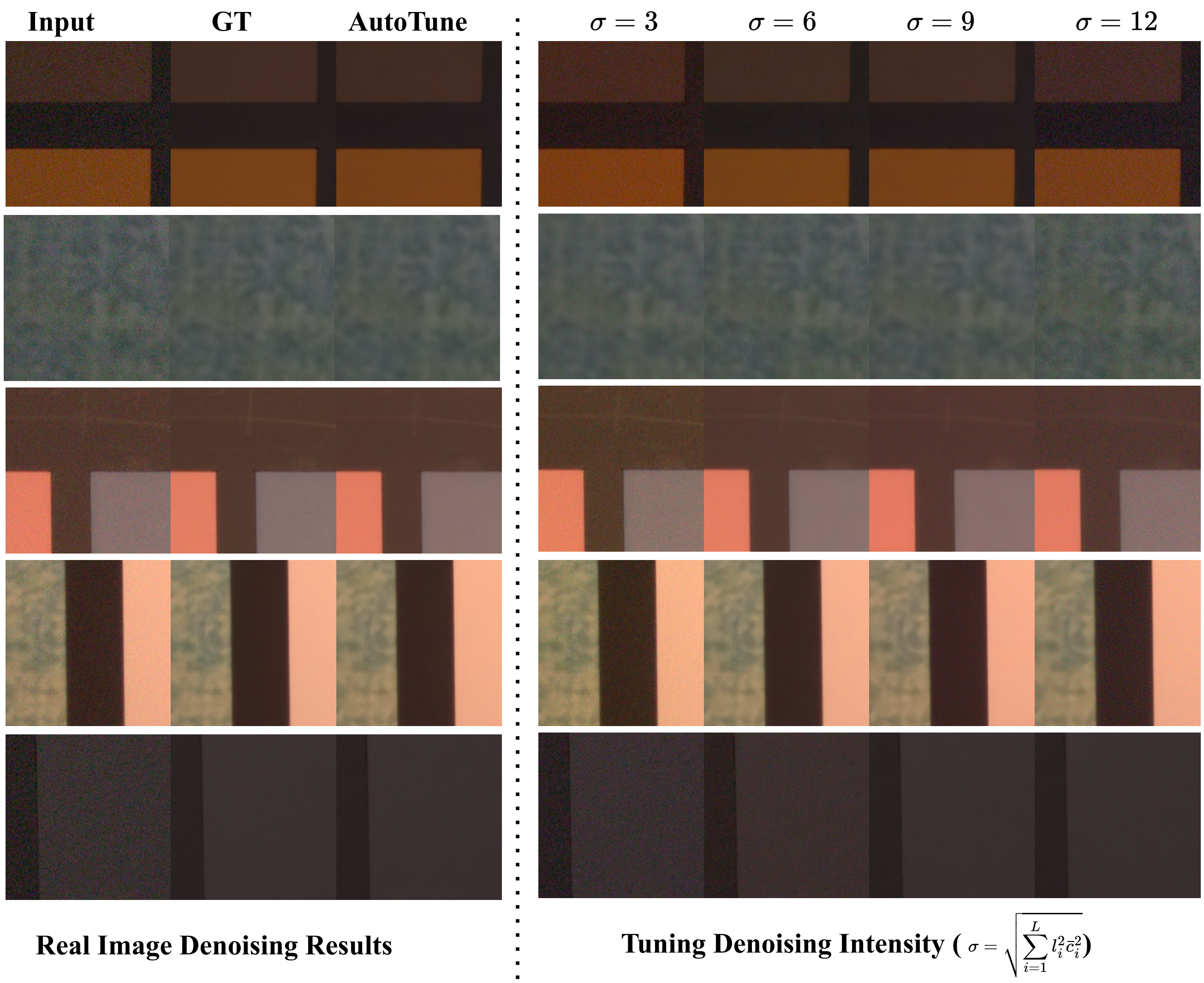


Figure 1. RCD real image denoising results on SIDD. GT: ground truth. AutoTune: AutoTune results of RCD.

## A. More Visualization Results

This section shows more visual results to demonstrate the effectiveness of our proposed RCD. Besides, we also provide **demo video** for showing features of RCD (Please see in attached files of supplementary material).

**Real Image Denoising.** We visualize RCD denoising results on SIDD test set in Fig.1. The left part shows the comparison of RCD (AutoTune) and real image ground truth, and the right part gives RCD results by tuning the noise level. As demonstrated, RCD can support controllable real image denoising and yield high visual quality results.

**Video denoising results.** We further show the qualitative performance of FastDVD-RCD in Fig.2, with comparison to baseline uncontrollable FastDVDnet. Consistent with image denoising, FastDVD-RCD can recover more details of some degraded images, which may be benefited from RCD's richer representation capacity by integrating multiple noise maps

**Comparison of RCD and AdaFM on SIDD.** In Fig.3 we show the comparison of RCD and representative conventional controllable denoising method AdaFM. Compared to RCD and GT, AdaFM results have more artifacts and remained noises.

## B. Implementation Details

**Choice of Basic Image Model**. Considering the application of real-time image controllable denoising, we need to select the base models with acceptable running time and parameters. Besides, the base model is required to support prior-free blind denoising to be applied on real-world data and should be able to be trained in an end-to-end manner for level loss to be pluged-in readily. Our models on single

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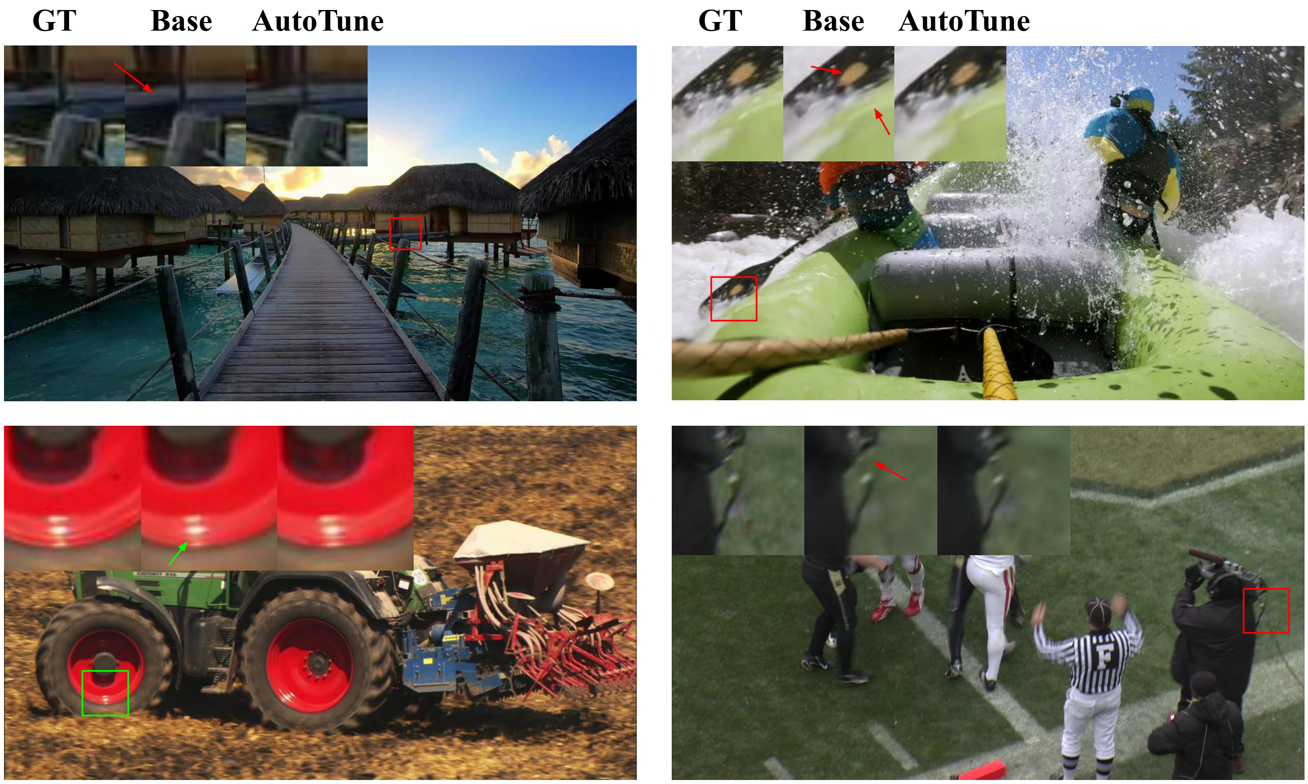


Figure 2. Video denoising results. Base: uncontrollable baseline.

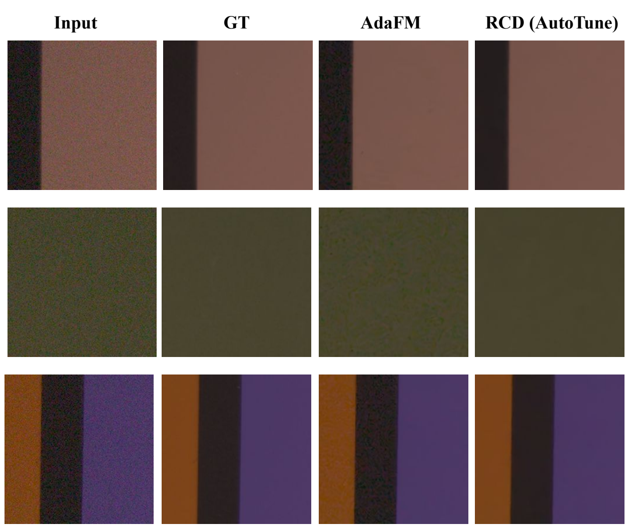


Figure 3. Comparison of RCD and AdaFM on SIDD real image denoising.

image denoising are based on the SOTA restoration model NAFNet [1], which can be scaled flexibly from 1.1 GMACs to 65 GMACs. To balance the running time and the performance, we adopt NAFNet with width 16/32 and number of blocks 8. We also conduct experiments on NAFNet base model with width 32 and number of blocks 36 to verify the effectiveness of RCD on relatively larger model.

**Alteration of Basic Model** Only two adjustments of the base model are required to support our proposed editable denoising. First, we alter the output channel number of the base model ending layer from output image channel number to $L\times$ output image channel number, $L$ is the number of the predefined noise level. For example, when training noise level from 0 to 60, the uniform noise level gap between each noise map is 5 and there are 13 of them in total ([0,5,10,...55,60]). Then we apply noise decorrelation on the those fixed-level noise maps generated by our model and also feed them to the AutoTune module. Second, for your AutoTune module, we add an additional CNN layer to predict a feature-map. After the adaptive average pooling layer and temperatured softmax activation, we attain a series of weights to fuse the 13 noise maps as model-suggested guidance to the user.

**Model Variants Details.** We calculate the parameters of NAFNet base model and our NAFNet-RCD model. Compared with NAFNet, NAFNet-RCD only has alterations on two CNN layers, which is negligible for normal-size networks. Specifically, these additional parameters account for 0.03%, 3.60%, and 9.17% of total parameters for model size 1) NAFNet-RCD: width 32, number of blocks 36, 2)

NAFNet-RCD-small: width 16, number of blocks 8, 3) NAFNet-RCD-tiny: width 16, number of blocks 8. Please be noted that the number of additional parameters is only 7.7K even though it accounts for 9.17% of light model NAFNet-RCD-tiny.

## C. Additional Experiments

**Results on other real-world datasets.** We further evaluate our RCD models on the PolyU [3] and Nam [2] benchmarks. Both the RCD and baseline models are trained on SIDD real-world data. Table 1 shows that on both benchmarks, the RCD models can still perform controllable denoising without sacrificing much performance, and on Nam, the RCD models even slightly outperform their uncontrollable baselines.

Table 1. Image denoising results on PolyU and Nam. **PolyU**: results on real-world PolyU test sets. **Nam**: results on real-world Nam test set.

| Method | PolyU | | Nam | |
|---|---|---|---|---|
| | PSNR | SSIM | PSNR | SSIM |
| NAFNet-tiny | 38.52 | **0.9827** | 38.93 | 0.9881 |
| **NAFNet-RCD-tiny** | 38.36 | 0.9826 | **39.03** | 0.9881 |
| NAFNet | 39.11 | 0.9837 | 39.54 | 0.9894 |
| **NAFNet-RCD** | 39.07 | 0.9837 | **39.67** | **0.9896** |

**Q4. Results on more architectures.**

We also test our RCD using the Restormer [4] model. As shown in Table 2, Restormer-RCD slightly outperforms its baseline, consistent with NAFNet.

Table 2. Restormer results on SIDD test set with additive Gaussian noise ($\sigma$ from 0 to 50 ).

| Method | SIDD Synthetic noise | |
|---|---|---|
| | PSNR | SSIM |
| Restormer | 41.31 | 0.9763 |
| **Restormer-RCD** | **41.79** | **0.9781** |

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