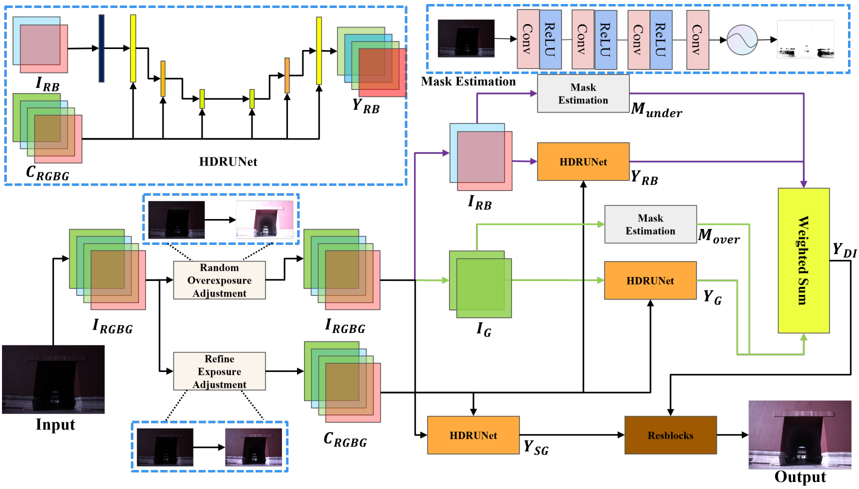

Fig. 1: The Network Architecture of our proposed MHDRUNet.

1 Network Architecture

We introduce MHDRUNet, a model that utilizes the emphasis on different channel information in raw images for exposure guidance, subsequently used for HDR reconstruction of single-frame RAW images. The model framework is shown in Fig. 1. Inspired by RAWHDR [4], raw images have higher intensity values in green channels compared to red and blue. Therefore, we We split I_{RGBG} into I_{RB} and I_G, using the RB channels for exposure estimation to derive an underexposure mask M_{under}, and then reconstruct the underexposed areas based on the G channel to get Y_G. Similarly, we use the G channel for exposure estimation to obtain an overexposure mask M_{over}, and then reconstruct the overexposed regions using the RB channels to get Y_{RB}. We combine Y_G and Y_{RB} through a weighted sum. To ensure smoothness in HDR reconstruction across the global range, we utilize the original RAW data for global exposure-guided reconstruction. The exposure reconstruction network is comprised of the complete HDRUNet [1], with inputs including the raw image and a condition image, which by default matches the raw image. The exposure estimation mask module consists of a CNN with residual connections, and the exposure reconstruction is carried out by the complete HDRUNet network. Secondly, we propose the method of Refine Exposure Adjustment. By analyzing the distribution of values in the input raw image, we can estimate the areas of exposure and underexposure. For images where the area of the underexposure mask is greater than that of the overexposure mask, we consider it to be underexposed; conversely, if larger for the overexposure mask, it is considered overexposed. Based on this, we make appropriate exposure adjustments on the original RAW data, bringing underexposed images to a slightly underexposed state and overexposed images to a slightly overexposed state. These are then used as the condition images inputted into the HDRUNet network, thereby achieving better reconstruction results.

2 Training strategy

We use the dataset proposed by HDR Reconstruction from a Single Raw Image challenge. Before training, we pre-process the data by cropping images into 768×768. During training, the mini-batch size is set to 1 and Adam [3] optimizer and Kaiming-initialization [2] are adopted for training. The initial learning rate is set to $1e-4$ and all models are built on the PyTorch framework and trained with NVIDIA 3090 GPU. It's noteworthy that we find the HDR reconstruction task for overexposed images to be more challenging compared to that for underexposed images. Therefore, we propose the training strategy of Random Overexposure Adjustment. Specifically, during training, we randomly apply varying degrees of overexposure adjustments to the input underexposed images to generate pseudo-overexposed images for data augmentation, thereby enhancing the model's robustness. During training, we use tanh L2 loss [1] and SSIM loss to achieve better training effects. Additionally, we employ a constraint loss L_{mask} [4], which guides the learning of the mask.

References

1. Chen, X., Liu, Y., Zhang, Z., Qiao, Y., Dong, C.: Hdrunet: Single image hdr reconstruction with denoising and dequantization. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 354–363 (2021) 1, 2
2. He, K., Zhang, X., Ren, S., Sun, J.: Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In: Proceedings of the IEEE international conference on computer vision. pp. 1026–1034 (2015) 2
3. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980 (2014) 2
4. Zou, Y., Yan, C., Fu, Y.: Rawhdr: High dynamic range image reconstruction from a single raw image. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 12334–12344 (2023) 1, 2