Physically Inspired Dense Fusion Networks for Relighting
Runner Up of NTIRE 2021 Depth-Guided Relighting Challenge

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June 19 2021
Fusion Strategy

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- The fused output:
  \[ \hat{I}_{\text{relit}} = wI_{\text{direct-relit}} + (1 - w)I_{\text{intrinsic-relit}} \]
One-to-one Intrinsic Decomposition Direct RelightNet \(^1\)

**Figure** – Our proposed OIDDR-Net. The shading estimate is adjusted using the normals of the surfaces in the scene provided by the normal extraction module.

1. For the implementation details please visit: github/Relighting

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Any-to-any Multiscale Intrinsic-Direct RelightNet

**Figu re** – Our proposed AMIDR-Net. The multi-scale block helps the model systematically learn to upsample and downsample the inputs according to the features it needs.
Loss Function

Training Loss

\[ \mathcal{L} = \mathcal{L}_{total} + \lambda_1 \mathcal{L}_{IID} + \lambda_2 \mathcal{L}_{direct} + \lambda_3 \mathcal{L}_{SSIM} + \lambda_4 \mathcal{L}_{lighting} \]
Training Loss

\[
\mathcal{L} = \mathcal{L}_{total} + \lambda_1 \mathcal{L}_{IID} + \lambda_2 \mathcal{L}_{direct} + \lambda_3 \mathcal{L}_{SSIM} + \lambda_4 \mathcal{L}_{lighting}
\]

\[
\mathcal{L}_{total} = ||\hat{I}_{relit} - Y_{relit}||_2^2
\]

\[
\mathcal{L}_{IID} = ||\hat{A} \odot \hat{S} - Y_{relit}||_2^2 + ||\hat{A} - A||_2^2 + ||\hat{S} - S||_2^2
\]

\[
\mathcal{L}_{direct} = ||I_{direct-relit} - Y_{relit}||_2^2
\]

\[
\mathcal{L}_{SSIM} = 1 - SSIM(\hat{I}_{relit}, Y_{relit})
\]

\[
\mathcal{L}_{lighting} = ||g(\hat{I}_{relit}) - g(Y_{relit})||_2^2 - \sum_{i=1}^{8} Y_{dir-guide}^{i} \log(\hat{Y}_{dir}^{i}) - \sum_{j=1}^{5} Y_{color-guide}^{j} \log(\hat{Y}_{color}^{j})
\]
# One-to-one Relighting

<table>
<thead>
<tr>
<th>Team</th>
<th>Author</th>
<th>MPS ↑</th>
<th>SSIM ↑</th>
<th>LPIPS ↓</th>
<th>PSNR ↑</th>
<th>Run-time</th>
<th>Platform</th>
<th>GPU</th>
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</table>

**TABLE** — NTIRE 2021 Depth-Guided Image Relighting Challenge Track 1 (One-to-one relighting) results. The MPS is used to determine the final ranking.
Any-to-any Relighting

**Figure** – Comparing our AMIDR-Net with other methods on samples from VIDIT’20 [3] dataset.
Thank You!

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http://signal.ee.psu.edu