Single image dehazing network based on U-net

1. Goal: -

To implement end-to-end network with encoding–decoding structure and jumping layers for single image dehazing.

2. Related work: -

traditional enhancement methods to remove the haze from a single image, such as histogram equalization methods and the Retinex-based methods but due to the difference between the histogram of a hazy image and a haze-free image, histogram equalization methods are used to improve the contrast of image. Although such kind of method is effective for dehazing, it is often accompanied by serious color distortion and missing details. Later, according to the Retinex theory, researchers proposed some dehazing methods to solve the remaining problems of histogram methods. However, while the edge details are preserved better, other noises which may cause unsmooth images and halo artifacts appear.

3. Approach: -

The atmospheric scattering model, which is proposed by McCartney in 1976 and developed by Narasimhan, describes the image degradation and can be written as

$$I(x) = J(x)t(x) + A (1 - t(x))$$

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

$$J(x) = (1/t(x))\, I(x) + A\, (1/t(x)) + A$$

Here we can modify the following equation as -

$$J (x) = K(x)\, I(x) - K (x) + b$$

$$K (x) = ((1/ t(x))\, (I (x) - A) + (A - b)))\, /\, (I (x) - 1)$$

Here- I(x): Hazy image, J(x): clean image, t(x): transmission map, A: atmospheric light, d(x): depth of the scene.

k(x) is a new variable that integrates both parameters **(x)** and **A,** a constant bias **b** that is set as 1.0. In this, we can reduce the accumulation of errors.

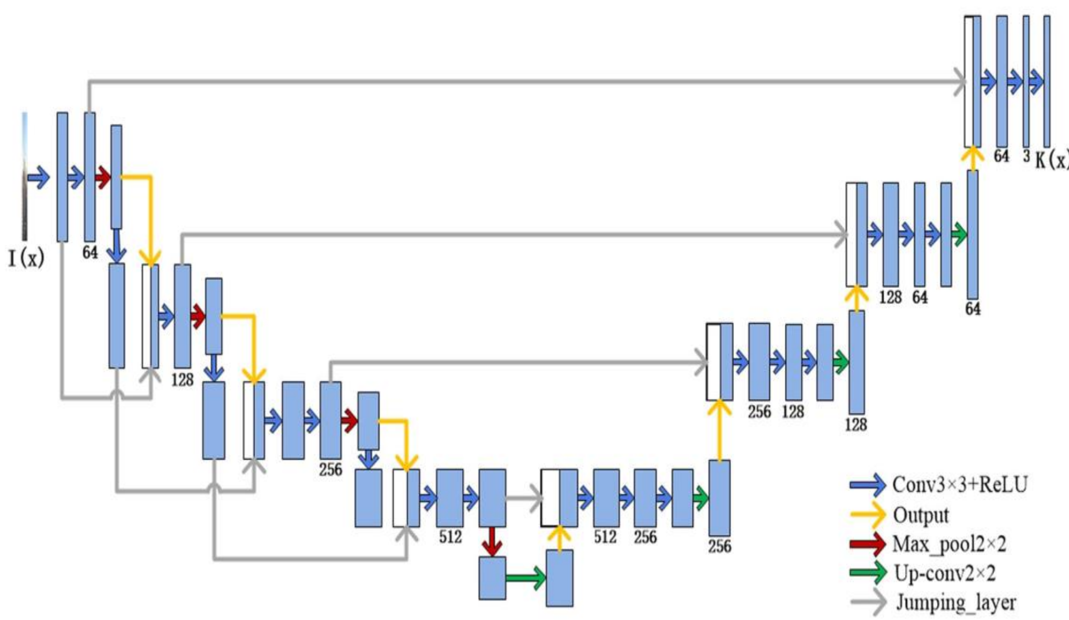
From here we can estimate the **k(x)** by learning method and after that reconstruct the clean image.

4. Network and training: -

The proposed network to estimate the **K(x)** is inspired by **U-net.** Here we use encoding and decoding structures as in encoding part - two ReLU activation layers were added to every two 3*3 convolution operations separately, and then a 2*2 max-pooling layer was increased. After two groups of the whole operations described above, three ReLU activation layers were added to every three 3*3 convolution operations separately, and then the same 2*2 max-pooling layer was performed. Similarly, after two groups of the operations.

Now in decoding - Inspired by the U-net, one up-sampling layer and two 3*3 convolution layers and ReLU activation layers were utilized, and then the K (x) estimation was finished after four groups of that operations.

In network there are two types of jumping layers one in encoding part to extract and retain more image features, in order to preserve the image details more completely, another type of jumping layers in overall structure was added.



Training: -

Loss function – MSE

Optimizer – Adam optimizer

No. Of epochs = 10

Learning rate = 0.0001

Dataset - kaggle datasets - ‘dehaze’

Size of dataset is about 2GB with 840 clear images and around 13k hazy images with different scattering coefficient β and different atmospheric light A.

We split the data into 90:10 for training and validation.

Batch size = 32

5. Result and Conclusion: -

It will take around 9 to 10 min to train one epoch, we trained it for 10 epochs.

Final training loss: 0.955074

Final validation loss: 0.10212

Total time: 2hr for training.

It is observed that the model doesn’t perform well on images with dense haze and complex structures.

Result...


Hazy Image
Ground Truth Image
Predicted
Hazy Image
Ground Truth Image
Predicted


Hazy Image
Ground Truth Image
Predicted
Hazy Image
Ground Truth Image
Predicted