DehazeNet: An End-to-End System for Single Image Haze Removal

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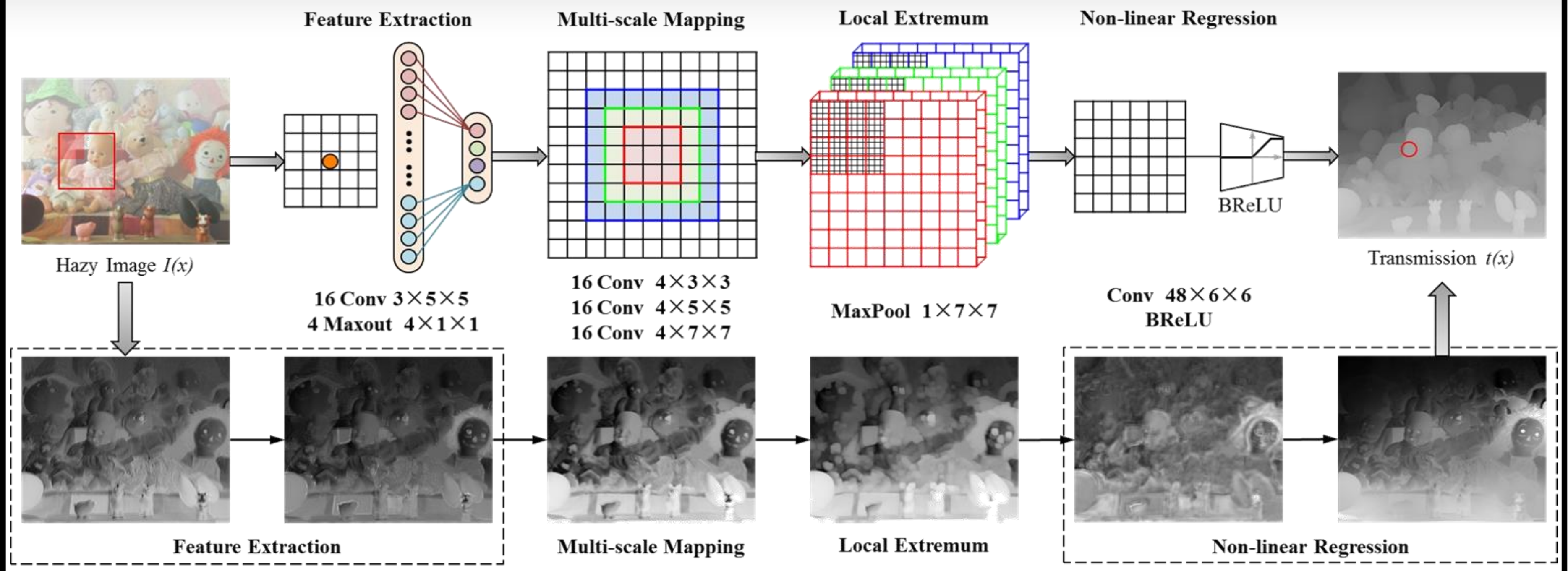
Abstract



We propose a trainable end-to-end system called **DehazeNet**, for medium transmission estimation. **DehazeNet** adopts deep CNN, whose layers are specially designed to embody the established priors in image dehazing. Specifically, layers of Maxout units are used for feature extraction, which can generate almost all haze-relevant features. We also propose a novel nonlinear activation function called BReLU, which is able to improve the quality of recovered haze-free image.

DehazeNet

1. Feature Extraction

Inspired by extremum processing of haze-relevant features, an unusual function called Maxout is selected for Feature Extraction.

$$F_1^i(x) = \max_{j \in [1,k]} g^{i,j}(x), g^{i,j} = W_1^{i,j} * I + B_1^{i,j}$$

2. Multi-scale Mapping

Multi-scale features have been proven effective for haze removal, and is also effective to achieve scale invariance.

$$F_2^i = W_2^{\lceil i/3 \rceil,(i \backslash 3)} * F_1 + B_2^{\lceil i/3 \rceil,(i \backslash 3)}$$

3. Local Extremum

The local extremum is in accordance with the assumption that the medium transmission is locally constant, and it is commonly to overcome the noise of transmission estimation.

$$F_3^i(x) = \max_{y \in \Omega(x)} F_2^i(y)$$

4. Non-linear Regression

Inspired by Sigmoid and ReLU, BReLU as a novel linear unit keeps bilateral restraint and local linearity.

$$F_4 = \min(t_{\max}, \max(t_{\min}, W_4 * F_3 + B_4))$$

DehazeNet Connections with Traditional Methods

We present layer designs of DehazeNet, and discuss how these designs are related to ideas in existing image dehazing methods.

- When W_1 is an opposite and B_1 is a unit bias, the maximum output of F_1 is equivalent to the minimum of color channels, which is similar to **dark channel** $D(x)$.

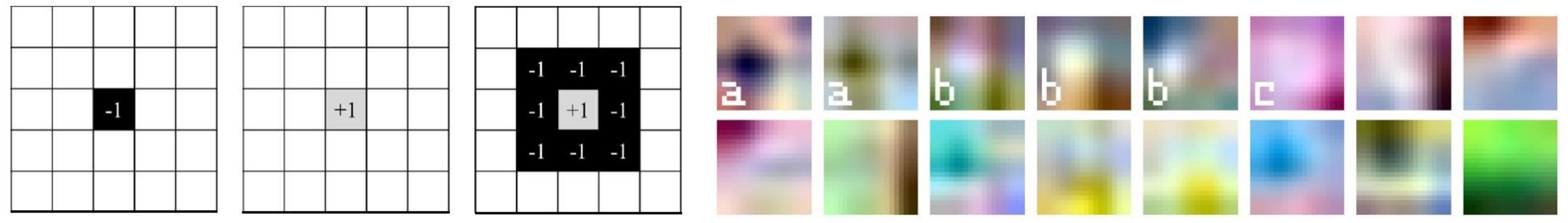
$$D(x) = \min_{y \in \Omega_r(x)} \left(\min_{c \in \{r,g,b\}} I^c(y) \right)$$

- When the weight is a round filter W_1, F_1 is similar to the **maximum contrast** $C(x)$.

$$C(x) = \max_{y \in \Omega_r(x)} \sqrt{\frac{1}{|\Omega_s(y)|} \sum_{z \in \Omega_s(y)} \|I(z) - I(y)\|^2}$$

- When W_1 includes all-pass/opposite filters, F_1 is similar to the max/min feature maps, which are atomic operations of the color transformation, then the **color attenuation** $A(x)$ and **hue disparity** $H(x)$ features are extracted.

$$\begin{cases} I^v(x) = \max_c I^c(x) \\ I^s(x) = \dfrac{\max_c I^c(x) - \min_c I^c(x)}{\max_c I^c(x)} \end{cases} \Rightarrow \begin{cases} A(x) = I^v(x) - I^s(x) \\ H(x) = |I_{si}^h(x) - I^h(x)| \end{cases}$$

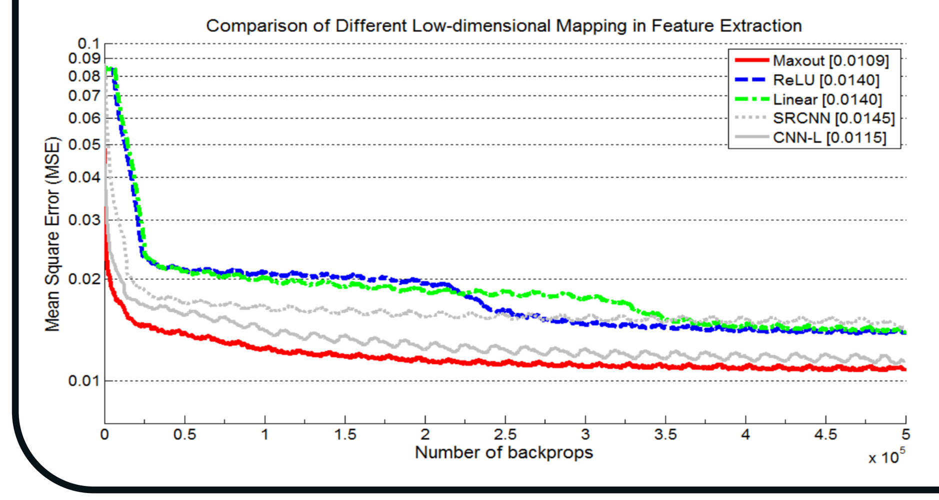


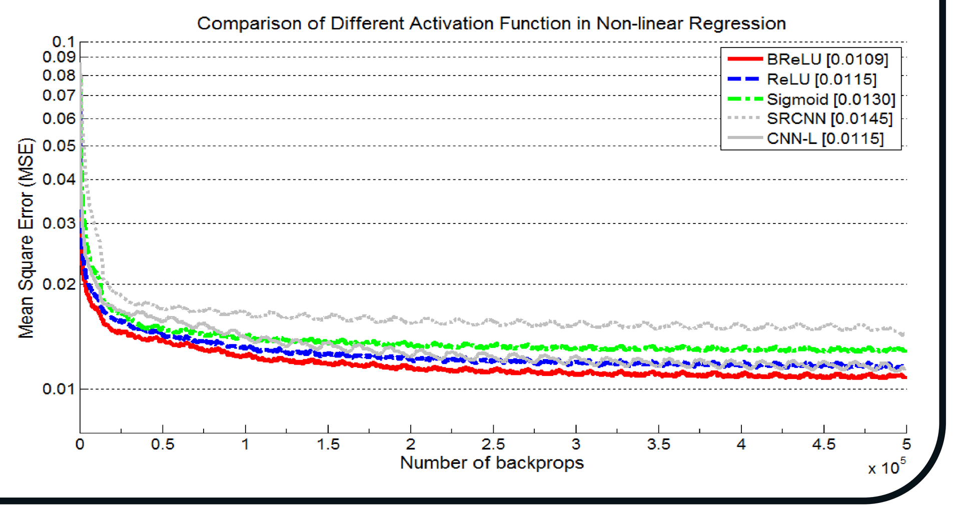
(a) Opposite filter (b) All-pass filter (c) Round filter (e) The actual kernels learned from DehazeNet

- Based on the assumption that the scene depth, local maximum filters of F_3 remove the local estimation error.
- BReLU in F_4 restricts the values to alleviate noise, which is equivalent to the boundary constraints used in traditional methods.

Experiments

1. Model and performance



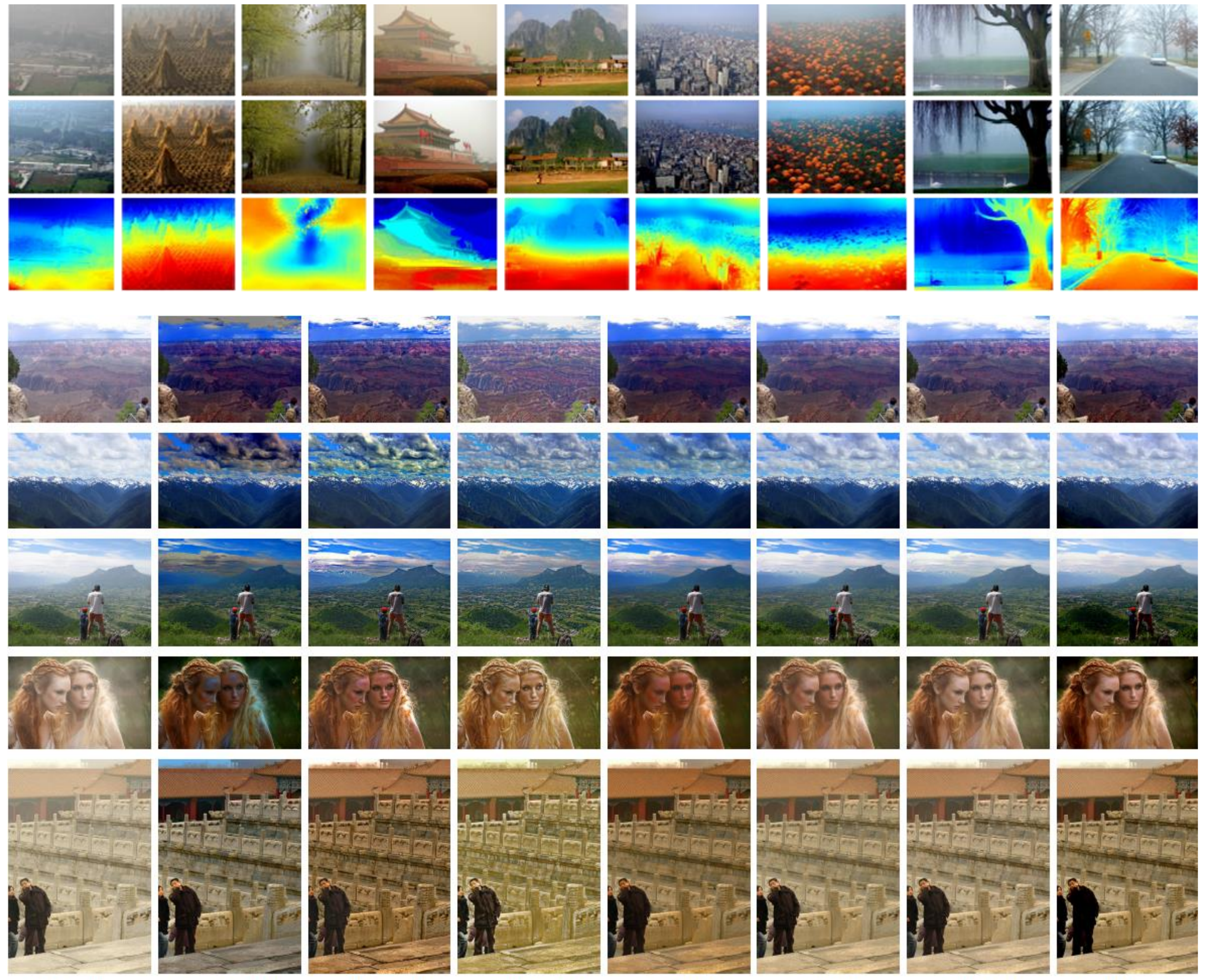


2. Quantitative results on synthetic images

Metric	Hazy	ATM [39]	BCCR [11]	FVR [38]	DCP [9]	CAP²[18]	RF [17]	DehazeNet
MSE	0.0481	0.0689	0.0243	0.0155	0.0172	0.0075 (0.0068)	0.0070	**0.0062**
SSIM	0.9936	0.9890	0.9963	0.9973	0.9981	0.9991 (0.9990)	0.9989	**0.9993**
PSNR	61.5835	60.8612	65.2794	66.5450	66.7392	70.0029 (70.6581)	70.0099	**70.9767**
WSNR	8.5958	7.8492	12.6230	13.7236	13.8508	16.9873 (17.7839)	17.1180	**18.0996**

Evaluation		Hazy	ATM [39]	BCCR [11]	FVR [38]	DCP [9]	CAP²[18]	RF [17]	DehazeNet
CRE ($\beta =$)	0.75	0..0311	0.0581	0.0269	0.0122	0.0199	**0.0043** (0.0042)	0.0046	0.0063
	1.00	0.0481	0.0689	0.0243	0.0155	0.0172	0.0077 (0.0068)	0.0070	**0.0062**
	1.25	0.0658	0.0703	0.0230	0.0219	0.0147	0.0141 (0.0121)	0.0109	**0.0084**
	1.50	0.0833	0.0683	0.0219	0.0305	0.0134	0.0231 (0.0201)	0.0152	**0.0127**
CRE Average		0.0571	0.0653	0.0254	0.0187	0.0177	0.0105 (0.0095)	0.0094	**0.0084**
ARE ($\alpha =$)	[1.0, 1.0, 1.0]	0.0481	0.0689	0.0243	0.0155	0.0172	0.0075 (0.0068)	0.0070	**0.0062**
	[0.9, 1.0, 1.0]	0.0437	0.0660	0.0266	0.0170	0.0210	0.0073 (0.0069)	**0.0071**	0.0072
	[1.0, 0.9, 1.0]	0.0435	0.0870	0.0270	0.0159	0.0200	**0.0070** (0.0067)	0.0073	0.0074
	[1.0, 1.0, 0.9]	0.0421	0.0689	0.0239	0.0152	0.0186	0.0081 (0.0069)	0.0083	**0.0062**
ARE Average		0.0443	0.0727	0.0255	0.0159	0.0192	0.0075 (0.0068)	0.0074	**0.0067**
SRE ($s =$)	0.40	0.0478	0.0450	0.0238	0.0155	0.0102	0.0137 (0.0084)	0.0089	**0.0066**
	0.60	0.0480	0.0564	0.0223	0.0154	0.0137	0.0092 (0.0071)	0.0076	**0.0060**
	0.80	0.0481	0.0619	0.0236	0.0155	0.0166	0.0086 (0.0066)	0.0074	**0.0062**
	1.00	0.0481	0.0689	0.0243	0.0155	0.0172	0.0077 (0.0068)	0.0070	**0.0062**
SRE Average		0.0480	0.0581	0.0235	0.0155	0.0144	0.0098 (0.0072)	0.0077	**0.0062**
NRE ($\sigma =$)	10	0.0484	0.0541	0.0138	0.0150	0.0133	0.0065 (0.0070)	0.0086	**0.0059**
	15	0.0488	0.0439	0.0144	0.0148	0.0104	0.0072 (0.0074)	0.0112	**0.0061**
	20	0.0493	–	0.0181	0.0151	0.0093	0.0083 (0.0085)	0.0143	**0.0058**
	25	0.0500	–	0.0224	0.0150	0.0082	0.0100 (0.0092)	0.0155	**0.0051**
	30	0.0508	–	0.0192	0.0151	0.0085	0.0119 (0.0112)	0.0191	**0.0049**
NRE Average		0.0495	–	0.0255	0.0150	0.0100	0.0088 (0.0087)	0.0137	**0.0055**

3. Qualitative results on real-world images



(a) Hazy image (b) ATM [39] (c) BCCR [11] (d) FVR [38] (e) DCP [9] (f) CAP [18] (g) RF [17] (h) DehazeNet