SINGLE IMAGE DEHAZING USING DEEP CONVOLUTION NEURAL NETWORKS

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ABSTRACT

Haze removal is urgently desired in multi-media system. In this paper, a deep learning-based method, called dehazingCNN, is proposed to estimate an approximate clear image for a hazy image. Our method attempts to recover a clear image by a learning model, which is different from traditional learning based method. Our method also adopts Deep Convolution Neural Networks (CNN) which takes the hazy image as the input and outputs the corresponding approximate clear image. As shown in experiment results section, the output of the network is high quality except some block artifacts and color distortions. We can remove the color distortion in the approximate clear image via atmospheric scattering model and guided filter effectively. Experimental results on different type of images, such as synthetic and benchmark of hazy images, demonstrate that the proposed method comparative to and even better than the more complex state-of-the-art methods in term of the dehazing effect.

Index Terms— Haze removal, image restoration, Deep Convolution Neural Networks

1. EXPERIMENT RESULTS

In this section, we evaluate our method on a large dataset containing both synthetic and natural images and compare our performance to state-of-art methods [1, 20, 21, 14, 15]. First, we show a comprehensive compare with other state-of-the-art method on outdoor synthetic hazy images. Second, we show a comprehensive compare with other state-of-the-art method on indoor synthetic hazy images. Third, we show a comprehensive compare with other state-of-the-art method on natural images. In this section, we use the $L1err = \frac{1}{N}\sum_{c\in R,G,B}|\mathbf{J}^c - \mathbf{G}^c|$, as metric, where $\mathbf{J}$ resents the dehazing result image and $\mathbf{G}$ resents the ground truth image. In order to evaluate the dehazing methods, we generate an indoor hazy image dataset. This dataset is based on the indoor RGBD dataset [22], we use $\mathbf{A} = [0.78, 0.78, 0.78]$ and choose three value for β as $0.06, 0.3, 0.54$ to generate hazy image [15]. The outdoor image dataset is from [20].

1.1. Synthetic hazy images

In this subsection, we compare our method with state-of-the-art methods on both indoor and outdoor synthetic hazy images. Although our deep network is trained on synthetic outdoor images, we note that it can be applied for indoor images as well. First, we compare our method with other state-of-the-art methods, and list the overall results. Second, we show some results on all images in Fattal's dataset and some images in our dataset.

An outdoor synthetic hazy images dataset was introduced by [20], which is available online. This dataset contains eleven haze-free images, and corresponding simulated hazy images. These images (its intensity scaled to $[0, 1]$) were added an identically-distribute zero-mean Gaussian noise with three different noise level: $\sigma = 0.01, 0.025, 0.05$. For this dataset, we sum all L1 error as quality standard. As shown in table 1, we can see that our results are best. In this section, we also compare our method with some state-of-art methods [1, 20, 21] on some images in dataset. As shown in Fig. 1, OurJ is the result of adding $\mathbf{A}$ to $\mathbf{J}_A(x)$, which is the output of our DCNN.

type	He et al.	Fattal	Berman et al.	Our
outdoor	5.77	4.54	5.96	3.87

Table 1: Quantitative comparison on Fattal's dataset.

type	Ren et al.	Berman et al.	Our
indoor	1.58e+03	1.05e+03	0.85e+03

Table 2: Quantitative comparison on our dataset.

image	He et al.	Fattal	Berman et al.	Our
church-D1	0.135	0.130	0.308	0.127
church-D2	0.117	0.107	116	0.113
church-D3	0.112	0.083	0.170	0.087
church-S10	0.140	0.160	0.127	0.130
church-S25	0.164	0.291	0.171	0.174
church-S50	0.226	0.400	0.241	0.226
church	0.117	0,107	0.116	0.113

Table 3: Quantitative comparison on church.

image	He et al.	Fattal	Berman et al.	Our
lawn1-D1	0.150	0.915	0.299	0.086
lawn1-D2	0.142	0.084	0.060	0.062
lawn1-D3	0.152	0.050	0.107	0.074
lawn1-S10	0.146	0.94	0.072	0.077
lawn1-S25	0.165	0.156	.122	0.116
lawn1-S50	0.213	0.269	0.224	0.186
lawn1	0.142	0.086	0.060	0.062

Table 4: Quantitative comparison on lawn1.

We compare our method with some state-of-art methods [15, 21]. We use our Synthetic hazy images to evaluate our performance. We use total L1err to evaluate the performance of the method.

Outdoor Hazy Images: In this part, we also compare our method with some state-of-art methods [1, 20, 21] on every image in dataset. We show the results in Table 3, 4, 5, 6 and 7. As we can see from the results, our method can get a very similar results to the ground truths in general and also can get high quality result for particular image. In Fig. 1 we show some results on two hazy images. As we can see our network output is very similar to haze-free image.

Indoor Hazy Images:In this part, we compare our method with Ren et al. [15] and Berman et al. [21]. The structural similarity (S-

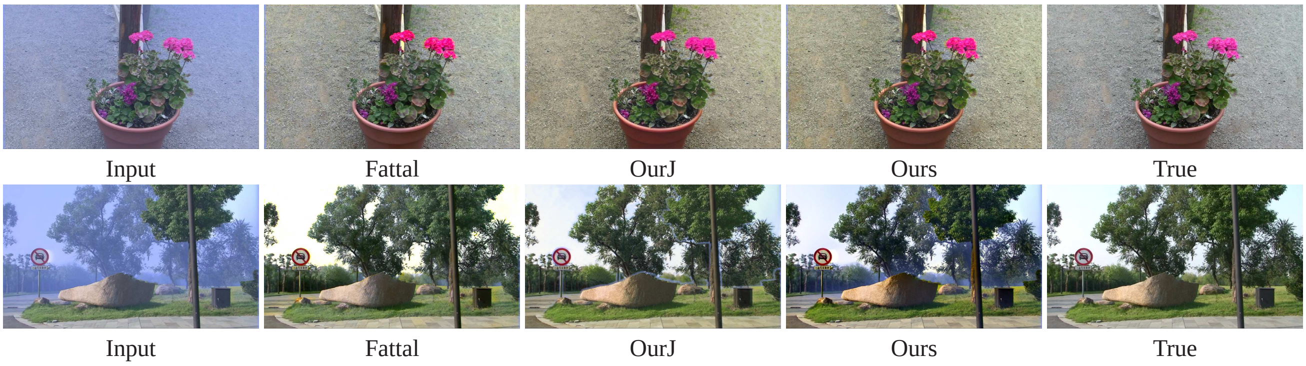

Fig. 1: Comparison on Outdoor hazy images.

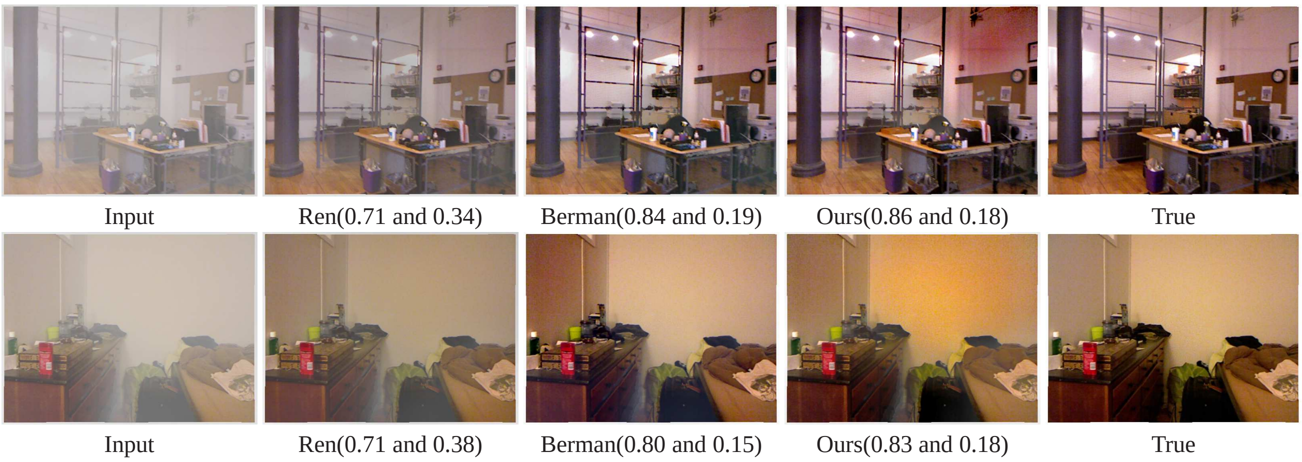

Fig. 2: Comparison on Indoor hazy images. The number in left is ssim value and the right is L1ERR

image	He et al.	Fattal	Berman et al.	Our
mansion-D1	0.92	0.067	0.267	0.072
mansion-D2	0.085	0.052	0.100	0.052
mansion-D3	0.088	0.036	0.198	0.044
mansion-S10	0.080	0.065	0.115	0.060
mansion-S25	0.089	0.106	0.146	0.084
mansion-S50	0.149	0.159	0.190	0.134
mansion	0.085	0.049	0.100	0.052

Table 5: Quantitative comparison on mansion.

image	He et al.	Fattal	Berman et al.	Our
raindeer-D1	0.150	0.091	0.329	0.140
raindeer-D2	0.147	0.074	0.094	0.055
raindeer-D3	0.145	0.050	0.165	0.040
raindeer-S10	0.140	0.087	0.103	0.060
raindeer-S25	0.139	0.110	0.131	0.080
raindeer-S50	0.171	0.169	0.187	0.123
raindeer	0.147	0.071	0.094	0.055

Table 6: Quantitative comparison on raindeer.

image	He et al.	Fattal	Berman et al.	Our
road1-D1	0.121	0.08	0.300	0.106
road1-D2	0.101	0.069	0.080	0.083
road1-D3	0.093	0.055	0.148	0.056
road1-S10	0.115	0.081	0.090	0.093
road1-S25	0.142	0.139	0.125	0.121
road1-S50	0.202	0.243	0.192	0.179
road1	0.101	0.069	0.080	0.083

Table 7: Quantitative comparison on road1.

image	He et al.	Fattal	Berman et al.	Our
couch	0.083	0.108	0.063	0.074
flower1	0.210	0.039	0.048	0.076
flower2	0.203	0.032	0.099	0.069
lawn2	0.144	0.081	0.070	0.071
moebius	0.311	0.159	0.173	0.099
road2	0.0122	0.089	0.082	0.083

Table 8: Quantitative comparison on left images in Fattal's dataset.

SIM) image quality assessment index [23] is used to evaluate performance of the methods. The higher value of SSIM shows the dehazing result is better. First we compare all image in our dataset, we can get highest SSIM score for 2393 images in 4347 image. Second, we show some results use SSIM and L1Err.

1.2. Quantitative Evaluation on Benchmark Natural Images Dataset

In this subsection, we compare our method with state-of-the-art methods [1, 17, 20, 11, 21, 14, 15]. As previously pointed by [1], the image after dehazing might look dim, since the scene radiance is usually not as bright as the airlight. For display, we perform a global linear contrast stretch on the output, clipping 0.5% of the pixel values both in the shadows and in the highlights.

Fig. 3 compares our method with state-of-the-art methods [1, 17, 24, 11, 14, 15]. Some of the results are provided by Fattal [20] , Berman [21] and Cai [14], which are online. We also get some results via the program provided by Ren [15]. As shown in Fig. 3, Ancuti et al.'s method can't remove haze completely. The result of Luzón-González et al. [24] can't deal with the boundary between segments well, which results in a lot of artifacts. He et al.'s method can yields an excellent results in general but lack some micro-contrast details when compared to [20] and ours. This is obvious in the zoomed-in buildings shown in Cityscape results, where in our result and [20] the windows are clearer than in [1]. The results of velly show that our method get a high quality results, which can recover more image detail and vivid color than other state-of-the-art methods.

2. CONCLUSIONS

In this material, we describe much detail of experiments. You can find the complete L1ERR of Fattal's dataset.

3. REFERENCES

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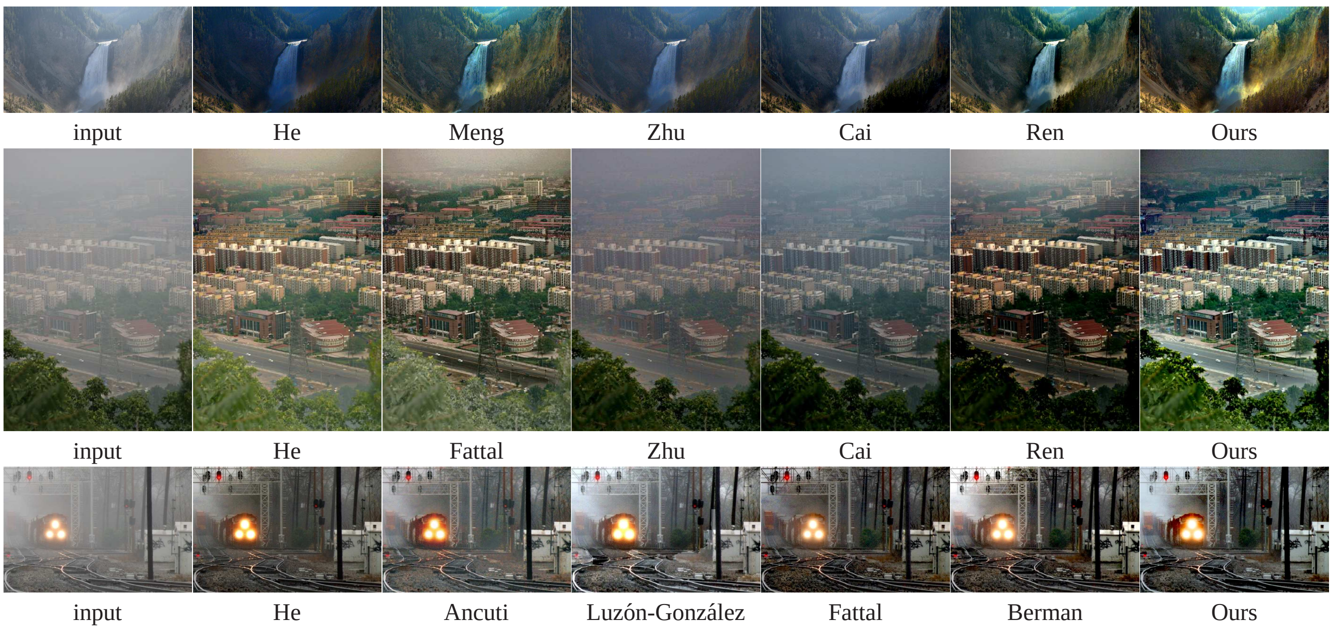

Fig. 3: Comparison on natural images:[Left] Input images. [Right] Our result. Middle columns display results by several methods, since each paper reports results on a different set of images.