Reflection Removal via Realistic Training Data Generation

Youxin Pang
NLPR-CASIA
School of AI, UCAS
pangyouxin2020@ia.ac.cn

Mengke Yuan
NLPR-CASIA
School of AI, UCAS
mengke.yuan@nlpr.ia.ac.cn

Qiang Fu
KAUST
qiang.fu@kaust.edu.sa

Dong-Ming Yan
NLPR-CASIA
School of AI, UCAS
yandongming@gmail.com

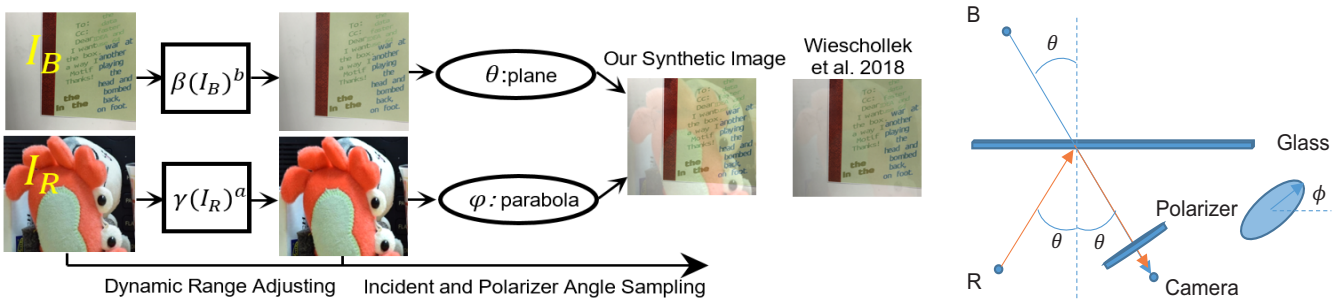

Figure 1: Left: training data synthesis pipeline.(*Image courtesy Dennis Sng(Rose Lab)*) Right: polarization model.

ABSTRACT

We present a valid polarization-based reflection contaminated image synthesis method, which can provide adequate, diverse and authentic training dataset. Meanwhile, we enhance the neural network by introducing the reflection information as guidance and utilizing adaptive convolution kernel size to fuse multi-scale information. We demonstrate that the proposed approach achieves convincing improvements over state of the arts.

KEYWORDS

Reflection removal, Polarization, Network enhancement

ACM Reference Format:
Youxin Pang, Mengke Yuan, Qiang Fu, and Dong-Ming Yan. 2020. Reflection Removal via Realistic Training Data Generation. In *Special Interest Group on Computer Graphics and Interactive Techniques Conference Posters (SIGGRAPH '20 Posters), August 17, 2020.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3388770.3407419

1 INTRODUCTION

Recent data-driven reflection removal neural networks [Fan et al. 2017; Wei et al. 2019; Wieschollek et al. 2018] achieve promising results for removing distractive reflection from single image captured behind glass, but their performances show great inconsistency when dealing with real-world scenarios. The challenges stem from : (i) Ground-truths are scant for training, since collecting precise and dense labels in real scenarios is labor-intensive, existing synthetic datasets possess different characteristics comparing with natural images. (ii) Neither reflection information nor multi-scale context is utilized to regularize the reflection/transmission decomposition.

In this poster, we take the physical polarization property of reflection light into account, thus mimic the attenuation of reflection under different incident and polarizer angles to synthesize more realistic and diverse training data. Furthermore, we integrate reflection information as guidance in training procedure and multi-scale convolution kernel selection units to enhance the neural network. The experiments show the newly constructed dataset and enhanced neural network improve the reflection removal results significantly.

2 OUR APPROACH

Realistic dataset generation. We first propose a more accurate physically-based dataset construction pipeline to enhance the verisimilitude and diversity of sythetic dataset. Two randomly selected images, I_R and I_B, are treated as reflection layer and background layer to compose the target image I. As shown in Fig. 1(right), placing a polarizer ahead of the camera, with incidence angle θ and polarization angle ϕ, the intensity of each pixel $I(\boldsymbol{x})$ can be computed according to [Kong et al. 2013] as follows:

$$
\begin{aligned}
I(\boldsymbol{x}) &= \alpha(\theta,\phi)\frac{I_R(\boldsymbol{x})}{2} + (1-\alpha(\theta,\phi))\frac{I_B(\boldsymbol{x})}{2} \\
\alpha(\theta,\phi) &= R_\perp(\theta)\sin^2(\phi_\parallel - \phi) + R_\parallel(\theta)\cos^2(\phi_\parallel - \phi) \\
R_\perp(\theta,\kappa) &= \frac{\sin^2(\theta-\theta_t(\theta,\kappa))}{\sin^2(\theta+\theta_t(\theta,\kappa))}, R_\parallel(\theta,\kappa) = \frac{\tan^2(\theta-\theta_t(\theta,\kappa))}{\tan^2(\theta+\theta_t(\theta,\kappa))},
\end{aligned}
\tag{1}
$$

where x is the index of input images. $\alpha(\theta,\phi)$ represents the mixing coefficient. $\phi_\parallel$ is the angle for the orientation of the intersection line between the polarizer and the plane of incidence. $R_\perp$ and $R_\parallel$ are orthogonal decomposing coefficients of reflection light. Moreover, according to Snell's law, we use $\theta_t(\kappa = \frac{1}{1.474}, \theta) = \arcsin(\frac{1}{1.474}\sin\theta)$.

To promote the reflection/transmission decomposing capacity of the neural network, we discard the assumption that the intensity of transmitted light should surpass the reflected portion [Wieschollek et al. 2018], and utilize a more flexible formulation to adjust the

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

SIGGRAPH '20 Posters, August 17, 2020, Virtual Event, USA

© 2020 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-7973-1/20/08.
https://doi.org/10.1145/3388770.3407419