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1. Introduction of Low Light Image Enhancement

**Background:**
High-level task are heavily dependent on the quality of the input images. Insufficient light during capture can result in information loss and noise in the dark regions of the images.

**Operations:**
Long exposure -> blur, High ISO -> noise amplified, Flash -> unbalanced lighting

**Challenge:**
When amplifying the intensity/brightness, noise also amplifies. In low-light conditions, camera sensors are sensitive and non-linear to insufficient photons, which causes color distortion.
1. Introduction of Low Light Image Enhancement

Data driven method mostly uses **paired data** to train an enhancement model.

**Powerful input:**
- SNR map
- Light attention map
- Edge map
- Reflection map

**Powerful model:**
- Complex CNN
- Unet
- Transform
- GAN

**Powerful loss:**
- MSE loss
- Color loss
- Light loss
- VGG loss
2. Motivation

- Low Light:
  ![Images of low light conditions]

- Light-Effects/Glare/Floodlight:
  ![Images of light effects, glare, and floodlight conditions]
2. Motivation

- Existing low-light enhancement methods:
  - ✓ Enhance low-light regions
  - × Over-enhance light-effects regions

- Existing night dehazing methods:
  - × Enhance low-light regions
  - ✓ Suppress glow; × Suppress light-effects

Main task: Boost dark regions, at the same time, suppress light-effects.
3. Challenge

1. Lack of paired training data, hard to collect ground truth
2. Synthesizing physically correct night light-effects images is challenging

Solution: propose an unsupervised night image enhancement method.
- Model-based Layer Decomposition
- Unpaired Light-Effects Suppression

Our decomposition is based on the following image-layer model:

\[ I = R \odot L + G \]

This idea is based on Retinex theory. It is a ill-posed question.

Deep learning method based on Retinex theory (2019 ACMMMM Kind)

Four unsupervised loss:

**Light-Effects and Shading Initialization**

\[ \mathcal{L}_{\text{init}} = |G - G_i|_1 + |L - L_i|_1. \]

\(L_i\) is max value of RGB channels. \(G_i\) is second-order Laplacian filter from the input image.

**Gradient Exclusion Loss**

\[ \mathcal{L}_{\text{excl}} = \sum_{n=1}^{3} \left\| \text{tanh}(\lambda_{G_i^{\text{in}}} |\nabla G_i^{\text{in}}|) \circ \text{tanh}(\lambda_{J_{\text{init}}^{\text{in}}} |\nabla J_{\text{init}}^{\text{in}}|) \right\|_F, \]

**Color Constancy Loss**

\[ \mathcal{L}_{\text{cc}} = \sum_{(c_1, c_2)} (|J_{\text{init}}^{c_1} - J_{\text{init}}^{c_2}|_1), \quad \text{where } (c_1, c_2) \in \{(r, g), (r, b), (g, b)\} \]

**Reconstruction Loss**

\[ \mathcal{L}_{\text{recon}} = |I - (R \odot L + G)|_1. \]
4. Method Part 2: Light-effects Suppression
4. Method Part 2: Light-effects Suppression

\[ \mathcal{L}_{\text{atten}} = - \left( \mathbb{E} \left[ \log(\Gamma_{\text{gen}}(f_e)) \right] + \mathbb{E} \left[ \log(1 - \Gamma_{\text{gen}}(f_{ef})) \right] \right). \]
4. Method Part2: Light-effects Suppression

\[ \mathcal{L}_{\text{adv}} = \mathbb{E} \left[ \log (\phi_{\text{dis}}(J_{\text{ef}})) \right] + \mathbb{E} \left[ \log (1 - \phi_{\text{dis}}(J_{\text{refine}})) \right] \]

Losses

\[
\sum: \text{Weighted Sum} \quad c \in (r, g, b)
\]

Input \( I \)

\( I_c \)

\( w_c \)

\( I_{gray} \)

\( \phi_{HF}(I_{gray}) \)

\( \phi_{VGG}(I_{gray}) \)

\( J_{refine} \)

Losses
Results on Light-Effects Suppression

Results on Light-Effects Suppression

- Dark Zurich Dataset

![Image showing comparison of different methods for light-effects suppression.](image-url)
## Results on Low-light Enhancement

### Quantitative comparisons on the LOL-test dataset

<table>
<thead>
<tr>
<th>Learning</th>
<th>Method</th>
<th>LOL-test</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>MSE($\times 10^3$)</td>
<td>PSNR↑</td>
<td>SSIM↑</td>
<td>LPIPS↓</td>
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<tr>
<td>Opti</td>
<td>LIME [14]</td>
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<td>16.760</td>
<td>0.560</td>
<td>0.350</td>
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<tr>
<td>SL</td>
<td>RetinexNet [7]</td>
<td>1.651</td>
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<td>KinD++ [47]</td>
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<td>0.760</td>
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<td>Afifi [1]</td>
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<tr>
<td>SL</td>
<td>RUAS [24]</td>
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<tr>
<td>ZSL</td>
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<tr>
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<td>UL</td>
<td>EnlightenGAN [15]</td>
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<tr>
<td>UL</td>
<td>Ours</td>
<td><strong>1.070</strong></td>
<td><strong>21.521</strong></td>
<td><strong>0.763</strong></td>
<td><strong>0.235</strong></td>
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</table>

### Quantitative comparisons on the LOL-Real dataset

<table>
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<th>Opti</th>
<th>Opti</th>
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<th>ZSL</th>
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<tr>
<td>PSNR↑</td>
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<td>9.72</td>
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<td>17.34</td>
<td>17.34</td>
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<tr>
<td>SSIM↑</td>
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<td>0.18</td>
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<td>0.68</td>
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<td>SL</td>
<td>SL</td>
<td>SL</td>
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<td>SSL</td>
<td>UL</td>
<td>SSL</td>
<td>UL</td>
</tr>
<tr>
<td>PSNR↑</td>
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<td>17.56</td>
<td>15.47</td>
<td>13.27</td>
<td>19.40</td>
<td>16.38</td>
<td>19.66</td>
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<td><strong>25.53</strong></td>
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<tr>
<td>SSIM↑</td>
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<td>0.54</td>
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<td>0.69</td>
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<td>0.76</td>
<td>0.61</td>
<td>0.64</td>
<td><strong>0.88</strong></td>
</tr>
</tbody>
</table>
Results on Low-light Enhancement

- **LOL-test dataset**

- **LOL-Real dataset**

<table>
<thead>
<tr>
<th>Input</th>
<th>Ground Truth</th>
<th>Ours</th>
<th>Sharma</th>
<th>EG</th>
</tr>
</thead>
</table>
Conclusion

- We presented an **unsupervised learning** framework for night image enhancement, which boost dark regions and suppress light-effects simultaneously.

- With light-effects layer guidance, our method separate **white/multi-colored light-effects** more properly.

- With unsupervised structure and HF-features consistency loss, our method **restore the background details**.