1st Solution Places for PBDL2024 Raw Image Based Over-Exposure Correction Challenge

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Abstract

In this technical report, we briefly describe the solutions of our "gxj" team in CVPR 2024 PBDL: Raw Image Based Over-Exposure Correction Challenge. In this task, we propose an efficient framework for correction of overexposure based on original images. Specifically, first to Raw image data preprocessing, in order not to reduce the performance of the model itself, the image of different exposure ratio conversion into RGB format for training, and then based on the effective area perception exposure correction network, through adaptive learning and bridging different area exposure representation to process mixed exposure. Subsequently, we employed an effective image super-resolution model on the corrected resulting maps at 2x super-resolution. Our framework is able to handle different types of overexposed dataset provided during the final testing phase and rank first on the final leaderboard.

1 Introduction

This technical report describes the Physics Based Vision meets Deep Learning (PBDL2024): Raw Image Based Over-Exposure Correction Challenge Solution. Because overexposed images pose a unique set of unique challenges that can severely compromise image integrity.overexposure can cause faded areas, missing important details, color fading or complete bleaching, and the overall contrast of the image is affected. This performance decline is particularly detrimental for applications that rely on fine-grained visual cues (such as pattern recognition and texture analysis). Given these problems, advances in overexposed correction techniques have become an important task in the field of image processing, with participants' tasks designed to retrieve lost information in the overexposed region, rebalancing the color distribution, and restoring the dynamic range.

As shown in **Figure 1**, to drive research forward in this field, the competition used a real-world paired overexposed (RPO) dataset based on RAW images introduced by Professor Fu's team in [1], which was shot using a Canon EOS 5D Mark IV camera. The RPO dataset includes paired images collected from various scenarios. Each short exposure (normal exposure) image is paired with a long exposure (overexposure) image with four ratios (x3, x5, x8, x10). Also, long exposure (overexposure) images of four proportions (x3, x5, x8, x10) were provided in the final test phase. The overexposed images of each ratio included 88 images. The evaluation index for this stage is the average score calculated in combination with the standard peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM) gray scale commonly used in the literature.

We propose a multistage framework to mitigate the effects caused by overexposure. Firstly, according to the format conversion process of the test data set, the training data set is uniformly converted to a similar RGB format, based on the effective area perception exposure correction network, adaptive learning in the preprocessed training data set, bridging the area exposure representation to process the mixed exposure, and then using the image super resolution model to unify the format and complete the results to further improve the quality of the output image. Our framework can handle different types of overexposure datasets and rank first on the final leaderboard.

The technical report is organized as follows: In Section 2, we briefly describe our recovery framework. Section 3 presents the experimental details and the experimental results, demonstrating the performance of our framework relative to this task. Section 4 is summarized.

Figure 1: Visual examples of images with different levels of exposure.

2 Methods

Our solution of the whole task as shown in **Figure 2**, for the original excessive exposure image, first data pretreatment to RGB format, and then after area perception exposure correction network RECNet back to normal light state, the image light level is normal, but there are differences in resolution, after super resolution model OmniSR will double the resolution to get the final result.

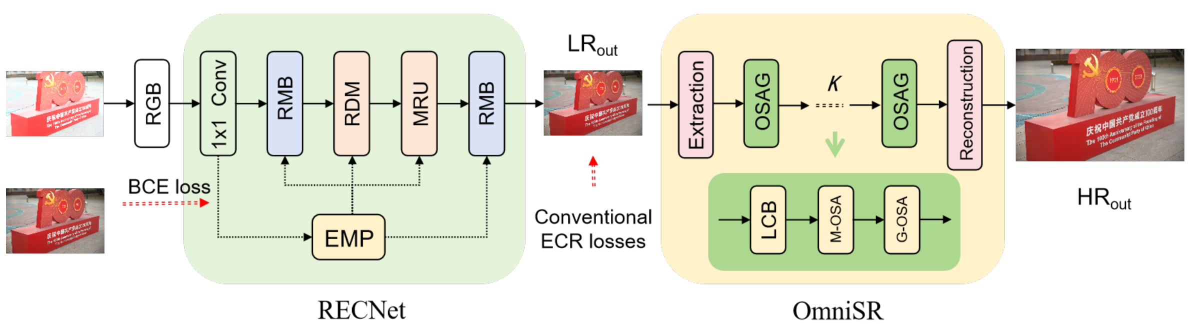

Figure 2: Framework diagram of the model.

The key of the task is for the color correction of exposure area, but because the test file format directly with existing models, so we first convert the existing data set format, then choose compatible with low exposure and excessive exposure area perception exposure correction network (RECNet), through adaptive learning and bridging different area exposure representation to handle the mixed exposure, then the super resolution model (OmniSR) for the final result, finally achieve high excessive exposure image quality recovery.

2.1 Data preprocessing

Since the final test stage of this task provides the processed mat format files, in order to make the model better correct the test image, we further converted the image in mat format based on the existing RAW format data set and then converted the JPG format file which is more acceptable to the model. In general, the data set used for training is transformed into an image distribution file similar to the input of the test image. In this process, because the original image size is too large, we modified all the images to unify the size of the test set as the data for the training model.

2.2 Exposure correction

Correction for image exposure has been studied for a long time. Traditional methods will rely mainly on manual adjustment of models, such as histogram equilibria and gamma correction. Although existing methods achieve commendable results in exposure correction, many of them rely on complex manual designs or struggle with excessive limitations that ultimately lead to suboptimal results.

After investigating the existing model and analyzing the data set, and also being inspired by the RECNet model, the exposure correction model used in this task was finally selected. When processing single images with mixed exposures, the network is difficult to stably converge, due to the large difference in over-and under-exposed regions, resulting in unbalanced performance for different exposures. To this end, the model takes into account the locality of different exposures to reduce the adverse effects of inconsistent optimization.To achieve this, the model adopt the idea of the divide and conquer strategy, and design aregion-aware exposure correction framework consisting of two well-designed modules concatenated in a chain of consecutive RMBs.

The model mainly contains a series of Blocks (RMB) with Region-aware De-exposure Module (RDM) and Mixed-scale Restoration Unit (MRU). The RDM maps exposure features Fin to a three-branched exposure-invariant feature Fn, while the MRU integrates the features Fs and Fc by the spatial-wise and channel-wise restoration, respectively. The exposure mask predictor (EMP) assists in generating the underexposure feature Fu and overexposure feature.It optimize the model with Exposure Contrastive Regularization (ECR).

2.3 Image super resolution

To match the results after exposure correction with the size of the resulting images required for the task, we used the Omni-SR model to achieve a 2x super-resolution of the resulting images. Specifically, the model proposes a Omni Self-Attention (OSA) block based on the principle of dense interaction, which can model the pixel interaction from both the dimensions of space and channel, and mine the potential correlation between the global axis (i. e., space and channel). Combined with mainstream window partition strategies, OSA can achieve superior performance with a compelling computational budget. Second, a multi-scale interaction scheme is proposed to alleviate suboptimal ERFs in the shallow model, promoting local propagation and meso global scale interactions to form full-scale aggregate blocks.

3 Experiments

3.1 Implement Detail

3.1.1 RECNet[2]

We processed and merged the existing datasets, yielding a total of 1200 images, including 1120 images as the training set and 80 images as the validation set. No pre-training model was loaded, with training from scratch, where the training parameter batch size is 8, lr is 1e-4, and iter is 300000, using a single NVIDIA RTX 4090 GPU.

3.1.2 Omni-SR[3]

The pre-trained model of epoch885 with OmniSR on the DF2K dataset was used to treat the exposure-corrected images for 2x super-resolution.

3.2 Results

The experimental results are shown in **Figure 3**, including the results and scores obtained by the original data after the recovery of the process structure.

Figure 3: Different ratio result image examples and scores.

4 Conclusion

The title is dedicated to the correction task of overexposed images. In this report, it details our team's data processing methods and the use of models in this task. For the recovered images, the image quality is improved again through the super-resolution model, and better results are obtained. The experiments proved that our strategy to solve this task is reasonable and effective, and we finally achieved a score of 21.58 in the Ratio = 3 track of this task data set.

5 Reference

References

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