Deep Learning on Image Denoising: An Overview

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Abstract

Deep learning techniques have obtained much attention in image denoising. However, deep learning methods of different types deal with the noise have enormous differences. Specifically, discriminative learning based on deep learning can well address the Gaussian noise. Optimization model methods based on deep learning have good effect on estimating of the real noise. So far, there are little related researches to summarize different deep learning techniques for image denoising. In this paper, we make such a comparative study of different deep techniques in image denoising. We first classify the (1) deep convolutional neural networks (CNNs) for additive white noisy images, (2) deep CNNs for real noisy images, (3) deep CNNs for blind denoising and (4) deep CNNs for hybrid noisy images, which is the combination of noisy, blurred and low-resolution images. Then, we analyze the motivations and principles of deep learning methods of different types. Next, we compare and verify the state-of-the-art methods on public denoising datasets in terms of quantitative and qualitative analysis. Finally, we point out some potential challenges and directions of future research.

Keywords: Deep learning, Image denoising, Real noisy images, Blind denoising, Hybrid noisy images, A survey

1. Introduction

Digital image devices have widely applied in many fields, such as individual recognition [106, 49, 193], and remote sensing [43]. The captured image is a degraded image from the latent observation, where the degradation processing is affected by some factors, such as lighting and noise corruption [228, 219]. Specifically, the noise is generated in the processing of transmission and compression from the unknown latent observation. Thus, at first, it is very essential to

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use image denoising techniques to remove the noise and recover the latent observation from the given degraded image.

Image denoising techniques have attracted much attention in recent 20 years [199, 201]. As the pioneer, sparse-based methods have been successfully applied in image denoising [39]. Specifically, a non-locally centralized sparse representation (NCSR) method used nonlocal self-similarity to optimize the sparse method, and obtain great performance for image denoising [42]. To reduce the computational cost, a dictionary learning method was used to quickly filter the noise [46]. To recover the detailed information of the latent clean image, priori knowledge (i.e. total variation regularization) can smooth the noisy image to deal with the corrupted image [147]. More competitive methods for image denoising can be found in [136, 238, 222], including the Markov random field (MRF) [162], weighted nuclear norm minimization (WNNM) [62], learned simultaneous sparse coding (LSSC) [136], cascade of shrinkage fields (CSF) [162], trainable nonlinear reaction diffusion (TNRD) [31] and gradient histogram estimation and preservation (GHEP) [238].

Although most of the above methods have achieved reasonably good performance in image denoising, they suffer from the following drawbacks [132]: (1) optimization methods for the test phase, (2) manual setting parameters, and (3) a certain model for single denoising task. Recently, owing to the flexible architectures, deep learning techniques have strong abilities to effectively overcome the drawbacks of these methods [132].

The original deep learning technologies were found in image processing in 1980s [53] and were used in image denoising in 1980s by Zhou et al. [34, 236]. That is, the proposed denoising work first used a neural network with both of the known shift-invariant blur function and additive noise to recover the latent clean image. After that, the neural network used weighting factor to remove complex noise [34]. To handle high computational cost, a feed-forward network was proposed to make a tradeoff between denoising efficiency and performance [175]. The feed-forward network can smooth the given corrupted image by Kuwahara filters, which was similar to convolutions. Also, this research proved that the mean squared error (MSE) acted as loss function was not unique for neural networks [41, 61]. Subsequently, more optimization algorithms were used to accelerate the convergence of the trained network and promote the denoising performance [15, 40, 54]. Combining maximum entropy and primadual Lagrangian multipliers to enhance expressive ability of neural networks was a good tool for image denoising [14]. To further make a tradeoff between fast execution and denoising performance, the greedy algorithm and asynchronous algorithm were applied in neural networks [148]. Alternatively, designing novel network architecture was very competitive to eliminate the noise, such as increasing the depth or changing activation function [167]. Cellular neural networks (CENNs) mainly used nodes with templates to obtain the averaging function and effectively suppress the noise [167, 145]. Although this proposed method can obtain good denoising result, it need manually set the parameters of the templates. To resolve this problem, the gradient descent was developed [217, 103]. To a certain degree, these deep techniques can improve the denoising performance. However, these networks were not easy to add new plug-in units, which limited their applications in the real world [52].

Base on the reasons above, convolutional neural networks (CNNs) were proposed [127, 108]. The CNN as well as LeNet had a real-world application in hand-written digit recognition [102]. However, due to the following drawbacks, they were not widely applied into computer systems [98]. Firstly, deep CNNs can generate vanishing gradients. Secondly, activation functions (i.e.

sigmoid [139] and tanh [81]) resulted in high computational cost. Thirdly, the hardware platform did not support the complex network. That was broken by AlexNet in 2012 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [98]. After that, deep network architectures (e.g. VGG [166] and GoogleNet [173]) were widely applied in fields of image [194, 188], video [124, 112], nature language processing [45] and speech processing [230], especially low-level computer vision [153, 179].

Deep network was first applied in image denoising in 2015 [115, 202]. The proposed network need not manually set parameters for removing the noise. After then, deep network were widely applied in speech [231] and image restoration [138]. Mao et al. [138] used multiple convolutions and deconvolutions to suppress the noise and recover the high-resolution image. For addressing multiple low-level tasks via a model, a denoising CNN (DnCNN) [222] consisting of convolutions, batch normalization (BN) [78], rectified linear unit (ReLU) [143] and residual learning (RL) [68] was proposed to deal with image denoising, super-resolution, and JPEG image deblocking. Taking into account between denoising performance and speed, a color non-local network (CNLNet) [105] combined non-local self-similarity (NLSS) and CNN to efficiently remove color-image noise.

In terms of blind denoising, a fast and flexible denoising CNN (FFDNet) [224] presented different noise levels and the noisy image patch as input of denoising network to improve denosing speed and process blind denoising. For handling unpaired noisy images, a generative adversarial network (GAN) CNN blind denoiser (GCBD) [28] used two phases to resolve this problem. The first phase was used to generate the ground truth. The second phase utilized obtained ground truth into the GAN to train the denoiser. Alternatively, a convolutional blind denoising network (CBDNet) [64] removed the noise from the given real noisy image by two sub-networks. One was in charge of estimating the noise of the real noisy image. The other was used to obtain latent clean image. For more complex corrupted images, a deep plug-and-play super-resolution (DPSR) [226] method was developed to estimate blur kernel and noise, and recover a high-resolution image. There were also other important researches have done in the field of image denoising in recent years, however, there was only few reviews to summarize the deep learning technique in image denoising [180]. Although Ref. [180] referred to a lot of work, it lacked more detailed classification information of deep learning for image denoising. To give an example, related work of unpaired real noisy images were not covered. To this end, we have a aim to provide a comprehensive overview of deep learning for image denoising both applications and method analysis. That referred to all tables and visual figures can make readers more quickly understand this filed. Finally, we empirically provide some discussion about the state-of-the-arts for image denoising, which can be further expanded to the challenges and potential research directions in the future. Outline of this survey is shown in Fig. 1.

This overview covers more than 200 papers about deep learning for image denoising in recent years. The main contributions in this paper can be summarized as follows.

1. The overview illustrates the effect of deep learning methods on the whole field of image denoising.

2. The overview summarizes the solutions of deep learning techniques for different types of noise (i.e. additive white noise, blind noise, real noise and hybrid noise) and analyzes the motivations and principles of these methods in image denoising. Finally, we evaluate the denoising

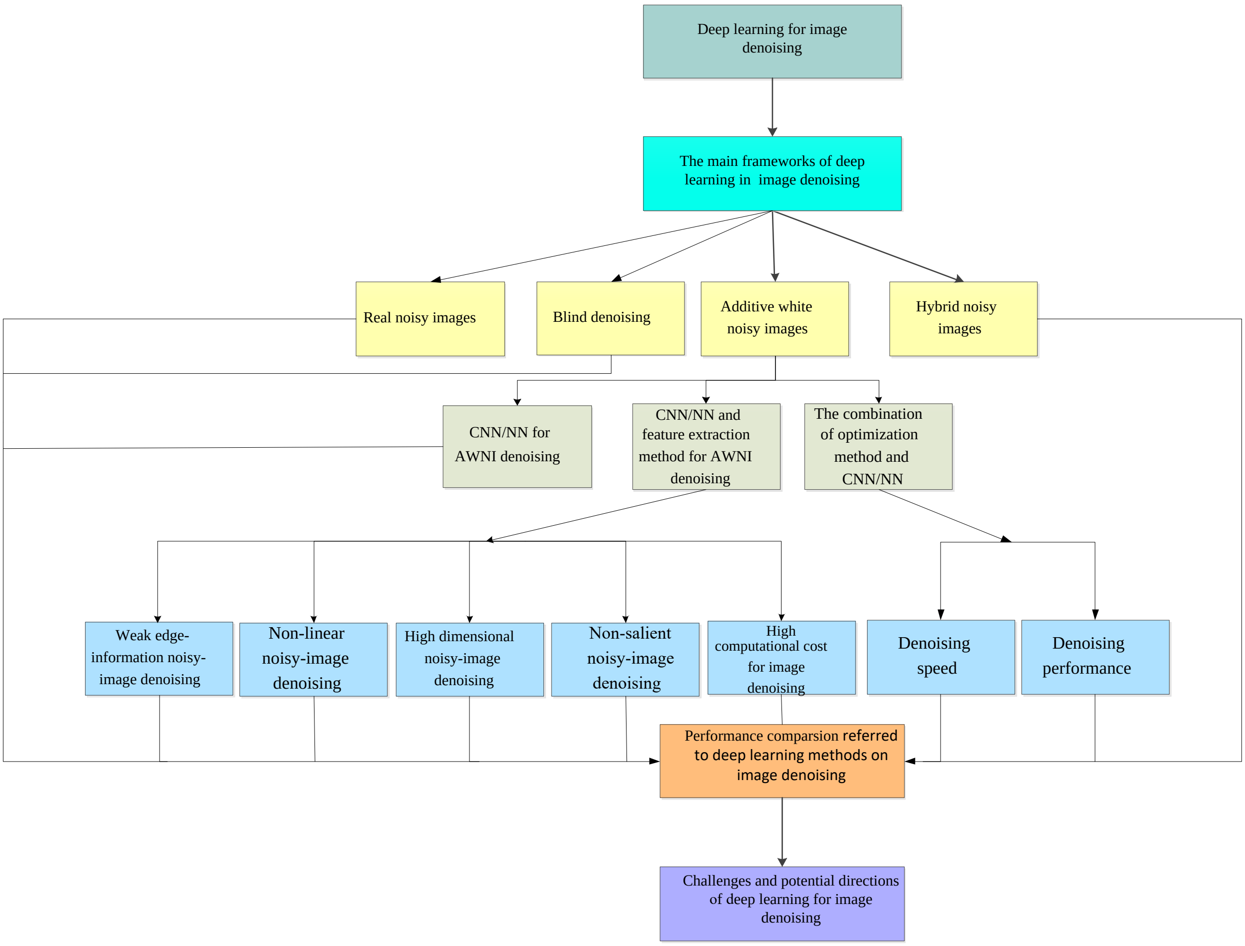

Figure 1: Outline of the survey. It consists of four parts, including basic frameworks, categories, performance comparison, challenges and potential directions. Specifically, categories comprise additive white noisy images, real noisy images, blind denoising and hybrid noisy images.

performance of these methods in terms of quantitative and qualitative analysis.

3. The overview points out some potential challenges and directions of deep learning for image denoising.

The rest of this overview is organized as followed.

Section 2 introduces the popular deep learning frameworks for image applications. Section 3 presents the main categories of deep learning in image denoising, that is, additive white noisy images, real noisy images, blind denoising and hybrid noisy images. And we compare and analyze the differences of these methods. Section 4 gives the performance comparison of these denoising methods. Section 5 discusses the challenges and potential research directions in the future. Section 6 offers the conclusions.

2. Foundation frameworks of deep learning methods for image denoising

This section offers an illustration of deep learning, including the notions, main network frameworks (techniques), and hardware and software, which is basis of deep learning techniques for image denoising in this survey.

2.1. Machine learning methods for image denoising

Machine learning methods comprise supervised and unsupervised learning methods in general. The supervised learning methods [119, 196] use the given label to make obtained features closer to target for learning parameters and training the denoising model. To give an example, 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 kth 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 parameters and m denotes the given noise level.

Unsupervised learning methods [104] use given training samples to find patterns rather than label matching and finish specific task, such as unpair real low-resolution images [215]. The recently proposed Cycle-in-Cycle generative adversarial network (CinCGAN) used two steps to recover a high-resolution image. The first step estimated the high-resolution image as label. The second step exploited the obtained label and loss function to train the super-resolution model.

2.2. Neural networks for image denoising

Neural networks are on the basis of machine learning methods, which are pioneer of deep learning techniques [161]. Most of neural networks comprise 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 [139, 93] and Tanh [81, 47] can convert the linear input into non-linearity through W and b as follows.

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

It is noted that if the neural network has multiple layers, it is regarded as multilayer perceptron (MLP) [22]. Also, the middle layers are treated as hidden layers beside the input and output layers. This process can be expressed as

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

where n is the final layer of the neural network. To make readers easier understand the neural network, we use a visual example to show the principle of the neural network as shown in Fig. 2.

The two-layer fully connected neural network includes two layers: hidden layer and output layer (input layer is not regarded as a layer of neural network in general). There are parameters to be defined: x_1, x_2, x_3 and o_1 represent inputs and output of this neural network, respectively. $w_1, w_2, ..., w_{11}, w_{12}$ and b_1, b_2, b_3, b_4 are the weights and biases, respectively. To give an example, output of one neuron h_1 via Eqs. (3) and (4) is obtained as follows:

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

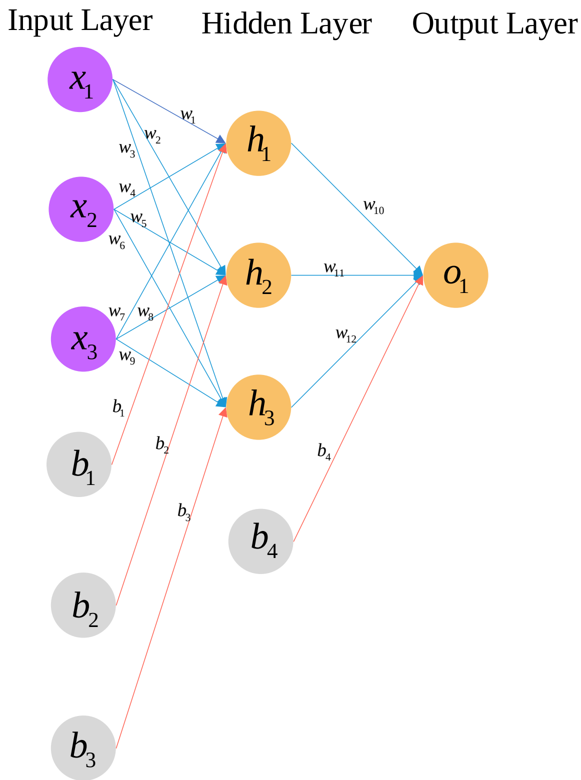

Figure 2: Two-layer neural network.

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

First, the output of the network o_1 is obtained. Then, the network uses back propagation (BP) [73] 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 the layers of a neural network is over 3, it is also referred to as a deep neural network. Specifically, stacked auto-encoder (SAR) [72] and deep belief network (DBN) [16, 71] are typical deep neural networks. They used stacked layers in an unsupervised manner to train the models and obtain good performance. However, these networks were not simple to implement and need a lot of manual settings to achieve an optimal model. Owing to this reason, end-to-end connected networks, especially CNN, were proposed [208]. CNNs have wide applications in the field in image processing, especially image denoising, and they are presented in detail in next section.

2.3. Convolutional neural networks for image denoising

Due to plug-and-play network architectures, CNNs have obtained great success in image processing [221, 131]. As pioneers of CNNs, LeNet [102] used convolutional kernels of different sizes to extract features and obtain good performance in image classification. However, due to the activation function, Sigmoid, LeNet had a slow convergence speed, which was a shortcoming for real applications.

After LeNet, the proposed AlexNet [98] was a milestone for deep learning. Its success had the following reasons. Firstly, graphics processing unit (GPU) [139] provided strong computational ability. Secondly, random clipping (i.e. dropout) can solve the overfitting problem. Thirdly, ReLU [143] can improve the speed of stochastic gradient descent (SGD) rather than Sigmoid [20]. Fourthly, data augmentation method can further address the overfitting problem. Although AlexNet has obtained good performance, it could result in high memory due to big convolutional kernels. That limited applications in the real world, such as smart cameras. After that, deeper network architectures with small filters were preferred to improve the performance and reduce computational costs from 2014 to 2016. Specifically, VGG [166] used stacked more convolutions with of small kernel size to win the ImageNet large scale visual recognition (LSVR) challenge 2014 via stacked more convolutions with of small kernels. To give an example, we use Fig. 3 to visually show the network architecture.

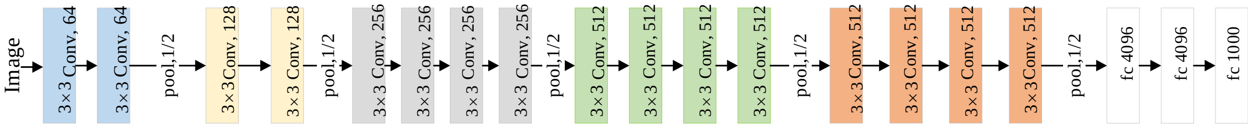

Figure 3: Network architecture of VGG.

On the top of deeper networks, increasing the width was very popular. GoogleNet [173] increased the width to improve the performance for image applications. Moreover, the GoogleNet transformed a big convolutional kernel into two small convolution kernels to reduce the number of parameters and computational cost. Additionally, the GoogLeNet used the inception module [118] as well as Inception 1. Its visual network figure was descripted in Fig. 4.

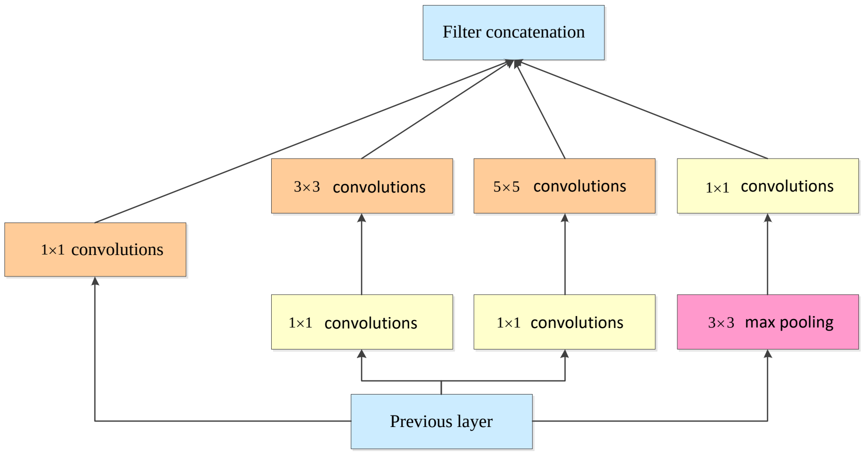

Figure 4: Network architecture of GoogLeNet (Inception 1).

Although VGG and GoogLeNet methods are effective for image applications, they are faced with the following drawbacks: (1) if network is very deep, this network may result in vanishing or exploding gradients. (2) If network is very wide, it may encounter overfitting phenomenon. For overcoming these problems, ResNet [68] was proposed in 2016. That is, each block was added residual learning operation in the ResNet to improve the performance of image recognition, which also won ImageNet LSVR 2015. Here we use Fig. 5 to visually show the idea of the residual learning.

Since 2014, deep networks have been widely used in the fields of image application in real

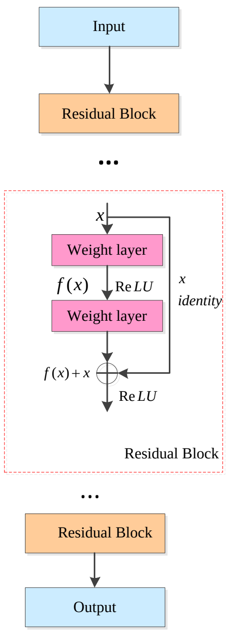

Figure 5: Network architecture of ResNet.

world. However, captured images of many applications, such as real noisy images are not enough, deep CNNs have poor performance of image applications. Generative Adversarial Networks (GAN) [156] was developed based on this reason. The GAN had two networks: generative and discriminative networks. The generative network (also referred to as generator) is used to generate samples, according to input samples. The other network (also as well as discriminator) is used to judge truth of both input samples and generated samples. Two networks are adversarial. It is noted that if the discriminator can accurately distinguish real samples and generate samples from generator, the trained model is regarded to finishing. The network architecture of the GAN can be seen in Fig. 6. Due to the strong ability of constructing supplement training samples, the GAN is very effective for small sample tasks, such as face recognition [183] and complex noisy image denoising [28].

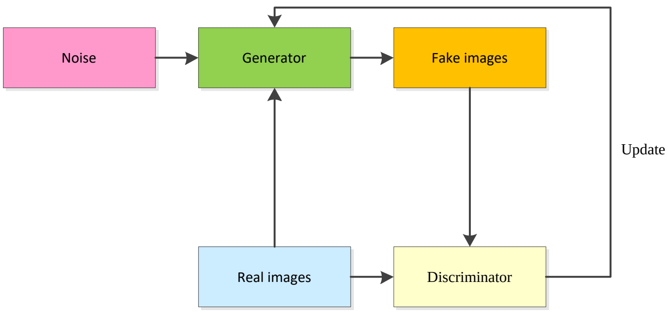

Figure 6: Network architecture of GAN.

2.4. *Hardware and software of deep learning techniques*

One reason of the success of deep learning is GPU. The GPU uses CUDA [146], OpenCL [170] and Cudnn [33] to obtain stronger parallel computing ability, which exceeds 10-30 times than CPU in speed. The CPU consists of a NVIDIA consumer (i.e. GTX 680, GTX 980, GTX 1070, GTX 1070Ti, GTX1080, GTX 1080Ti, RTX 2070, RTX 2080 and RTX 2080Ti), NVIDIA (i.e. Tesla K40c, Tesla K80, Quadro M6000, Quadro GP100, Quadro P6000 and Tesla V100) and AMD (i.e. Radeon Vega 64 and FE) [99].

Another important factor of deep learning techniques is software. The software can provide some interfaces to call GPU and allow the users to implement functions, according to their demands. Further, the popular software packages are presented as follows:

(1) Caffe [85] based on C++ is clear and efficient for deep learning. It provides C++, Python and Matlab interfaces, which can also run on both CPU and GPU, respectively. It is widely used for object detection task. However, the Caffe requires developers to master strong C++ basic knowledge.

(2) Theano [17] is a compiler of math expressions to deal with large-scale neural networks. The Theano provides Python interface and it is used in image super-resolution, denoising and classification in general.

(3) Matconvnet [186] offers Matlab interface. It is usually utilized in image classification, denoising and super-resolution, and video tracking. However, it requires users to expertly master Matlab.

(4) Tensorflow [1] is relatively high-order machine learning libraries. It is also faster than Theano for compilation. The Tensorflow offers C++ and Python interfaces. It is suitable to object detection, image classification, denoising and super-resolution and so on.

(5) Keras [36] based on Tensorflow and Theano is implemented by Python. The Keras offers Python interface. It can be applied in image classification, object detection, image resolution, image denoising and action recognition.

(6) Pytorch [152] is implemented by Python. The Pytorch presents Python interface. Additionally, it is employed in image classification, object detection, image segment, action recognition, image super-resolution, image denoising and video tracking.

3. Deep learning techniques in image denoising

3.1. *Deep learning techniques for additive white noisy-image denoising*

Due to insufficiency of real noisy images, additive white noisy images (AWNI) have been widely used to train the denoising model [91]. The AWNI includes Gaussian, Poisson, Salt, Pepper and multiplicative noisy images [48]. Moreover, there are a lot of deep learning techniques (i.e. CNN/NN, the combination of CNN/NN and common feature extraction methods and the combination of optimization method and CNN/NN) for AWNI denoising.

3.1.1. *CNN/NN for AWNI denoising*

Automatic feature extraction methods are important to reduce computational costs for image applications [207, 159, 129]. CNNs based on this reason are developed for image denoising [140, 120]. Zhang et al. [222] proposed a model as well as DnCNN to deal with multiple low-level

Table 1: CNN/NN for AWNI denoising.

References	Methods	Applications	Key words (remarks)
Zhang et al. (2017) [222]	CNN	Gaussian image denoising, super-resolution and JPEG deblocking	CNN with residual learning, and BN for image denoising
Wang et al. (2017) [190]	CNN	Gaussian image denoising	CNN with dilated convolutions, and BN for image denoising
Bae et al. (2017) [12]	CNN	Gaussian image denoisng, super-resolution	CNN with wavelet domain, and residual learning (RL) for image restoration
Jin et al. (2017) [90]	CNN	Medical (X-ray) image restoration	Improved Unet from iterative shrinkage idea for medical image restoration
Tai et al. (2017) [174]	CNN	Gaussian image denoisng, super-resolution and JPEG deblocking	CNN with recursive unit, gate unit for image restoration
Anwar et al. (2017) [11]	CNN	Gaussian image denoisng	CNN with fully connected layer, RL and dilated convolutions for image denoising
McCann et al. (2017)] [91]	CNN	Inverse problems (i.e. denoising, deconvolution, super-resolution)	CNN for inverse problems
Ye et al. (2018) [209]	CNN	Inverse problems(i.e. Gaussian image denoising, super-resoluion)	Signal processing ideas guide CNN for inverse problems
Yuan et al. (2018) [214]	CNN	Hyper-spectral image denoising	CNN with multiscale, multilevel features techniques for hyper-spectral image denoising
Jiang et al. (2018) [87]	CNN	Gaussian image denoising	Multi-channel CNN for image denoising
Chang et al. (2018) [25]	CNN	Hyper-spectral image (HSI) denoising, HIS restoration	CNN consolidated spectral and spatial coins for hyper-spectral image denoising
Jeon et al. (2018) [82]	CNN	Speckle noise reduction from digital holographic images	Speckle noise reduction of digital holographic image from Multi-scale CNN
Gholizadeh-Ansari et al. (2018) [56]	CNN	Low-dose CT image denoising, X-ray image denosing	CNN with dilated convolutions for low-dose CT image denoising
Uchida et al. (2018) [185]	CNN	Non-blind image denoising	CNN with residual learning for non-blind image denoising
Xiao et al. (2018) [195]	CNN	Stripe noise reduction of infrared cloud images	CNN with skip connection for infrared-cloud-image denoising
Chen et al. (2018) [30]	CNN	Gaussian image denoisng, blind denoising	CNN based on RL and perceptual loss for edge enhancement
Yu et al. (2018) [213]	CNN	Seismic, random, linear and multiple noise reduction of images	A survey on deep learning for three applications
Yu et al. (2018) [212]	CNN	Optical coherence tomography (OCT) image denoising	GAN with dense skip connection for optical coherence tomography image denoising
Li et al. (2018) [107]	CNN	Ground-roll noise reduction	An overview of deep learning techniques on ground-roll noise
Abbasi et al. (2018) [2]	CNN	OCT image denoising	Fully CNN with multiple inputs, and RL for OCT image denoising
Zarshenas et al. (2018) [218]	CNN	Gaussian noisy image denoising	Deep CNN with internal and external residual learning for image denoising
Chen et al. (2018) [26]	CNN	Gaussian noisy image denoising	CNN with recursive operations for image denoising
Panda et al. (2018) [149]	CNN	Gaussian noisy image denoising	CNN with exponential linear units, and dilated convolutions for image denoising
Sheremet et al. (2018) [163]	CNN	Image denoising from info-communication systems	CNN on image denoising from info-communication systems
Chen et al. (2018) [27]	CNN	Aerial-image denoising	CNN with multi-scale technique, and RL for aerial-image denoising
Pardasani et al. (2018) [150]	CNN	Gaussian, poisson or any additive-white noise reduction	CNN with BN for image denoising
Couturier et al. (2018) [37]	NN	Gaussian and multiplicative speckle noise reduction	Encoder-decoder network with multiple skip connections for image denoising
Park et al. (2018) [151]	CNN	Gaussian noisy image denoising	CNN with dilated convolutions for image denoising
Priyanka et al. (2019) [155]	CNN	Gaussian noisy image denoisng	CNN with symmetric network architecture for image denoising
Lian et al. (2019) [171]	CNN	Poisson-noise-image denoising	CNN with multi scale, and multiple skip connections for Poisson image denoising
Tripathi et al. (2018) [184]	CNN	Gaussian noisy image denoising	GAN for image denoising
Zheng et al. (2019) [234]	CNN	Gaussian noisy image denoising	CNN for image denoising
Remez et al. (2018) [158]	CNN	Gaussian and Poisson image denoising	CNN for image denoising

vision tasks, i.e. image denoising, super-resolution and deblocking through CNN, batch normalization [78] and residual learning techniques [68]. Wang et al. [190], Bae et al. [12] and Jifara et al. [90] also presented a residual learning and deeper CNN for image denoising, respectively. However, deeper CNN technique depended on deeper layer rather than shallow layer, which resulted in long-term dependency problem. To tackle this problem, a lot of signal-base methods were proposed. Tai et al. [174] exploited recursive and gate units to adaptively mine more accurate features and recover clean images. Inspired by low-rank Hankel matrix in low-level vision, Ye et al. [209] 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), a lot of recent works try to extract more useful information by improved CNN [25, 70, 212, 125]. For example, Yuan et al. [214] combined deep CNN, residual learning and multiscale knowledge to remove the noise from hyperspectral-noisy images. However, using these operations may increase computational costs and memory consumption, which was not optimistic for real applications. For addressing the phenomenon, Gholizadeh et al. [56] utilized dilated convolutions [55] to enlarge receptive field and reduce depth of network at no bring extra cost for CT image denoising. Lian et al. [171] proposed a residual network via multi-scale cross-path concatenation to suppress the noise. It is known from most of methods above relied on improved CNNs to deal with the noise. Thus, designing network architectures is important for image denoising [151, 107].

Changing network architectures has the following ways in general [213, 135]: (1) fusing features from multiple inputs of a CNN. (2) Changing the loss function. (3) Increasing depth or width of the CNN. (4) Adding some auxiliary plug-ins into CNNs. 5) Using skip connections or cascade operations into CNNs. Specifically, the first way included three types: 1) different parts of one sample as multiple inputs from different networks [2]. 2) Different perspectives for the one sample as input, such as multiple scales [82, 27]. 3) Different channels of a CNN as input [87]. The second way mainly designed different loss function according to characteristic of nature images to extract more robust features [9]. For example, Chen et al. [30] jointed Euclidean and perceptual loss functions to mine more edge information for image denoising. The third way enlarged receptive field size to improve denoising performance via increasing the depth or width of network [185, 218, 163]. The fourth way applied plug-ins, i.e. activation function, dilated convolution, fully connected layer and pooling operations to enhance the expressive ability of the CNN [149, 155, 150]. The final way utilized skip connections [195, 26, 37, 11] or cascade operations [171, 32] to provide complementary information for deep layer in CNN. Table 1 provides an overview of CNNs for AWNI denoising.

3.1.2. CNN/NN and common feature extraction methods for AWNI denoising

Feature is used to represent the whole image in image processing, and it is important for machine learning [116, 130, 205]. However, deep learning technique is black box, and cannot choose features, which cannot guarantee obtained features are the most robust [164, 192]. Motivated by this reason, common feature extraction method embedded into CNN was conducted in image denoising. That can be divided into five categories: weak edge-information, non-linear, high dimensional and non-salient noisy images, and high computational costs.

For weak edge-information noisy images, CNN with transformation domain method including Guan et al. [63], Li et al. [109], Liu et al. [123], Latif et al. [100] and Yang et al. [204] was very popular to remove the noise. Specifically, in [123], it used wavelet method and U-net to eliminate the gridding effect of dilated convolutions on enlarging receptive field for image restoration.

For non-linear noisy images, CNN with kernel method was useful [13, 203]. These methods had three steps in general [142]. First step used CNN to extract features. Second step utilized kernel method to convert obtained non-linear features into linearity. Final step exploited the RL to construct the latent clean image.

For high dimensional noisy images, the combination of CNN and dimensional reduction method were proposed [197, 65]. For example, Khaw et al. [95] used CNN with principal component analysis (PCA) for image denoising. This had three phases. First phase used convolution operations to extract features. Second phase utilized the PCA to reduce the dimension of obtained features. Final phase employed convolutions to deal with obtained features from the PCA and reconstruct a clean image.

For non-salient noisy images, signal processing idea can guide CNN to extract salient features [83, 92, 157, 2]. Specifically, skip connection operation was a typically operation of signal processing [92].

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

References	Methods	Applications	Key words (remarks)
Bako et al. (2017) [171]	CNN	Monte Carlo-rendered images denoising	CNN with kernel method for estimating noise piexls
Ahn et al. (2017) [7]	CNN	Gaussian image denoising	CNN with NSS for image denoising
Khaw et al. (2017) [95]	CNN	Impulse noise reduction	CNN with PCA for image denoising
Vogel et al. (2017) [187]	CNN	Gaussian image denoising	U-net with multi scales technique for image denoising
Mildenhall et al. (2018) [142]	NN	Low-light synthetic noisy image denoising, real noise	Encoder-decoder with multi scales, and kernel method for image denoising
Liu et al. (2018) [123]	CNN	Gaussian image denoisng, super-resolution and JPEG deblocking	U-net with wavelet for image restoration
Yang et al. (2018) [204]	CNN	Gaussian image denoisng	CNN with BM3D for image denoising
Guo et al. (2018) [65]	CNN	Image blurring and denoising	CNN with RL, and sparse method for image denoising
Jia et al. (2018) [83]	CNN	Gaussian image denoisng	CNN with multi scales, and dense RL operations for image denoising
Ran et al. (2018) [157]	CNN	OCT image denoising, OCT image super-resolution	CNN with multi views for image restoration
Li et al. (2018) [140]	CNN	Medical image denoising, stomach pathological image denoising	CNN consolidated wavelet for medical image denoising
Ahn et al. (2018) [8]	CNN	Gaussian image denoisng	CNN with NSS for image denoising
Xie et al. (2018) [197]	CNN	Hyper-spectral image denoising	CNN with RL, and PCA for low-dose CT image denoising
Kadimesetty et al. (2019) [92]	CNN	Low-Dose computed tomography (CT) image denoising	CNN with RL, batch normalization (BN) for medical image denoising
Guan et al. (2019) [63]	CNN	Stripe noise reduction	CNN with wavelet-image denoising
Abbasi et al. (2019) [2]	NN	3D magnetic resonance image denoising, medical image denoising	GAN based on encoder-decoder and RL for medical denoising
Xu et al. (2019) [203]	CNN	Synthetic and real noisy and video denoising	CNN based on deformable kernel for image and video denoising

For high computational cost tasks, CNN with nature of image was very effective to decrease complex [2, 8, 7]. For example, Ahn et al. [7] used CNN with NSS to filter the noise, where similar characteristics of the given noisy image can accelerate speed of extraction feature and reduce computational cost.

More detailed information of these methods mentioned are summarized in Table 2.

3.1.3. The combination of optimization method and CNN/NN for AWNI denoising

It is known that machine learning uses optimization techniques [76, 114] and discriminative learning methods [110, 121] to deal with image applications in general. Although optimization methods have good performance on different low-level vision tasks, these methods need manual setting parameters, which were time-consuming. The discriminative learning methods have fast speed in image restoration. However, they are not flexible for various low-level vision tasks. To make a tradeoff between efficiency and flexibility, discriminative learning optimization-based method [141, 18] was presented for image applications, such as image denoising. The CNN with prior knowledge via regular term of loss function is common method in image denosing [74], which can mainly divide two categories to filter the noise: 1) improvement of denoising speed. 2) Improvement of denoising performance.

For improving denoising speed, optimization method cooperated CNN was a good tool to rapidly find optimal solution in image denoising [35, 51]. For example, a GAN with maximum a posteriori (MAP) was used to estimate the noise and deal with other tasks, such as image inpainting and super-resolution [210]. An experience-based greedy and transfer learning strategies with CNN can accelerate genetic algorithm to obtain a clean image [122]. Noisy image and noise level mapping were as inputs of CNN, which had faster execution in predicting the noise [178].

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

References	Methods	Applications	Key words (remarks)
Hong et al. (2018) [74]	CNN	Gaussian image denoising	Auto-Encoder with BN, and ReLU for image denoising
Cho et al. (2018) [35]	CNN	Gaussian image denoising	CNN with separable convolution, and gradient prior for image denoising
Fu et al. (2018) [51]	CNN	Salt and pepper noise removal	CNN with non-local switching filter for salt and pepper noise
Yeh et al. (2018) [210]	CNN	Image denoising super-resolution and inpainting	GAN with MAP for image restoration
Liu et al. (2018) [122]	CNN	Medical image denoising, computed tomography perfusion for image denoising	CNN with genetic algorithm for medical image denoising
Tassano et al. (2019) [178]	CNN	Gaussian image denoisng	CNN with noise level, upscaling, downscaling operation for image denoising
Heckel et al. (2018) [69]	CNN	Image denoisng	CNN with deep prior for image denoising
Jiao et al. (2017) [89]	CNN	Gaussian image denoisng, image inpainting	CNN with inference, residual operation for image restoration
Wang et al. (2017) [189]	CNN	Image denoising	CNN with total variation for image denoising
Li et al. (2019) [113]	CNN	Image painting	CNN with split Bregman iteration algorithm for image painting
Sun et al. (2018) [172]	CNN	Gaussian image denoisng	GAN with skip-connections, and ResNet blocks for image denoising
Zhi et al. (2018) [235]	CNN	Gaussian image denoising	GAN with multiscale for image denoising
Du et al. (2018) [44]	CNN	Gaussian image denoising	CNN with wavelet for medcial image restoration
Liu et al. (2019) [126]	CNN	Gaussian image denoising, real noisy image denoising, rain removal	Dual CNN with residual operations for image restoration
Khan et al. (2019) [94]	CNN	Symbol denoising	CNN with quadrature amplitude modulation for symbol denoising
Zhang et al. (2019) [229]	CNN	Image Possian denoising	CNN with variance-stabilizing transformation for poisson denoising
Cruz et al. (2018) [38]	CNN	Gaussian image denoising	CNN with nonlocal filter for image denoising
Jia et al. (2019) [84]	CNN	Gaussian image denoising	CNN based on a fractional-order differential equation for image denoising

For improving the denoising performance, CNN combined optimization methods to make noisy image smooth [69, 58, 89]. CNN with total variation (TV) reduced the effect of noise pixels [189]. Spliting Bregman iteration algorithm and CNN [113] can enhance pixels through image depth to obtain the latent clean image. A dual-stage CNN with feature matching can better recover the detailed information of the clean image, especially noisy images [172]. The GAN with nearest neighbor had good effect between noisy and clean images, and filtered the noisy image [235]. Wavefront coding jointed CNN to enhance pixels of latent clean image via transform domain [44]. Additionally, there are other excellent denoising methods as shown in [126, 94, 59]. Table 3 shows that detailed information of the combination of optimization method and CNN/NN in AWNI denoising.

3.2. Deep learning techniques for real noisy image denoising

The main focus of real applications on deep learning for image denoising has two kinds: single end-to-end CNN and the combination of prior knowledge and CNN.

For the first method, changing the network architecture is popular to remove the noise from the given real corrupted image. Multiscale is very effective for image denoising. For example, a CNN comprising of convolution, ReLU and RL employed different phase features to enhance the expressive ability of the low-light image denoising model [177]. To overcome the blurry and false image artifacts, a dual U-Net with skip connection was proposed for CT image reconstruction [66]. To address resource-constraint problem, Tian et al. [182] used a dual CNN with batch renormalization [77], RL and dilated convolutions to deal with real noisy image. According to the nature of light image, two CNNs utilized anisotropic parallax analysis to generate structural parallax information for real noisy images [29]. Additionally, using CNN to resolve remote sense [86] and medical images [96] under low-light condition is very effective [88]. To extract more detailed information, recurrent connections were used to enhance the representative ability to deal with corrupted image in the real world [57, 232]. To deal with unknown real noisy images, a residual structure was utilized to facilitate low-frequency features, then, an attention mechanism [181] can be applied to extract more potential features from channels [10]. From the point of view of producing the noisy image, imitating cameral pipelines to construct the degradation model was very effective to filter the real noisy [80]. Detailed information of these researches can be shown in Table 4.

Table 4: CNNs for real noisy image denoising.

References	Methods	Applications	Key words (remarks)
Tao et al. (2019) [177]	CNN	Real noisy image denoising, low-light image enhancement	CNN with ReLU, and RL for real noisy image denoising
Chen et al. (2018) [28]	CNN	Real noisy image denoising, blind denoising	GAN for real noisy image denoising
Han et al. (2018) [66]	CNN	CT image reconstruction	U-Net with skip connection for CT image reconstruction
Chen et al. (2018) [29]	CNN	Real noisy image denoising	CNNs with anisotropic parallax analysis for real noisy image denoising
Jian et al. (2018) [86]	CNN	Low-light remote sense image denoising	CNN for image denoising
Khoroushadi et al. (2019) [96]	CNN	Medical image denoising, CT image denoising	CNN for image denoising
Jiang et al. (2018) [88]	CNN	Low-light image enhancement	CNN with symmetric pathways for low-light image enhancement
Godard et al. (2018) [57]	CNN	Real noisy image denoising	CNN with recurrent connections for real noisy image denoising
Zhao et al. (2019) [232]	CNN	Real noisy image denoising	CNN with recurrent conncetions for real noisy image denoising
Anwar et al. (2019) [10]	CNN	Real noisy image denoising	CNN with RL, attention mechanism for real noisy image denoising
Jaroensri et al. (2019) [191]	CNN	Real noisy image denoising	CNN for real noisy image denoising
Green et al. (2018) [60]	CNN	CT image denoising, real noisy image denoising	CNN for real noisy image denoising
Brooks et al. (2019) [21]	CNN	Real noisy image denoising	CNN with image processing pipeline for real noisy image denoising
Tian et al. (2020) [182]	CNN	Gaussian image denoising and real noisy image denoising	CNN with BRN, RL and dilated convolutions for image denosing
Tian et al. (2020) [181]	CNN	Gaussian image denoising, blind denoising and real noisy image denoising	CNN with attention mechanism and sparse method for image denoising

For the second method, combining CNN and prior can better deal with both speed and complex noise task in real noisy image. Zhang et al. [223] proposed to use half quadratic splitting (HQS) and CNN to estimate the noise from the given real noisy image. After that, Guo et al. [64] proposed a three-phase denoising method. The first phase used Gaussian noise and in-cameral processing pipeline to synthesize noisy image. The synthetic and real noisy images are merged to better represent real noisy images. The second phase used sub-network with asymmetric and total variation losses to estimate the noise of real noisy image. The third phase exploited original noisy image and estimated noise to recover the latent clean image. Additionally, CNN with channel prior was effective for low-light image enhancement [176]. To make readers easily observe, we use Table 5 to show the detailed information of these researches.

Table 5: CNNs for real noisy image denoising.

References	Methods	Applications	Key words (remarks)
Zhang et al. (2017) [223]	CNN	Real-noisy image denoising	CNN with HQS for real noisy image
Guo et al. (2019) [64]	CNN	Real-noisy image denoising	CNN and cameral processing pipeline for real noisy image
Tao et al. (2019) [176]	CNN	Low-light image enhancement	CNN with channel prior for low-light image enhancement
Ma et al. (2018) [134]	CNN	Tomography image denoising	GAN with edge-prior for CT image denoising
Yue et al. (2018) [216]	CNN	Real-noisy image denoising, blind denoising	CNN with variational inference for blind denoising and real-noisy image denoisng
Song et al. (2019) [169]	CNN	Real noisy image denoising	CNN with dynamic residual dense block for real noisy image denoising
Lin et al. (2019) [117]	CNN	Real noisy image dneoising	GAN with attentive mechanism and noise domain for real noisy image denoising

3.3. Deep learning techniques for blind denoising

In the real world, the image is easily corrupted and noise is complex. Thus, blind denoising technique is important [128]. At first, FFDNet [224] used noise level and noise as the input of CNN to train a denoiser for unknown noisy image. Then, scholars proposed a lot of methods to solve blind denoisng problem. According to the mechanism of image device, Kenzo et al. [79] utilized soft shrinkage to adjust the noise level for blind denoising. For unpaired noisy image, using CNNs to estimate noise became a good tool [168]. Yang et al. [206] used known noise level to train a denoiser, then, they utilized this denoiser to estimate the level of noise. For random noise attenuation problem, CNN with RL was used to filter complex noise [220, 165]. Additionally, changing network architecture can promote the denoising performance for blind denoising. Majumdar et al. [137] presented to use auto-encoder to tackle unknown noise. For mixed noise, cascaded CNNs were effective to remove the AWAG and impulse noise, respectively [4]. To clear show these denoising methods, Table 6 is designed as follows.

Table 6: Deep learning techniques for blind denoising.

References	Methods	Applications	Key words (remarks)
Zhang et al. (2018) [224]	CNN	Blind denoising	CNN with varying noise level for blind denoising
Kenzo et al. (2018) [79]	CNN	Blind denoising	CNN with soft shrinkage for blind denoising
Soltanayev et al. (2018) [168]	CNN	Blind denoising	CNN for unpaired noisy images
Yang et al. (2017) [206]	CNN	Blind denoising	CNNs with RL for blind denoising
Zhang et al. (2018) [220]	CNN	Blind denoising, random noise	CNN with RL for blind denoising
Si et al. (2018) [165]	CNN	Blind denoising, random noise	CNN for image denoising
Majumdar et al. (2018) [88]	NN	Blind denoising	Auto-encoder for blind denoising
Abiko et al. (2019) [57]	CNN	Blind denoising, complex noisy image denoising	cascaded CNNs for blind denoising
Cha et al. (2019) [206]	CNN	Blind denoising	GAN for blind image denoising

3.4. Deep learning techniques for hybrid noisy image denoising

In the real world, the captured images were affected by complex environments. Motivated by that, hybrid-noisy-image denoising techniques were proposed. Li et al. [111] proposed the combination of CNN and warped guidance to resolve the noise, blur, JPEG compression questions. Zhang et al. [225] used a model to deal with multiple degradations, such as noise, blur kernel and low-resolution image. To enhance the raw sensor data, Kokkinos et al. [97] presented residual CNN with iterative algorithm for image demosaicking and denoising. To handle arbitrary blur kernels, Zhang et al. [226] proposed to use cascaded deblurring and SISR networks to recover plug-and-play super-resolution image. These hybrid noisy image denoising methods are presented in Table 7 as follows.

Table 7: Deep learning techniques for hybrid noisy image denoising.

References	Methods	Applications	Key words (remarks)
Li et al. (2018) [111]	CNN	Noise, blur kernel, JPEG compression	The combination of CNN and warped guidance for multiple degradations
Zhang et al. (2018) [225]	CNN	Noise, blur kernel, low-resolution image	CNN for multiple degradations
Kokkinos et al. (2019) [97]	CNN	Image demosaicking and denoising	Residual CNN with iterative algorithm for image demosaicking and denoising

4. Experimental results

4.1. Datasets

4.1.1. Training Datasets

Training Datasets are divided into two categories: gray- and color- noisy images. Gary noisy image datasets can be used to train Gaussian denoiser and blind denoiser. They included BSD400 [19] and Waterloo Exploration Database [133]. The BSD400 was composed of 400 images with format of '.png'. And this dataset was cropped into size of 180×180 for training a denoisng model. The Waterloo Exploration Database consisted of 4,744 nature images with format of '.png'. Color noisy image included BSD432 [222], Waterloo Exploration Database and polyU-Real-World-Noisy-Images dataset [198]. Specifically, the polyU-Real-World-Noisy-Images consisted of 100 real noisy images. The 100 real noisy images were obtained by five cameras, such as Nikon D800, Canon 5D Mark II, Sony A7 II, Cannon 80D and Canon 600D with size of $2,784 \times 1,856$.

4.1.2. Test Datasets

Test Datasets included gray- and color- noisy image datasets. The gray noisy image dataset was composed of Set12 and BSD68 [222]. The Set12 had 12 different scenes. The BSD68 had 68 different nature images. They were used to test the Gaussian denoiser, denoiser of blind noise. The color noisy image dataset included CBSD68, Kodak24 [50], McMaster [227], cc [144], DND [154], NC12 [101], SIDD [3] and Nam [144]. The Kodak24 and McMaster contained 24 and 18 color noisy images, respectively. The cc was composed of 15 real noisy image of different ISO, i.e. 1,600, 3,200 and 6,400. The DND contained 50 real noisy image and the clean images were captured by low-ISO images. The NC12 had 12 noisy images and it did not ground-truth clean image. The SIDD was real noisy images from smart phones, which consisted of 320 image pairs of noisy and ground-truth images. The Nam included 11 different scenes, where was saved as the format of 'JPEG'.

4.2. Experimental results

To verify the denoising performance of some methods above in Section 3, we conduct some experiments on Set12, BSD68, CBSD68, Kodak24, McMaster, DND, SIDD, Nam, cc and NC12 in terms of quantitative and qualitative evaluations. The quantitative evaluation mainly uses peak signal to noise ration (PSNR) [75] values of different denoisers to test the denoising effects. Additionally, we use running time of denoising of an image to support the PSNR for quantitative evaluation. The qualitative evaluation uses some visual figures to show the recovered clean images. The more information of quantitative and qualitative analysis is given in next subsections.

4.2.1. Deep learning techniques for additive white noisy-image denoising

It is known that denoising methods should be compared in the same standard. However, additive white noise include Gaussian, Poisson, low-light noise, salt and pepper noise with different noise levels has big difference. Also, different tools of different methods have influence on denoising results. For the reasons above, we choose typical Gaussian noise to test the denoising performance of different methods. Additionally, most of denoising methods use PSNR as quantitative index. Thus, we use the BSD68, Set12, CBSD68, Kodak24 and McMaster to test the denoising performance of deep learning techniques for additive white noisy-image denoising as follows. For quantitative analysis, Table 8 shows that PSNR values of different networks with different noise levels for gray additive white noisy image denoising. To test the ability of dealing with single gray additive white noisy image from different networks, the Set12 is used to conduct experiments as illustrated in Table 9. Table 10 proves the denoising performance of different methods for color additive white noisy image denoising. Additionally, we use Table 11 to present the efficiency of different methods for image denoising. For qualitative analysis, we magnify one area in the latent clean image from different methods as observation. As shown Figs. 7-10, the observed area is clearer, the corresponding method has better denoising performance.

4.2.2. Deep learning techniques for real-noisy image denoising

For testing the denoising performance of deep learning techniques for real-noisy image, the public datasets, such as DND, SIDD, Nam and CC are chosen to design experiments. Because

Table 8: PSNR (dB) of different methods on the BSD68 for different noise levels (i.e. 15, 25 and 50).

Methods	15	25	50
BM3D [39]	31.07	28.57	25.62
WNNM [62]	31.37	28.83	25.87
EPLL [237]	31.21	28.68	25.67
MLP [22]	-	28.96	26.03
CSF [162]	31.24	28.74	29.11
TNRD [31]	31.42	28.92	25.97
ECNDNet [179]	31.71	29.22	26.23
RED [138]	-	-	26.35
DnCNN [222]	31.72	29.23	26.23
DDRN [190]	31.68	29.18	26.21
PHGMS [12]	31.86	-	26.36
MemNet [174]	-	-	26.35
EEDN [30]	31.58	28.97	26.03
NBCNN [185]	31.57	29.11	26.16
NNC [218]	31.49	28.88	25.25
ELDRN [149]	32.11	29.68	26.76
PSN-K [9]	31.70	29.27	26.32
PSN-U [9]	31.60	29.17	26.30
DDFN [37]	31.66	29.16	26.19
CIMM [11]	31.81	29.34	26.40
DWDN [109]	31.78	29.36	-
MWCNN [123]	31.86	29.41	26.53
BM3D-Net [204]	31.42	28.83	25.73
MPFE-CNN [92]	31.79	29.31	26.34
IRCNN [223]	31.63	29.15	26.19
FFDNet [224]	31.62	29.19	26.30
BRDNet [182]	31.79	29.29	26.36
ETN [189]	31.82	29.34	26.32
ADNet [181]	31.74	29.25	26.29
NN3D [38]	-	-	26.42
FOCNet [84]	31.83	29.38	26.50

the ground-truth clean images from the NC12 are unavailable, we give up the NC12. Also, to make readers better understand these methods, we add some traditional denoising methods such as BM3D as comparative methods. From Tables 12 and 13, we can see that the DRDN obtains the best results on the DND and SSID in real-noisy image denoising, respectively. For compressed noisy images, the AGAN obtains excellent performance as listed in Table 14. For real noisy images of different ISO values, the SDNet and BRDNet achieve the best and second denoising performance, respectively, as descripted in Table 15.

4.2.3. Deep learning techniques for blind denoising

It is known that noise is ruleless and complex in the real world. Thus, blind denoising techniques, especially deep learning techniques are developed. For this reason, comparing the denoising performance of different deep learning techniques is very meaningful. The state-of-the-art denoising methods such as DnCNN, FFDNet, SCNN and G2G1 on the BSD68 and Set12 are chosen to design experiments. As shown in Tables 16 and 17, the FFDNet is superior to other methods in blind denoising.

4.2.4. Deep learning techniques for hybrid-noisy-image denoising

In the real world, the corrupted image may include multi noise [67], which is very hard to recover the latent clean image. For resolving this problem, base multi-degradation idea deep

Table 9: PSNR (dB) of different methods on the Set12 for different noise levels (i.e. 15, 25 and 50).

Images	C.man	House	Peppers	Starfish	Monarch	Airplane	Parrot	Lena	Barbara	Boat	Man	Couple	Average
Noise Level	$\sigma = 15$												
BM3D [39]	31.91	34.93	32.69	31.14	31.85	31.07	31.37	34.26	33.10	32.13	31.92	32.10	32.37
WNNM [62]	32.17	35.13	32.99	31.82	32.71	31.39	31.62	34.27	33.60	32.27	32.11	32.17	32.70
EPLL [237]	31.85	34.17	32.64	31.13	32.10	31.19	31.42	33.92	31.38	31.93	32.00	31.93	32.14
CSF [162]	31.95	34.39	32.85	31.55	32.33	31.33	31.37	34.06	31.92	32.01	32.08	31.98	32.32
TNRD [31]	32.19	34.53	33.04	31.75	32.56	31.46	31.63	34.24	32.13	32.14	32.23	32.11	32.50
ECNDNet [179]	32.56	34.97	33.25	32.17	33.11	31.70	31.82	34.52	32.41	32.37	32.39	32.39	32.81
DnCNN [222]	32.61	34.97	33.30	32.20	33.09	31.70	31.83	34.62	32.64	32.42	32.46	32.47	32.86
PSN-K [9]	32.58	35.04	33.23	32.17	33.11	31.75	31.89	34.62	32.64	32.52	32.39	32.43	32.86
PSN-U [9]	32.04	35.03	33.21	31.94	32.93	31.61	31.62	34.56	32.49	32.41	32.37	32.43	32.72
CIMM [11]	32.61	35.21	33.21	32.35	33.33	31.77	32.01	34.69	32.74	32.44	32.50	32.52	32.95
IRCNN [223]	32.55	34.89	33.31	32.02	32.82	31.70	31.84	34.53	32.43	32.34	32.40	32.40	32.77
FFDNet [224]	32.43	35.07	33.25	31.99	32.66	31.57	31.81	34.62	32.54	32.38	32.41	32.46	32.77
BRDNet [182]	32.80	35.27	33.47	32.24	33.35	31.85	32.00	34.75	32.93	32.55	32.50	32.62	33.03
ADNet [181]	32.81	35.22	33.49	32.17	33.17	31.86	31.96	34.71	32.80	32.57	32.47	32.58	32.98
Noise Level	$\sigma = 25$												
BM3D [39]	29.45	32.85	30.16	28.56	29.25	28.42	28.93	32.07	30.71	29.90	29.61	29.71	29.97
WNNM [62]	29.64	33.22	30.42	29.03	29.84	28.69	29.15	32.24	31.24	30.03	29.76	29.82	30.26
EPLL [237]	29.26	32.17	30.17	28.51	29.39	28.61	28.95	31.73	28.61	29.74	29.66	29.53	29.69
MLP [22]	29.61	32.56	30.30	28.82	29.61	28.82	29.25	32.25	29.54	29.97	29.88	29.73	30.03
CSF [162]	29.48	32.39	30.32	28.80	29.62	28.72	28.90	31.79	29.03	29.76	29.71	29.53	29.84
TNRD [31]	29.72	32.53	30.57	29.02	29.85	28.88	29.18	32.00	29.41	29.91	29.87	29.71	30.06
ECNDNet [179]	30.11	33.08	30.85	29.43	30.30	29.07	29.38	32.38	29.84	30.14	30.03	30.03	30.39
DnCNN [222]	30.18	33.06	30.87	29.41	30.28	29.13	29.43	32.44	30.00	30.21	30.10	30.12	30.43
PSN-K [9]	30.28	33.26	31.01	29.57	30.30	29.28	29.38	32.57	30.17	30.31	30.10	30.18	30.53
PSN-U [9]	29.79	33.23	30.90	29.30	30.17	29.06	29.25	32.45	29.94	30.25	30.05	30.12	30.38
CIMM [11]	30.26	33.44	30.87	29.77	30.62	29.23	29.61	32.66	30.29	30.30	30.18	30.24	30.62
IRCNN [223]	30.08	33.06	30.88	29.27	30.09	29.12	29.47	32.43	29.92	30.17	30.04	30.08	30.38
FFDNet [224]	30.10	33.28	30.93	29.32	30.08	29.04	29.44	32.57	30.01	30.25	30.11	30.20	30.44
BRDNet [182]	31.39	33.41	31.04	29.46	30.50	29.20	29.55	32.65	30.34	30.33	30.14	30.28	30.61
ADNet [181]	30.34	33.41	31.14	29.41	30.39	29.17	29.49	32.61	30.25	30.37	30.08	30.24	30.58
Noise Level	$\sigma = 50$												
BM3D [39]	26.13	29.69	26.68	25.04	25.82	25.10	25.90	29.05	27.22	26.78	26.81	26.46	26.72
WNNM [62]	26.45	30.33	26.95	25.44	26.32	25.42	26.14	29.25	27.79	26.97	26.94	26.64	27.05
EPLL [237]	26.10	29.12	26.80	25.12	25.94	25.31	25.95	28.68	24.83	26.74	26.79	26.30	26.47
MLP [22]	26.37	29.64	26.68	25.43	26.26	25.56	26.12	29.32	25.24	27.03	27.06	26.67	26.78
TNRD [31]	26.62	29.48	27.10	25.42	26.31	25.59	26.16	28.93	25.70	26.94	26.98	26.50	26.81
ECNDNet [179]	27.07	30.12	27.30	25.72	26.82	25.79	26.32	29.29	26.26	27.16	27.11	26.84	27.15
DnCNN [222]	27.03	30.00	27.32	25.70	26.78	25.87	26.48	29.39	26.22	27.20	27.24	26.90	27.18
PSN-K [9]	27.10	30.34	27.40	25.84	26.92	25.90	26.56	29.54	26.45	27.20	27.21	27.09	27.30
PSN-U [9]	27.21	30.21	27.53	25.63	26.93	25.89	26.62	29.54	26.56	27.27	27.23	27.04	27.31
CIMM [11]	27.25	30.70	27.54	26.05	27.21	26.06	26.53	29.65	26.62	27.36	27.26	27.24	27.46
IRCNN [223]	26.88	29.96	27.33	25.57	26.61	25.89	26.55	29.40	26.24	27.17	27.17	26.88	27.14
FFDNet [224]	27.05	30.37	27.54	25.75	26.81	25.89	26.57	29.66	26.45	27.33	27.29	27.08	27.32
BRDNet [182]	27.44	30.53	27.67	25.77	26.97	25.93	26.66	29.73	26.85	27.38	27.27	27.17	27.45
ADNet [181]	27.31	30.59	27.69	25.70	26.90	25.88	26.56	29.59	26.64	27.35	27.17	27.07	27.37

learning techniques are proposed, where more information is offered in Section 3.4. Here we introduce the denoising performance of the multi-degradation model as shown in Table 18, where the WarpNet method is very competitive in comparison with other popular denoising methods such as the DnCNN and MemNet.

Table 10: PSNR (dB) of different methods on the CBSD68, Kodak24 and McMaster for different noise levels (i.e. 15, 25, 35, 50 and 75).

Datasets	Methods	$\sigma = 15$	$\sigma = 25$	$\sigma = 35$	$\sigma = 50$	$\sigma = 75$
CBSD68	CBM3D [39]	33.52	30.71	28.89	27.38	25.74
	DnCNN [222]	33.98	31.31	29.65	28.01	-
	DDRN [190]	33.93	31.24	-	27.86	-
	EEDN [30]	33.65	31.03	-	27.85	-
	DDFN [37]	34.17	31.52	29.88	28.26	-
	CIMM [11]	31.81	29.34	-	26.40	-
	BM3D-Net [204]	33.79	30.79	-	27.48	-
	IRCNN [223]	33.86	31.16	29.50	27.86	-
	FFDNet [224]	33.80	31.18	29.57	27.96	26.24
	BRDNet [182]	34.10	31.43	29.77	28.16	26.43
	GPADCNN [35]	33.83	31.12	29.46	-	-
	FFDNet [178]	33.76	31.18	29.58	-	26.57
	ETN [189]	34.10	31.41	-	28.01	-
	ADNet [181]	33.99	31.31	29.66	28.04	26.33
Kodak24	CBM3D [39]	34.28	31.68	29.90	28.46	26.82
	DnCNN [222]	34.73	32.23	30.64	29.02	-
	IRCNN [223]	34.56	32.03	30.43	28.81	-
	FFDNet [224]	34.55	32.11	30.56	28.99	27.25
	BRDNet [182]	34.88	32.41	30.80	29.22	27.49
	FFDNet [178]	34.53	32.12	30.59	-	27.61
	ADNet [181]	34.76	32.26	30.68	29.10	27.40
McMaster	CBM3D [39]	34.06	31.66	29.92	28.51	26.79
	DnCNN [222]	34.80	32.47	30.91	29.21	-
	IRCNN [223]	34.58	32.18	30.59	28.91	-
	FFDNet [224]	34.47	32.25	30.76	29.14	27.29
	BRDNet [182]	35.08	32.75	31.15	29.52	27.72
	ADNet [181]	34.93	32.56	31.00	29.36	27.53

Table 11: Running time of 12 popular denoising methods for the noisy images of sizes 256×256, 512×512 and 1024×1024.

Methods	Device	256×256	512×512	1024×1024
BM3D [39]	CPU	0.65	2.85	11.89
WNNM [62]	CPU	203.1	773.2	2536.4
EPLL [237]	CPU	25.4	45.5	422.1
MLP [22]	CPU	1.42	5.51	19.4
CSF [162]	CPU	2.11	5.67	40.8
CSF [162]	GPU	-	0.92	1.72
TNRD [31]	CPU	0.45	1.33	4.61
TNRD [31]	GPU	0.010	0.032	0.116
ECNDNet [179]	GPU	0.012	0.079	0.205
DnCNN [222]	CPU	0.74	3.41	12.1
DnCNN [222]	GPU	0.014	0.051	0.200
FFDNet [224]	CPU	0.90	4.11	14.1
FFDNet [224]	GPU	0.016	0.060	0.235
IRCNN [223]	CPU	0.310	1.24	4.65
IRCNN [223]	GPU	0.012	0.038	0.146
BRDNet [182]	GPU	0.062	0.207	0.788
ADNet[181]	GPU	0.0467	0.0798	0.2077

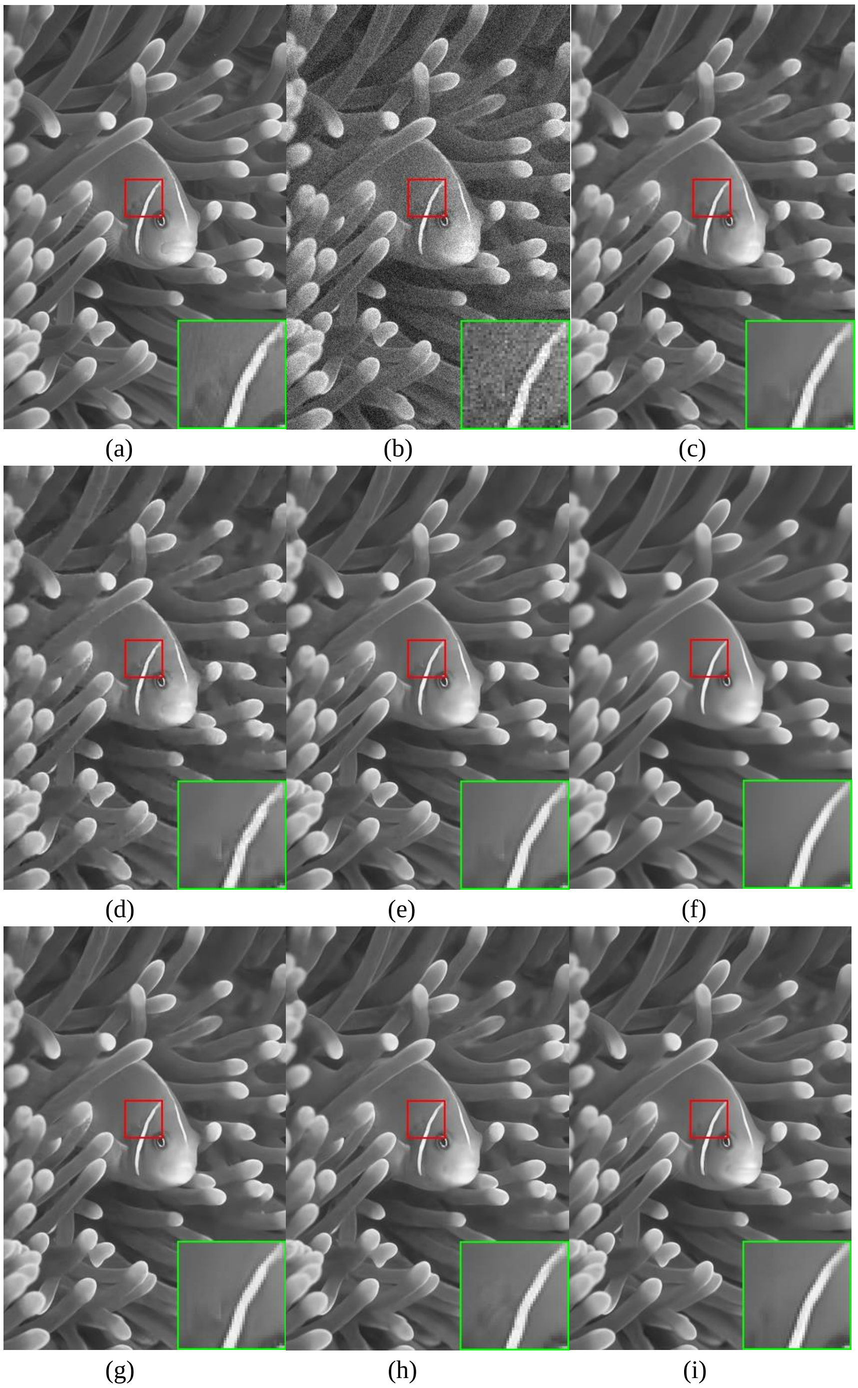

Figure 7: Denoising results of different methods on one image from the BSD68 with σ=15: (a) original image, (b) noisy image/24.62dB, (c) BM3D/35.29dB, (d) EPLL/34.98dB, (e) DnCNN/36.20dB, (f) FFDNet/36.75dB, (g) IRCNN/35.94dB, (h) ECNDNet/36.03dB, and (i) BRDNet/36.59dB.

5. Discussion

Deep learning techniques in image denoising have been widely applied in recent years. This paper has offered a survey to make readers comprehensively understand these methods. The pre-

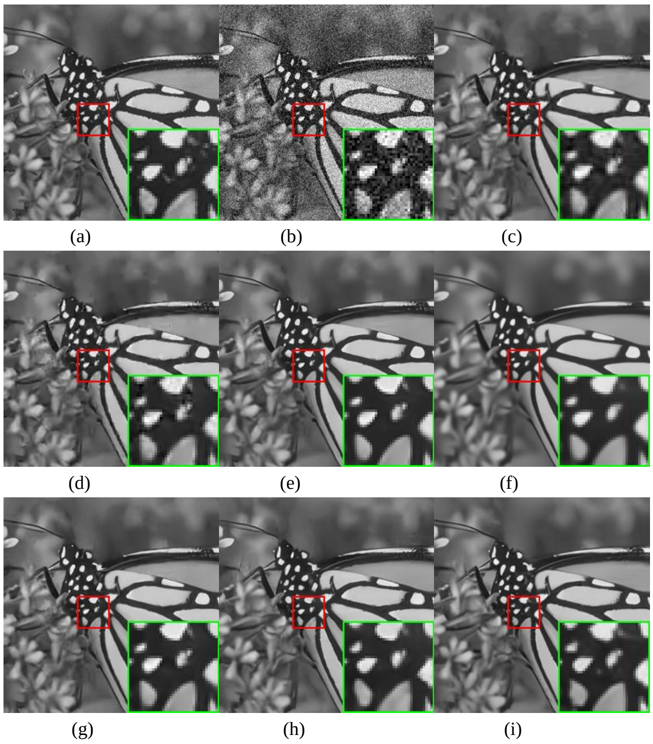

Figure 8: Denoising results of different methods on one image from the Set12 with σ=25: (a) original image, (b) noisy image/20.22dB, (c) BM3D/29.26dB, (d) EPLL/29.44dB, (e) DnCNN/30.28dB, (f) FFDNet/30.08dB, (g) IR-CNN/30.09dB, (h) ECNDNet/30.30dB, and (i) BRDNet/30.50dB.

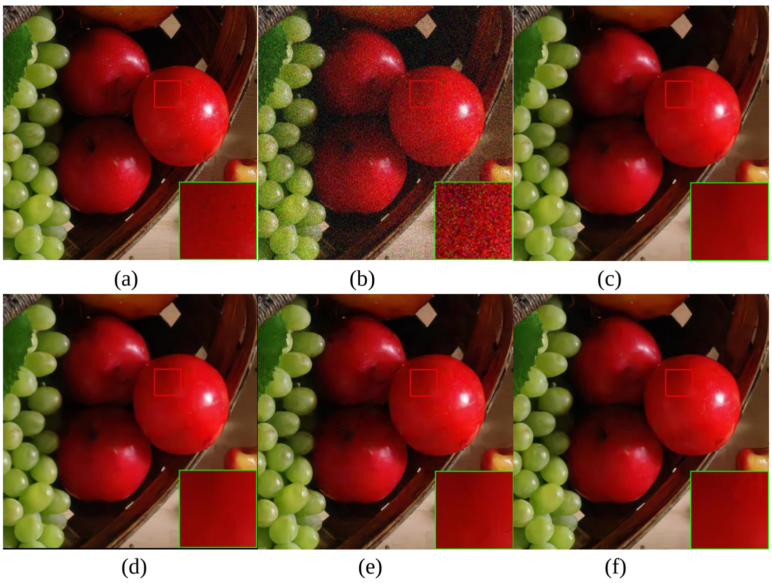

Figure 9: Denoising results of different methods on one image from the McMaster with σ=35(a) original image, (b) noisy image/18.46dB, (c) DnCNN/33.05B, (d) FFDNet/33.03dB, (e) IRCNN/32.74dB, and (f) BRDNet/33.26dB.

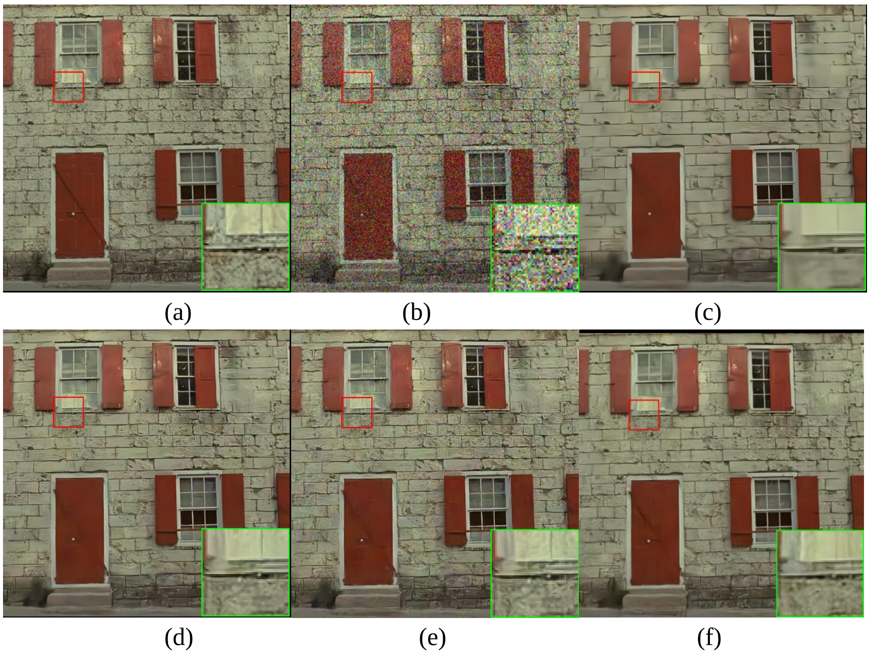

Figure 10: Denoising results of different methods on one image from the Kodak24 with σ=50: (a) original image, (b) noisy image/14.58dB, (c) DnCNN/25.80B, (d) FFDNet/26.13dB, (e) IRCNN/26.10dB, and (f) BRDNet/26.33dB.

Table 12: PSNR (dB) of different methods on the DND for real-noisy image denoising.

Methods	DND
EPLL [237]	33.51
TNRD [31]	33.65
NCSR [42]	34.05
MLP [22]	34.23
BM3D [39]	34.51
FoE [160]	34.62
WNNM [62]	34.67
KSVD [6]	36.49
CDnCNN-B [222]	32.43
FFDNet [224]	34.40
MCWNNM [123]	37.38
TWSC [200]	37.94
GCBD [28]	35.58
CIMM [11]	36.04
CBDNet [64]	37.72
VDN [216]	39.38
DRDN [169]	39.40
AGAN [117]	38.13

vious sections have shown the detailed information of existing methods. This section mainly presents the potential research points for image denoising and points out unsolved problems as follows.

Base deep learning techniques image denoising mainly has good effect on denoising performance, denoising efficiency and complex denoising task. For promoting the denoising perfor-

Table 13: PSNR (dB) of different methods on the SIDD for real-noisy image denoising.

Methods	SIDD
CBM3D [39]	25.65
WNNM [62]	25.78
MLP [22]	24.71
DnCNN-B [222]	23.66
CBDNet [64]	33.28
VDN [216]	39.23
DRDN [169]	39.60

Table 14: PSNR (dB) of different methods on the Nam for real-noisy image denoising.

Methods	Nam
NI [5]	31.52
TWSC [200]	37.52
BM3D [39]	39.84
NC [101]	40.41
WNNM [62]	41.04
CDnCNN-B [222]	37.49
MCWNNM [123]	37.91
CBDNet [64]	41.02
CBDNet(JPEG) [64]	41.31
DRDN [169]	38.45
AGAN [117]	41.38

Table 15: PSNR (dB) of different methods on the cc for real-noisy image denoising.

Camera Settings	CBM3D [39]	MLP [22]	TNRD [31]	DnCNN [222]	NI [5]	NC [101]	WNNM [62]	BRDNet [182]	SDNet [233]	ADNet[181]
Canon 5D ISO=3200	39.76	39.00	39.51	37.26	35.68	38.76	37.51	37.63	39.83	35.96
	36.40	36.34	36.47	34.13	34.03	35.69	33.86	37.28	37.25	36.11
	36.37	36.33	36.45	34.09	32.63	35.54	31.43	37.75	36.79	34.49
Nikon D600 ISO=3200	34.18	34.70	34.79	33.62	31.78	35.57	33.46	34.55	35.50	33.94
	35.07	36.20	36.37	34.48	35.16	36.70	36.09	35.99	37.24	34.33
	37.13	39.33	39.49	35.41	39.98	39.28	39.86	38.62	41.18	38.87
Nikon D800 ISO=1600	36.81	37.95	38.11	35.79	34.84	38.01	36.35	39.22	38.77	37.61
	37.76	40.23	40.52	36.08	38.42	39.05	39.99	39.67	40.87	38.24
	37.51	37.94	38.17	35.48	35.79	38.20	37.15	39.04	38.86	36.89
Nikon D800 ISO=3200	35.05	37.55	37.69	34.08	38.36	38.07	38.60	38.28	39.94	37.20
	34.07	35.91	35.90	33.70	35.53	35.72	36.04	37.18	36.78	35.67
	34.42	38.15	38.21	33.31	40.05	36.76	39.73	38.85	39.78	38.09
Nikon D800 ISO=6400	31.13	32.69	32.81	29.83	34.08	33.49	33.29	32.75	33.34	32.24
	31.22	32.33	32.33	30.55	32.13	32.79	31.16	33.24	33.29	32.59
	30.97	32.29	32.29	30.09	31.52	32.86	31.98	32.89	33.22	33.14
Average	35.19	36.46	36.61	33.86	35.33	36.43	35.77	36.73	37.51	35.69

Table 16: Different methods on the BSD68 for different noise levels (i.e. 15, 25 and 50).

Methods	15	25	50
DnCNN-B [222]	31.61	29.16	26.23
FFDNet [224]	31.62	29.19	26.30
SCNN [79]	31.48	29.03	26.08
DnCNN-SURE-T [168]	-	29.00	25.95
DnCNN-MSE-GT [168]	-	29.20	26.22
G2G1(LM,BSD) [24]	31.55	28.93	25.73

mance, there are the following solutions.

Table 17: Average PSNR (dB) results of different methods on Set12 with noise levels of 15, 25 and 50.

Images	C.man	House	Peppers	Starfish	Monarch	Airplane	Parrot	Lena	Barbara	Boat	Man	Couple	Average
Noise Level	$\sigma = 25$												
DnCNN-B [222]	29.94	33.05	30.84	29.34	30.25	29.09	29.35	32.42	29.69	30.20	30.09	30.10	30.36
FFDNet [224]	30.10	33.28	30.93	29.32	30.08	29.04	29.44	32.57	30.01	30.25	30.11	30.20	30.44
DNCNN-SURE-T [168]	29.86	32.73	30.57	29.11	30.13	28.93	29.26	32.08	29.44	29.86	29.91	29.78	30.14
DNCNN-MSE-GT [168]	30.14	33.16	30.84	29.40	30.45	29.11	29.36	32.44	29.91	30.11	30.08	30.06	30.42
Noise Level	$\sigma = 50$												
DnCNN-B [222]	27.03	30.02	27.39	25.72	26.83	25.89	26.48	29.38	26.38	27.23	27.23	26.91	27.21
FFDNet [224]	27.05	30.37	27.54	25.75	26.81	25.89	26.57	29.66	26.45	27.33	27.29	27.08	27.32
DNCNN-SURE-T [168]	26.47	29.20	26.78	25.39	26.53	25.65	26.21	28.81	25.23	26.79	26.97	26.48	26.71
DNCNN-MSE-GT [168]	27.03	29.92	27.27	25.65	26.95	25.93	26.43	29.31	26.17	27.12	27.22	26.94	27.16

Table 18: Different methods on the VggFace2and WebFace for image denoising.

Methods	VggFace2 [23]		WebFace [211]	
	4 ×	8 ×	4 ×	8 ×
DnCNN [222]	26.73	23.29	28.35	24.75
MemNet [174]	26.85	23.31	28.57	24.77
WarpNet [111]	28.55	24.10	32.31	27.21

1) Enlarging the receptive field can capture more context information to improve the denoising performance. Increasing the depth and width of the networks are the common ways to enlarge the receptive field. However, that results in higher computational cost and more memory consumption. For resolving the problem, dilated convolution technique is a good choice to make performance and efficiency, which is very effective to mine more edge information.

2) The simultaneous use of extra information (also called prior) and CNN is very beneficial to facilitate more accurate features. That is implemented by designing the loss function.

3) Combining local and global information can enhance the memory abilities of the shallow layers on deep layers to better filter the noise. The residual operation and recursive operation are typical methods to address this problem.

4) Single processing methods can better suppress the noise. Inspired by that, the single processing technique fused into the deep CNN can pursue excellent performance. For example, the wavelet technique is gathered into the U-Net to deal with image restoration [123].

5) Data Augmentation, such as horizontal flip, vertical flip and color jittering can make the denoising methods learn more types of noise, which can enhance the expressive ability of the denoising models. Additionally, using the GAN to construct virtual noisy image is also useful for image denoising.

6) Transfer learning, graph and neural architecture search methods can obtain good denoising results.

7) Improving the hardware or camera mechanism can reduce the effect of noise on the captured image.

For improving denoising efficiency, compressing deep network has obtained great success. Reducing the depth or the width of deep network can reduce the complexity of deep network in image denoising. Also, using small convolutional kernel and group convolution can reduce the number of parameters for accelerating the speed of training. Fusion of dimension reduction method, such as principal component analysis (PCA) and CNN also better improves the denoising efficiency.

For tackling complex noisy image, step-by-step processing is very popular. For example, using two-step mechanism deals with a noisy image with low-resolution. The first step recovers a high-resolution image by a CNN. The second step uses a novel CNN to filter the noise of the high-resolution image. The two CNNs are implemented via cascade operation. Additionally, utilizing CNN to deal with unsupervised noise is also a good choice.

Although deep learning techniques have obtained great success in three aspects above, there are still some challenges in image denoising.

1) Deeper denoising networks require more memory resource.

2) Training deeper denoising networks is not stable for real noisy image, unpaired noisy image and multi-degradation tasks.

3) Real noisy images are not easily captured, which results in inadequate training samples.

4) Deep CNNs are difficult to solve unsupervised denoising task.

5) Find more accurate metrics for image denoising. The PSNR and SSIM are popular metrics for image restoration task. However, the PSNR suffers from excessing smoothing, which may recognize the difference of between indistinguishable images. The SSIM depends on brightness, contrast and structure, which can not accurately evaluate image perceptual quality. Thus, more useful metrics for image denoising are extremely urgent.

6. Conclusion

In this paper, we comparatively study and systematcially summarize different deep networks on image denoising. First, we show the basic frameworks of deep learning for image denoising. Then, deep learning techniques for different noisy tasks, including additive white noisy images, blind denoising, real noisy images and hybrid noisy images are presented. Next, for each category of different noisy tasks, we analyze the motivation and theory of denoising networks. Finally, we compare the denoising results, efficiency and visual effects of different networks on benchmark datasets and give the crossing comparisons among different types of image denoising methods with different types of noise. Further, some potential research points and challenges of deep learning in image denoising are offered.

Over the past few years, Gaussian noisy image denoising techniques have obtained great success, where the Gaussian noise is regular. However, in the real world the noise is complex and irregular. Improving the hardware device to suppress the noise for capturing a high-quality image is very important. Also, the obtained image may be blurry, low-resolution and corrupted. Thus, how to effectively recover the latent clean image from the superposed noisy image is very critical. Additionally, using deep learning techniques to learn features need the ground truth. However, the obtained real noisy images do not have the ground truth. These challenges are very urgent to address for scholars in the future.

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