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Terrain Traversability Analysis with Image Dehazing

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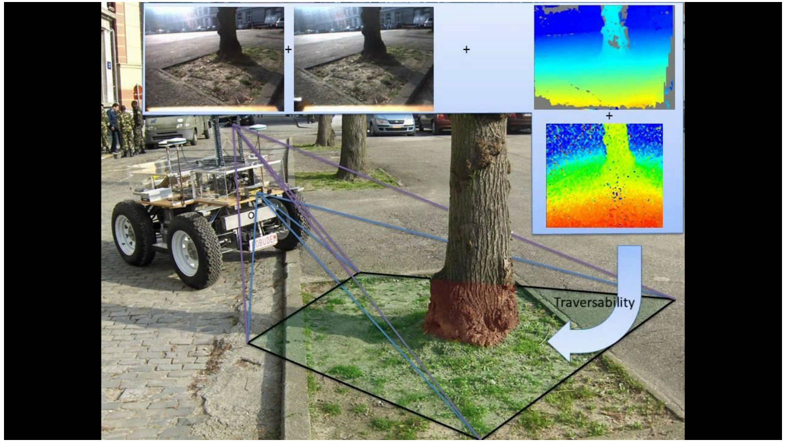
Core Idea Overview

1. **Motivation/Objective**
2. **RUGD and Hazy Dataset**
3. **Dehazing methods (DCP, CNN, GAN)**
4. **Segmentation (GANav)**

Motivation



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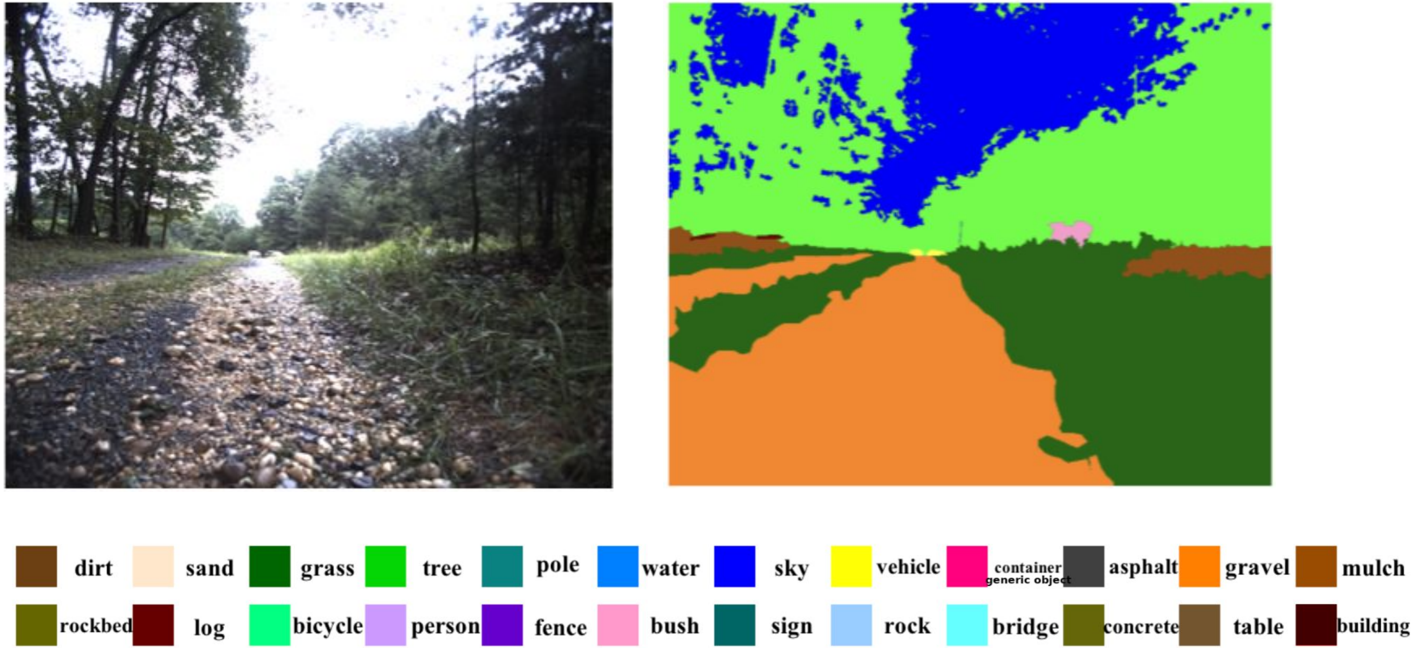
RUGD and Hazy Dataset



7436 images with 50032 labeled objects 24 different classes

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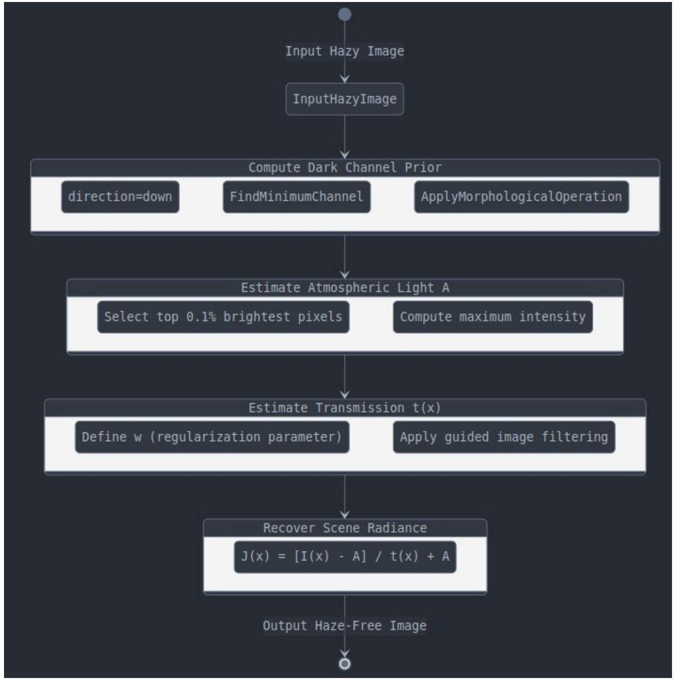
RUGD and Hazy Dataset

Dehazing methods (DCP)

Most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel. Using this prior with the haze imaging model, we can directly estimate the thickness of the haze and recover a high quality haze-free image.



J(x) is the scene radiance.
I(x) is the observed intensity
A is global atmospheric light
t(x) is medium transmission
(describing the portion of the light that is not scattered and reaches the camera)

Kaiming He, Jian Sun and Xiaoou Tang, "Single image haze removal using dark channel prior," *2009 IEEE Conference on Computer Vision and Pattern Recognition*

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Variation of Dehazing with patch size

Patch-size of 15x15

Patch-size of 75x75

Comparison of t-map refinement techniques

Original Blurry Image

Guided Filter

Inference time: 2.05 sec

Soft Matting

Inference time: 20.43 sec

Dehazing methods (CNN based)

$$J(x) = \frac{1}{t(x)} I(x) - A \frac{1}{t(x)} + A$$

Atmospheric Scattering Model (used for denoising haziness from air)

J: Clean image, I: Hazy image

A: global atmospheric light (constant), often as highest intensity value eg. sky

t: transmission, amount of light reaches (smaller value = higher scattering/absorption)

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

where β is the scattering coefficient of the atmosphere, and $d(x)$ is the distance between the object and the camera.

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B. Li, X. Peng, Z. Wang, J. Xu and D. Feng, "AOD-Net: All-in-One Dehazing Network," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 2017, pp. 4780-4788, doi: 10.1109/ICCV.2017.511. keywords: {Atmospheric modeling;Image restoration;Scattering;Computational modeling;Visualization;Estimation},

Dehazing methods (CNN based)

$$J(x) = \frac{1}{t(x)} I(x) - A\frac{1}{t(x)} + A$$

$$\downarrow$$

$$J(x) = K(x)\,I(x) - K(x) + b, \text{ where}$$

$$K(x) = \frac{\frac{1}{t(x)}(I(x) - A) + (A - b)}{I(x) - 1}$$

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Dehazing methods (CNN based)

$$J(x) = K(x)\, I(x) - K(x) + b, \text{ where}$$

$$K(x) = \frac{\frac{1}{t(x)}\left(I(x) - A\right) + (A - b)}{I(x) - 1}.$$

(K shows relative depth/haziness)

Previously (traditional methods)

Estimate t(x) using algorithms such as DCP

Statistical approach to find A

$$J(x) = \frac{1}{t(x)} I(x) - A\frac{1}{t(x)} + A$$

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

But now,

AOD-Net, end-to-end fully-supervised CNN-based architecture

predict K(x) through the CNN based network

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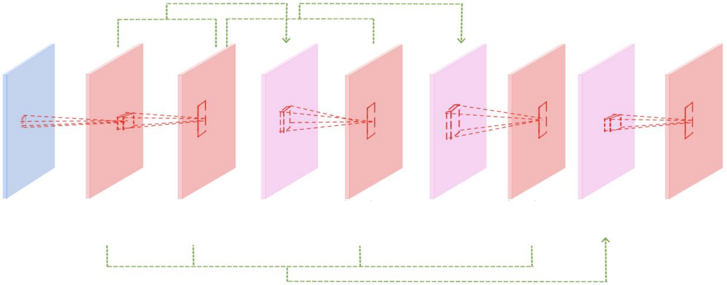
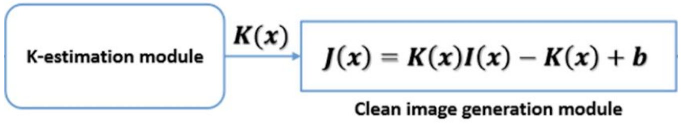
Dehazing methods (CNN based)

AOD-Net: All-in-One Dehazing Network





Predict K(x) through the network

Five (2d) Conv layers: low, high-level feature extractions

Concatenations: to combine and preserve

Non-linearities: estimate complex equation

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Dehazing methods (CNN based)

Modifications

Baseline

Learning rate with scheduler Batch size added

Laplacian loss added

Residual added

Dehazing methods (GAN)

Used ID-CGAN as basis

Another environmental GAN that was used to remove rainy images

Original paper used small manually photoshopped images as basis

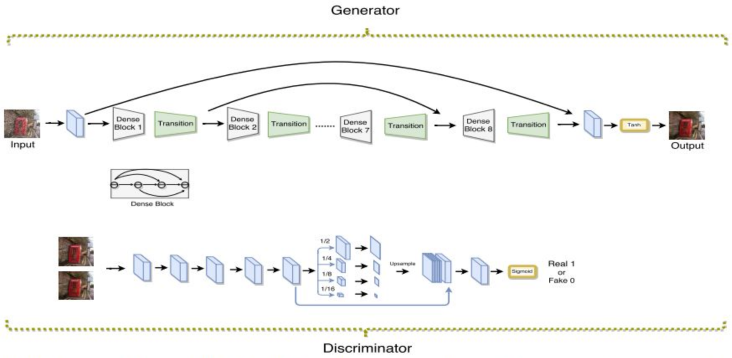
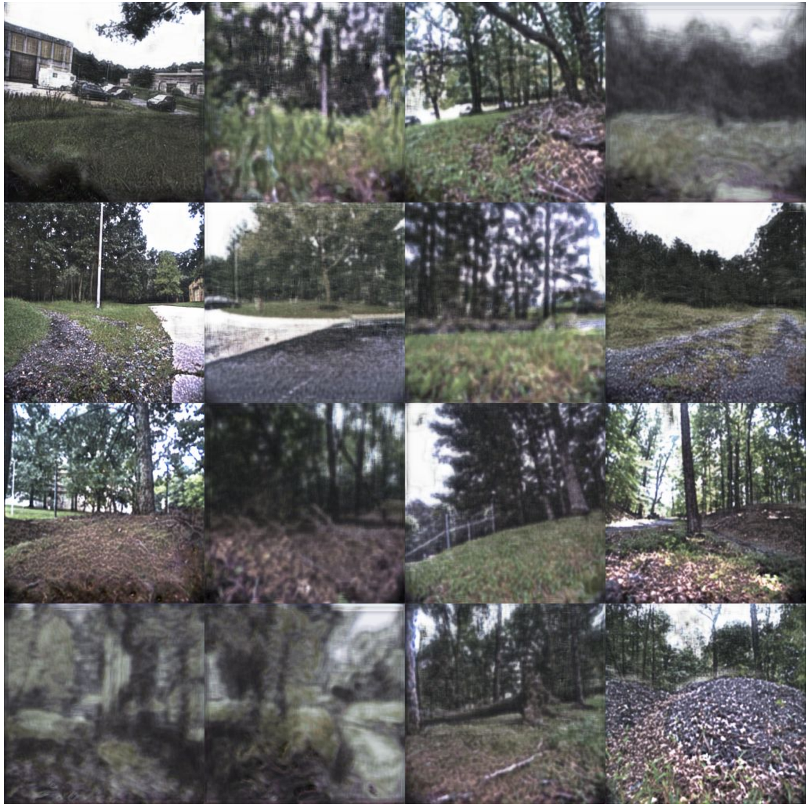


Fig. 3: An overview of the proposed ID-CGAN method for single image de-raining. The network consists of two sub-networks: generator G and discriminator D.



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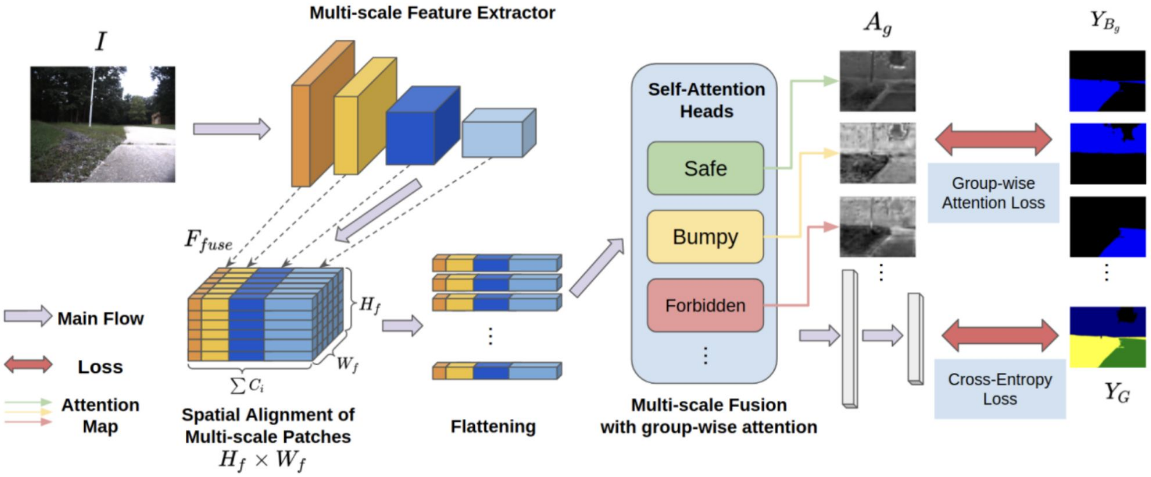
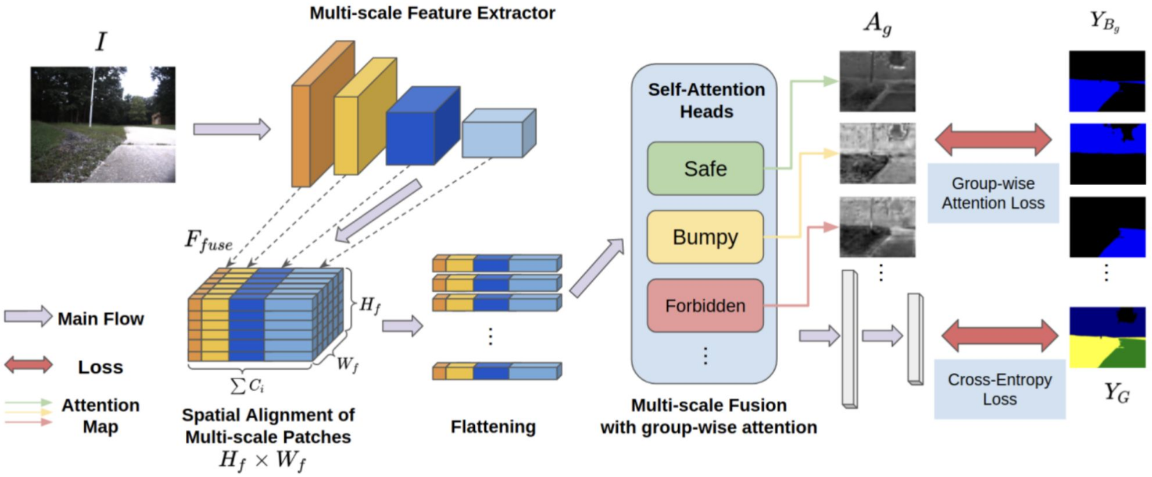
Segmentation (GANav)



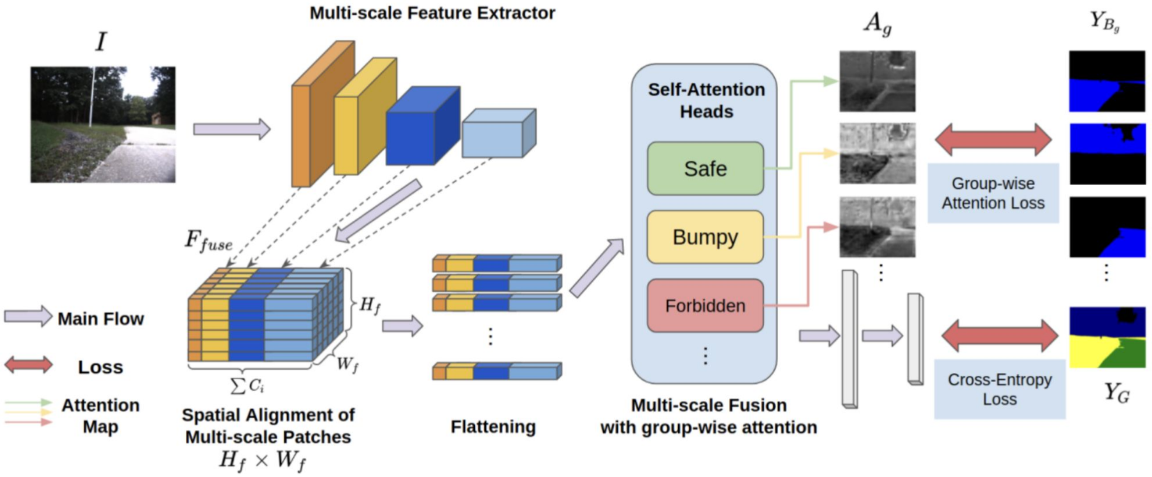
GA-Nav architecture presents coarse-grained segmentation method
'smooth', 'bumpy', 'rough', 'forbidden', 'obstacle', 'background' labeled regions

Segmentation (GANav)



multi-scaled feature extractions
smaller height and width are chosen then bilinear interpolated to align the dimensionality

Segmentation (GANav)



Multi-Head Self Attention (MHSA) learn different groups to focus on (pixel, scale relationships) output A, which is calculated by $A_{out} = softmax\left(k(A_{in})^T \cdot q(A_{in})^T\right) \cdot v(A_{in})$

then output P, probability map for each group using 1x1 convolutions and upsampling

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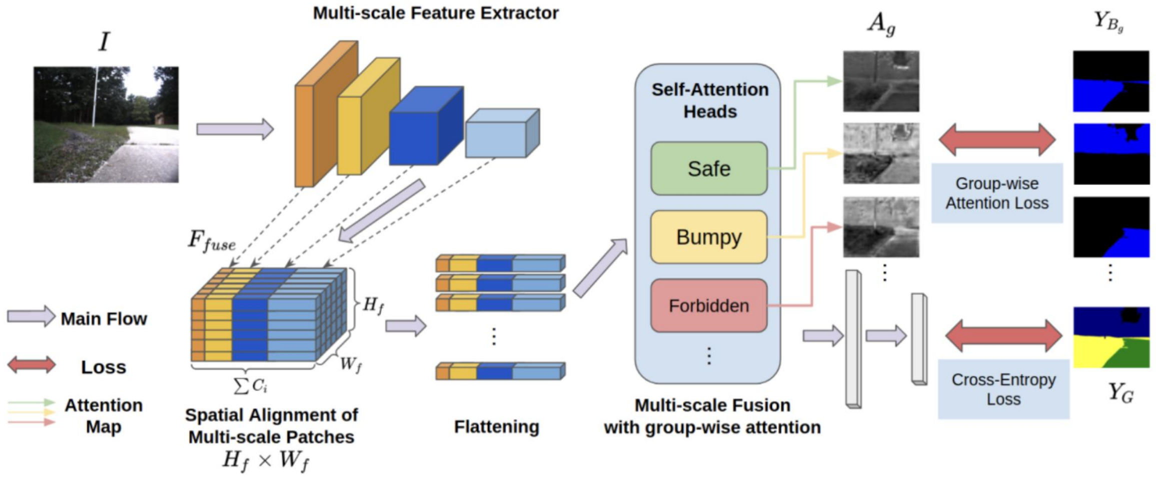
Segmentation (GANav)



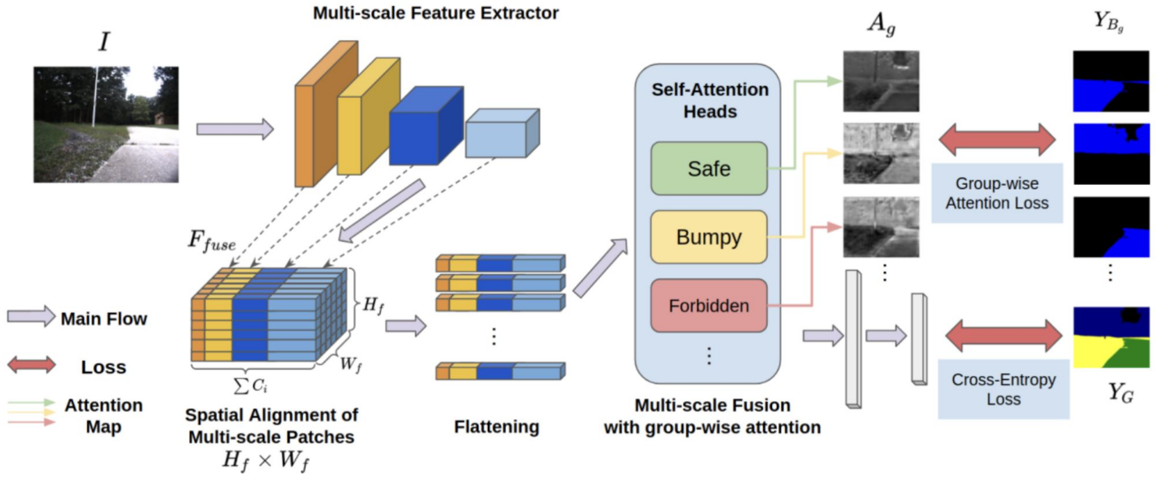
$$\mathcal{L}_{GA}^{g} = -\sum_{h,w} y_G \log(B_g)$$

Binary cross-entropy loss for group-wise attention loss

$$\mathcal{L}_{CE} = -\sum_{h,w}\sum_{g\in G} y_{GT} \log(P_g)$$

Cross-entropy loss for optimize the model

Segmentation (GANav)



Intersection over Union (IoU) for class i:

$$IoU_i = \frac{\sum_I \sum_{x,y} \mathbb{1}(P(x,y) = i \text{ and } G(x,y) = i)}{\sum_I \sum_{x,y} \mathbb{1}(P(x,y) = i \text{ or } G(x,y) = i)}$$

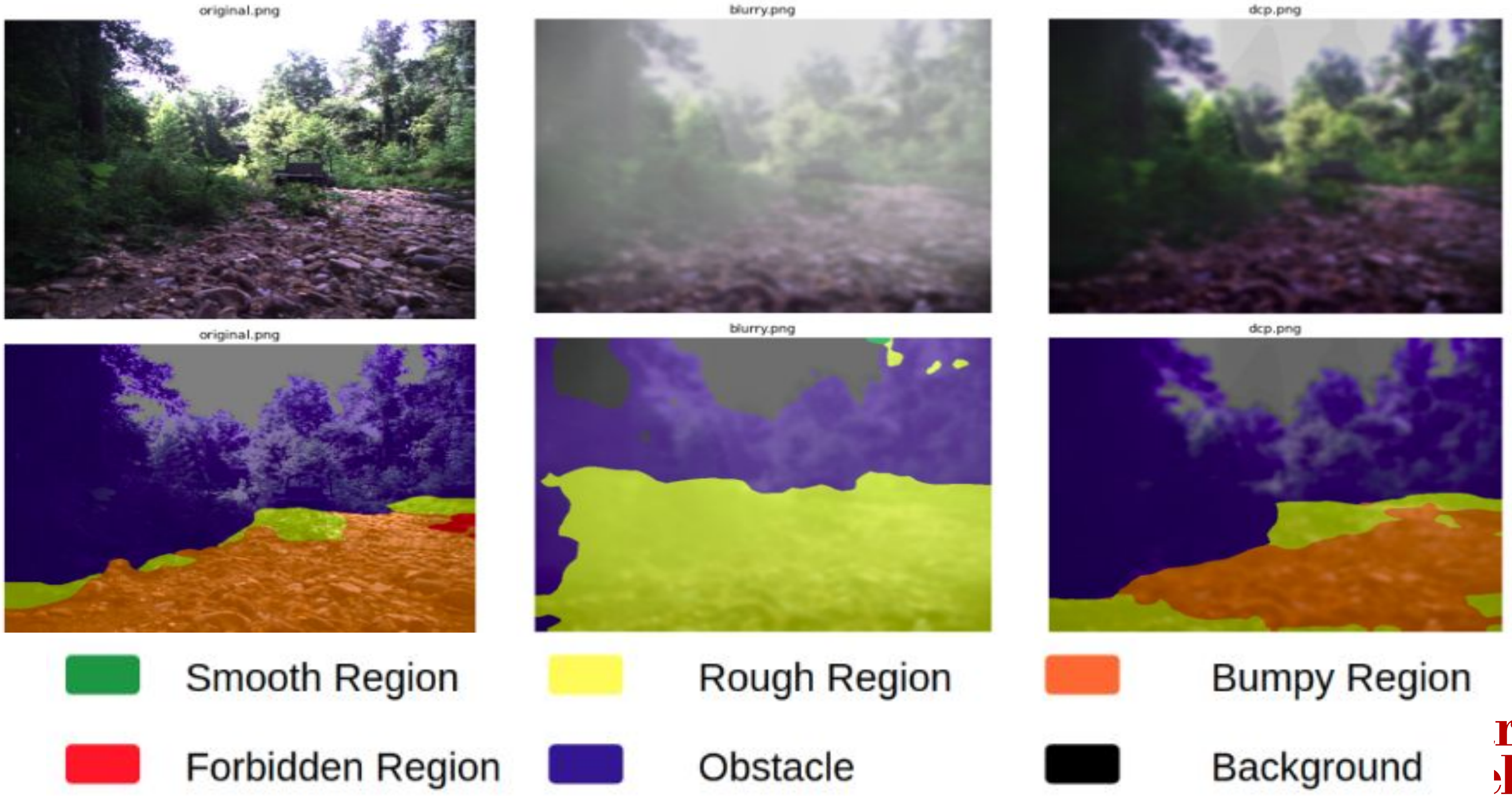
Mean IoU (mIoU):

$$mIoU = \frac{\sum_i mIoU_i}{\sum_B 1}$$

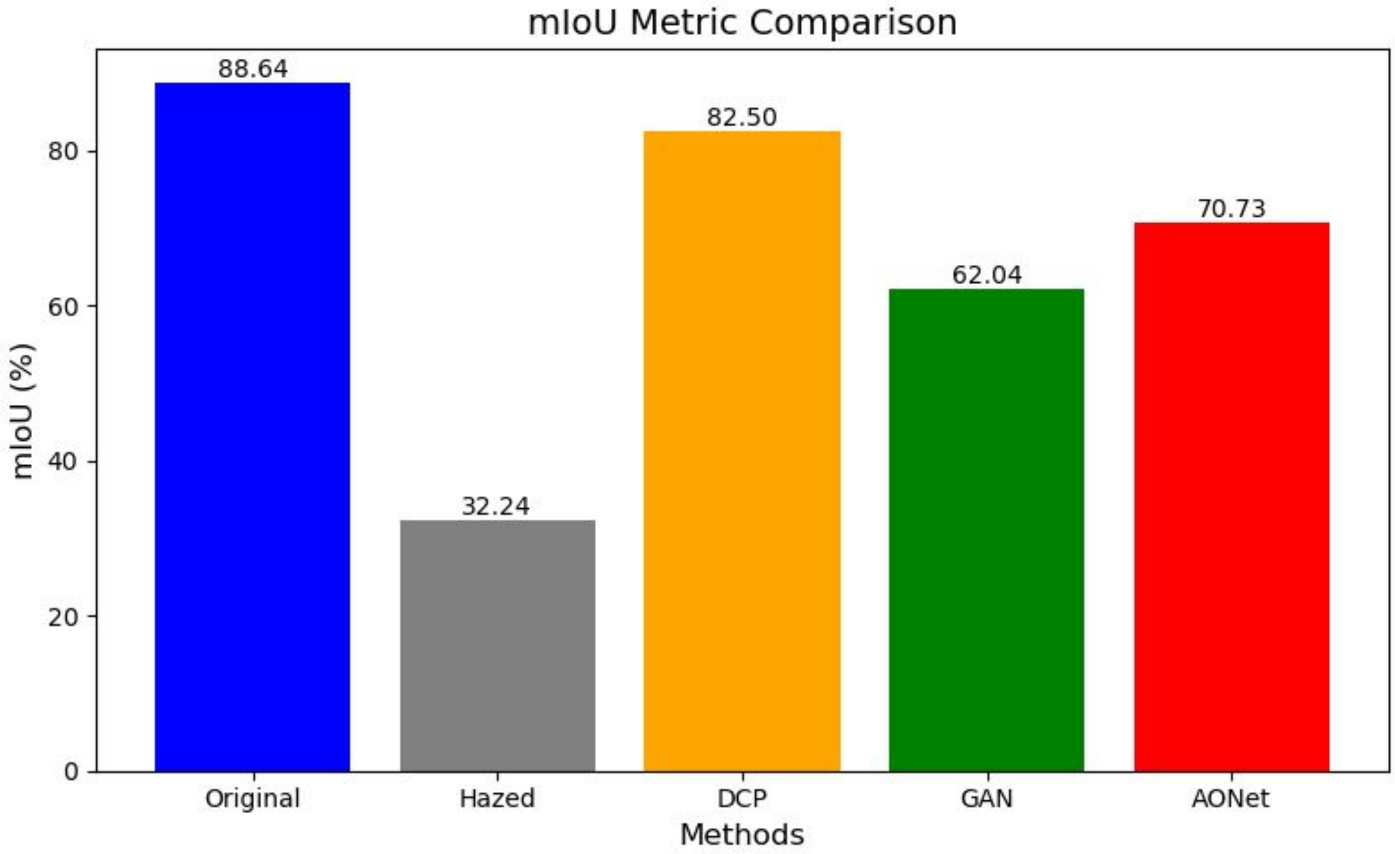
Mean Pixel Accuracy (mAcc):

$$mAcc = \frac{\sum_{i \in B}(\sum_I \sum_{x,y,G(x,y)=i} \mathbb{1}(P(x,y) = G(x,y)))}{\sum_B 1}$$

Sample result



Demo



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