图像复原新视角
从学习“映射关系”到探索“因果关系”
Image Restoration Problem

The inverse problem: $Y = X * k + n$

- Image denoising
- Image deblurring
- Image dehazing
- Image deraining
- Image super-resolution
- ...

Observation $Y$  

Recovery $X$
<table>
<thead>
<tr>
<th>Year</th>
<th>Dehazing</th>
<th>Deraining</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009-2015</td>
<td>DCP (He et al.)</td>
<td>Decomposition (Kang et al.)</td>
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<tr>
<td></td>
<td>CAP (Zhu et al.)</td>
<td>GMM (Li et al.)</td>
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<td></td>
<td>NLP (Berman et al.)</td>
<td>DSC (Luo et al.)</td>
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<td>2016-2017</td>
<td>DehazeNet (Cai et al.)</td>
<td>JORDER (Yang et al.)</td>
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<td></td>
<td>MSCCNN (Ren et al.)</td>
<td>DDN (Fu et al.)</td>
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<td></td>
<td>AOD-Net (Li et al.)</td>
<td>ID_CGAN (Zhang et al.)</td>
</tr>
<tr>
<td>2018</td>
<td>DCPDN (Zhang et al.)</td>
<td>RESCAN (Li et al.)</td>
</tr>
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<td></td>
<td>GFN (Ren et al.)</td>
<td>DID-MDN (Zhang et al.)</td>
</tr>
<tr>
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<td>GCA-Net (Chen et al.)</td>
<td>AttentiveGAN (Qian et al.)</td>
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<td>2019</td>
<td>BidNet (Pang et al.)</td>
<td>SPA-Net (Wang et al.)</td>
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<td>GridDehazeNet (Liu et al.)</td>
<td>Pre-Net (Ren et al.)</td>
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<td>FFA-Net (Qin et al.)</td>
<td>DAF-Net (Hu et al.)</td>
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<td>2020-2021</td>
<td>PFDN (Dong et al.)</td>
<td>MSPFN (Jiang et al.)</td>
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<td>PSD (Chen et al.)</td>
<td>RCD-Net (Wang et al.)</td>
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<tr>
<td></td>
<td>AECR-Net (Wu et al.)</td>
<td>RL-Net (Chen et al.)</td>
</tr>
</tbody>
</table>
From Model-Based to Data-Driven

**Weak generalization**

Real Rainy Image

RESSCAN (ECCV’18)

PReNet (CVPR’19)

SPANet (CVPR’19)

RCDNet (CVPR’20)

Ours
Collecting paired training data is extremely challenging
Domain gap between the training and test data
Limit their generality and scalability in real-world applications
...
From Fully-supervised to Semi/Un-supervised

Weak constraint

Rainy Image

RESCAN (full-sup)

SIRR (semi-sup)

CycleGAN (un-sup)

Ours (un-sup)

Ground Truth
From “Mapping Relationship” to “Causal Relationship”

- Paired data
- Network structure
- ...

Learn “Mapping Relationship”

Open a New Perspective

Explore “Causal Relationship”

- Unpaired data
- Deep feature space
- ...

Degraded Image Domain

Clean Image Domain
Motivation

Unpaired Adversarial Learning for Single Image Deraining with Rain-Space Contrastive Constraints

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➢ Since the ground truth labeled data is not fully available, how to model the latent-space representation by exploring the relationship between the rainy inputs and clean outputs is important for the deep learning-based methods.

➢ Given that clean images can be easily obtained, it is also important to develop an effective method that can explore properties of the clean exemplars to facilitate image restoration when paired data is not available.
Contrastive Learning in Low-level Vision

- Wu et al. Contrastive Learning for Compact Single Image Dehazing
- Han et al. Single Underwater Image Restoration by Contrastive Learning
- Zhang et al. Blind Image Super-Resolution via Contrastive Representation Learning
- Dong et al. Residual Contrastive Learning for Joint Demosaicking and Denoising
- ...

Our primary finding is that the features extracted from rainy image patches share some mutual information to the features extracted from rain-free image patches.
Contrastive DeRain-GAN

Figure 1: The overview architecture of Contrastive DeRain-GAN (CDR-GAN). There are two cooperative branches, bidirectional translation branch (BTB) and contrastive guidance branch (CGB). Our rain-space contrastive constraints aim to learn a representation to pull similar feature distribution (e.g., clean $\rightarrow\leftarrow$ clean) and push disimilar (e.g., rain $\leftarrow\rightarrow$ clean) apart.
“Causal Relationship” in Deep Feature Space

Figure 2: Visualization results of t-SNE.
Double Benefit for Encouraging Deraining

Adversarial Learning

Contrastive Learning

cycle-consistent constraint

contrastive constraint

share some commonalities

## Quantitative Results

<table>
<thead>
<tr>
<th>Datasets</th>
<th>Test100</th>
<th>Test1200</th>
<th>Test1400</th>
<th>Test1000</th>
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<tr>
<td><strong>Metrics</strong></td>
<td>PSNR</td>
<td>SSIM</td>
<td>PSNR</td>
<td>SSIM</td>
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<td>Prior-based methods</td>
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<tr>
<td>DSC</td>
<td>18.56</td>
<td>0.599</td>
<td>24.24</td>
<td>0.827</td>
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<td>GMM</td>
<td>20.46</td>
<td>0.730</td>
<td>25.66</td>
<td>0.817</td>
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<td>Paired / Supervised methods</td>
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<tr>
<td>DDN</td>
<td>21.16</td>
<td>0.732</td>
<td>27.93</td>
<td>0.853</td>
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<td>DID-MDN</td>
<td>21.89</td>
<td>0.795</td>
<td>29.66</td>
<td>0.899</td>
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<td>RESCAN</td>
<td>24.09</td>
<td>0.841</td>
<td>32.25</td>
<td>0.907</td>
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<td>SPANet</td>
<td>24.37</td>
<td><strong>0.861</strong></td>
<td>30.05</td>
<td>0.934</td>
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<td>Semi-supervised methods</td>
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<tr>
<td>SIRR</td>
<td>/</td>
<td>/</td>
<td>30.57</td>
<td>0.910</td>
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<td>Syn2Real</td>
<td>23.74</td>
<td>0.799</td>
<td>/</td>
<td>/</td>
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<tr>
<td>Unpaired / Without paired supervised methods</td>
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<td></td>
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<tr>
<td>CycleGAN</td>
<td>22.95</td>
<td>0.783</td>
<td>28.68</td>
<td>0.875</td>
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<td>RR-GAN</td>
<td>23.51</td>
<td>0.756</td>
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<td><strong>Ours</strong></td>
<td><strong>26.43</strong></td>
<td>0.810</td>
<td><strong>32.58</strong></td>
<td><strong>0.937</strong></td>
</tr>
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</table>

Table 1: Comparison of quantitative results on four benchmark datasets. Bold and *italic* indicate the best and second-best results.
Figure 3: Qualitative evaluations on the Test100 and Test1000 dataset. Best viewed zoomed in.
Figure 4: Comparison of visual and quantitative results on real images, with the description of NIQE/BRISQUE under the images. Note that lower values (marked red) indicate better performance. Best viewed zoomed in.
Figure 5: Comparison results tested on the Google Vision API. (a-b) Object recognition results for the input rainy image and our derained image. (c) The averaged confidences in recognizing rain. Note that lower scores indicate better performance.
Explore More “Causal Relationship”

- Meta Learning
- Bayesian Inference
- Feature Interpretability
- Deep Latent Space Translation
- ...

Repositories

https://github.com/cxtalk/DehazeZoo

https://github.com/cxtalk/You-Can-See-Clearly-Now