SF-CNN: A Fast Compression Artifacts Removal via Spatial-to-Frequency Convolutional Neural Networks

Taeoh Kim  Hyeongmin Lee  Hanbin Son  Sangyoun Lee
Image and Video Pattern Recognition Lab, Yonsei University

Abstract

• We Propose Efficient CNNs for Image Restoration, Especially for DeJPEG
• Computational Complexity of Most of the CNN-based Image Restoration Networks is $H \times W \times C_{in} \times C_{out} \times K_H \times K_W \times L$
• Our Goal is to Reduce $H \times W$ via Spatial Downsampling

Related Works

CNNs for Compression Artifacts Removal
• Full-Resolution, Shallow Network [1]
• Full-Resolution, Better Performance [3, 6, 8]
• Downsampling by 2 [2, 5]
• Encoder-Decoder Shape and Skip-Connections [4, 7]

SF-CNN

• Reshaping from Spatial to a Channel Can Reduce Spatial Dimension in Networks. Our Network Predicts Reshaped Desired Output from the Input.
• However, to Reshape in the Spatial Domain Does Not Fit in Convolutional Filters (S2F)
• Spatial-to-Frequency Network is More Suitable (S2F)
• We Used 1x1 Convolution without Gradient for Block-wise DCT and IDCT Layers as in [8]

Results

<table>
<thead>
<tr>
<th>Network</th>
<th>F2F</th>
<th>S2S</th>
<th>S2F(Ours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSNR</td>
<td>31.59</td>
<td>31.67</td>
<td>31.72</td>
</tr>
</tbody>
</table>

Ablation Study between Two Domains

PSNR/Complexity Plot on LIVE1 QF=20, Full-HD Resolution

Qualitative Results on sailing2, paintedhouse and buildings (QF=10)

References

[1] Chao Dong et al., ARCNN, CVPR 2015
[4] Lukas Cavigelli et al., CAS-CNN, IJCNN 2017
[5] Leonardo Galteri et al., DGACAR (ARGAN), ICCV 2017
[7] X. Zhang et al., DMCNN, ICIP 2018