The network for unambiguous edge disparity estimation:

Motivation: The background and reflection images usually have different disparity ranges, which can help us separate the background and reflection images.

Problem: The image disparity values are ambiguous after two images are superimposed.

Solution:
1. The edges of two images are seldomly overlapped. Thus, the disparities on edges should be independent and unambiguous.
2. We use an edge emphasized disparity estimation network for estimating disparity values on image edges.

The WGAN trained for background edge regeneration:

Problem: The disparity ranges of background and reflection may be partially overlapped.

Solution:
1. Only extract edges with large and small disparity values. Those edges tend to only belong to one image layer.
2. Send those edges to a WGAN for regenerating complete background edges.

\[
\min_{\alpha} \max_{\beta} \mathcal{L}_{\alpha}^{E} + \lambda_1 (\mathcal{L}_{\alpha}^{E} + \mathcal{L}_{\alpha}^{E})
\]

3. The adversarial terms \(\mathcal{L}_{\alpha}^{E}\) and \(\mathcal{L}_{\alpha}^{E}\) for background and reflection edges respectively in the WGAN can force the estimated edges to better follow distributions of natural image edges.

Another WGAN trained for background image reconstruction:

Motivation: 1. Improving the speed over traditional optimization-based approaches.

2. Obtaining better performance via exploiting the strong prediction ability of DNN. However, a normal L2 norm pixel loss term may lead to a blurry result.

\[
\min_{\alpha} \max_{\beta} \mathcal{L}_{\alpha}^{E} + \lambda_2 L_{\alpha}^{E} + \lambda_3 (\mathcal{L}_{\alpha}^{E} + \mathcal{L}_{\alpha}^{E})
\]

Solution: 1. Use a VGG perceptual feature term \(\mathcal{L}_{\alpha}^{E}\) to improve the perceptual similarity between the background result and ground truth.

2. Use the adversarial terms \(\mathcal{L}_{\alpha}^{E}\) and \(\mathcal{L}_{\alpha}^{E}\) to guide the background result to better follow natural image distributions.

Method | PSNR values of Background results | Ave. Time |
<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Original images</td>
<td>13.09</td>
<td>NA</td>
</tr>
<tr>
<td>LS-LFGS</td>
<td>21.71</td>
<td>69.51s</td>
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<tr>
<td>LS-SIIFT</td>
<td>18.91</td>
<td>130.59s</td>
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<tr>
<td>LS-DS</td>
<td>18.85</td>
<td>17.01s</td>
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<tr>
<td>CEILNet</td>
<td>17.71</td>
<td>0.82s</td>
</tr>
<tr>
<td>PLNet</td>
<td>19.09</td>
<td>1.15s</td>
</tr>
<tr>
<td>Proposed</td>
<td>24.22</td>
<td>1.08s</td>
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