Removing Raindrops from a Single Image using Synthetic Data

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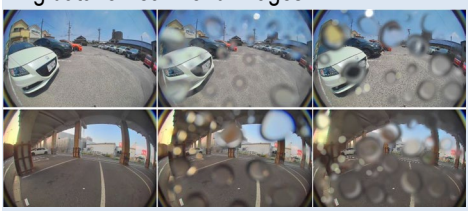
Abstract

We simulated the exact features of raindrops on a camera lens and conducted an experiment to evaluate the performance of a network trained to remove raindrops.

In this study, **we focused on generating raindrop shapes that are closer to reality** with After categorizing raindrops by type, we further separated each raindrop type into its constituent elements, generated each element separately, and finally combined the generated elements.

The evaluation results proved that images with synthetic raindrops can be used as training data for real-world images.



reference real synthetic

Previous Method

1) Raindrop generation using CNN

Considering the difficulty of dataset preparation, we attempted to generate raindrops images using Mask-shadowGAN(2019), a weakly-supervised method that does not require paired images.

input generated reference

There are some raindrops whose shapes lack logical consistency.

2) Raindrop generation using physics theory

Reproduce raindrops adhesion state by inversion of the mathematically represented raindrop model.

Porav et al.(2019) generated raindrops based on physical characteristics and then modeled the interactions between the raindrops.

real synthetic

The considerable discrepancy in the way the two images looks is easy to see.

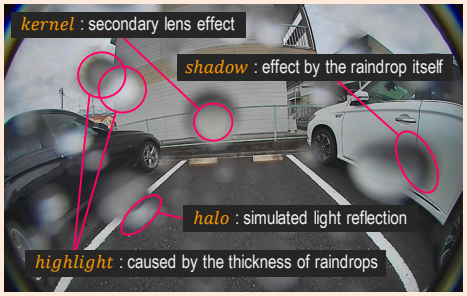
Raindrop Formulation

We divided the raindrops into two types, and simulated the state of each type separately.

Normal raindrops Glare raindrops

A) Normal raindrop

We break raindrops down into the following four constituent elements.



spherical distortion: coordinate transitions in the ROI caused by secondary lens effect (each raindrop is defined as ROI)

$$x' = R \cdot \cos\left(\arctan\left(\frac{y}{x}\right)\right) \cdot \sin\left(\frac{\pi\sqrt{x^2+y^2}}{2R}\right)$$

$$y' = R \cdot \sin\left(\arctan\left(\frac{y}{x}\right)\right) \cdot \sin\left(\frac{\pi\sqrt{x^2+y^2}}{2R}\right)$$

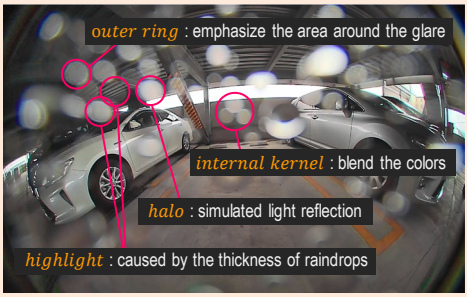
wave distortion: shape of a raindrop can also change as a result of gravity or by the camera being bumped during operation

$$x' = A \cdot \cos\left(\theta_0 + \delta \cdot y\right), (x, y) = (x + x', y)$$

spherical distortion spherical + wave

B) Glare raindrop

We break raindrops down into the following four constituent elements.



To more realistically simulate raindrops, our method scans the light source and adds a refrection according to its position.

Raindrop Type Selection

We discovered through experience that the position of the ambient light has a considerable effect on generated raindrops type.

glare probability map: given the image size and the coordinate (x, y) of the light source

$$I_{i,j} = I_{i,j} + W \cdot D_2, \quad \text{for} \quad 0 \le i \le w, \quad 0 \le j \le h$$

$$D_1 = \max\left\{\sqrt{(x-w)^2+(y-h)^2}, \sqrt{x^2+(y-h)^2}, \sqrt{(x-w)^2+y^2}, \sqrt{x^2+y^2}\right\}$$

$$W = -\frac{1}{D_1}, \quad D_2 = \sqrt{(i-x)^2+(j-y)^2}, \text{ for } 0 \le i \le w,\ 0 \le j \le h$$

reference synthetic effect

Dataset & Experimental Setup

We evaluate two types models proposed in AttentiveGAN(2018), and the lightweight version of that model.

AttentivGAN estimates raindrop position and uses it as an attention to focus on raindrops.

Model Type	Full Model		Light Model	
Input Resolution	200 × 320px		400×640px	
Metric	Flops	Params	Flops	Params
Attention	10.76G	0.17M	0.42G	0.08M
Image	20.00G	6.06M	1.78G	0.38M
Attention+Image	30.76G	6.23M	2.20G	0.46M

***α*) Collecting paired images from a real**

Water droplets were sprayed directly on the lens surface using a fixed camera to acquire paired images of the same background.

***β*) Generating synthetic images**

We implemented the generation of synthetic raindrops according to our proposed method as a tool.

➡ size, occupancy, reflection, w/o glare …

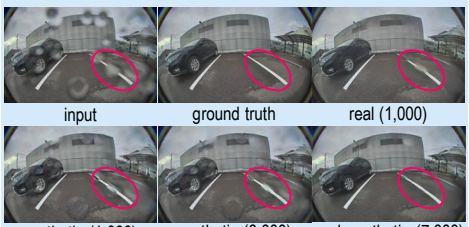
GUI tool (CUI version also exists)

Experimental Result

evaluation result

Training Dataset	Real (1,000pair)		Synthetic (1,000pair)	
Evaluation Method	PSNR	SSIM	PSNR	SSIM
Full Model	25.46	0.8329	23.90	0.8037
Light Model	21.20	0.6815	19.59	0.6520
Training Dataset	Synthetic (6,000pair)		Synthetic (7,000pair)	
Evaluation Method	PSNR	SSIM	PSNR	SSIM
Full Model	23.71	0.8030	**26.36**	**0.8499**
Light Model	20.73	0.6737	**21.73**	**0.6891**

restoration result visualized



input ground truth real (1,000)

synthetic (1,000) synthetic (6,000) real+synthetic (7,000)