Image Reflection Removal

Project Proposal

Project ID : 42

Github Link : Repo

Team Members

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Problem Definition

Images taken through glass windows often contain undesirable reflection artifacts which ruin the image. In this project, the original image is considered to be composed of a reflection layer (undesirable) and a transmission layer (desirable).

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

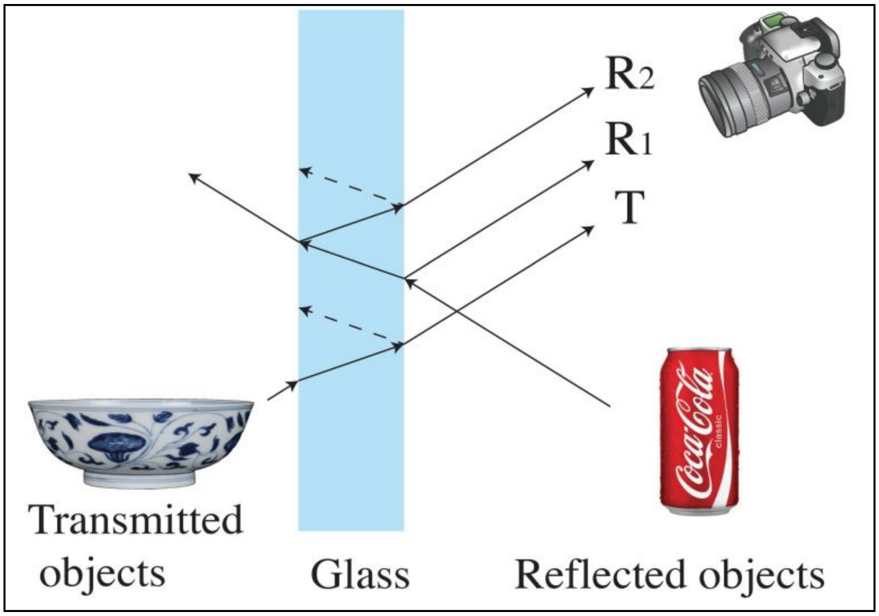
where I is Original Image
T is Transmission layer
R is Reflection layer
k is two-pulse kernel
n is additive Gaussian noise

The original image is modeled as a mixture of these layers and the desirable image component is recovered after removing the undesired reflection layer.

(a) *Input* **(b)** *Close-up of ghosting*

(c) *Recovered Transmission* **(d)** *Recovered Reflection*

For double pane windows, each pane reflects the shifted and attenuated versions of the objects on the same side of the glass as the camera. For single pane windows, the two surfaces of the pane are used as ghosting cues.



The algorithm consists of two parts :

- Layer Separation Algorithm
- Ghosting kernel estimation

1. Layer Separation Algorithm

Given a ghosting kernel *k*, a loss expression can be constructed for reconstruction using T and R:

$$L(T, R) = \frac{1}{\sigma^2}\|I - T - R \otimes k\|_2^2$$

Additional priors are required to regularize this optimization problem. The research paper applies a patch-based prior based on Gaussian Mixture Models (GMM). The prior captures the covariance structure and pixel dependencies over a specified patch size.

The regularizer minimizes the following cost function:

$$\boxed{-\sum_i \log(\mathbf{GMM}(P_i T)) - \sum_i \log(\mathbf{GMM}(P_i R))}$$

We use a pre-trained zero-mean Gaussian Mixture Model with 200 mixture components and a patch size of 8x8 from the paper '*From learning models of natural image patches to whole image restoration*' by D. Zoran and Y. Weiss.

The final combined cost function would be:

$$\begin{aligned}
\min_{T,R,z_T,z_R} \; & \frac{1}{\sigma^2}\|I - T - R \otimes k\|_2^2 \\
& + \frac{\beta}{2}\sum_i \left(\|P_i T - z_T^i\|^2 + \|P_i R - z_R^i\|^2\right) \\
& - \sum_i \log(\mathbf{GMM}(z_T^i)) - \sum_i \log(\mathbf{GMM}(z_R^i)) \\
& \text{s.t. } 0 \le T, R \le 1
\end{aligned}$$

which is a non-convex optimization problem due to the GMM prior. Auxiliary variables are introduced to perform the optimization and increasing values of β is used. Alternating minimization is performed for the auxiliary variables and T & R.

Equation with auxiliary variables :

$$\boxed{\begin{aligned}\min_{T,R}\quad & \frac{1}{\sigma^2}\|I - T - R\otimes k\|_2^2 - \textstyle\sum_i \log(\mathrm{GMM}(P_i T)) \\ & - \textstyle\sum_i \log(\mathrm{GMM}(P_i R)),\ \text{s.t. } 0 \le T, R \le 1\end{aligned}}$$

2. Estimating the ghosting kernel *k*

The ghosting convolution kernel k, is parameterized by a spatial shift vector, $\boldsymbol{d_k}$ and an attenuation factor, $\boldsymbol{c_k}$ between the primary reflection and secondary reflection.

The spatial shift vector is estimated using the autocorrelation map of the laplacian of the input image. The shifted copies of the reflection layer create local maximum on the autocorrelation map. After some processing, the largest local maxima is considered as the spatial shift vector.

The attenuation factor is calculated using the spatial shift vector. Interest points are detected from the input image using Haris Corner detector. A 5x5 normalized contrast patch was extracted from each region of a corner feature. Patches that have a strong correlation with patches at spatial offset $\boldsymbol{d_k}$ are assumed to be due to either of the reflection layers. Attenuation between a pair of matching patches is calculated as :

$$a_{ij} = \sqrt{\frac{var[p_i]}{var[p_j]}}$$

And $\boldsymbol{c_k}$ is given as

$$c_k = \frac{1}{Z}\sum_{ij} w_{ij} a_{ij} \quad \text{where } w_{ij} = e^{-\frac{\| p_i - p_j \|^2}{2\theta^2}}$$

Goals

- Separating the reflection and transmission layers by using a novel heuristic 'ghosting cues'
- Exploit asymmetry between the layers, and use cues that arise from shifted double reflections of the reflected scene off the glass surface.
- Develop an automatic method that requires a single input image.

Milestones & Timeline

Timeline	Milestones
September 27	Project Proposal submission
First week of October	Understand the paper and discussions with the TA. Reading relevant papers in this domain
Second and third week of October	Implementation of the paper with constant TA reviews
Last week of October	Finalize implementation and demo preparation
First week of November	Submission

Expected Results

- Develop an automatic tool that can separate the reflection and transmission layers given a single input image which can either be synthetic or real-world image.
- Model the ghosted reflection using a double-impulse convolution kernel, and automatically estimate the spatial separation and relative attenuation of the ghosted reflection components.
- To separate the layers, implement an algorithm that uses a Gaussian Mixture Model for regularization.

Applications of the work

- Image classification on the recovered transmissions
- Automated de-ghosting for product photography
- Automated driver assistance systems with dashboard cameras for object detection.