

End-to-End Learning for Joint Image Demosaicing, Denoising and Super-Resolution

Wenzhu Xing and Karen Egiazarian

Computational Image Group, Tampere University, Finland

Fwenzhu.xi ng, karen. egiazari an@tuni . fi

Abstract

Image denoising, demosaicing and super-resolution are key problems of image restoration well studied in the recent decades. Often, in practice, one has to solve these problems simultaneously. A problem of finding a joint solution of the multiple image restoration tasks just begun to attract an increased attention of researchers. In this paper, we propose an end-to-end solution for the joint demosaicing, denoising and super-resolution based on a specially designed deep convolutional neural network (CNN). We systematically study different methods to solve this problem and compared them with the proposed method. Extensive experiments carried out on large image datasets demonstrate that our method outperforms the state-of-the-art both quantitatively and qualitatively. Finally, we have applied various loss functions in the proposed scheme and demonstrate that by using the mean absolute error as a loss function, we can obtain superior results in comparison to other cases.

1. Introduction

Image demosaicing, denoising, and super-resolution (SR) are classical image restoration problems. With the recent advancement of deep convolutional neural networks (CNNs) and their application in image restoration, several deep learning-based methods achieve the state-of-the-art (SOTA) performance [19, 42, 37, 47].

In many practical applications an acquired image is distorted by multiple degradations, thus the above mentioned individual image restoration problems have to be solved simultaneously. A most natural choice is to apply best methods of individual image restoration tasks in a sequence. However, the existing solutions are not ideal. Addressing a problem of image denoising, most of the algorithms smooth out high-frequency content, such as image details and texture, while eliminating noise in flat areas. Image demosaicing and super-resolution algorithms often introduce color artifacts especially in the texture regions and around image

edges. Thus, a sequential application of the individual image restoration methods will result in an accumulation of errors produced by the individual methods. Another drawback of the sequential methods is an increased complexity of a solution (considering both speed and memory).

As an alternative to this, joint solutions for the combined problems have been proposed in the literature [3, 6, 7, 8, 18, 21, 26, 36, 44, 49]. However, the problem of finding a joint solution for a triplet of problems of image demosaicing, denoising and SR has received much less attention [26, 29]. In 2019, Qian *et al.* [29] proposed a trinity network (TENet) to jointly solve this composite problem. Although the TENet is an end-to-end network, the execution order of different tasks is fixed. To this end, Qian *et al.* have divided the network into two modules and calculated the middle loss to supervise the functionality of the first module and optimize the network. Recently, Liu *et al.* proposed another solution to the joint problem, SGNet [26]. In order to improve the performance of demosaicing, SGNet introduces two self-guidance methods, the green channel guidance and the density map guidance.

In this paper, we comprehensively study various solutions of this combined problem. First, in subsection 3.1, we adjust the execution order, and investigate possible joint solutions under this execution order. Then, in subsection 3.2, we propose an end-to-end learning for the combined problem by designing a very deep convolutional neural network $JD_N D_M SR$. Differently from TENet and SGNet, our network uses the residual channel connection block (RCAB) [47] instead of residual-in-residual dense block (RRDB) [37] as the basic block (see subsection 6.1). We have carried out numerous experiments and demonstrate that the proposed method outperforms other joint solutions both quantitatively and qualitatively (Section 4). To further optimize the proposed network, different loss functions are utilized, and the comparative analysis of the resulting solutions is demonstrated in subsection 5.1. A comparison with the state-of-the-art method TENet [29] and the ablation study (see Fig. 1) are presented in subsection 5.2 and Section 6, respectively.

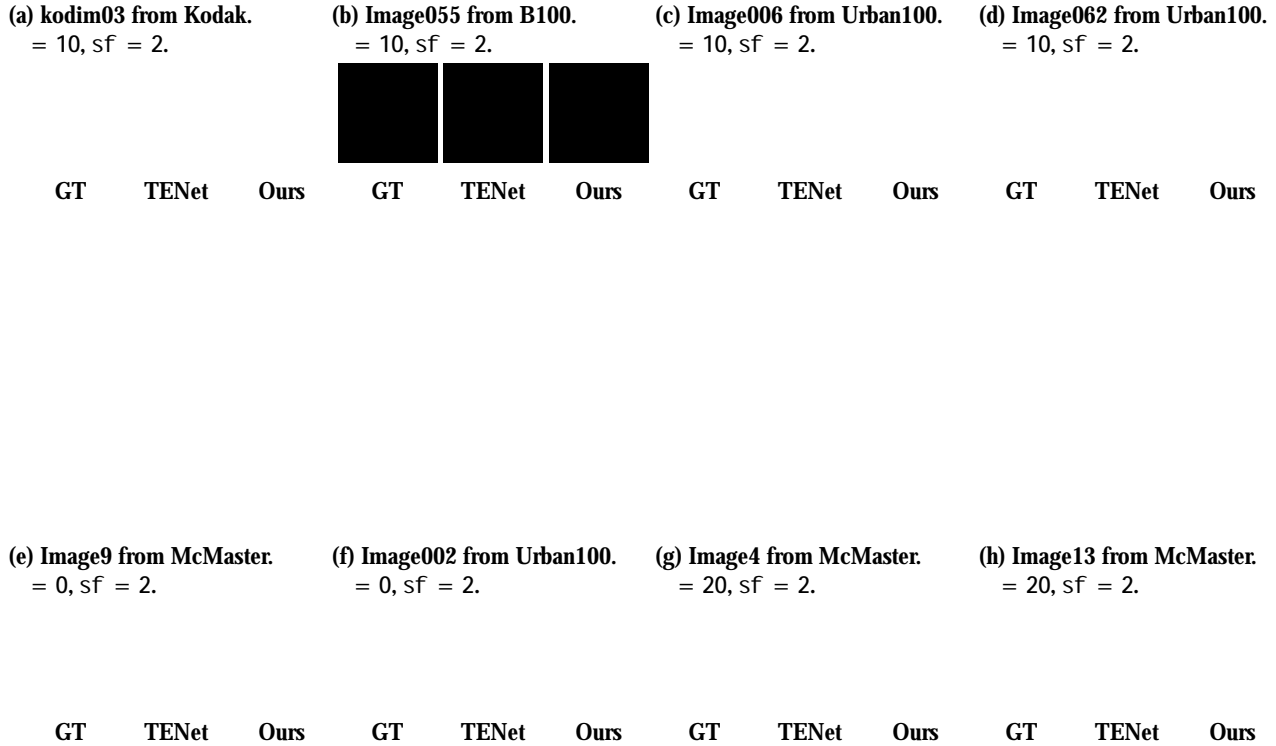


Figure 1: Qualitative comparison between the SOTA model TENet and the proposed $JD_N D_M SR^+$. sf means the scale factor. The noise levels () of (e-f), (a-d), (g-h) are 0, 10 and 20, respectively.

The main contributions of this paper are listed below.

1. We propose an end-to-end network ($JD_N D_M SR^+$) based on residual channel attention blocks for joint image demosaicing, denoising and super-resolution. This network is universal: one can turn off denoising and/or super-resolution operations of the network by setting the noise level parameter to 0 and the scale factor parameter to 1.
2. We systematically compare our $JD_N D_M SR^+$ with diverse solutions to the joint problem. The quantitative and qualitative experimental results on the benchmark datasets show that the proposed method not only surpasses other solutions, but also outperforms the state-of-the-art, including cases when denoising or super-

resolution operations are not performed.

2. Related work

Denoising The advanced image denoising methods can be classified into two main categories: model-based and deep learning-based methods. BM3D [4], often regarded as a denoising benchmark, belongs to the first category. In 2017, Zhang *et al.* applied a deep convolutional neural network (CNN), called DnCNN [42]. DnCNN adopts residual learning and batch normalization on CNN for blind Gaussian denoising and attains top performance. Later on, many other machine-learning based methods of image denoising have appeared [2, 15, 38, 42, 43].

Demosaicing To reduce manufacturing costs, most digital camera sensors capture only one color (red, green and

blue) at each pixel. The camera sensor is covered by the color filter arrays (CFAs). Image demosaicing is the process of interpolating full-resolution color image from incomplete color samples output by an image sensor. Most demosaicing methods have been specifically designed for the Bayer CFA which is the most popular CFA. Existing algorithms can be also classified into two categories: model-based methods [12, 27, 31, 45], which recover images based on mathematical models and image priors in the spatial-spectral domain; and learning-based methods [11, 32], based on process mapping learned from abundant training data. The deep learning methods [9, 17, 33] of image demosaicing also attain the state-of-the-art performance.

Single image super-resolution. Single image super-resolution aims at recovering a high-resolution (HR) image from its corresponding low-resolution (LR) image. The emergence of convolutional neural network has made the performance of super-resolution methods advance by leaps and bounds. In 2015, Dong *et al.* proposed SRCNN [5], which utilizes a three-layers CNN in a single image super-resolution task. Inspired by VGG-net, Kim *et al.* have presented a very deep residual learning super-resolution network, VDSR [19]. To reduce the occupation of memory and accelerate the speed of computation, Shi *et al.* have introduced a sub-pixel CNN ESPCN [30] to upscale feature maps to the desired solution. In 2017, Ledig *et al.* [23] have applied ResNet architecture in SR and proposed a SRResNet scheme. EDSR [24] further ameliorate the residual block and develop a very deep and wide CNN to enhance the performance of SR. In 2018, Zhang *et al.* have presented RDN, which is a residual dense network for SR. They have also proposed an attention-based network, RCAN [47], which introduces the channel attention into residual blocks (RCAB). Wang *et al.* [37] have proposed a perceptual-driven method ESRGAN based on the proposed Residual-in-Residual Dense Block (RRDB). In 2020, Liu *et al.* [25] proposed the RFANet by improving the chain of residual modules and adding an enhanced spatial attention (ESA) block at the end of each residual block.

Joint solutions. In practical applications, multiple image restoration problems appear simultaneously, resulting in the combined problems that one needs to solve. Recently, the combined solutions to the mixture problem of multiple image distortions replace traditional sequential solutions. Examples are joint denoising and demosaicing [3, 6, 8, 10, 16, 18, 21], joint demosaicing and SR [7, 36, 39, 49], and joint denoising and SR [44, 50]. However, a research on the triplet of denoising, demosaicing and SR is still lacking a special attention. In 2019, Qian *et al.* [29] proposed a trinity network to jointly solve this composite problem. In 2020, Liu *et al.* proposed the SGNet [26] for joint image demosaicing and super-resolution, which also can handle the mixture problem of denoising, demosaicing and SR.

In this paper, we propose the end-to-end solution of demosaicing, denoising and SR, $J D_N D_M SR$, and compared it with the sequential application of SOTA methods for each of these sub-problems, as well as with the state-of-the-art method to solve this mixture problem.

3. Proposed method

In what follows, we first study the execution order of image demosaicing, denoising and super-resolution. Then, solutions of this execution order are analysed. Later, we propose a deep CNN for the mixture problem. Note that we only consider the CNN-based methods in this paper.

3.1. Joint solutions

For the mixture problem of image demosaicing, denoising and super-resolution, a clean high-resolution color image I_{HR} should be estimated from its noisy low-resolution raw image $I_{LR_M^N}$. For the execution order, demosaicing should follow denoising, like in [29], to avoid complications in filtering correlated noise after demosaicing. In addition, the demosaicing should be performed before super-resolution because the correlation across color channels can be exploited when super-resolving color image. Besides this reason, performing super-resolution on raw image will destroy the original mosaic pattern, which increases the difficulty of demosaicing. Therefore, for the fixed execution order: $D_N D_M SR$, the first solution is to sequentially utilize three targeted methods to solve the corresponding image restoration problems one by one:

$$I_{HR} = M_{SR}(M_{D_M}(M_{D_N}(I_{LR_M^N}))). \quad (1)$$

where M denotes image restoration method, D_N , D_M , SR denote denoising, demosaicing and super-resolution, respectively, and I_{HR} is the estimation of high-resolution image I_{HR} .

Naturally, another approach is to combine two image restoration tasks and then execute the remaining one:

$$I_{HR} = M_{SR}(M_{J D_N D_M}(I_{LR_M^N})), \quad (2)$$

and

$$I_{HR} = M_{J D_M SR}(M_{D_N}(I_{LR_M^N})), \quad (3)$$

where J indicates joint processing. Similarly, the third solution is a fully combined end-to-end solution:

$$I_{HR} = M_{J D_N D_M SR}(I_{LR_M^N}). \quad (4)$$

A comparison of the solutions (Eqn. 1-4) is presented in Section 4.2.

Figure 2: The featured visualization of the proposed deep joint denoising, demosaicing and super-resolution network $JD_N D_M SR$.

3.2. Network architecture

The proposed end-to-end solution of the mixture problem is based on the deep CNN-based network, $JD_N D_M SR$ shown in Fig. 2, and consists of three parts: color extraction, feature extraction and reconstruction. Inspired by the method presented in [8], the Bayer input is first reshaped to a quarter-resolution multi-channel image, which is concatenated with the noise level estimation input. In this paper, we assume that a noise level is known in advance or is properly estimated, thus, one can parametrize a network with it. One way is to add a noise level input σ , and replicate it spatially, concatenating with the packed mosaic vector. Every layer downstream depends on it, which effectively parametrizes the learned filters. The color extraction step includes a convolutional layer with a large filter (256), and a transposed convolution layer to upscale the feature maps to the prime resolution. Upsampling the features before the next module improves the performance of the network (Section 6.2). The feature extraction module is composed of several basic blocks and a Long Skip Connection (LSC). The basic block can be any effective block applied in SOTA, such as the residual block (RB) [24], the residual-in-residual dense block (RRDB) [37], or the residual group (RG) with residual channel attention block (RCAB) [47]. Through the ablation study of the basic blocks (see Section 6.1), we have chosen the RCAB to be our basic block of feature extraction module. We utilize 4 residual groups in the $JD_N D_M SR$ network structure, each group including 20 RCABs. In the reconstruction part, the transposed convolution layer is used again to convert the extracted features into full resolution features. The following is the final convolutional layer to generate the desired resolution color image. The proposed $JD_N D_M SR$ can be changed to a noise-free version $JD_M SR$ by removing the noise level input ($\sigma = 0$). The experiments presented in Section 5 will demonstrate that the proposed $JD_N D_M SR$ and $JD_M SR$ achieve notable performance improvement in comparison with the other solutions including the state-of-the-art.

4. Experiments

4.1. Settings

For the training, we have applied Nvidia Tesla P100 GPU with 16 GB memory from the Tampere University TCSC Narvi computing cluster. All experiments run on a Linux computer with 3.4 GHz Intel i7-3770 CPU, 32 GB of RAM, and Nvidia GTX 1050Ti GPU with 4GB of memory.

Dataset. For network training and validation, we used publicly available dataset DIV2K [1] consisting of 900 2K resolution images (800 for training, 100 for validation). We compared different joint solutions on two public datasets, McMaster [46] and Kodak, widely used in the papers on image restoration [8, 19, 29, 35, 40, 42].

Data preprocessing. For data preprocessing of denoising, noisy input images are generated by adding Gaussian noise with the noise levels (σ) 10, 20 and 30. For data preprocessing of demosaicing, we mosaic the color image to a single-channel image in the Bayer CFA pattern. For data preprocessing of super-resolution, the HR image is BICUBIC down scaled with the scale factors (SF) 2.

Training details. Data augmentation is performed on images, which are randomly rotated by 90°, 180°, 270° and flipped horizontally. For each training epoch, the mini-batch size is 16, and the patch size is 64×64 . All models are implemented in Python with the platform Keras. For the optimization of network parameters, we use Adam [20] with $\alpha_1 = 0.9$, $\alpha_2 = 0.999$ and the learning rate is initialized to 0.001. All training continue 100 epochs. There are 2000 training steps and 200 validation steps in each epoch. For the first 10 epochs, the learning rate is constant, then the learning rate is decreased by 10 times for the remaining 90 epochs. Only a model with the smallest validation loss is saved.

Loss function. The proposed $JD_N D_M SR$ is optimized with different loss functions. Given a training set $\{I_{LR_M}^i, I_{HR}^i\}_{i=1}^N$, which contains N low-resolution inputs and corresponding high-resolution counterparts, the goal of

Table 1: Quantitative comparison of different solutions on the mixture problem of joint denoising, demosaicing and super-resolution using datasets Kodak and McMaster [46]. represents the model is re-trained by our. The noise level is 10 and the scale factor is set to 2. The best, second and third best results are highlighted with red, blue and green, respectively. The efficiency is computed as an average time to process an image.

Solution type			Pipeline			McMaster		Kodak		Parameters	Efficiency
						cPSNR	SSIM	cPSNR	SSIM		
D_N	D_M	SR	DnCNN	DJDD	VDSR	25.99	0.8522	26.18	0.7868	21.1MB	0.36s
			DnCNN	DJDD	VDSR	29.14	0.9248	28.53	0.8913		
Joint $D_N D_M$		SR	DJDD	VDSR		28.40	0.9248	28.13	0.8812	14.2MB	0.23s
			DJDD	VDSR		28.88	0.9212	28.43	0.8887		
D_N	Joint D_M	SR	DnCNN	$J D_M$ SR		25.91	0.8522	26.11	0.7846	85.1MB	0.77s
			DnCNN	$J D_M$ SR		29.51	0.9293	28.75	0.8948		
Joint $D_N D_M$	SR		$J D_N D_M$ SR			29.34	0.9274	28.80	0.8942	78.2MB	0.64s
			$J D_N D_M$ SR ⁺			29.56	0.9296	28.80	0.8965		

training $J D_N D_M$ SR is to minimize the loss function:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N L(J D_N D_M \text{SR}(\mathbf{I}_{LR_M}^i), \mathbf{I}_{HR}^i). \quad (5)$$

where θ denotes the parameter set of $J D_N D_M$ SR. The models in this part are trained with mean squared error (MSE). We also further optimize our network by training it with different error criteria and comparing the results by different loss functions (see Section 5.1).

4.2. Comparison of solutions

In this section, we compare the joint solutions, presented in Eqns. (1)-(4), of the mixture problem of image demosaicing, denoising and super-resolution. Except $M_{J D_M \text{SR}}$ in Eqn. (3), solved by the proposed $J D_M$ SR, other methods in Eqn. (1)-(3) are replaced by the state-of-the-art image restoration networks, DnCNN [42], DJDD [8], and VDSR [19], used for denoising, demosaicing and super-resolution, respectively. It should be noted that there are two versions of DJDD (for noisy and noise-free inputs). The noisy version model is used in Eqn. (2) for joint demosaicing and denoising ($M_{J D_N D_M}$). In contrast, the noise-free version is adopted in Eqn. (1) for M_{D_N} . Here we mainly focus on the comparison of various joint solutions, rather than aiming at obtaining state-of-the-art results. Therefore, we chose simple yet effective methods instead of computationally more demanding ones with better performances. Similar to [41], we introduce a transfer-learning strategy to further improve $J D_N D_M$ SR (we name the transfer-learning method as $J D_N D_M$ SR⁺). $J D_N D_M$ SR⁺ transfers the learned parameters from the trained model of $J D_M$ SR for joint $\times 2$ super-resolution and image demosaicing. The details of the pre-trained $J D_M$ SR model and the ablation study of transfer learning are provided in the supplementary material.

Quantitative results. Quantitative analysis was performed with cPSNR and SSIM metrics, by calculating them on full RGB image. The results are averaged over whole dataset. For super-resolved image, the borders of the image are shaved off, with the scaling factor as the width of the shaved border.

Table 1 shows the quantitative comparison of all solutions for joint image demosaicing, denoising and super-resolution. We fix a noise level to 10 and a scale factor to 2. The loss function used in this comparison is MSE. Since CNN models are sensitive to the input data, all models in (Eqn. (1)-(3)) are re-trained with the specific input and output pairs. In order to reduce the interaction among different tasks, a model should input the results of the previous model and try to correct the errors produced by the previous processing at the same time. Comparing to other solutions, our combined solution $J D_N D_M$ SR⁺ performs better on both datasets. Even without transfer-learning, our closest combined solution $J D_N D_M$ SR also outperforms most of the compared solutions. On the other hand, the re-trained models can obtain better performance than the directly exploiting trained models. We also presented the qualitative results in Fig. 3. Our $J D_N D_M$ SR⁺ not only eliminates the noise but also recovers more details in high frequency region.

Effects of combined solution. In Table 1, one can observe that our $J D_N D_M$ SR is the third best joint solution. In contrast, the specific re-trained models of solution in Eqn. (3) achieves the second best performance. In addition, the fourth best solution is the retrained version of Eqn. (1). These two solutions both begin from the specific re-trained DnCNN model. Therefore, a specific trained DnCNN model can support a good start for joint denoising, demosaicing and SR.

However, our $J D_N D_M$ SR can achieve a comparable performance by the additional noise level estimation input. Our $J D_N D_M$ SR⁺ demonstrates a superior performance.

This observation indicates that the combined solution can avoid an accumulation of errors. According to Table 1, the combined solution, $JD_N D_M SR^+$, outperforms other solutions in consideration of performance, storage, and computation efficiency.

5. Optimization

5.1. Comparison on cost functions

In subsection 4.2, the proposed $JD_N D_M SR^+$ surpasses other joint solutions both quantitatively and qualitatively. In order to further optimize $JD_N D_M SR^+$, we train several models with different cost functions besides MSE, including MAE, SSIM, MS-SSIM, Mix1. Inspired by [48], the Mix1 cost function is defined as $L_{MS-SSIM} + (1 - \alpha)L_1$ ¹. These five models are compared on three evaluation metrics: cPSNR, SSIM, and MS-SSIM. The results of their comparison on McMaster and Kodak datasets are shown in Table 2. As one can see, the model trained with MAE (mean absolute error) cost function attains the best performance for all image quality metrics and on both datasets. Compared with the model trained with MSE, the cPSNR values of MAE version is improved by 0.25dB on two datasets.

Table 2: Quantitative comparison of different cost functions. The results are averaged both on McMaster and Kodak. The noise level is 10 and the scale factor is 2. For cPSNR, SSIM, MS-SSIM, the value reported here has been obtained as an average of the three color channels. Best results are shown in bold.

Metric	Training cost function				
	MSE	MAE	SSIM	MS-SSIM	Mix1
cPSNR	28.48	28.73	26.64	26.64	27.36
SSIM	0.8991	0.9041	0.8513	0.8531	0.8733
MS-SSIM	0.9452	0.9487	0.9312	0.9326	0.9297

5.2. Comparison with State-of-the-Art

In this section, we compare the proposed $JD_N D_M SR^+$ -MAE with the state-of-the-art method TENet [29] on four datasets with four noise levels (see Table 3). For a fair comparison, we re-trained the TENet network and our $JD_N D_M SR^+$ -MAE on both DIV2K and Flickr2K [34] datasets with $\times 2$ scale factor and the noise level randomly sampled from [0, 20]. In addition to McMaster and Kodak datasets, we also test them on B100 [28] and Urban100 [14] datasets, which are often applied in the comparison of different super-resolution methods. The dataset B100 contains 100 human segmented natural images, and the dataset Urban100 contains 100 urban images with many similar structures. For the

¹We tested a few different values for α , and set $\alpha = 0.1$

pre-processing of the test images, the scale factor is set to 2 and the noise levels to 0, 10, 20 and 30. We use cPSNR and SSIM metrics for the quantitative evaluation. As shown in Table 3, our model outperforms the TENet over all noise levels on all datasets. We also present the visual comparison both on noisy and noise-free versions in Fig. 1. In comparison with the resulting images of TENet, our $JD_N D_M SR^+$ -df2k enables to reconstruct the high resolution images more accurately with less blur and less color artifacts. Although $JD_N D_M SR^+$ -df2k can handle higher noise ($\sigma > 20$), more details are eliminated along with the noise (see our supplementary material).

Joint denoising and demosaicing. As it was mentioned above, our $JD_N D_M SR^+$ can switch off denoising by setting the parameter β to 0. In addition, the super-resolution can also be turned off by setting the scale factor to 1. Based on this idea, we train our $JD_N D_M SR$ network with scale factor 1 on DIV2K dataset, named as $JD_N D_M$. We compare the $JD_N D_M$ with three state-of-the-art methods: DJDD [8], Kokkinos [22], and SGNet [26]. The comparison on three datasets with four noise levels is shown in Table 4². This table demonstrates that the performance of our $JD_N D_M$ surpasses the state-of-the-art joint denoising and demosaicing methods on both noisy and noise-free data. When the noise level of $JD_N D_M$ is 0, the model works as demosaicing only, *i.e.* denoising and super-resolution are turned off. Therefore, our $JD_N D_M SR$ network can be adjusted according to different requirements, including switching on/off super-resolution, switching on/off denoise, and setting scale factor and noise level. Meanwhile, our $JD_N D_M SR$ attains favorable performance on different mixture problems, such as denoising and demosaicing (Table 4), demosaicing and super-resolution (Table 3), and denoising, demosaicing and super-resolution (Table 3).

6. Ablation study

6.1. Basic blocks of feature extraction module

In order to study the effects of each component in the proposed model $JD_N D_M SR^+$, we gradually modify the baseline $JD_N D_M SR^+$ model and compare their differences. The investigation starts from the selection of the basic blocks of feature extraction module. We compare three types of residuals in the residual blocks: RRDB [37], RCAB [13] and RAB [47]. For a fair comparison, we tuned the number of three basic blocks to keep all networks to have similar parameters (Table 5). The performance curves of different basic blocks is shown in Fig. 4. With a similar model size, the network with RCAB blocks performs bet-

²For fair comparison, the models we tested for noise-free data are the noisy version supported by the authors. The max noise level of Kokkinos is 10. Since the public pre-trained model are not available, the values of SGNet are from the corresponding paper.

Table 3: Quantitative comparison for joint denoising, demosaicing and super-resolution. The evaluation metrics are cPSNR and SSIM. The best values are shown in bold. The scale factor is 2 and the noise levels are 0, 10, 20 and 30.

Noise level	McMaster		Kodak		B100		Urban100	
	TENet	$JD_N D_M SR^+$	TENet	$JD_N D_M SR^+$	TENet	$JD_N D_M SR^+$	TENet	$JD_N D_M SR^+$
0	31.48/0.9574	32.59/0.9652	30.80/0.9386	31.49/0.9456	29.24/0.9200	29.87/0.9283	28.05/0.9225	28.99/0.9331
10	29.28/0.9269	29.66/0.9315	28.70/0.8963	28.85/0.8982	27.25/0.8711	27.37/0.8725	26.53/0.8872	26.89/0.8922
20	27.29/0.8943	27.54/0.9000	27.04/0.8558	27.13/0.8595	25.60/0.8230	25.67/0.8250	24.98/0.8464	25.22/0.8524
30	25.88/0.8636	26.11/0.8724	25.90/0.8226	26.03/0.8309	24.50/0.7854	24.57/0.7924	23.75/0.8072	24.01/0.8156

Table 4: Quantitative comparison for joint denoising and demosaicing. The best values are shown in bold.

Method	Noise level	McMaster		Kodak		Urban100	
		cPSNR	SSIM	cPSNR	SSIM	cPSNR	SSIM
DJDD[8]	5	35.48	0.9775	36.21	0.9749	34.04	0.9728
kokkinos[22]		32.41	0.9601	34.65	0.9665	33.09	0.9654
SGNet[26]		—	—	—	—	34.54	0.9533
$JD_N D_M$		36.05	0.9805	36.87	0.9782	35.07	0.9767
DJDD[8]	10	33.14	0.9629	33.22	0.9537	31.80	0.9547
kokkinos[22]		29.30	0.9253	30.70	0.9215	30.02	0.9246
SGNet[26]		—	—	—	—	32.14	0.9229
$JD_N D_M$		33.74	0.9677	33.90	0.9599	32.83	0.9619
DJDD[8]	15	31.49	0.9478	31.43	0.9323	30.14	0.9356
kokkinos[22]		25.98	0.8517	27.17	0.8295	26.74	0.8492
SGNet[26]		—	—	—	—	30.37	0.8923
$JD_N D_M$		32.11	0.9550	32.05	0.9420	31.25	0.9477
DJDD[8]	0	37.90	0.9880	40.33	0.9918	36.47	0.9858
kokkinos[22]		33.82	0.9655	37.64	0.9815	33.94	0.9570
$JD_N D_M$		38.85	0.9904	42.23	0.9947	38.34	0.9895

Table 5: Performance comparison of different basic blocks. The performance is the best cPSNR value on McMaster dataset.

Basic block	Amounts	Total parameters	Performance
RAB	7	3,247,063	28.55
RRDB	6	3,299,031	28.59
RCAB	40	3,504,855	28.97

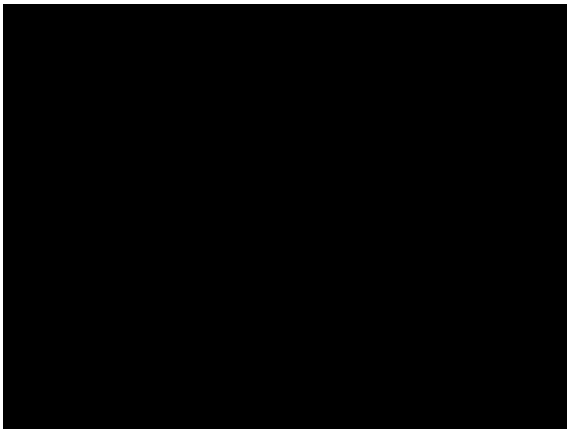


Figure 4: The comparison of convergence curves of different basic modules.

6.2. Color extraction module

Fig. 2 shows that the color extraction module of our network is composed of two layers: a convolutional layer with a large filter (256) for color extraction (CE) and a deconvolutional layer for upsampling (UP1). In this part, we prove the importance of this module. Table 6 displays the effect of the CE layer and the position of the deconvolutional layer. When the features are upsampled before feature extraction, performance of the network improves by 0.19 dB compared to the case when the features are upsampled after feature extraction. The CE layer can also provide a small performance improvement.

Table 6: Investigation of color extraction module. The models are tested on McMaster dataset. The scale factor is set to 2 and the noise sigma is 10.

CE?				
UP1?	After	After	Before	Before
cPSNR on McMaster	28.86	28.87	29.05	29.07

7. Conclusion

We have systematically compared possible solutions of the joint problem of image demosaicing, denoising and super-resolution, under fixed execution order. Extensive experiments have demonstrated that the proposed end-to-end learning-based solution, $JD_N D_M SR^+$ surpasses others, both quantitatively and qualitatively. Besides, the performance of $JD_N D_M SR^+$ is improved by training with the mean absolute error cost function used instead of mean square error. The performance of this optimized model surpassed the state-of-the-art method TENet on four benchmark datasets for noisy and noise-free data. In addition, the denoising operation and the super-resolution operation of the proposed network can be turned off (by setting the noise level to 0 and the scale factor to 1). When the super-resolution operation is switched off, our $JD_N D_M$ model for joint denoising and demosaicing outperforms the state-of-the-art methods. In the future, we will explore more prior information to further improve the performance of joint image demosaicing, denoising and super-resolution.

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