Image Dehazing Using Deep Learning

Mid Term Presentation by

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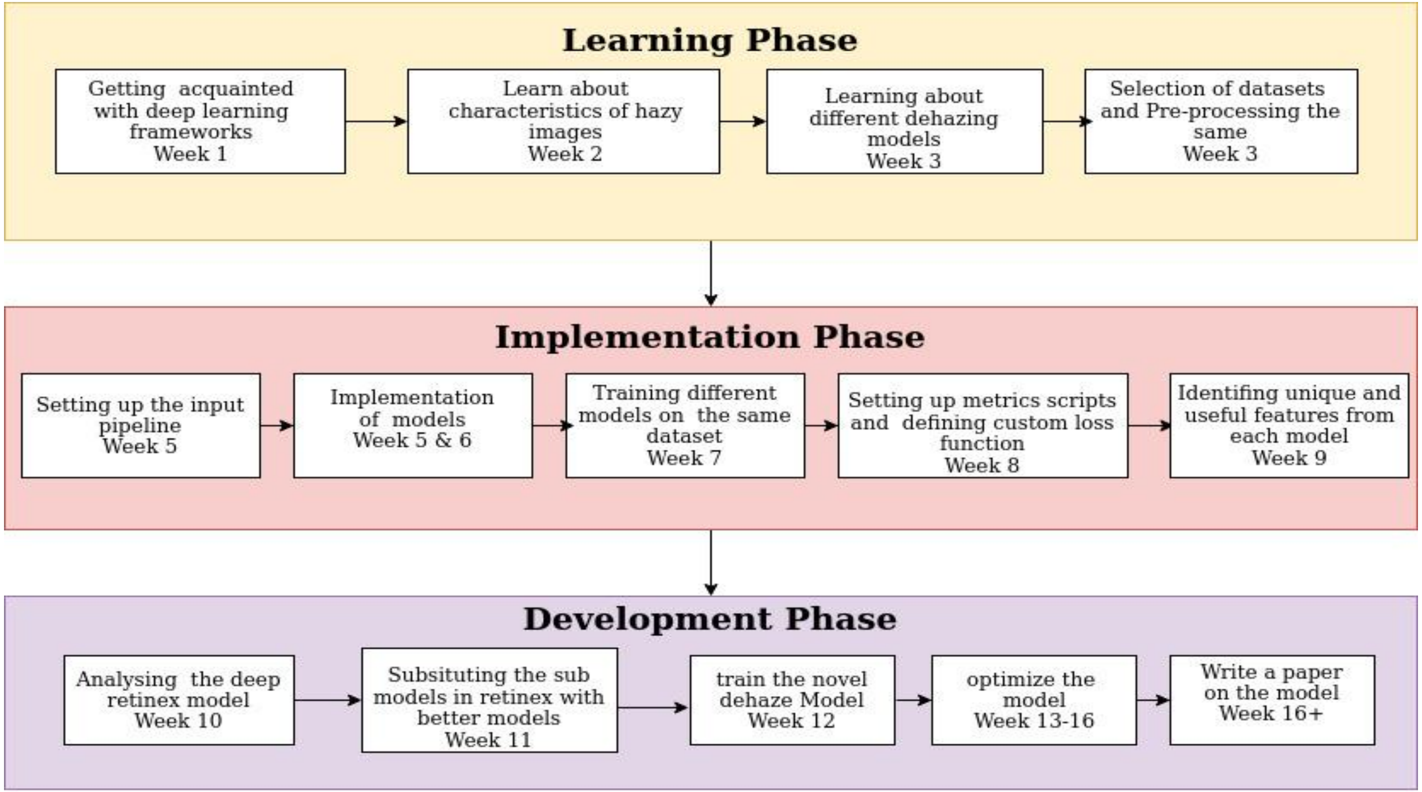
OVERVIEW

- Many modern-day applications require a clear image to analyse and extract information, but generally the presence of a turbid medium hinders their performance
- The dehazing methods can be extended to applications such as image enhancement, denoising, colour correction etc
- As a part of our study, we looked at the SOTA models and implemented them on TensorFlow framework. After implementing them we performed a comparative study to identify best features of each model and used those unique features in developing a novel model based on Deep-Retinex model.

OBJECTIVES

- To compare various SOTA dehazing algorithms and compare them using common performance metrics.
- To develop a novel model by taking inspiration from deep retinex model.
- To Extend the application of the model from single image dehazing to sequence of image dehazing (Video dehazing).
- Analyse different areas of application for the algorithm and suggest the most suitable area of use.
- To present the new architecture, and a suitable metrics a research article.

PROJECT FLOW



Comparative study of present models

State of the Art | Image Dehazing on RESIDE

Dark Channel Prior

1. Reasonably good results based on prior.
2. Overestimates Density of haze.
3. Contrast over enhanced leading to loss of naturalness in image.
4. The refinement of transmission map is a time consuming step.
5. Prior doesn't hold at all times. (Sky images)

Hazy Image

Ground Truth

Dehazed Image

Light Convolutional Autoencoder

1. An encoder-decoder network with the modern CNN with no atmospheric scattering assumptions.
2. Emphasizes on computational efficiency for real-time purposes and faster network.
3. The model uses some max pool layers which lead to loss of information in the final output(blurring effect)

Hazy Image

Ground Truth

Dehazed Image

Generic Model-Agnostic Convolutional Network (GMAN)

1. It does not estimate any atmospheric scattering model and only depends on trainable parameters and hence it learns complex hazy features and structures
2. The paper boasts a generative network that uses encoder-decoder structure with down and up-sampling factor of 2
3. As it is a new type of network there is not any concrete papers and research on this network.

DehazeNet

1. Proposes 4 step method for dehazing- Feature extraction, Multi scale Mapping, local extremum, Non-Linear regression.
2. The 4 steps estimate transmission map & atmospheric light is estimated by conventional methods.
3. Light network with around 8K trainable parameters.
4. Does not totally remove haze but constructs a reasonably good dehazed image and as it is based on global atmospheric light model different regions have different amount of dehazing done.

Hazy Image

Ground Truth

Dehazed Image

Gated Context Aggregation (GCA)

1. Using the modern smoothed dilation technique with dilated convolution in the network which increases field of kernel and also uses a gated sub-network which blends features from multiple scales of the same image.
2. The network is currently ranked second best on basis of PSNR on RESIDE dataset.
3. The model is quite computationally heavy and we were unable to increases batch size from four when training on colab (GPU). It is also a very complex net with around 500k trainable parameters. The model also takes around 200 sec for one epoch (batch size 4 & 372 images).
4. We also observed that when objects are too near the model forms black regions .

Hazy Image

Ground Truth

Dehazed Image

U- net

1. Uses squeeze and excitation blocks and nearest neighbour upsampling.
2. Very heavy network with around 2 million parameters.
3. The generated dehazed image has lot of noise present, but the haze density is reduced. We think if a simple denoising network is added in the end the performance can drastically improve

Back Projected Pyramid Network (BPP)

1. A novel technique named pyramid convolution is introduced for dehazing to obtain spatial features of multiple scales structural information.
2. UNet block for image dehazing tasks to make the generator learn different and complex features of haze without the loss of local and global structural information.
3. Extensive experimentation is done on four contemporary challenging datasets, namely I-Haze and O-Haze datasets of NTIRE 2018 challenge, Dense-haze dataset
4. Uses a combination of MSE (L2 loss), adversarial loss Ladv, content loss Lcon, and structural similarity loss LSSIM.
5. Drawback - color preservation and seamless color cast

Feature Fusion Attention network (FFA)

1. Current best ranked model for single image dehazing. Proposes Feature Attention (FA) module combines Channel Attention with Pixel Attention mechanism.
2. Uses concept of groups i.e. similar small models for a block and many such blocks for a group. The work proposes 3 groups of 19 blocks each.
3. FFA network has a powerful advantage in the restoration of image detail and color fidelity.
4. The network is very heavy and we had to downsize it so we used 3 groups which consists of 6 blocks each and while training this model also batch size couldn’t be increases from 1.

Hazy Image

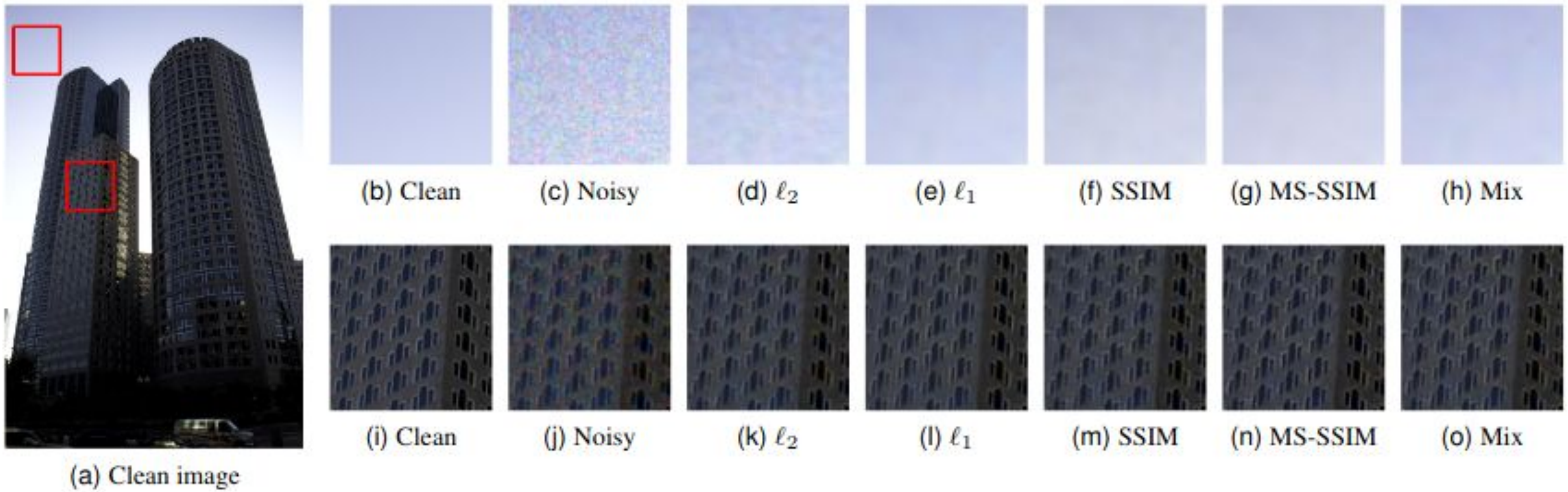
Ground Truth

Dehazed Image

Comparison

Metrics	LCA	DHZ	DEHZ+ ATTN	DCP	GMAN	GCA	FFA	U-NET
PSNR	17.07	17.23	17.00	12.00	14.8	20.13	**20.67**	19.38
SSIM	0.65	0.66	0.67	0.61	0.64	0.77	**0.79**	0.73
FADE	0.95	0.5	0.87	**0.39**	0.65	0.91	1.24	0.68
NQIE	4.42	2.93	3.12	2.85	2.70	2.70	**2.67**	3.71
CEIQ	3.27	3.33	3.25	3.19	3.22	3.22	**3.42**	3.4

New approach to loss functions for image reconstruction tasks




```python
def custom_loss(orig,pred):
  a=tf.keras.losses.MAE(orig,pred)
  a=tf.math.reduce_mean(a,axis=None)
  b=tf.image.ssim_multiscale(orig,pred,max_val=1)
  b=tf.math.reduce_mean(b,axis=None)
  alpha=0.025
  return alpha*b+(1-alpha)*a
```

Fig: comparison of different loss fn [15]

Atmospheric Scattering Model

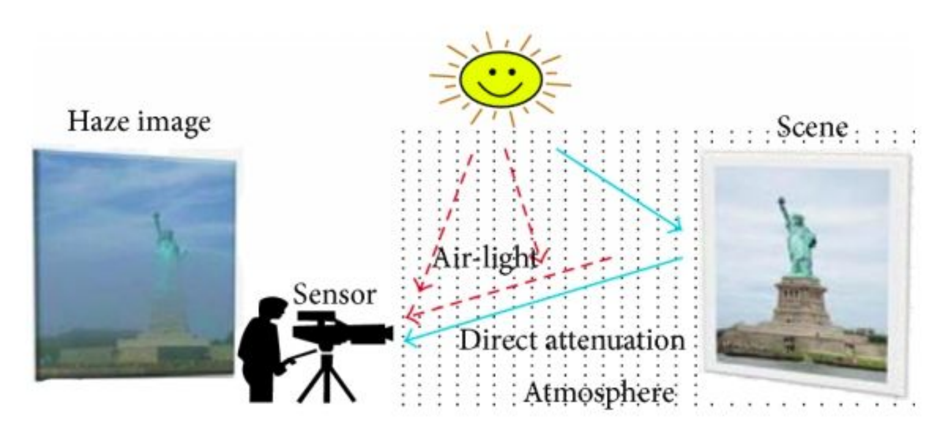


Fig: atmosphere scattering model by Lie quan He

The haze present in a image is due to two features:

1. Direct Attenuation: results from decay in the medium

2. Air light: occurs due to the scattering of light in the surrounds

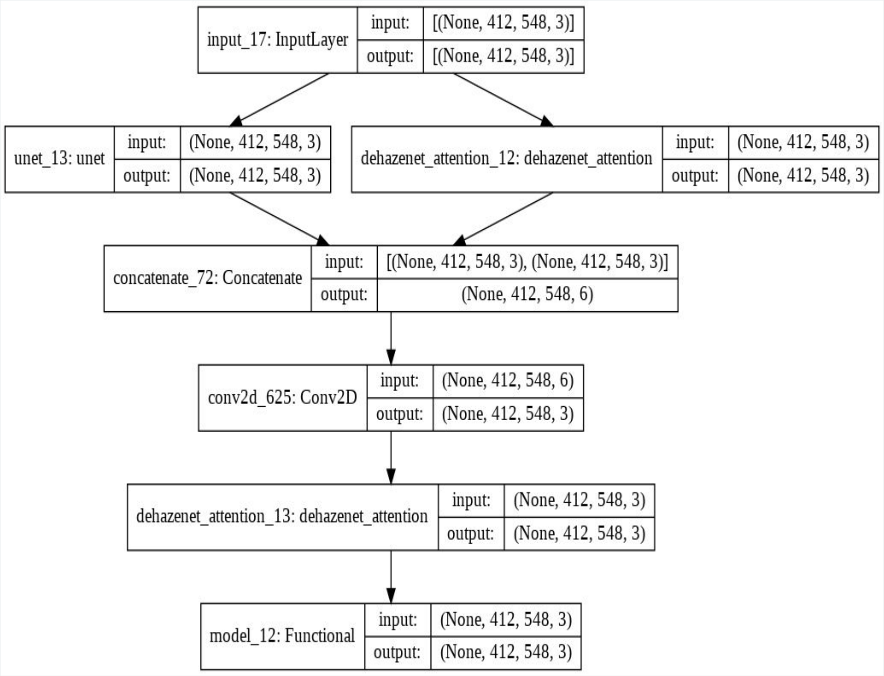
$$I(x) = J(x)t(x) + A(1-t(x))$$

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

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

Where β is the scattering coefficient of the atmosphere and d(x) is distance from the scene point It indicates that the scene radiance is attenuated exponentially with the scene depth. The model assumes homogeneous scattering of light and a constant scattering coefficient.

Initial Approach



1. We started of trying to combine best features of the discussed models.
2. Emulated the basic structure of dehazenet with each sub block were replaced by complete models.
3. The models started to get very heavy with no considerable increase in performance.

Base model

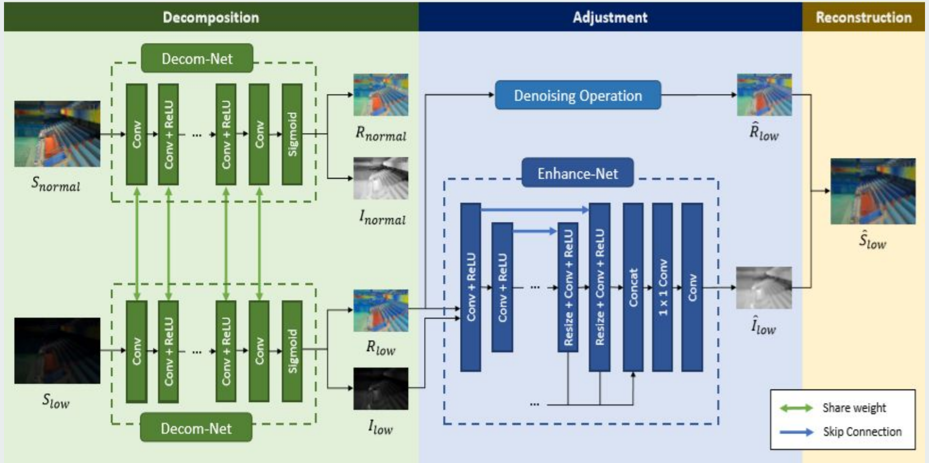
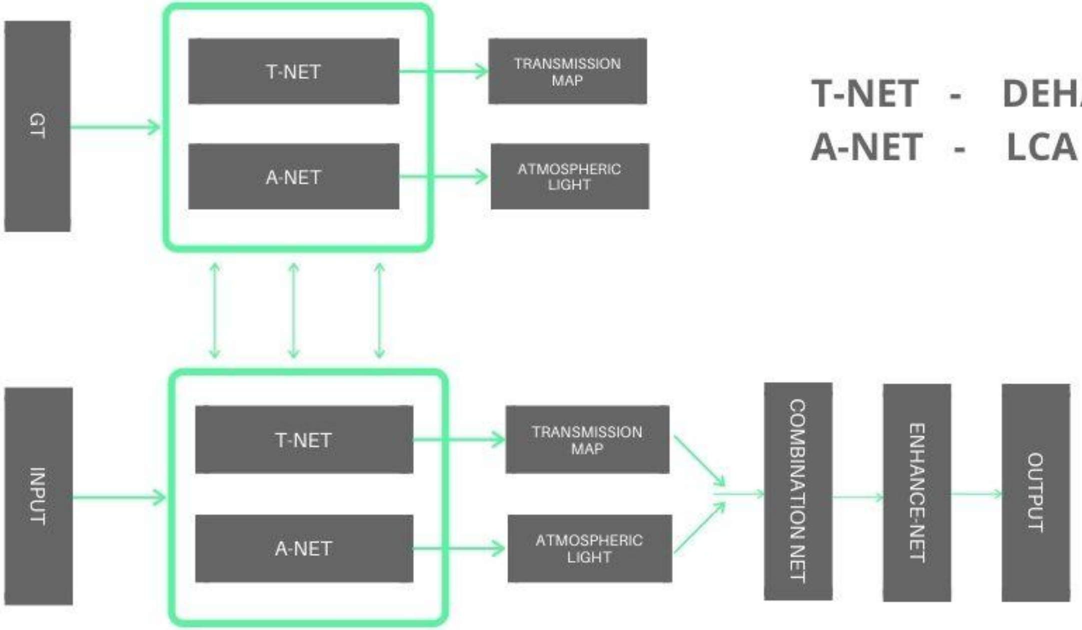


Fig: Deep retinex decomposition [14]

1. Looked into various domains and singled out Deep retinex decomposition model as a very suitable one for building novel dehazing network.
2. The model was chosen as it is currently one of the best for low light enhancement and the field is very similar to image dehazing as both deal with loss of contrast.
3. The model further has sub blocks which can be replaced with dehazing specific blocks

Proposed Model



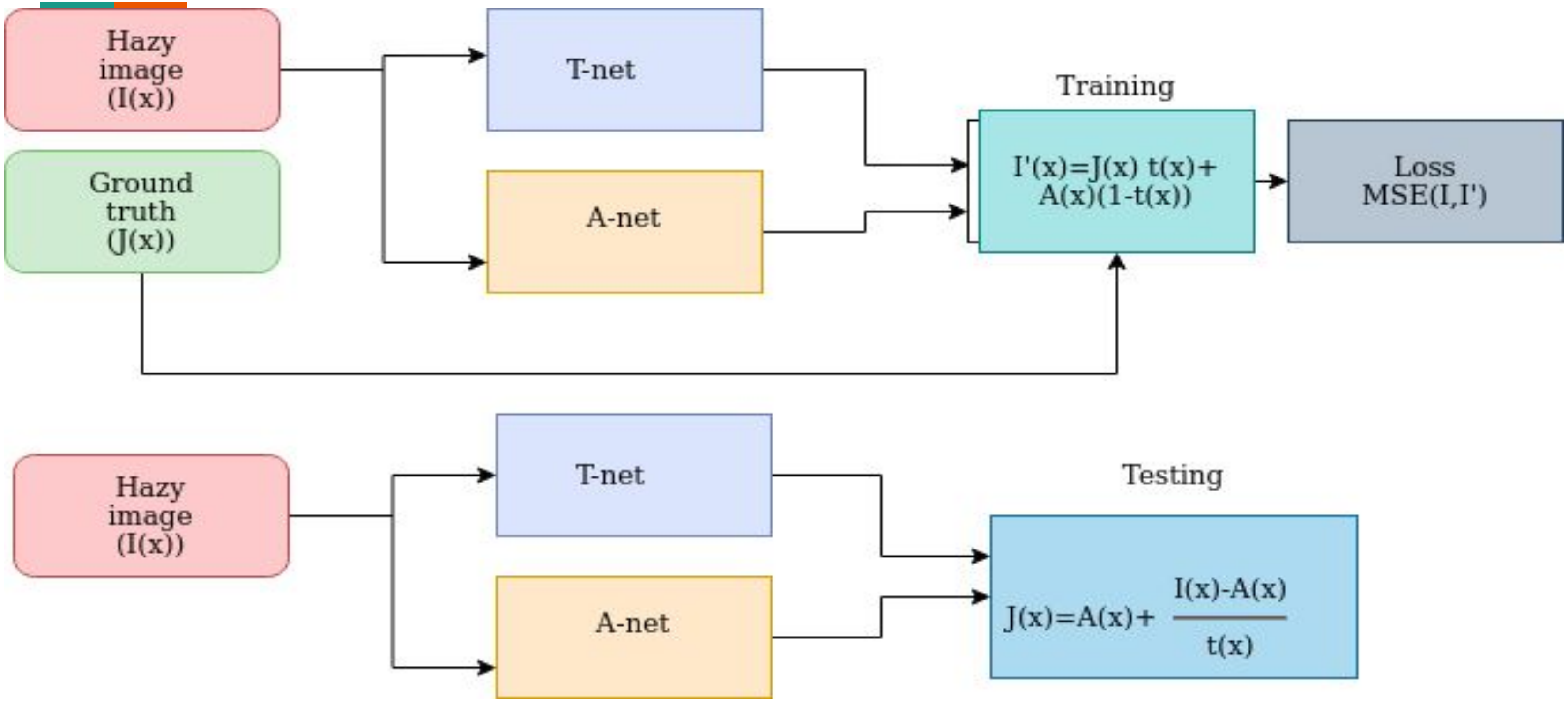
Decom-net

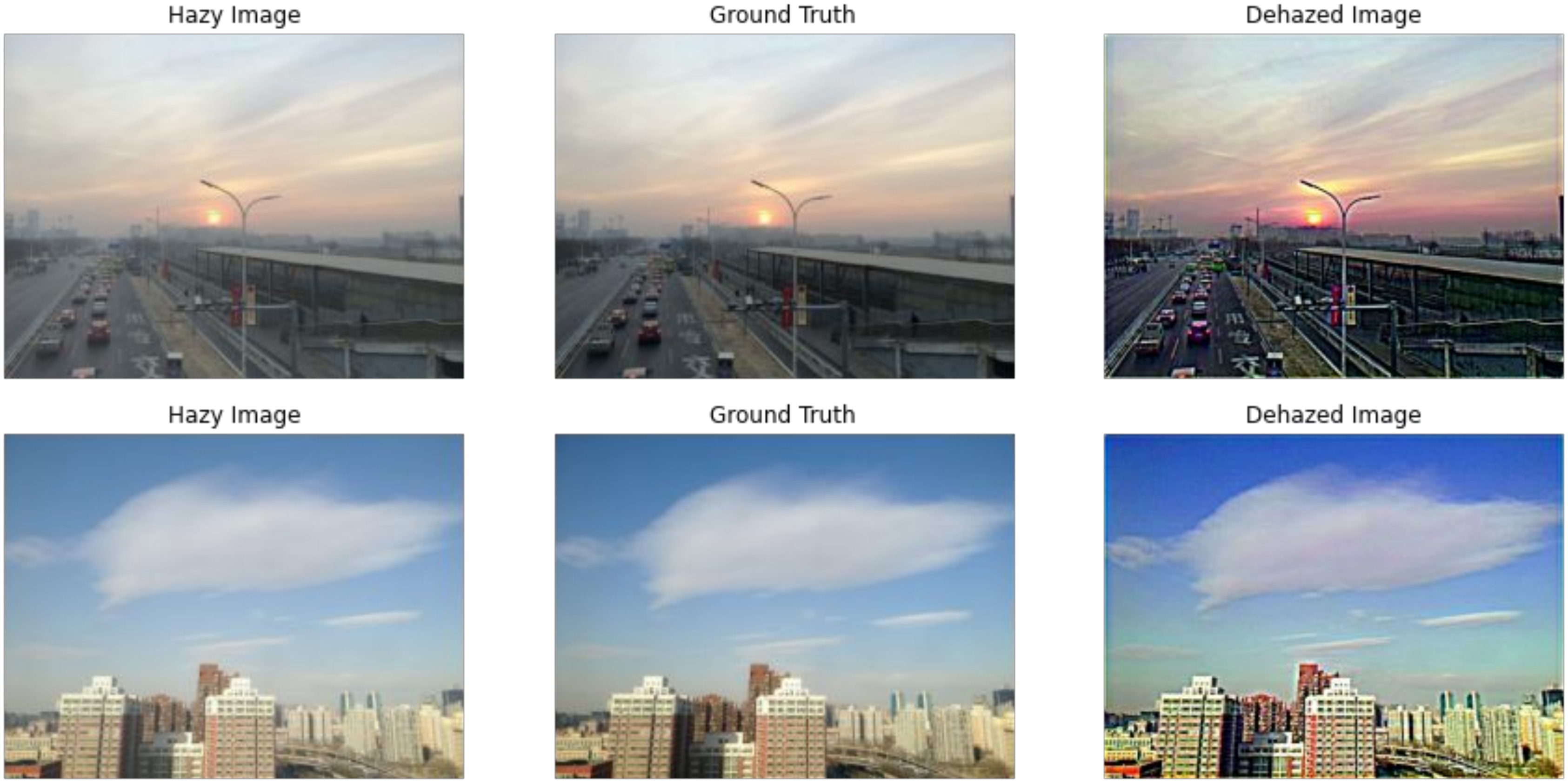
T-NET - DEHAZENET
A-NET - LCA

Current work

1. We use the dehazenet as T-net to get transmission map
2. We also selected LCA network because of its simplicity to gather information on atmospheric light.
3. Later T-net, A-net and J(Ground Truth) are combined to generate a nazy image which is used for loss computation.
4. During testing the outputs are combined to generate J i.e. dehazed image.

Training of T-net and A-net




Hazy Image
Ground Truth
Dehazed Image
Hazy Image
Ground Truth
Dehazed Image

references

[1] K. He, J. Sun and X. Tang, "Single Image Haze Removal Using Dark Channel Prior," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 12, pp. 2341-2353, Dec. 2011, doi: 10.1109/TPAMI.2010.168.
[2] K. He, J. Sun, and X. Tang. Guided image filtering. In ECCV, pages 1–14. 2010.
[3] Q. Zhu, J. Mai and L. Shao, "A Fast Single Image Haze Removal Algorithm Using Color Attenuation Prior," in *IEEE Transactions on Image Processing*, vol. 24, no. 11, pp. 3522-3533, Nov. 2015, doi: 10.1109/TIP.2015.2446191.
[4] K. Tang, J. Yang and J. Wang, "Investigating Haze-Relevant Features in a Learning Framework for Image Dehazing," 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, 2014, pp. 2995-3002, doi: 10.1109/CVPR.2014.383.
[5] B. Li et al., "Benchmarking Single-Image Dehazing and Beyond," in IEEE Transactions on Image Processing, vol. 28, no. 1, pp. 492-505, Jan. 2019, doi: 10.1109/TIP.2018.2867951.
[6] C. O. Ancuti, C. Ancuti, R. Timofte and C. De Vleeschouwer, "O-HAZE: A Dehazing Benchmark with Real Hazy and Haze-Free Outdoor Images," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, UT, USA, 2018, pp. 867-8678, doi: 10.1109/CVPRW.2018.00119.
[7] A. Pavan & Bennur, Adithya & Gaggar, Mohit & S S, Shylaja. (2020). LCA-Net: Light Convolutional Autoencoder for Image Dehazing.
[8] B. Cai, X. Xu, K. Jia, C. Qing and D. Tao, "DehazeNet: An End-to-End System for Single Image Haze Removal," in IEEE Transactions on Image Processing, vol. 25, no. 11, pp. 5187-5198, Nov. 2016, doi: 10.1109/TIP.2016.2598681.

[9] Z. Liu, B. Xiao, M. Alrabeiah, K. Wang and J. Chen, "Single Image Dehazing with a Generic Model-Agnostic Convolutional Neural Network," in IEEE Signal Processing Letters, vol. 26, no. 6, pp. 833-837, June 2019, doi: 10.1109/LSP.2019.2910403.

[10] Chen, D, He, M, Fan, Q, Liao, J, Zhang, L, Hou, D, Yuan, L & Hua, G 2019, Gated context aggregation network for image dehazing and deraining. in *Proceedings - 2019 IEEE Winter Conference on Applications of Computer Vision, WACV 2019.*, 8658661, Proceedings - IEEE Winter Conference on Applications of Computer Vision, WACV , IEEE, pp. 1375-1383, 19th IEEE Winter Conference on Applications of Computer Vision (WACV 2019), Waikoloa Village, United States, 7/01/19.

[11] Ronneberger, Olaf & Fischer, Philipp & Brox, Thomas. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. LNCS. 9351. 234-241. 10.1007/978-3-319-24574-4_28.

[12] Singh, Ayush & Bhave, Ajay & Prasad, Dilip. (2020). Single Image Dehazing for a Variety of Haze Scenarios Using Back Projected Pyramid Network. 10.1007/978-3-030-66823-5_10.

[13] Qin, Xu & Wang, Zhilin & Bai, Yuanchao & Xie, Xiaodong & Jia, Huizhu. (2019). FFA-Net: Feature Fusion Attention Network for Single Image Dehazing.

[14] Wang, Wenjing & Yang, Wenhan & Liu, Jiaying. (2018). Deep Retinex Decomposition for Low-Light Enhancement.

[15] H. Zhao, O. Gallo, I. Frosio and J. Kautz, "Loss Functions for Image Restoration With Neural Networks," in IEEE Transactions on Computational Imaging, vol. 3, no. 1, pp. 47-57, March 2017, doi: 10.1109/TCI.2016.2644865.

[16] Mittal, Anish & Moorthy, Anush & Bovik, Alan & Chen, Chang-Wen & Chatzimisios, Periklis & Dagiuklas, Tasos & Atzori, Luigi. (2015). No‐Reference Approaches to Image and Video Quality Assessment. 10.1002/9781118736135.ch5.

[17] L. K. Choi, J. You and A. C. Bovik, "Referenceless Prediction of Perceptual Fog Density and Perceptual Image Defogging," in IEEE Transactions on Image Processing, vol. 24, no. 11, pp. 3888-3901, Nov. 2015, doi: 10.1109/TIP.2015.2456502.

[18] Y. Liu and X. Li, "No-Reference Quality Assessment for Contrast-Distorted Images," in IEEE Access, vol. 8, pp. 84105-84115, 2020, doi: 10.1109/ACCESS.2020.2991842.