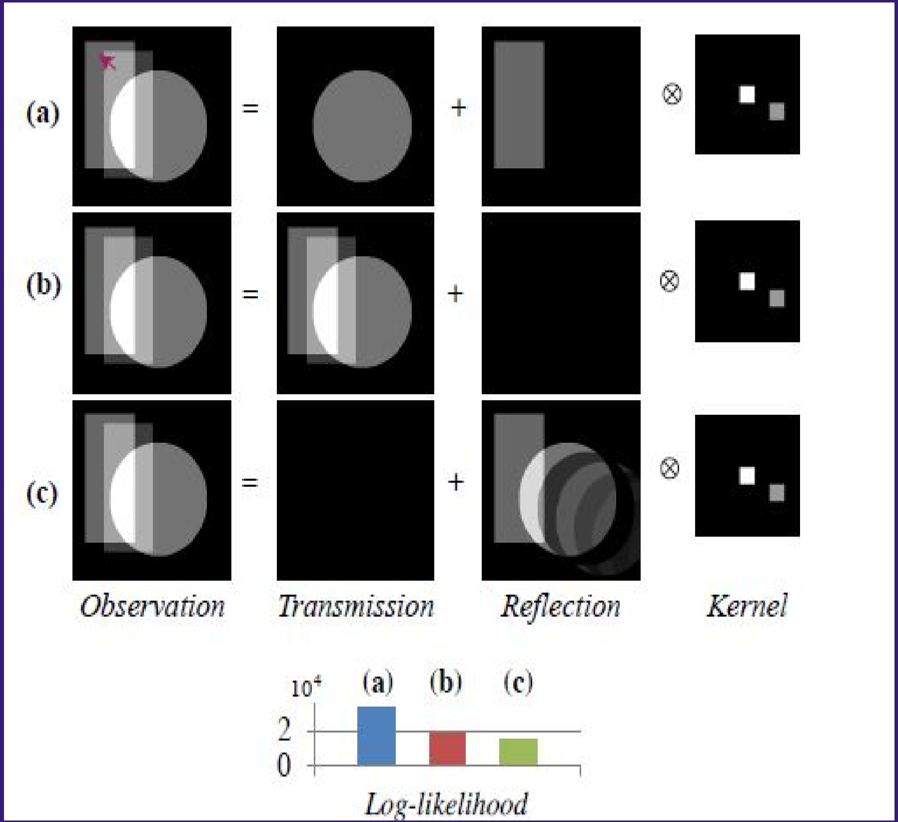
Modelling Ghosting

Using a two-pulse kernel k.

$$I = T + R \otimes k$$



Parameterize k by the separation of the two reflections **d** and an attenuation factor **c** depending on the camera view angle $k(\mathbf{x}) = \delta(\mathbf{x}) + \alpha\delta(\mathbf{x} - \mathbf{d})$



Toy Example

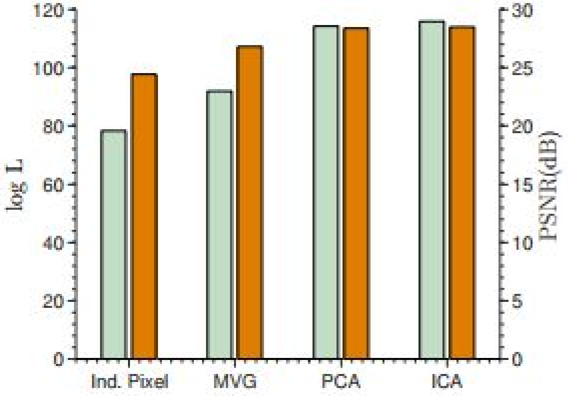
A synthetic example with a circle as the transmission layer and a rectangle as the reflection layer.

We compare the log likelihoods of the various possible decompositions under a GMM Model.

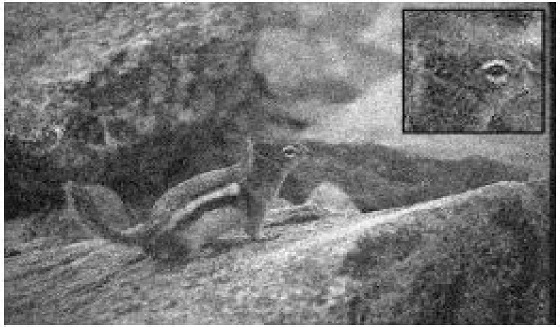
The log likelihood of the a) is the highest, (implying is most "Natural") which is indeed the ground truth.

Why GMM?

It performs well for image restoration when compared to other methods.



Expected Patch Log Likelihood: Image denoising



(a) Noisy Image - PSNR: 20.17

(b) KSVD - PSNR: 28.72

(c) LLSC - PSNR: 29.30

(d) EPLL GMM - PSNR: 29.39

Source : From Learning Models of Natural Image Patches to Whole Image Restoration

Expected Patch Log Likelihood: Image deblurring

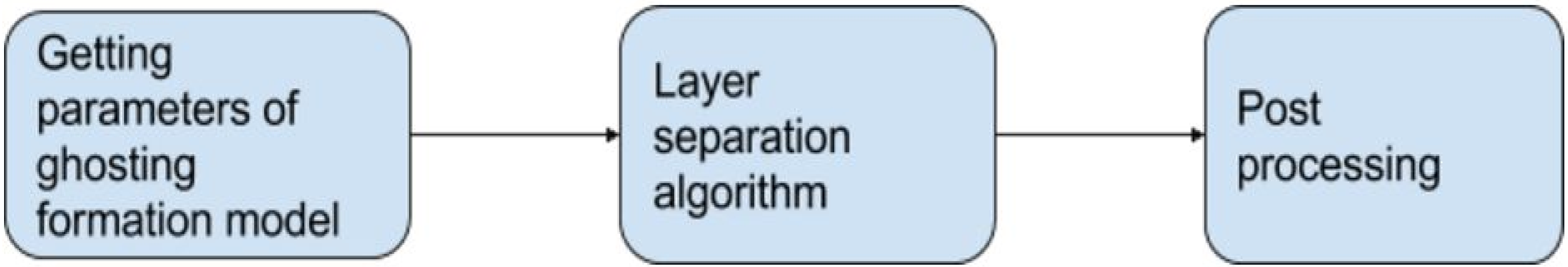
(a) Blurred (b) Krishnan et al. (c) EPLL GMM

	Krishnan et al.	EPLL-GMM
Kernel 1 17 × 17	25.84	27.17
Kernel 2 19 × 19	26.38	27.70

Figure 8: Deblurring experiments

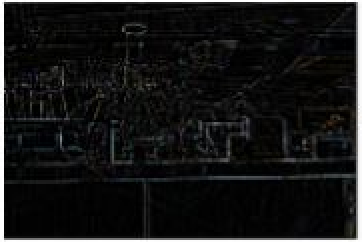
Source : From Learning Models of Natural Image Patches to Whole Image Restoration

The BIG PICTURE..

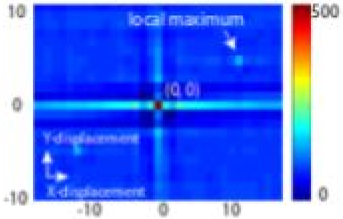


Estimating KERNEL PARAMETERS

Input Image



Laplacian



Autocorrelation Map

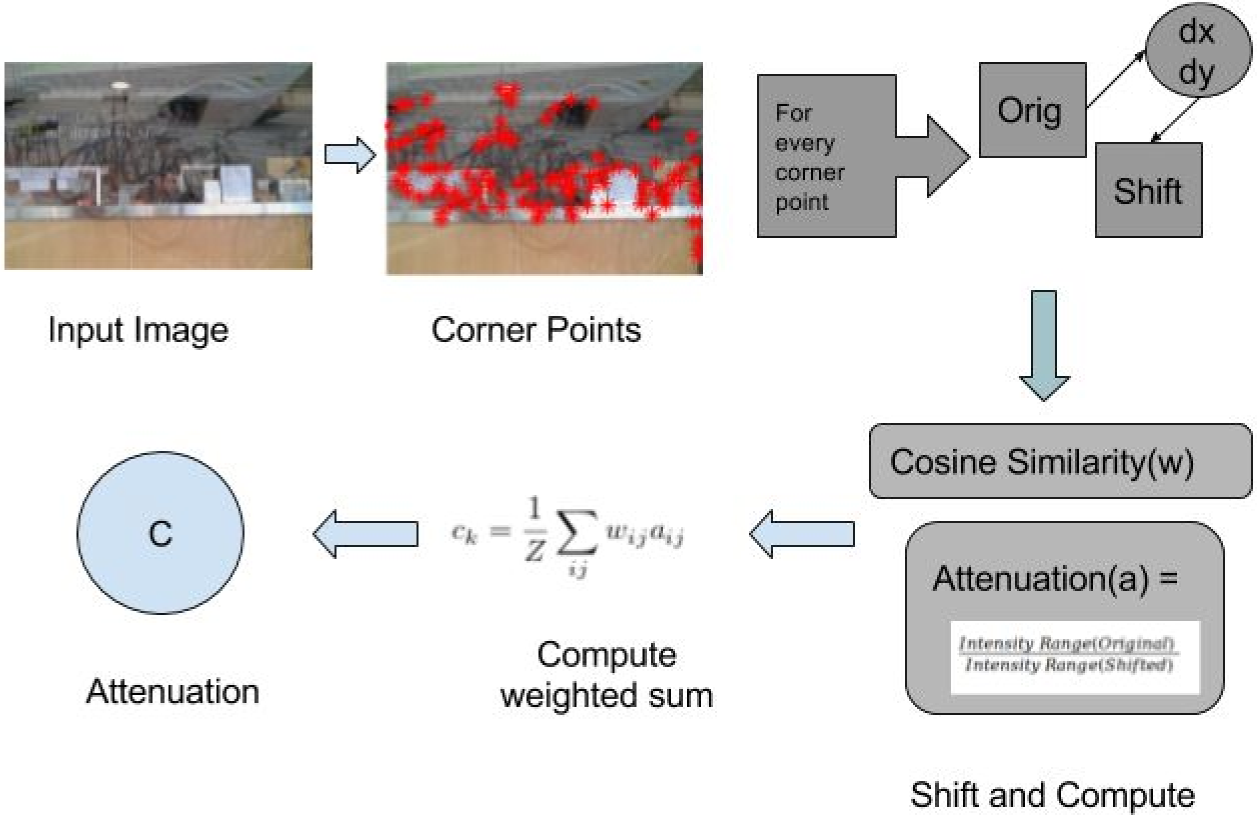
Thresholding
Remove incorrect maxima due to locally flat or repetitive structures.

Pick Max among correct local minima

dx dy

Shift

Estimating KERNEL PARAMETERS



Optimization

To recover the transmission $\boldsymbol{T}$ and reflection $\boldsymbol{R}$, we minimize the following:

Minimizing COST:

$$\underbrace{\frac{1}{\sigma^2}\|I - T - R\otimes k\|_2^2}_{\textbf{Reconstruction cost}} - \underbrace{\sum_i \log(GMM(P_iT)) - \sum_i \log(GMM(P_iR))}_{\textbf{Image prior (Gaussian Mixture Model)}} \quad \underbrace{\text{s.t. } 0 \le T,\, R \le 1}_{\textbf{Non-negativity [3]}}$$

Non Convex
Due to GMM
prior

Modelled as half
quadratic optimization

Zit

Zir

Per Patch
Auxiliary
Variables

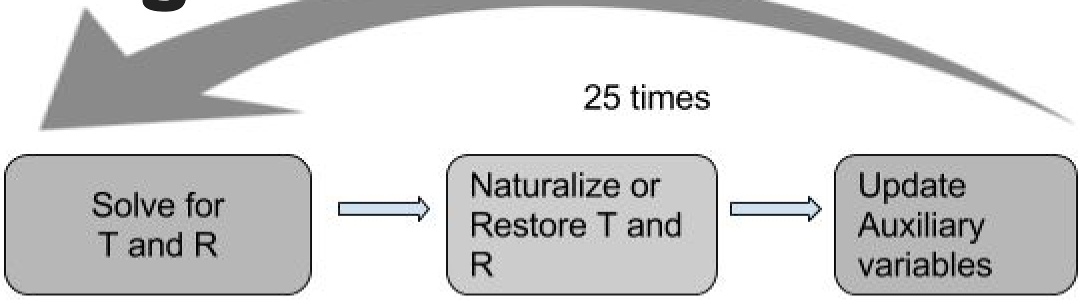
$$\min_{T,R,z_T,z_R} \frac{1}{\sigma^2}\|I - T - R\otimes k\|_2^2 \tag{7a}$$

$$+\frac{\beta}{2}\sum_i \left(\|P_iT - z_T^i\|^2 + \|P_iR - z_R^i\|^2\right) \tag{7b}$$

$$-\sum_i \log(\mathrm{GMM}(z_T^i)) - \sum_i \log(\mathrm{GMM}(z_R^i)) \tag{7c}$$

$$\text{s.t. } 0 \le T, R \le 1 \tag{7d}$$

Alternating minimization



Auxiliary variables fixed

zit zir

Solve using LBFGS

$$\min_{T,R,z_T,z_R} \frac{1}{\sigma^2}\|I - T - R \otimes k\|_2^2 + \frac{\beta}{2}\sum_i \left(\|P_i T - z_T^i\|^2 + \|P_i R - z_R^i\|^2\right)$$

$$\text{s.t. } 0 \leq T, R \leq 1$$

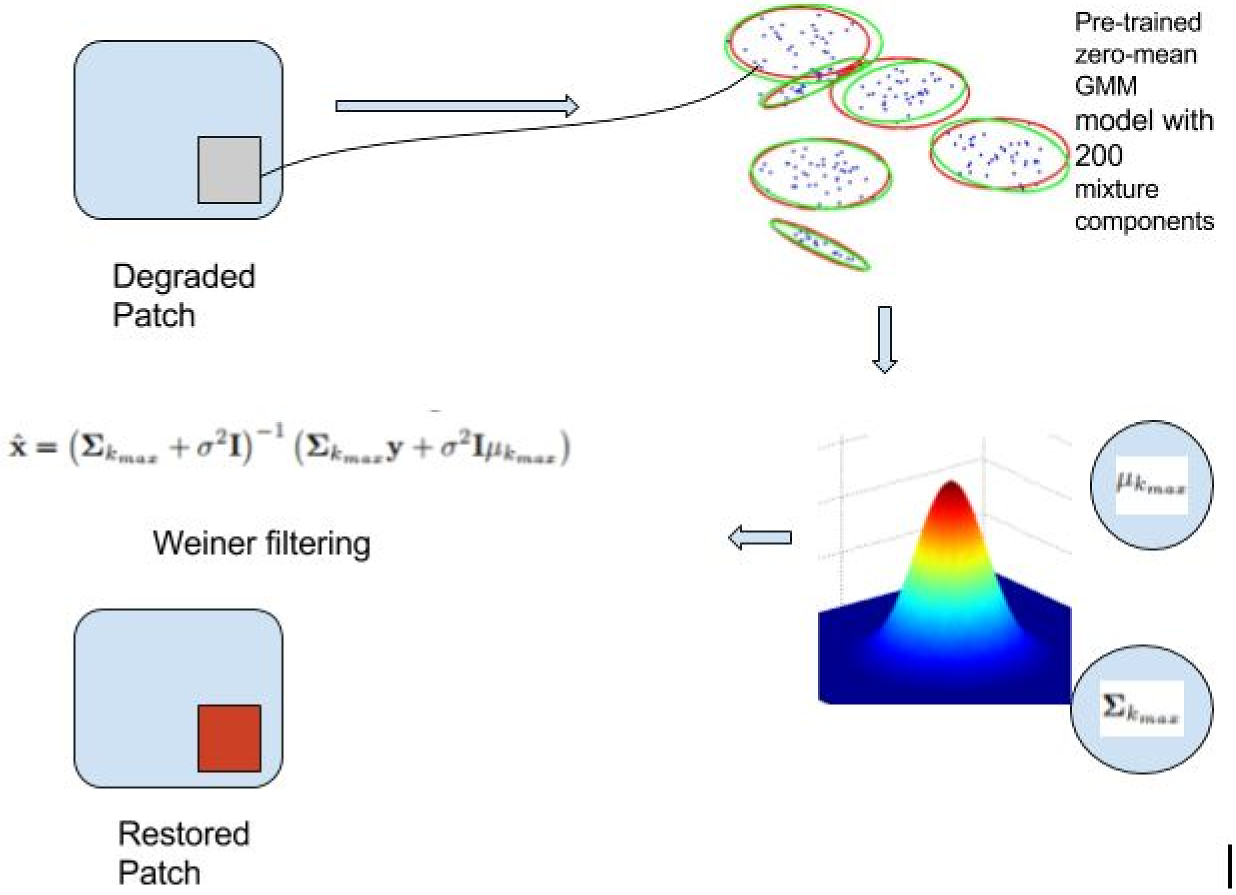
Solve using Estimated Patch log likelihood (EPLL)

$$-\sum_i \log(\text{GMM}(z_T^i)) - \sum_i \log(\text{GMM}(z_R^i))$$

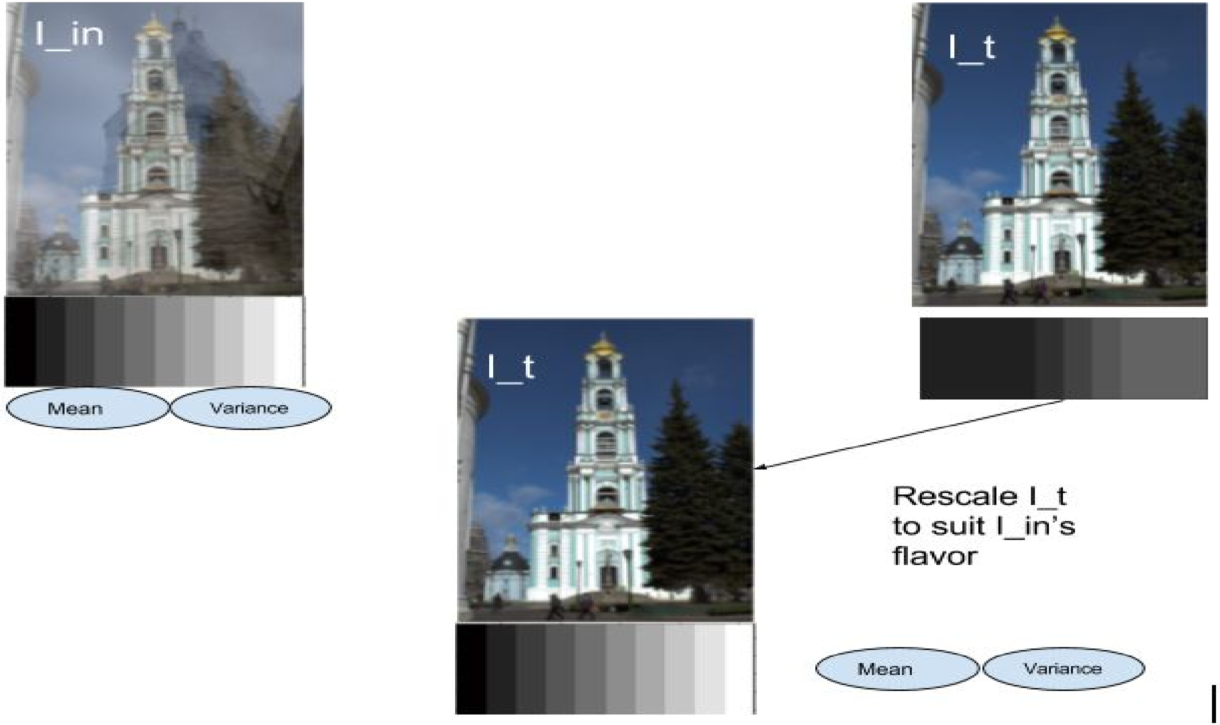
$$\frac{\beta}{2}\sum_i \left(\|P_i T - z_T^i\|^2 + \|P_i R - z_R^i\|^2\right)$$

As Beta tends to infinity, zix's need to be equated to pix's to get a finite product value

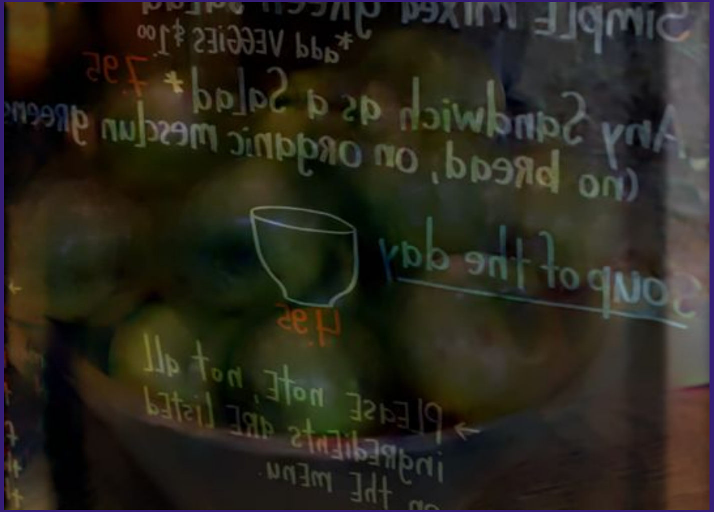
Estimated Patch Log Likelihood (EPLL)



Post-processing



Results



Results

Results

Results



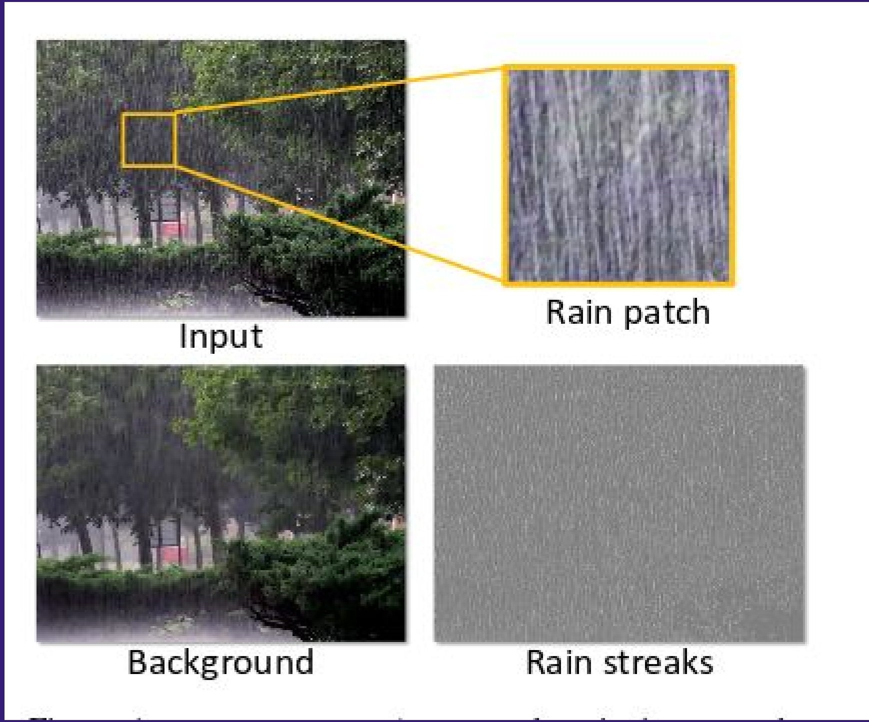
Failure cases

Failure cases

Limitations

- Requires double paned windows
- Sensitive to patterned reflection layers
- We assume spatially-invariant ghosting.
  - the reflection layer does not have large depth variations
  - when the angle between camera and glass normal is not too oblique

Applications : Rain Streak Removal Using Layer Priors



$$\mathbf{O} = \mathbf{B} + \mathbf{R}.$$

$$\begin{aligned}\min_{\mathbf{B},\mathbf{R}} \quad & \|\mathbf{O} - \mathbf{B} - \mathbf{R}\|_F^2 + \alpha\|\nabla \mathbf{B}\|_1 + \beta\|\mathbf{R}\|_F^2 - \\ & \gamma \sum_i \log\left(\mathcal{G}_{\mathbf{B}}(\mathcal{P}(\mathbf{B}_i)) + \log \mathcal{G}_{\mathbf{R}}(\mathcal{P}(\mathbf{R}_i))\right) \\ \text{s.t.} \quad & \forall i \;\; 0 \leq \mathbf{B}_i, \mathbf{R}_i \leq \mathbf{O}_i.\end{aligned}$$

Future Work : Obstruction Removal

Future Work: Approach

- Using Obstruction Priors
- Using Repetitions/Patterns in an image