Raw Image Based Over-Exposure Correction Challenge

Guoxin Li, Qiong Gao, Chenyue Che, Long Sun, Xu Liu, Shuyuan Yang
Intelligent Perception and Image Understanding Lab, Xidian University
Xi'an, Shanxi Province, 710071, China
lguoxin49@gmail.com

Abstract

In this technical report, we briefly introduce the solution of the "LiGoxin" team in the Raw Image Based Over-Exposure Correction Challenge. In this task, in order not to reduce the performance of the model, we first preprocessed the image data and modified the image saving format and channel order. Then, we used the pre-trained model pre-trained on the SOF dataset and fine-tuned on the RPO dataset to process the exposed images. After processing, we adjusted the images of different ratios and enlarged the size of the corrected images. It ranked third in the final leaderboard.

1 Introduction

This report documents our participation in the Raw Image Based Over-Exposure Correction competition.Overexposed images present a unique set of challenges that can severely undermine image integrity. Overexposure can lead to washed-out regions, where important details are lost, colors appear faded or completely bleached, and the overall contrast of the image is compromised. This degradation can be particularly detrimental for applications relying on fine-grained visual cues, such as pattern recognition and texture analysis. In light of these issues, the advancement of overexposure correction techniques has become a crucial endeavor in the field of image processing, aiming to retrieve lost information in overexposed areas, rebalance color distributions, and reinstate the dynamic range that is crucial for maintaining visual fidelity. This work is integral to improving the robustness of computer vision systems when faced with images that have been excessively exposed to light.

The dataset provided by the competition consists of two parts: short exposure images and long exposure images. Short exposure images (normal, GT) were taken in each scene using a camera mounted on a tripod. The camera was set to automatic mode to find the best aperture and exposure time settings, and then switched to manual mode to lock these settings. Images were taken using a remote mobile application to control the shutter, thereby minimizing lens vibration. Long exposure images (overexposure, OE) were taken after the short exposure GT images were taken, using a mobile application to adjust only the "exposure time" setting to simulate real overexposure caused by incorrect settings. Four predetermined overexposure ratios ($\times 3$, $\times 5$, $\times 8$, $\times 10$) were used. Make sure that the camera is not touched during long and short exposure capture to prevent any misalignment due to lens vibration.

The technical report is organized as follows: Section 2 briefly describes our method. Section 3 presents the experimental results, showing the performance of our framework on this task. Section 4 is the conclusion.

2 Methods

We use CGNet[1] as a solution to the problem.CGNet contains two branches, namely a main branch based on U-net and a non-green channel guided (NGCG) branch, as shown in Figure 1.

The main branch is based on a basic U-net with four encoder (downsampling) and decoder (upsampling) stages. Specifically, the model first extracts initial features from a four-channel RAW image through a standard 3×3 convolution. In the encoder part, the model uses a HIN block to expand the receptive field and improve the robustness of the features at each scale. During the downsampling

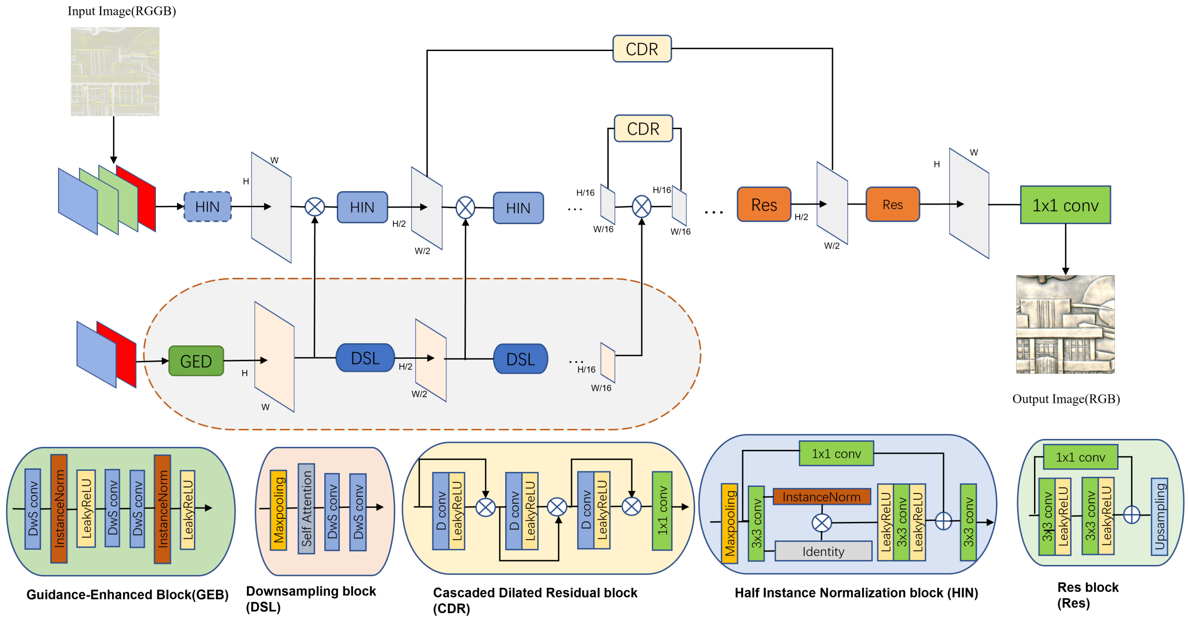

Figure 1: Architecture of CGNet for image over-exposure correction

operation, the number of channels in the feature map is doubled. In the decoder part, the model uses a residual block to better extract high-level features. For skip connections, the model uses a novel cascaded dilated residual (CDR) block to extract multi-scale features and fuse them with features from the encoder part to compensate for the loss of detail information caused by downsampling. Specifically, each CDR block contains three residual connections with dilated convolutions and LeakyReLU activation functions, followed by a 1×1 convolution layer. This allows the CDR block to make good use of features from each stage of the encoder and fully explore local texture information. In addition, the dilated convolution used here can effectively expand the receptive field of the CDR block for multi-scale context feature extraction.

For the NGCG branch, the pixels belonging to the corresponding position of the red (or blue) channel are first extracted in each 2×2 block of the Bayer image. Then, the red and blue channels are input into the NGCG branch to produce an initial estimate of the corresponding elements in the output sRGB image. The NGCG branch consists of a Guidance-Enhanced Block (GEB) and four downsampling blocks, guiding 5 corresponding encoder blocks. GEB contains 2 3×3 convolutional layers (followed by instance normalization and LeakyReLU) and 3×3 convolution operations between them. It is worth noting that the model uses depthwise separable convolution instead of standard 3×3 convolution to fully extract local information. The downsampling block consists of a maximum pooling layer, an improved self-attention structure, and two depthwise separable convolutional layers.

3 Experiments

3.1 DataSet

The training data set consists of 300 gt and corresponding overexposed images (ratio=3,5,8,10). The resolutions of RAW images and corresponding sRGB images are both 6744 x 4502.

The validation set processes RAW images into four-channel (RGGB) images, crops them and saves them as .mat files. Unlike the training set, the validation set only includes input files and does not have ground truth.

3.2 Implement Detail

For the test data, we converted the .mat file into a .png file and adjusted the channel order of the image.

We process the exposure images using a pre-trained model that is pre-trained on the SOF dataset and fine-tuned on the RPO dataset. After processing, we adjust the images at different ratios and upscale the corrected images.

3.3 Results

The experimental results are shown in **Figure 2**.

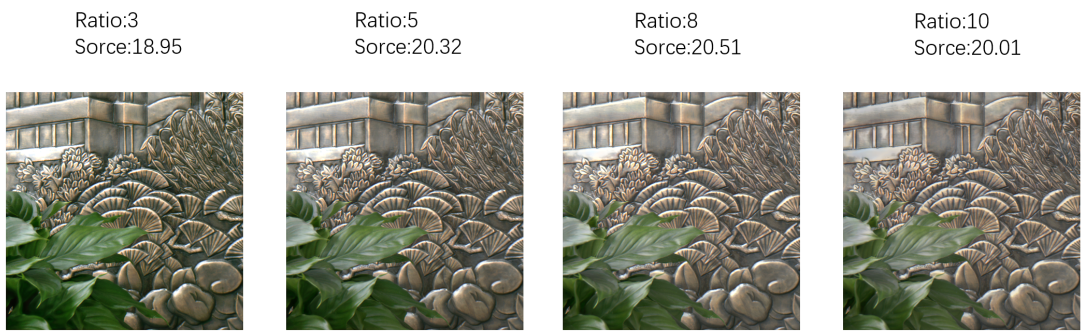

Figure 2: Different ratio examples and scores.

4 Conclusion

This report details our data processing methods and model usage in this task. Experiments have proven that our strategy for solving this task is reasonable and effective, and we ultimately achieved a score of 18.95 on the Ratio = 3 track of this task dataset, ranking third.

5 Reference

References

[1] Fu Y, Hong Y, Zou Y, et al. Raw Image Based Over-Exposure Correction Using Channel-Guidance Strategy[J]. IEEE Transactions on Circuits and Systems for Video Technology, 2023.