A review on Deep Learning based method focused on image denosing.

Tan Sy NGUYEN

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1 Motivation

Deep learning techniques have received much attention in the area of image denoising. However, there are substantial differences in the various types of deep learning methods dealing with image denoising. Specifically, discriminative learning based on deep learning can ably address the issue of Gaussian noise. Optimization models based on deep learning are effective in estimating the real noise. However, there has thus far been little related research to summarize the different deep learning techniques for image denoising. In this paper, we offer a comparative study of deep techniques in image denoising. I focus on the deep convolutional neural networks (CNNs) for additive white noisy images (AWNI). Firstly, I will present us the fundamental frameworks of deep learning methods for image denoising. After that, the deep learning techniques in image denoising will be explained which contains three main components including using a standalone CNN/NN, using a combination between a features extraction method and a CNN/NN on many kinds of images as well as using a combination between CNN/NN and a optimization problem to improve the performance beside speed (Fig. 1).

2 Fundamental frameworks of deep learning methods for image denoising

This section offers a discussion of deep learning, including the ideas behind it, the main network frameworks (techniques), which is the basis for the deep learning techniques for image denoising covered in this review.

2.1 Machine learning methods for image denoising

Machine learning methods consist of supervised, semi-supervised and unsupervised learning methods. Supervised learning methods [1, 2, 3] use the given label to put the obtained features closer to the target for learning parameters and training the denoising model. For

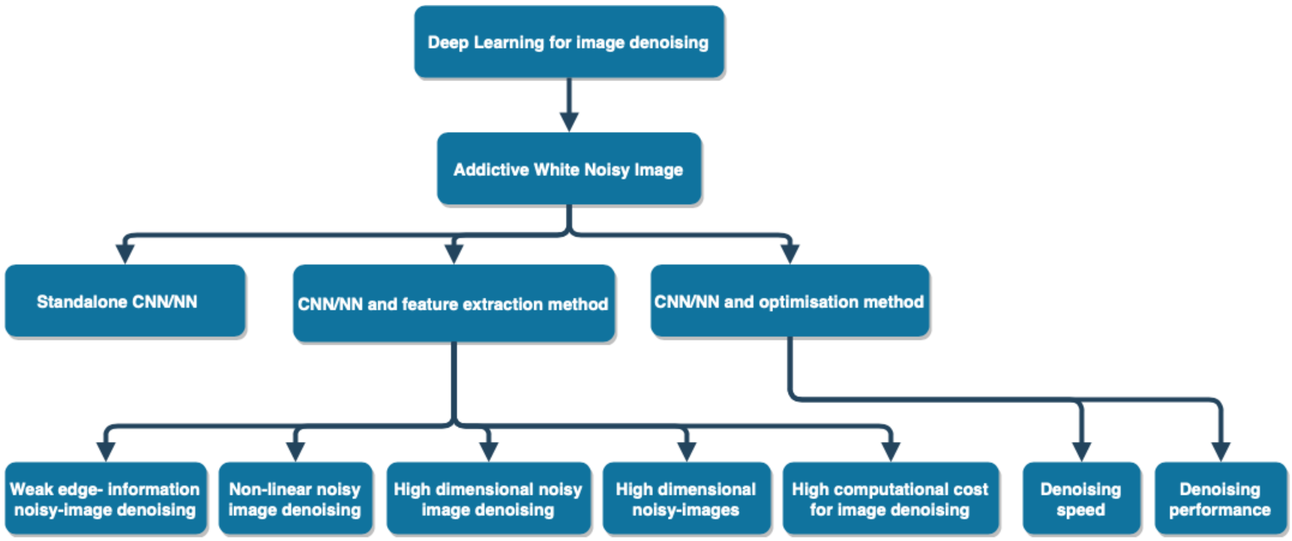

Figure 1: Outline of the review. It consists of three parts, including three kinds of DL-based method used to deal with image denoising problem

example, take a given denoising model $y = x + \mu$, where x, y and μ represent the given clean image, noisy image and additive Gaussian noise (AWGN) of standard deviation σ, respectively. From the equation above and Bayesian knowledge, it can be seen that the learning of parameters of the denoising model relies on pair $\{x_k, y_k\}_{k=1}^{N}$, where x_k and y_k denote the k^{th} clean image and noisy image, respectively. Also, N is the number of noisy images. This processing can be expressed as $x_k = f(y_k, \theta, m)$, where θ is the parameters and m denotes the given noise level.

Unsupervised learning methods [4] use given training samples to find patterns rather than label matching and finish specific tasks, such as unpairing real low-resolution images [5]. The recently proposed Cycle-in-Cycle GAN (CinCGAN) recovered a high-resolution image by first estimating the high-resolution image as a label, then exploiting the obtained label and loss function to train the super-resolution model.

Semi-supervised learning methods [6] apply a model from a given data distribution to build a learner for labeling unlabeled samples. This mechanism is favored by small sample tasks, such as medical diagnosis. A semi-supervised learned sinogram restoration network (SLSR-Net) can learn feature distribution from paired sinograms via a supervised network, and then, convert the obtained feature distribution to a high-fidelity sinogram from unlabeled low-dose sinograms via an unsupervised network [7].

2.2 Neural networks for image denoising

Neural networks are the basis of machine learning methods, which in turn are the basis of deep learning techniques [8]. Most neural networks consist of neurons, input X, activation function f , weights $W = [W^0, W^1, ..., W^{n-1}]$ and biases $b = [b^0, b^1, ..., b^n]$. The activation functions such as Sigmoid [9, 10] and $tanh$ [11, 12] can convert the linear input into non-linearity through W and b as follows.

$$f(X; W; b) = f(W^T X + b). \tag{1}$$

Note that if the neural network has multiple layers, it is regarded as multilayer perceptron (MLP) [13]. In addition, the middle layers are treated as hidden layers beside the input and output layers. This process can be expressed as

$$f(X; W; b) = f(W^n f(W^{n-1} ... f(W^0 X + b0) ... b^{n-1}) + b^n), \tag{2}$$

where n is the final layer of the neural network.

The two-layer fully connected neural network includes two layers: a hidden layer and output layer (the input layer is not generally regarded as a layer of a neural network). There are parameters to be defined: x_1, x_2, x_3 and o_1 represent the inputs and output of this neural network, respectively. $w_1; w_2; ::::; w_{11}; w12$ and b_1, b_2, b_3, b_4 are the weights and biases, respectively. For example, the output of one neuron h1 via Eqs. (3) and (4) is obtained as follows:

$$f(z_{h1}) = f(w_1 x_1 + w_4 x_2 + w_7 x_3 + b_1) \tag{3}$$

$$o(h_1) = f(z_{h1}) \tag{4}$$

First, the output of the network o1 is obtained. Then, the network uses back propagation (BP) [14] and loss function to learn parameters. That is, when the loss value is within specified limitation, the trained model is considered as well-trained. It should be noted that if the number of layers of a neural network is more than three, it is also referred to as a deep neural network.

Stacked auto-encoders (SARs) [15] and deep belief networks (DBNs) [16, 17] are typical deep neural networks. They used stacked layers in an unsupervised manner to train the models and obtain good performance. However, these networks are not simple to implement and require a good deal of manual settings to achieve an optimal model. Due to this, end-to-end connected networks, especially CNNs, were proposed [18]. CNNs have wide applications in the field of image processing, especially image denoising.

2.3 CNNs for image denosing

Due to their plug-and-play network architectures, CNNs have achieved great success in image processing [19, 20, 21]. As a pioneer in CNN technology, LeNet [22] used convolutional kernels of different sizes to extract features and obtain good performance in image classification.

However, due to the Sigmoid activation function, LeNet had a slow convergence speed, which was a shortcoming in real-world applications. After LeNet, the proposed AlexNet [23] was a milestone for deep learning. Its success was due to several reasons. First, the graphics processing unit (GPU) [9] provided strong computational ability. Second, random clipping (i.e., dropout) solved the overfitting problem. Third, ReLU [24] improved the speed of stochastic gradient descent (SGD) rather than Sigmoid [25]. Fourth, the data augmentation method further addressed the overfitting problem. Although AlexNet achieved good performance, it required substantial memory usage due to its large convolutional kernels. That limited its real-world applications, such as in smart cameras. After that, during the period of 2014 to 2016, deeper network architectures with small filters were preferred to improve the performance and reduce computational costs. Specifically, VGG [26] stacked more convolutions with small kernel sizes to win the ImageNet LSVR Challenge in 2014.

Since 2014, deep networks have been widely used in real-world image applications, such as facial recognition [27] and medical diagnosis [28]. However, in many applications, captured images, such as real noisy images, are not sufficient, and deep CNNs tend to perform poorly in image applications. For this reason, GANs [29] were developed. GANs consisted of two networks: generative and discriminative networks. The generative network (also referred to as the generator) is used to generate samples, according to input samples. The discriminative network (also called the discriminator) is used to judge the truth of both input samples and generated samples.

The two networks are adversarial. Note that if the discriminator can accurately distinguish real samples and generate samples from generator, the trained model is regarded as finished. Due to its ability to construct supplemental training samples, the GAN is very effective for small sample tasks, such as facial recognition [30] and complex noisy image denoising [31]. These mentioned CNNs are basic networks for image denoising.

3 Deep learning techniques in image denoising

Due to the insufficiency of real noisy images, additive white noisy images (AWNIs) are widely used to train the denoising model [32]. AWNIs include Gaussian, Poisson, Salt, Pepper and multiplicative noisy images [33]. There are several deep learning techniques for AWNI denoising, including CNN/NN; the combination of CNN/NN and common feature extraction methods; and the combination of the optimization method and CNN/NN.

3.1 Standalone CNN/NN for AWNI denoising

Automatic feature extraction methods can play a major role in reducing the computational costs for image applications [34, 35, 36]. For this reason, CNNs have been developed for image denoising [37, 38]. Zhang et al. [39] proposed a model as well as a DnCNN to deal with multiple low-level vision tasks, i.e., image denoising, super-resolution and deblocking through CNN, batch normalization [89] and residual learning techniques [40]. Wang et al. [41], Bae et al. [42] and Jifara et al. [43] also presented a residual learning into deeper CNN for image denoising. However, the deeper CNN technique relied on a deeper layer rather than a shallow layer, which resulted in a long-term dependency problem. Several signal-base methods were proposed to resolve this problem. Tai et al. [44] exploited recursive and gate units to adaptively mine more accurate features and recover clean images. Inspired by a low-rank Hankel matrix in low-level vision, Ye et al. [45] provided convolution frames to explain the connection between signal processing and deep learning by convolving local and nonlocal bases. For solving insufficient noisy images (i.e., hyperspectral and medical images), several recent works have attempted to extract more useful information through the use of improved CNNs [46, 47, 48]. For example, Yuan et al. [49] combined a deep CNN, residual learning and multiscale knowledge to remove the noise from hyperspectral-noisy images. However, these proposed CNNs led to the likelihood of increased computational costs and memory consumption, which was not conducive for real-world applications. To address this phenomenon, Gholizadeh et al. [50] utilized dilated convolutions to enlarge the receptive field and reduce the depth of network without incurring extra costs for CT image denoising. Lian et al. [51] proposed a residual network via multi-scale cross-path concatenation to suppress the noise. Most of the above methods relied on improved CNNs to deal with the noise. Therefore, designing network architectures is important for image denoising [52, 53].

Changing network architectures involves the following methods [54, 55, 56]: fusing features from multiple inputs of a CNN; changing the loss function; increasing depth or width of the CNN; adding some auxiliary plug-ins into CNNs; and introducing skip connections or cascade operations into CNNs. Specifically, the first method includes three types: different parts of one sample as multiple inputs from different networks [57]; different perspectives for the one sample as input, such as multiple scales [58, 59]; and different channels of a CNN as input [60]. The second method involves the design of different loss functions according to the characteristics of nature images to extract more robust features [10]. For example, Chen et al. [61] jointed Euclidean and perceptual loss functions to mine more edge information for image denoising. The third method enlarged the receptive field size to improve denoising performance via increasing the depth or width of the network [62, 63, 64]. The fourth method applied plug-ins, such as activation function, dilated convolution, fully connected layer and pooling operations, to enhance the expressive ability of the CNN [65, 66, 67]. The fifth method utilized skip connections [68, 69, 70, 71] or cascade operations [51] to provide complementary information for the deep layer in a CNN. Table 1 provides an overview of CNNs for AWNI denoising.

3.2 CNN/NN and common feature extraction methods for AWNI denoising

Feature extraction is used to represent the entire image in image processing, and it is important for machine learning [79]. However, because deep learning techniques are black box techniques, they do not allow the choice of choose features, and therefore cannot guarantee that the obtained features are the most robust [80]. Motivated by problem, researches embedded common feature extraction methods into CNNs for the purpose of image denoising. They did this for five reasons: weak edge-information noisy images, non-linear noisy images, high dimensional noisy images and non-salient noisy images, and high computational costs.

For weak edge-information noisy images, CNN with transformation domain methods were proposed by Guan et al. [81], Liu et al. [82], and Yang et al. [83]. However, they were not effective in removing the noise. Specifically, in [82], the proposed solution used the wavelet method and U-net to eliminate the gridding effect of dilated convolutions on enlarging the receptive field for image restoration.

For non-linear noisy images, CNNs with kernel methods proved useful [84]. These methods mostly consisted of three steps [85]. The first step used CNN to extract features. The second step utilized the kernel method to convert obtained non-linear features into linearity. The third step exploited the residual learning to construct the latent clean image.

Table 1: Standalone CNN/NN for AWNI denoising.

References	Methods	Applications	Key words (remarks)
Zhang et al. [39]	CNN	Gaussian image denoising, super-resolution and JPEG deblocking	CNN with residual learning, and BN for image denoising
Wang et al. [41]	CNN	Gaussian image denoising	CNN with dilated convolutions, and BN for image denoising
Bae et al. [42]	CNN	Gaussian image denoisng, super-resolution	CNN with wavelet domain, and residual learning (RL) for image restoration
Jin et al. [43]	CNN	Medical (X-ray) image restoration	Improved Unet from iterative shrinkage idea for medical image restoration
Tai et al. [44]	CNN	Gaussian image denoisng, super-resolution and JPEG deblocking	CNN with recursive unit, gate unit for image restoration
Anwar et al. [71]	CNN	Gaussian image denoisng	CNN with fully connected layer, RL and dilated convolutions for image denoising
McCann et al. [32]	CNN	Inverse problems (i.e., denoising, deconvolution, super-resolution)	CNN for inverse problems
Ye et al. [45]	CNN	Inverse problems(i.e., Gaussian image denoising, super-resoluion)	Signal processing ideas guide CNN for inverse problems
Yuan et al. [49]	CNN	Hyper-spectral image denoising	CNN with multiscale, multilevel features techniques for hyper-spectral image denoising
Jiang et al. [60]	CNN	Gaussian image denoising	Multi-channel CNN for image denoising
Chang et al. [46]	CNN	Hyper-spectral image (HSI) denoising, HIS restoration	CNN consolidated spectral and spatial coins for hyper-spectral image denoising
Jeon et al. [58]	CNN	Speckle noise reduction from digital holographic images	Speckle noise reduction of digital holographic image from Multi-scale CNN
Ansari et al. [50]	CNN	Low-dose CT image denoising, X-ray image denosing	CNN with dilated convolutions for low-dose CT image denoising
Uchida et al. [62]	CNN	Non-blind image denoising	CNN with residual learning for non-blind image denoising
Xiao et al. [68]	CNN	Stripe noise reduction of infrared cloud images	CNN with skip connection for infrared-cloud-image denoising
Chen et al. [61]	CNN	Gaussian image denoisng, blind denoising	CNN based on RL and perceptual loss for edge enhancement
Yu et al. [54]	CNN	Seismic, random, linear and multiple noise reduction of images	A survey on deep learning for three applications
Yu et al. [48]	CNN	Optical coherence tomography (OCT) image denoising	GAN with dense skip connection for optical coherence tomography image denoising
Li et al. [53]	CNN	Ground-roll noise reduction	An overview of deep learning techniques on ground-roll noise
Abbasi et al. [57]	CNN	OCT image denoising	Fully CNN with multiple inputs, and RL for OCT image denoising
Zarshenas et al. [63]	CNN	Gaussian noisy image denoising	Deep CNN with internal and external residual learning for image denoising
Chen et al. [69]	CNN	Gaussian noisy image denoising	CNN with recursive operations for image denoising
Panda et al. [65]	CNN	Gaussian noisy image denoising	CNN with exponential linear units, and dilated convolutions for image denoising
Sheremet et al. [64]	CNN	Image denoising from info-communication systems	CNN on image denoising from info-communication systems
Chen et al. [59]	CNN	Aerial-image denoising	CNN with multi-scale technique, and RL for aerial-image denoising
Pardasani et al. [67]	CNN	Gaussian, poisson or any additive-white noise reduction	CNN with BN for image denoising
Couturier et al. [70]	NN	Gaussian and multiplicative speckle noise reduction	Encoder-decoder network with multiple skip connections for imaged enoising
Park et al. [52]	CNN	Gaussian noisy image denoising	CNN with dilated convolutions for image denoising
Priyanka et al. [66]	CNN	Gaussian noisy image denoisng	CNN with symmetric network architecture for image denoising
Lian et al. [51]	CNN	Poisson-noise-image denoising	CNN with multi scale, and multiple skip connections for Poisson image denoising
Tripathi et al. [72]	CNN	Gaussian noisy image denoising	GAN for image denoising
Zheng et al. [73]	CNN	Gaussian noisy image denoising	CNN for image denoising
Tian et al. [74]	CNN	Gaussian noisy image denoising	CNN for image denoising
Remez et al. [75]	CNN	Gaussian and Poisson image denoising	CNN for image denoising
Tian et al. [76]	CNN	Gaussian image denoising and real noisy image denoising	CNN with BRN, RL and dilated convolutions for image denosing
Tian et al. [77]	CNN	Gaussian image denoising, blind denoising and real noisy image denoising	CNN with attention mechanism and sparse method for image denoising
Tian et al. [78]	CNN	Gaussian image denoising, blind denoising and real noisy image denoising	Two CNNs with sparse method for image denoising

For high dimensional noisy images, the combination of CNN and the dimensional reduction method was proposed [86, 87]. For example, Khaw et al. [88] used a CNN with principal component analysis (PCA) for image denoising. This consisted of three steps. The first step used convolution operations to extract features. The second step utilized the PCA to reduce the dimension of the obtained features. The third step employed convolutions to deal with the obtained features from the PCA and to reconstruct a clean image.

For non-salient noisy images, signal processing can guide the CNN in extracting salient features [89, 90, 91, 57]. Specifically, skip connection is a typical operation of signal processing [90].

For tasks involving high computational costs, a CNN with relations nature of pixels from an image was very effective in decreasing complexity [57, 92, 93]. For example, Ahn et al. [93] used a CNN with non-local self-similarity (NSS) to filter the noise, where similar characteristics of the given noisy image can accelerate the speed of extraction feature and reduce computational costs. More detailed information on these methods mentioned can be found in Table 2.

3.3 Combination of optimization method and CNN/NN for AWNI denoising.

Machine learning uses optimization techniques and discriminative learning methods to deal with image applications. Although optimization methods have good performance on different low-level vision tasks, these methods need manual setting parameters, which are time-consuming [95]. The discriminative learning methods are fast in image restoration. However, they are not flexible for low-level vision tasks. To achieve a tradeoff between efficiency and flexibility, a discriminative learning optimization-based method [96] was presented for image applications, such as image denoising. CNNs with prior knowledge via regular term of loss function is a common method in image denoising [97], which can be divided two categories: improvement of denoising speed and improvement of denoising performance.

For improving denoising speed, an optimization method using a CNN was an effective tool for rapidly finding the optimal solution in image denoising [98, 99]. For example, a GAN with the maximum a posteriori (MAP) method was used to estimate the noise and deal with other tasks, such as image inpainting and super-resolution [100]. An experience-based greed algorithm and transfer learning strategies with a CNN can accelerate a genetic algorithm to obtain a clean image [101]. Noisy image and noise level mapping were inputs of the CNN, which had faster execution in predicting the noise [102].

For improving denoising performance, a CNN combined optimization method was used to make a noisy image smooth [103, 104]. A CNN with total variation denoising reduced the effect of noise pixels [105]. Combining the Split Bregman iteration algorithm and CNN [106] can enhance pixels through image depth to obtain a latent clean image. A dual-stage CNN with feature matching can better recover the detailed information of the clean image, especially noisy images [107]. The GAN with the nearest neighbor algorithm was effective in filtering out noisy images from clean images [108]. A combined CNN used wavefront coding to enhance the pixels of latent clean images via the transform domain [109]. Other effective denoising methods using non-local filter as well as QAM (quadrature amplitude modulation)

Table 2: CNN/NN and common feature extraction methods for AWNI denoising.

References	Methods	Applications	Key words (remarks)
Bako et al. [51]	CNN	Monte Carlo-rendered images denoising	CNN with kernel method for estimating noise piexls
Ahn et al. [93]	CNN	Gaussian image denoising	CNN with NSS for image denoising
Khaw et al. [88]	CNN	Impulse noise reduction	CNN with PCA for image denoising
Vogel et al. [0]	CNN	Gaussian image denoising	U-net with multi scales technique for image denoising
Mildenhall et al. [85]	NN	Low-light synthetic noisy image denoising, real noise	Encoder-decoder with multi scales, and kernel method for image denoising
Liu et al. [82]	CNN	Gaussian image denoisng, super-resolution and JPEG deblocking	U-net with wavelet for image restoration
Yang et al. [83]	CNN	Gaussian image denoisng	CNN with BM3D for image denoising
Guo et al. [87]	CNN	Image blurring and denoising	CNN with RL, and sparse method for image denoising
Jia et al. [89]	CNN	Gaussian image denoisng	CNN with multi scales, and dense RL operations for image denoising
Ran et al. [91]	CNN	OCT image denoising, OCT image super-resolution	CNN with multi views for image restoration
Li et al. [94]	CNN	Medical image denoising, stomach pathological image denoising	CNN consolidated wavelet for medical image denoising
Ahn et al. [92]	CNN	Gaussian image denoisng	CNN with NSS for image denoising
Xie et al. [86]	CNN	Hyper-spectral image denoising	CNN with RL, and PCA for low-dose CT image denoising
Kadimesetty et al. [90]	CNN	Low-Dose computed tomography (CT) image denoising	CNN with RL, batch normalization (BN) for medical image denoising
Guan et al. [81]	CNN	Stripe noise reduction	CNN with wavelet-image denoising
Abbasi et al. [57]	NN	3D magnetic resonance image denoising, medical image denoising	GAN based on encoder-decoder and RL for medical denoising
Xu et al. [84]	CNN	Synthetic and real noisy and video denoising	CNN based on deformable kernel for image and video denoising

are shown in [94, 110, 111]. Table 3 shows detailed information about the combination of the optimization methods and CNN/NN in AWNI denoising.

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Table 3: The combination of the optimization method and CNN/NN for AWNI denoising.

References	Methods	Applications	Key words (remarks)
Hong et al. [97]	CNN	Gaussian image denoising	Auto-Encoder with BN, and ReLU for image denoising
Cho et al. [98]	CNN	Gaussian image denoising	CNN with separable convolution, and gradient prior for image denoising
Fu et al. [99]	CNN	Salt and pepper noise removal	CNN with non-local switching filter for salt and pepper noise
Yeh et al. [100]	CNN	Image denoising super-resolution and inpainting	GAN with MAP for image restoration
Liu et al. [101]	CNN	Medical image denoising, computed tomography perfusion for imagedenoising	CNN with genetic algorithm for medical image denoising
Tassano et al. [102]	CNN	Gaussian image denoisng	CNN with noise level, upscaling, downscaling operation for image denoising
Heckel et al. [103]	CNN	Image denoisng	CNN with deep prior for image denoising
Jiao et al. [104]	CNN	Gaussian image denoisng, image inpainting	CNN with inference, residual operation for image restoration
Wang et al. [105]	CNN	Image denoising	CNN with total variation for image denoising
Li et al. [106]	CNN	Image painting	CNN with split Bregman iteration algorithm for image painting
Sun et al. [107]	CNN	Gaussian image denoisng	GAN with skip-connections, and ResNet blocks for image denoising
Zhi et al. [108]	CNN	Gaussian image denoising	GAN with multiscale for image denoising
Du et al. [109]	CNN	Gaussian image denoising	CNN with wavelet for medcial image restoration
Liu et al. [94]	CNN	Gaussian image denoising, real noisy image denoising, rain removal	Dual CNN with residual operations for image restoration
Khan et al. [110]	CNN	Symbol denoising	CNN with quadrature amplitude modulation for symbol denoising
Cruz et al. [111]	CNN	Gaussian image denoising	CNN with nonlocal filter for image denoising

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