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 primaldual 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 (CENN) 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 (CNL-Net) [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) [23] 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 (CBD-Net) [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
The main frameworks of deep learning in image denoising

Real noisy images
Blind denoising
Additive white noisy images
Hybrid noisy images

CNN/NN for AWNI denoising
CNN/NN and feature extraction method for AWNI denoising
The combination of optimization method and CNN/NN

Weak edge-information noisy-image denoising
Non-linear noisy-image denoising
High-dimensional noisy-image denoising
Non-salient noisy-image denoising
High computational cost for image denoising
Denoising speed
Denoising performance

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.

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 \( \mu \) represent the given clean image, noisy image and additive Gaussian noise (AWGN) of standard deviation \( \sigma \), 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 \( \theta \) 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 \( W = [W^0, W^1, \ldots, W^{n-1}] \) and biases \( b = [b^1, b^2, \ldots, b^n] \). 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.

\[
f(X; W; b) = f(W^T X + b),
\]

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

\[
f(X; W; b) = f(W^n f(W^{n-1} \ldots f(W^0 X + b^0) \ldots b^{n-1}) + b^n),
\]

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. \( w_1, w_2, \ldots, w_11, w_{12} \) 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:

\[
f(z_{h1}) = f(w_1 x_1 + w_4 x_2 + w_7 x_3 + b_1).
\]
First, the output of the network $o_1$ is obtained. Then, the network uses back propagation (BP) 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) and deep belief network (DBN) 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. 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. As pioneers of CNNs, LeNet 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 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.](image)

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 described in Fig. 4.

![Figure 4: Network architecture of GoogLeNet (Inception 1).](image)

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.

Figure 6: Network architecture of GAN.

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].
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
### Methods
- Gaussian image denoising
- Blind denoising
- Optical coherence tomography (OCT) image denoising
- Poisson-noise-image denoising
- Ground-roll noise reduction
- Multi-channel CNN for image denoising
- CNN with multiscale, multilevel features techniques for hyper-spectral image denoising
- CNN with multi-scale and multiple skip connections for Poisson image denoising
- CNN with exponential linear units, and dilated convolutions for image denoising
- CNN with symmetric network architecture for image denoising
- CNN on image denoising from info-communication systems
- CNN with BN for image denoising
- CNN for inverse problems
- CNN with residual learning for non-blind image denoising
- CNN with fully connected layer, RL and dilated convolutions for image denoising
- CNN with fully connected layer, RL and dilated convolutions for image denoising
- CNN with recursive operations for image denoising
- CNN with recursive plug-ins for image denoising
- CNN with exponential linear units, and dilated convolutions for image denoising
- CNN with recursive unit, gate unit for image restoration
- CNN with recursive (de)composition (de)composition
- CNN with recursive (de)composition (decomposition)

### Applications
- Gaussian, poisson or any additive-white noise reduction
- Gaussian and Poisson image denoising
- Gaussian noisy image denoising
- Medical (X-ray) image restoration
- CNN for image denoising
- CNN for inverse problems
- CNN for inverse problems
- CNN for inverse problems
- CNN for inverse problems

### Key words (remarks)
- Image denoising from info-communication systems
- Low-dose CT image denoising, X-ray image denosing
- Gaussian and multiplicative speckle noise reduction
- Gaussian image denoising, super-resolution
- Gaussian image denoising, JPEG deblocking

### Table 1: CNN/NN for AWNI denoising.

| References | Method | Applications |
|------------|--------|--------------|
| Zhang et al. (2017) | CNN | Gaussian image denoising, super-resolution and JPEG deblocking |
| Wang et al. (2018) | CNN | Gaussian image denoising |
| Ren et al. (2018) | CNN | Gaussian image denoising, super-resolution |
| Jin et al. (2018) | CNN | Medical (X-ray) image restoration |
| Yao et al. (2018) | CNN | Gaussian image denoising, super-resolution |
| McCann et al. (2018) | CNN | Inverse problems (i.e. denoising, deconvolution, super-resolution) |
| Ye et al. (2018) | CNN | Gaussian image denoising, super-resolution |
| Zhang et al. (2018) | CNN | Gaussian image denoising |
| Chang et al. (2018) | CNN | Hyper-spectral image (HSI) denoising, HSI restoration |
| Jeon et al. (2018) | CNN | Speckle noise reduction from digital holographic images |
| Oshahizadeh-Ansari et al. (2018) | CNN | Low-dose CT image denoising, Ax-ray image denoising |
|Usadiya et al. (2018) | CNN | Non-blind image denoising |
| Xue et al. (2018) | CNN | Image noise reduction of infrared images |
| Chen et al. (2018) | CNN | Gaussian image denoising, blind denoising |
| Yu et al. (2018) | CNN | Axillary, random, linear and multiple noise reduction of images |
| Ye et al. (2018) | CNN | Optical coherence tomography (OCT) image denoising |
| He et al. (2018) | CNN | Ground-roll noise reduction |
| Almah et al. (2018) | CNN | OCT image denoising |
| Zhihong et al. (2018) | CNN | Gaussian noisy image denoising |
| Chen et al. (2018) | CNN | Gaussian noisy image denoising |
| Park et al. (2018) | CNN | Gaussian noisy image denoising |
| Shen et al. (2018) | CNN | Image denoising from info-communication systems |
| Chen et al. (2018) | CNN | Actual-image denoising |
| Fu et al. (2018) | CNN | Gaussian, Poisson or any additive white noise reduction |
| Almah et al. (2018) | CNN | Ground-roll noise reduction |
| Bae et al. (2018) | CNN | Gaussian noise image denoising |
| Liu et al. (2018) | CNN | Poisson-noise image denoising |
| Yang et al. (2018) | CNN | Gaussian noisy image denoising |
| Zhang et al. (2018) | CNN | Gaussian noisy image denoising |
| Ren et al. (2018) | CNN | Gaussian and Poisson 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 \[197,68\]. 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 (remark)                          |
|-----------------|---------|--------------------------------------------------|---------------------------------------------|
| Bako et al. (2017) | CNN     | Monte Carlo-rendered images denoising            | CNN with kernel method for estimating noise pixels |
| Ahn et al. (2017)  | CNN     | Gaussian image denoising                        | CNN with NSS for image denoising            |
| Khare et al. (2017) | CNN     | Impulse noise reduction                         | CNN with PCA for image denoising            |
| Vogel et al. (2019)  | CNN     | Gaussian image denoising                        | U-net with multi scales technique for image denoising |
| Mildenhall et al. (2018) | NN      | Low-light synthetic noisy image denoising, real noise | Encoder-decoder with multi scalable, and kernel method for image denoising |
| Yang et al. (2018)   | CNN     | Gaussian image denoising                        | CNN with BM3D for image denoising            |
| Guo et al. (2018)    | CNN     | Image blurring and denoising                    | CNN with RL, and sparse method for image denoising |
| Han et al. (2018)    | CNN     | Gaussian image denoising                        | CNN with multi scales, and tensor RL operations for image denoising |
| Li et al. (2018)     | CNN     | OCT image denoising, OCT image super-resolution | CNN with multi views for image restoration  |
| Ahn et al. (2018)    | CNN     | Gaussian image denoising                        | CNN with NSS for image denoising            |
| Xia et al. (2018)    | CNN     | Hyper-spectral image denoising                  | CNN with RL, and PCA for low-dose OCT image denoising |
| Kadavarty et al. (2019) | CNN     | Low-Dose computed tomography (CT) image denoising | CNN with RL, batch normalization (BN) for medical image denoising |
| Vianu et al. (2019)  | CNN     | Merge noise reduction                           | CNN with wavelet-image denoising            |
| Abbas et al. (2019)  | NN      | 3D magnetic resonance image denoising, medical image denoising | GAN based on encoder-decoder and RL for medical denoising |
| Xu et al. (2019)     | 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)  | CNN           | Gaussian image denoising              | Auto-Encoder with BN, and ReLU for image denoising |
| Cho et al. (2018)   | CNN           | Gaussian image denoising              | CNN with separable convolution, and gradient prior for image denoising |
| Fu et al. (2018)    | CNN           | Salt and pepper noise removal          | CNN with non-local switching filter for salt and pepper noise |
| Yeh et al. (2018)   | CNN           | Image denoising super-resolution and upsampling | GAN with MAP for image restoration |
| Liu et al. (2018)   | CNN           | Medical image denoising, computed tomography prefilter for image denoising | CNN with generic algorithm for medical image denoising |
| Kusonko et al. (2018)| CNN          | Gaussian image denoising               | CNN with noise level, upsampling, denoising, operating for image denoising |
| Heckel et al. (2018) | CNN         | Image denoising                        | CNN with deep prior for image denoising |
| Jiao et al. (2017)  | CNN           | Gaussian image denoising, image inpainting | CNN with inference, residual operation for image denoising |
| Wang et al. (2017)  | CNN           | Image denoising                        | CNN with total variation for image denoising |
| Le et al. (2017)    | CNN           | Image painting                         | CNN with split Bregman iteration algorithm for image painting |
| Sun et al. (2018)   | CNN           | Gaussian image denoising               | GAN with skip-connections, and ResNet blocks for image denoising |
| Zhu et al. (2018)   | CNN           | Gaussian image denoising               | GAN with multiscale for image denoising |
| Dye et al. (2018)   | CNN           | Gaussian image denoising               | CNN with wredNet for medical image restoration |
| Liu et al. (2019)   | CNN           | Gaussian image denoising, real noisy image denoising, rain removal | Dual CNN with residual operations for image restoration |
| Khan et al. (2019)  | CNN           | Symbol denoising                       | CNN with quadratic amplitude modulation for symbol denoising |
| Zhang et al. (2019) | CNN           | Image Poisson denoising                | CNN with variance-stabilizing transformation for poisson denoising |
| Chen et al. (2020)  | CNN           | Gaussian image denoising               | CNN with nonlocal filter for image denoising |
| Ju et al. (2019)    | 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]. Splitting 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, 89]. 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)                                      |
|---------------------|---------|-----------------------------------|----------------------------------------------------------|
| 1. Tao et al. (2019) | CNN     | Real noisy image denoising, low-light image enhancement | CNN with RL, and RL for real noisy image denoising       |
| 2. Chen et al. (2018) | CNN     | Real noisy image denoising, blind denoising | CNN with recurrent convolution for real noisy image denoising |
| 3. Harn et al. (2018) | CNN     | CT image reconstruction           | U-Net with skip connection for CT image reconstruction |
| 4. Chen et al. (2018) | CNN     | Real noisy image denoising        | CNN with anisotropic patch size analysis for real noisy image denoising |
| 5. Juan et al. (2018) | CNN     | Low-light remote sensor image denoising | CNN for image denoising                                  |
| 6. Khersoudade et al. (2019) | CNN | Medical image denoising, CT image denoising | CNN for image denoising                                  |
| 7. Zhang et al. (2018) | CNN     | Low-light image enhancement       | CNN with symmetric pathways for low-light image enhancement |
| 8. Gondar et al. (2018) | CNN     | Real noisy image denoising        | CNN with recurrent connections for real noisy image denoising |
| 9. Anwar et al. (2019) | CNN     | Real noisy image denoising        | CNN with RL, attention mechanism for real noisy image denoising |
| 10. Jareonset et al. (2019) | CNN | Real noisy image denoising        | CNN for real noisy image denoising                       |
| 11. Green et al. (2018) | CNN     | CT image denoising, real noisy image denoising | CNN for real noisy image denoising                       |
| 12. Brooks et al. (2019) | CNN | Real noisy image denoising        | CNN with image processing pipeline for real noisy image denoising |
| 13. Tao et al. (2019) | CNN     | Gaussian image denoising and real noisy image denoising | CNN with BRN, RL and dilated convolutions for image denoising |
| 14. Song et al. (2019) | CNN     | Real noisy image denoising        | CNN with dynamic residual dense block for real noisy 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)                                      |
|---------------------|---------|-----------------------------------|----------------------------------------------------------|
| 1. Zhang et al. (2017) | CNN     | Real-noisy image denoising        | CNN with HQS for real noisy image                        |
| 2. Guo et al. (2019) | CNN     | Real-noisy image denoising        | CNN and cameral processing pipeline for real noisy image |
| 3. Tao et al. (2019) | CNN     | Low-light image enhancement       | CNN with channel prior for low-light image enhancement   |
| 4. Mao et al. (2019) | CNN     | Tomography image denoising        | GAN with edge prior for CT image denoising               |
| 5. Yu et al. (2019)  | CNN     | Real-noisy image denoising, blind denoising | CNN with variational inference for blind denoising and real noisy image denoising |
| 6. Song et al. (2019) | CNN | Real noisy image denoising        | CNN with dynamic residual dense block for real noisy image denoising |
| 7. Lim et al. (2019)  | CNN     | Real noisy image denoising        | CNN with attention 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 denoising 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)  | CNN       | Blind denoising                     | CNN with varying noise level for blind denoising         |
| Kenzo et al. (2018) | CNN       | Blind denoising                     | CNN with soft shrinkage for blind denoising              |
| Soltanayev et al. (2018) | CNN | Blind denoising                     | CNN for unpaired noisy images                            |
| Yang et al. (2017)  | CNN       | Blind denoising                     | CNNs with RL for blind denoising                         |
| Zhang et al. (2018) | CNN       | Blind denoising, random noise       | CNN with RL for blind denoising                          |
| Si et al. (2018)    | CNN       | Blind denoising, random noise       | CNN for image denoising                                 |
| Majumdar et al. (2018) | NN      | Blind denoising                     | Auto-encoder for blind denoising                         |
| Abiko et al. (2019) | CNN       | Blind denoising, complex noisy image denoising | cascaded CNNs for blind denoising                      |
| Cha et al. (2019)   | 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) | 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 denoising 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 × 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 [27]     | 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 |
| ECNNet [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 [90]     | 31.58 | 28.99 | 26.03 |
| NRCNN [185]   | 31.57 | 29.11 | 26.16 |
| NNC [118]     | 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 [121]    | 31.66 | 29.16 | 26.19 |
| CRRNN [11]    | 31.81 | 29.34 | 26.40 |
| PDWDCN [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 [124]  | 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 | 26.59 |
| NN3D [38]     | -   | -   | 26.42 |
| POCNet [54]   | 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 described 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
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 | 27.38 |
|           | DDRN [180] | 33.93 | 31.24 | - | 27.86 | - |
|           | EEDN [30] | 33.65 | 31.03 | - | 27.85 | - |
|           | DDFN [27] | 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 | - |
|           | DDRN [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 [124] | 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 [178] | 34.47 | 32.25 | 30.76 | 29.14 | 27.29 |
|           | BRDNet [182] | 35.08 | 32.75 | 31.15 | 29.52 | 27.72 |
|           | ADNet [181] | 34.95 | 32.56 | 31.00 | 29.36 | 27.53 |

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

| Methods     | Device | 256 $\times$ 256 | 512 $\times$ 512 | 1024 $\times$ 1024 |
|-------------|--------|------------------|------------------|-------------------|
| BM3D [39]   | CPU    | 0.65             | 2.85             | 11.89             |
| WNNM [62]   | CPU    | 203.1            | 773.2            | 2336.4            |
| EPLL [237]  | CPU    | 25.4             | 45.5             | 422.1             |
| MLP [32]    | CPU    | 1.42             | 5.31             | 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              |
| ADNet [181] | GPU    | 0.010            | 0.032            | 0.116             |
| FFDNet [224]| GPADCNN [35] | 0.012 | 0.079 | 0.020 |
| DnCNN [222] | GPU    | 0.74             | 3.41             | 12.1              |
| DnCNN [222] | GPU    | 0.014            | 0.051            | 0.200             |
| FFDNet [224]| GPU    | 0.40             | 5.11             | 14.1              |
| TNRD [31]   | CPU    | 0.016            | 0.060            | 0.235             |
| IRCNN [223] | GPU    | 0.310            | 1.24             | 4.65              |
| IRCNN [223] | GPU    | 0.012            | 0.038            | 0.146             |
| BRDNet [182]| GPU    | 0.062            | 0.207            | 0.788             |
| ECNNDNet [179] | GPU | 0.0467 | 0.0798 | 0.2077 |
Figure 7: Denoising results of different methods on one image from the BSD68 with $\sigma=15$: (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 $\sigma=25$: (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 $\sigma=35$: (a) original image, (b) noisy image/18.46dB, (c) DnCNN/33.05dB, (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 $\sigma=50$: (a) original image, (b) noisy image/14.58dB, (c) DnCNN/25.80dB, (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 [23]     | 33.51|
| TNRD [31]     | 33.65|
| NCSR [42]     | 34.05|
| MLP [23]      | 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 [111]    | 36.04|
| CBDNet [64]   | 37.72|
| VDN [216]     | 39.38|
| DRDN [169]    | 39.40|
| AGAN [117]    | 38.13|

Previous 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]    | 23.65 |
| WNNM [62]     | 25.78 |
| MLP [22]      | 24.71 |
| DnCNN-B [222] | 23.66 |
| CBDNet [64]   | 33.28 |
| VDN [115]     | 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 [19] | MLP [22] | TNRD [11] | DnCNN [112] | 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  | 35.09    | 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  | 35.37    | 31.46     | 35.55        | 35.50       | 33.94       |
|                 | 35.07      | 36.20    | 36.37     | 34.48       | 36.16  | 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       | 38.21  | 39.05    | 39.95     | 39.67        | 40.87       | 38.24       |
|                 | 37.51      | 37.94    | 38.17     | 35.48       | 37.79  | 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       | 35.07       |
|                 | 34.42      | 38.15    | 38.21     | 33.11       | 40.15  | 36.76    | 29.73     | 38.85        | 39.78       | 38.09       |
| Nikon D800 ISO=6400 | 31.13      | 32.09    | 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         | 33.19      | 36.46    | 36.61     | 33.86       | 35.23  | 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 [179]       | 31.48| 29.03| 26.08|
| DnCNN-SURE-T [168] | -  | 29.00| 25.95|
| DnCNN-MSE-GT [118] | -  | 29.20| 26.22|
| G2G1(LM,BSD) [24] | 31.55| 28.93| 25.73|

In conclusion, 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  | σ = 15 |       |         |          |         |          |        |      |         |      |     |        |         |
| DnCNN-B [222] | 29.94 | 33.05 | 30.84   | 29.34   | 30.25   | 29.09    | 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    | 32.57  | 29.44| 30.25   | 30.11| 30.10| 30.44  |         |
| DNCNN-SURE-T [168] | 29.86 | 32.73 | 30.57   | 29.11   | 30.13   | 28.93    | 32.08  | 29.44| 30.08   | 30.11| 30.08| 30.14  |         |
| DNCNN-MSE-GT [168] | 30.14 | 33.16 | 30.84   | 29.40   | 30.45   | 29.11    | 32.44  | 29.91| 30.11   | 30.08| 30.06| 30.42  |         |
| Noise Level  | σ = 25 |       |         |          |         |          |        |      |         |      |     |        |         |
| DnCNN-B [222] | 27.03 | 30.02 | 27.39   | 25.72   | 26.83   | 25.89    | 26.48  | 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  | 25.66| 26.45   | 27.33| 27.29| 27.08  |         |
| DNCNN-SURE-T [168] | 26.47 | 29.20 | 26.78   | 25.39   | 26.53   | 25.65    | 26.21  | 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 VggFace2 and WebFace for image denoising.

| Methods            | VggFace2 [23] | WebFace [211] |
|--------------------|---------------|---------------|
|                    | 4 x           | 8 x           |
| DnCNN              | 26.73         | 28.35         | 24.75 |
| MemNet             | 26.85         | 28.57         | 24.77 |
| WarpNet            | 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 excessive 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 systematically 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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