# Semantic-Guided Zero-Shot Learning for Low-Light Image/Video Enhancement
## *Supplementary Material*

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## 1. Introduction

In this supplementary material, we first show the specific model architecture for our proposed model. Next, we display more images from our proposed dataset. After that, we conduct more visual comparisons on low-light images and low-light video frames. Competing models are previous state-of-the-arts including PIE [8], LIME [13], RetinexNet [48], MBLLEN [34], KinD [52], ZeroDCE [11] and EnlightenGAN [20]. For pure perceptual comparison, we select images from NPE [47], LIME [13], MEF [35], DICM [25], VV [1] and LOL [2]. For task-driven visual comparison we choose images from our proposed DarkBDD, which is selected from BDD10k [49], and DarkCityScape, which is synthesized from CityScape [4].

## 2. Specific model architecture

We present the specific model architecture of our enhancement factor extraction network (EFE) in Table 1 and the depthwise separable convolution layer in Table 2.

| **Require**: Input Image $x$ | |
|---|---|
| **Name** | **Details** |
| Conv1 | Input; DS(3,32); ReLU; |
| Conv2 | DS(32,32); ReLU; |
| Conv3 | DS(32,32);ReLU; |
| Conv4 | DS(32,32);ReLU; |
| Concat1 | Concat(Conv3, Conv4); |
| Conv5 | DS(64,32);ReLU; |
| Concat2 | Concat(Conv2, Conv5); |
| Conv6 | DS(64,32);ReLU; |
| Concat3 | Concat(Conv1, Conv6); |
| Conv7 | DS(64,3);Tanh; Output; |

Table 1. The architecture of EFE. Where "DS" is depthwise separable convolution layer with (input channel, output channel). "Concat" represents tensor concatenation. "ReLU" and "Tanh" are activation functions.

## 3. Samples images from proposed dataset

### 3.1. DarkBDD samples

Following are sample photos from our proposed DarkBDD dataset.

[1] https://sites.google.com/site/vonikakis/datasets

| **Require**: Input Channel $in$, Output Channel $out$ | |
|---|---|
| **Name** | **Details** |
| DConv | Conv($in$, $in$, 3, 1, 1, $in$) |
| PConv | Conv($in$, $out$, 1, 1, 0, 1) |

Table 2. The architecture of depthwise separable convolution layers. Where “Conv” stands for convolution operation with (input channel, output channel, kernel size, stride, padding, groups)

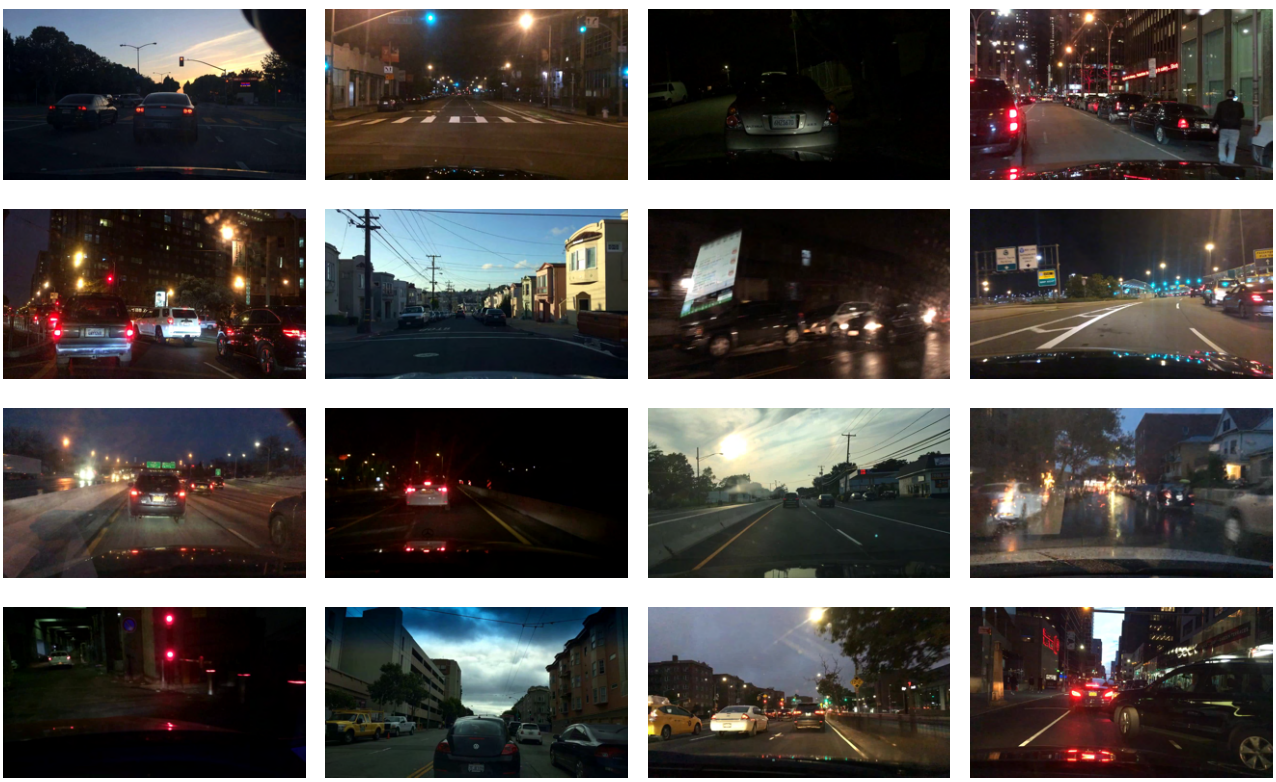


Figure 1. Example images from our DarkBDD dataset. Our selected low-light images have diverse brightness, contrast, and exposure. Due to its challenging nature, it is suitable as a low-light image enhancement benchmark.

### 3.2. DarkCityScape samples

Following are sample photos from our proposed DarkCityScape dataset.

Figure 2. Example images from our DarkCityScape dataset. Upper two rows: groundtruth normal-light images. Lower two rows: our synthesis low-light images. The low-light photos are synthesized using gamma correction. The synthesized dataset is challenging because it hides most image details from human perceptions.

## 4. More Visual Comparison on Low-Light Images

Fig. 3 shows that our model effectively enhances the low-light regions and makes superior edge preservation. In contrast, other models either fail to improve the image contrast or generate unpleasant artifacts.

(a) Dark

(b) MBLLEN [34]

(c) PIE [8]

(d) Retinex [48]

(e) ZeroDCE [11]

(f) Ours

Figure 3. Visual Comparison on DICM [25]

Fig. 4 shows that our model generates the most natural and balanced enhancement result. In comparison, other models either fail to enhance the dark regions or produce significant color deviation.

(a) Dark

(b) MBLLEN [34]

(c) PIE [8]

(d) Retinex [48]

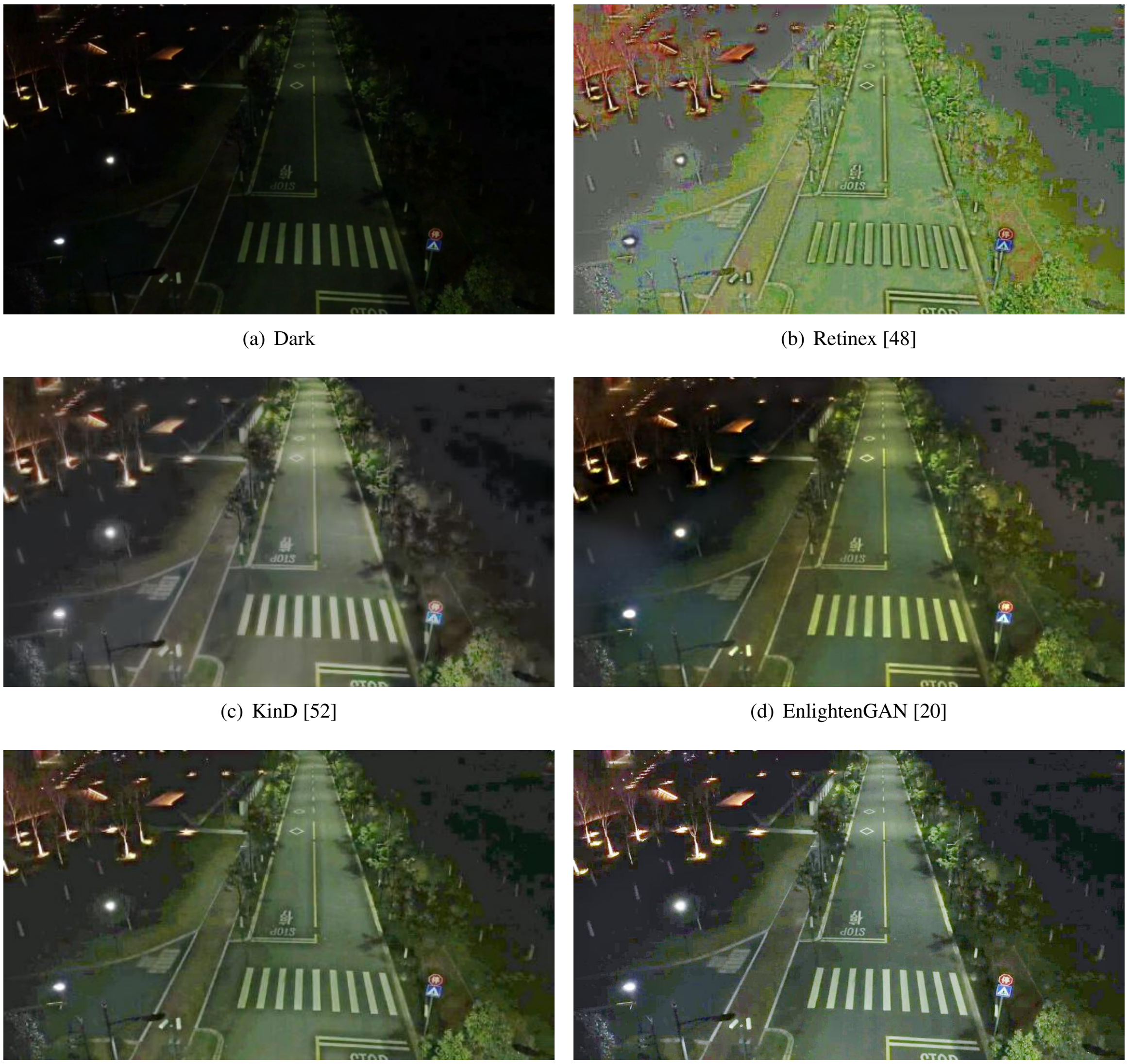
(e) ZeroDCE [11]

(f) Ours

Figure 4. Visual Comparison on VV

## 5. More Visual Comparison on Low-Light Video Frames

Fig. 5 shows that our model generates a natural appearance for the low-light video frame. As opposed to our result, other models either have severe color distortion or generate sub-optimal regional contrast.



(a) Dark
(b) Retinex [48]
(c) KinD [52]
(d) EnlightenGAN [20]
(e) ZeroDCE [11]
(f) Ours

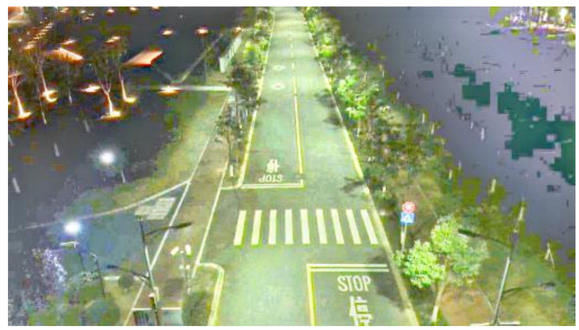
Figure 5. Visual Comparison on Low-Light Video Frames (1)

Fig. 6 shows that our model produces pleasing texture for the low-light video frame. Compared with our result, other models have significant over/under exposure with large background artifacts.


(a) Dark


(b) Retinex [48]


(c) KinD [52]




(d) EnlightenGAN [20]

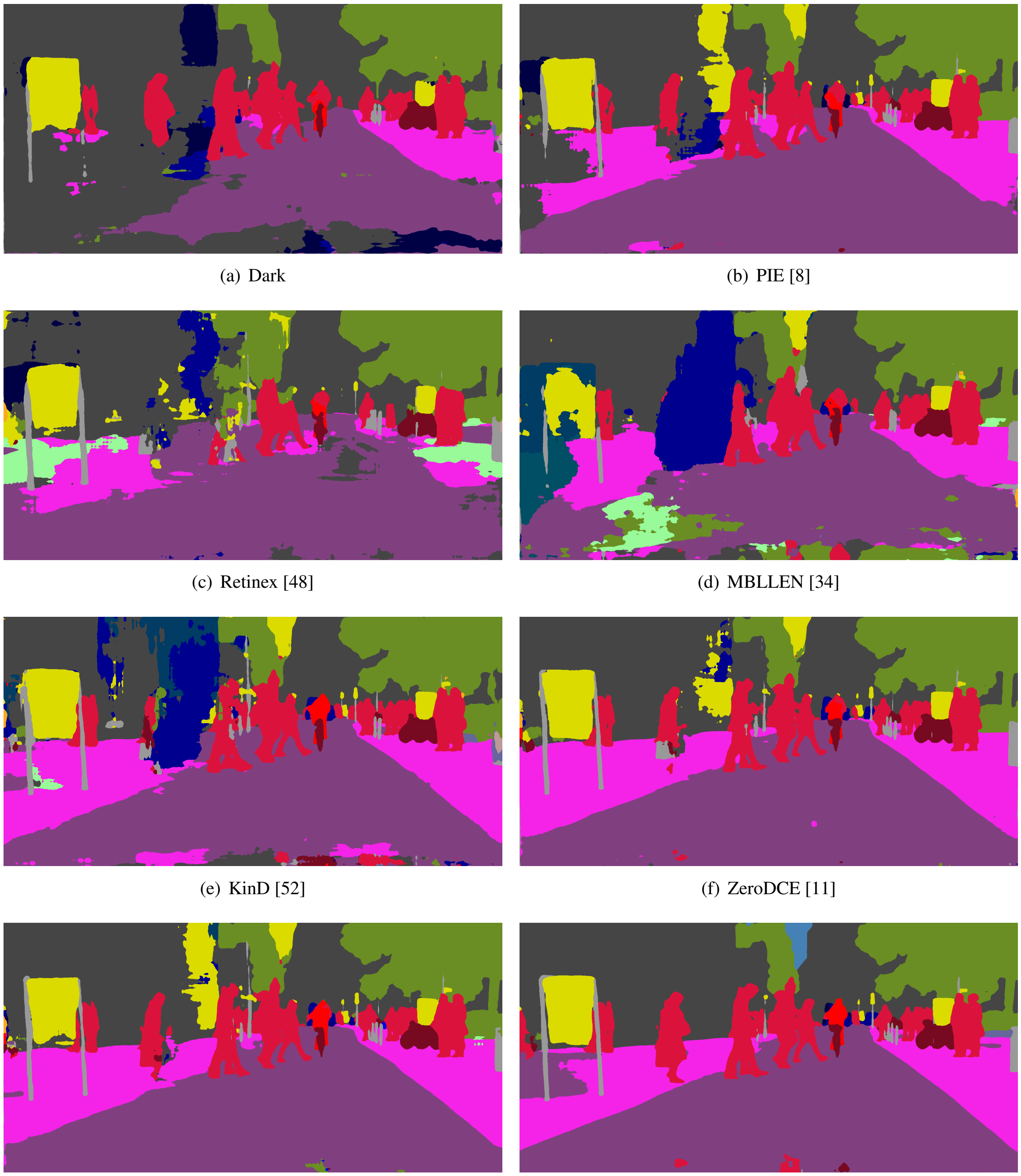

(e) ZeroDCE [11]


(f) Ours

Figure 6. Visual Comparison on Low-Light Video Frames (2)

## 6. More on Semantic Segmentation

Fig. 7 shows our model helps accurate semantic segmentation of most objects and is closest to the groundtruth. In comparison, other models result in large areas of incorrect segmentation.



(a) Dark (b) PIE [8]

(c) Retinex [48] (d) MBLLEN [34]

(e) KinD [52] (f) ZeroDCE [11]

(g) Ours (h) GT

Figure 7. Visual Comparison on Semantic Segmentation

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