Semantic-Guided Zero-Shot Learning for Low-Light Image/Video Enhancement

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Outline

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Figure 1: Sample Enhancement Result on a nighttime aerial video frame
Challenges

- Degraded Feature and Contrast
- Poor Low-Level Perceptual Quality
- Substandard Performances for High-Level Tasks

HOW TO ADDRESS THOSE CHALLENGES?
Existing Solutions: Camera and Software

Camera
• Higher ISO
• Longer Exposure Time
• Noise ! Motion Blur !

Software
• Photoshop, Lightroom
• High Artist Skills !
• Inefficient at Diverse Illumination !
Existing Solutions: Conventional Methods

Histogram Equalization
• Adjusting Photo Intensities
• BPDHE [Ibrahim and Kong, 2007]
• WTHE [Wang and Ward, 2007]

Retinex Theory
• Reflectance and Illumination
• NPE [Wang et al., 2013]
• PIE [Fu et al., 2015], SRIE [Fu et al., 2016]
• LIME [Guo et al., 2016]
Existing Solutions: DL Methods

Supervised
• LLNet [Lore et al., 2017]
• RetinexNet [Wei et al., 2018], KinD [Zhang et al., 2019]
• DeepUPE [Wang et al., 2019]

Unsupervised
• EnlightenGAN [Jiang et al., 2021]

Zero-Shot
• Zero-DCE [Guo et al., 2020], Zero-DCE++ [Li et al., 2021]
Model Architecture

Figure 2: Proposed model architecture. Our model aims at enhancement factor extraction (EFE), recurrent image enhancement (RIE), and unsupervised semantic segmentation (USS)
Enhancement Factor Extraction

Figure 3: Enhancement factor visualization. Left: Low-Light Images. Right: Enhancement Factors. Darker region indicates lower values for the enhancement factor.
Recurrent Image Enhancement

\[ X_t = X_{t-1} + X_r \star (X_{t-1}^{\text{Order}} - X_{t-1}) \]  

(1)

Figure 4: Recurrent image enhancement illustration with different enhancement factor \( X_r \) and different Order. Greater \( |X_r| \) indicates a more intense enhancement.
Loss Function

• Spatial consistency loss

\[
L_{\text{spa}} = \frac{1}{A} \sum_{i=1}^{A} \left[ \sum_{j \in \phi(i)} \left( \left| (Y_i - Y_j) \right| - \left| (I_i - I_j) \right| \right)^2 + \alpha \sum_{k \in \psi(i)} \left( \left| (Y_i - Y_k) \right| - \left| (I_i - I_k) \right| \right)^2 \right]
\]

• RGB loss

\[
L_{\text{rgb}} = \sum_{\forall (i,j) \in \zeta} \sqrt{\left( (Y_i^j) - (Y_j) \right)^2 + \varepsilon^2},
\]

\[
\zeta = \{(R, G), (R, B), (G, B)\}
\]
Loss Function

- Brightness loss
  \[ L_{bri} = \frac{1}{A} \sum_{a=1}^{A} |Y_a - E| \]  
  (4)

- TV loss
  \[ L_{tv} = \frac{1}{CHW} \sum_{c=1}^{C} \sum_{h=1}^{H} \sum_{w=1}^{W} \left[ (\nabla_x Y_c,h,w)^2 + (\nabla_y Y_c,h,w)^2 \right] \]  
  (5)

- Semantic loss
  \[ L_{sem} = \frac{1}{HW} \sum_{1 \leq i \leq H, 1 \leq j \leq W} -\beta (1 - p_{i,j})^\gamma \log p_{i,j} \]  
  (6)
Implementation Details

Training details

- Training Datasets: 2002 images, 512 X 512 resolutions
- Optimizer: Adam [Kingma and Ba, 2014]
- Framework: Pytorch [Paszke et al., 2019]
- Weight Initialization: N(0, 0.02)
- Batch Size: 6
- Epoch: 100
- Gradient Clipping: 0.1
Evaluation Dataset

| Name                          | Number | Format | Type  | Metric |
|-------------------------------|--------|--------|-------|--------|
| NPE [Wang et al., 2013]       | 10     | RGB    | Real  | N, B   |
| LIME [Guo et al., 2016]       | 84     | RGB    | Real  | N, B   |
| MEF [Ma et al., 2015]         | 17     | RGB    | Real  | N, B   |
| DICM [Lee et al., 2012]       | 64     | RGB    | Real  | N, B   |
| VV                            | 24     | RGB    | Real  | N, B   |
| LOL [Wei et al., 2018]        | 15     | RGB    | Real  | P, S, M|
| DarkBDD                       | 100    | RGB    | Real  | N, B   |
| DarkCityScape                 | 150    | RGB    | Synthesis | P, S, M |

Table 1: Dataset description. Where U, B stands for UNIQUE and BRISQUE, and P, S, M stands for PSNR, SSIM, MSE, respectively.
Ablation Study

Figure 5: Visual comparison on loss function ablations
**Quantitative Comparison: Efficiency**

| Method                    | RT↓   | Params↓ | FLOPs↓ | Score↑ |
|---------------------------|-------|---------|--------|--------|
| Retinex[Wei et al., 2018] | 0.121 | 0.555   | 587.5  | 2.30   |
| MBLLEN[Lv et al., 2018]  | 0.526 | 0.450   | 301.1  | 3.05   |
| KinD[Zhang et al., 2019] | 0.147 | 8.160   | 575.0  | 3.36   |
| EnlightenGAN[Jiang et al., 2021] | 0.008 | 8.637   | 273.2  | 2.94   |
| Zero-DCE[Guo et al., 2020] | 0.003 | 0.079   | 84.99  | 2.60   |
| **Ours**                  | 0.001 | 0.011   | 0.120  | 4.04   |

Table 2: Model Efficiency and User Study Score Comparison. We select an image of size $1200 \times 900$ for experiments. ‘RT’ is the inference time in seconds per image. ‘Params’ are the numbers of trainable parameters in millions per image, and ‘FLOPs’ are the numbers of floating-point operations in billions per image.
Quantitative Comparison: Others

| Dataset | Dark   | PIE    | Retinex | MBLLEN | KinD | Zero-DCE | Ours     |
|---------|--------|--------|---------|--------|------|----------|----------|
| LOL     | 13.20/0.48 | 20.18/0.77 | 17.59/0.54 | 21.21/0.84 | 19.29/0.76 | 20.38/0.78 | 20.60/0.79 |
| DCS     | 16.22/0.77 | 17.49/0.83 | 10.54/0.65 | 22.52/0.88 | 12.28/0.73 | 22.59/0.94 | 25.97/0.97 |

Table 3: PSNR ↑ / SSIM ↑ Comparison on Synthesized Low-Light Images

| Method   | NPE    | LIME   | MEF    | DICM   | VV     | DarkBDD | Average |
|----------|--------|--------|--------|--------|--------|---------|---------|
| Dark     | 0.793  / 19.81 | 0.826  / 21.81 | 0.738  / 23.56 | 0.795  / 21.57 | 0.826  / 23.62 | 0.799  / 61.62 | 0.796 / 28.67 |
| PIE      | 0.801  / 21.72 | 0.791  / 22.72 | 0.752  / 11.02 | 0.791  / 21.72 | 0.832  / 26.54 | 0.796  / 53.22 | 0.794 / 26.16 |
| LIME     | 0.786  / 18.24 | 0.774  / 20.44 | 0.722  / 15.25 | 0.758  / 23.48 | 0.820  / 27.14 | OME     / OME  | OME     / OME  |
| Retinex  | 0.828  / 16.04 | 0.794  / 31.47 | 0.755  / 20.08 | 0.770  / 29.53 | 0.824  / 29.58 | 0.792  / 50.77 | 0.794 / 29.57 |
| MBLLEN   | 0.793  / 34.46 | 0.768  / 30.26 | 0.717  / 37.44 | 0.787  / 32.44 | 0.719  / 26.13 | 0.772  / 51.40 | 0.759 / 35.35 |
| KinD     | 0.792  / 19.65 | 0.766  / 39.29 | 0.747  / 31.36 | 0.776  / 32.71 | 0.814  / 29.34 | 0.778  / 49.38 | 0.779 / 33.62 |
| Zero-DCE | 0.814  / 17.06 | 0.811  / 21.40 | 0.762  / 16.84 | 0.777  / 27.35 | 0.835  / 24.26 | 0.800  / 59.37 | 0.800 / 27.71 |
| Ours     | 0.786  / 13.25 | 0.807  / 19.99 | 0.785  / 13.92 | 0.801  / 26.12 | 0.836  / 31.72 | 0.815  / 57.06 | 0.805 / 27.01 |

Table 4: UNIQUE ↑ / BRISQUE ↓ Comparison on Real-World Low-Light Images.
Qualitative Comparison on VV Dataset

(a) Dark  (b) PIE  (c) LIME  (d) Retinex
(e) MBLLEN  (f) KinD  (g) Zero-DCE  (h) Ours
Low-Light Detection

Figure 6: Object Detection Results on DarkBDD
Low-Light Segmentation

Figure 7: Semantic Segmentation Results on DarkCityScape
Conclusion and Future Works

• Semantic-Guided, Zero-Shot LLIE Network
• EFE, RIE, USS with five non-reference loss functions
• No Paired Images, Unpaired Datasets, or Segmentation Labels
• Low-Level Enhancement and High-Level Semantics
• Efficient and Effective
• Future: Motion blur, Mirror Reflection
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