Image Denoise Methods Based on Deep Learning

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Abstract: Image denoising is widely used in image, video, nuclear magnetic imaging and so on. In the application scene, camera jitter, the rapid motion of objects, dark light environment and so on may cause the captured photos to be unclean, so the research of image denoising has essential research value. This paper reviews the related research in this field in recent years, introduces the basic theory of image denoising, lists the common image noise, and then summarizes some classical denoising algorithms from traditional denoising methods. In addition, the shortcomings of traditional methods are analyzed. After that, the image denoising method based on depth learning is summarized, including the image denoising method based on REDNet, DnCNN, CBDNet, GAN, Noise2Noise structure, the principle and structure of various methods are introduced. Finally, the challenges of image denoising are analyzed, and the future research direction has prospected.

1. Basis of Image Denoise Theory

1.1. Image noise concept
Image noise refers to some redundant information about digital image interference. Excess interference information can lead to unclear pictures and hinder people's viewing. Theoretically, the image's noise can not be predicted, and the probability statistics should be used to analyze its random error, so the image noise usually uses the probability distribution function to describe its random process.

Image denoising improves the image's quality through a series of methods while keeping the original information as much as possible while removing useless information from the signal. It is necessary to study the image denoising algorithm. In practical application, if denoising is not proper, it will cause significant risk and harm. For example, in processing medical images, minimal errors may affect the doctor's treatment and diagnosis and ultimately threaten the patient's life and health.

1.2. Characteristics of image noise
Image noise is randomly distributed in the image, its size and location are unknown, but the image and noise are usually related. For example, the camera's electrical signal is related to noise, the dark part has noise, and the light part has less [1] noise. In the series image transmission system, the power of the same type of sample in each part of different noise can be added together. That is, the noise has superposition.
1.3. Overview of image denoising models
The researchers will establish the corresponding probability density function according to the image's characteristics in the image's denoising analysis. The probability density function is the basis of describing the statistical characteristics of noise in image processing, and the corresponding data model is established according to it.

1.4. Common image noise
Image noise will blur the image and even make the feature disappear, which will make it difficult for the image analyst to understand the image well. In today's practical applications, common image noise usually includes the following:

1.4.1 Gaussian noise
A class of noise from the normal distribution of probability density function is called Gao Si noise. Gaussian function:

\[ f(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \]  \hspace{1cm} (1)

The Gaussian function image is shown in figure 1.

1.4.2 Larry Noise
The Rayleigh distribution follows the normal distribution. The average value of the two components of the random two-dimensional vector is 0, and their variance is the same. Rayleigh distribution function:

\[ f(x, \sigma) = \frac{x}{\sigma^2} \exp\left(-\frac{x^2}{2\sigma^2}\right) \]  \hspace{1cm} (2)

Expectations and variances of Rayleigh distribution:

\[ E(x) = \sqrt{\frac{\pi}{2\sigma}} \quad D(X) = \frac{4-\pi}{2\sigma^2} \]  \hspace{1cm} (3)

The Rayleigh function image is shown in figure 2.
1.4.3 gamma noise
Gamma noise, also called Erlang noise, is a kind of noise model in image processing. Gamma function:

\[ \Gamma(x) = \int_0^\infty t^{\alpha-1} e^{-t} dt \quad (x > 0) \]

(4)

The gamma function image is shown in figure 3.

1.4.4 exponentially distributed noise
The exponential noise distribution obeys the exponential curve, and the uniform distribution is usually used to realize the exponential distribution of noise. Exponential distribution function:

\[ f(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & x \leq 0 \end{cases} \]

(5)

The exponential function image is shown in figure 4.
Expectations and variances of exponential functions:

\[ E(x) = \frac{1}{\lambda}, \quad D(x) = \frac{1}{\lambda^2} \]  

1.4.5 Uniformly distributed noise
Uniform distribution function:

\[ f(x) = \begin{cases} 
\frac{1}{b-a} & a \leq x \leq b \\
0 & x < a, x > b 
\end{cases} \]

uniformly distributed expectations and variances:

\[ E(X) = \frac{a+b}{2}, \quad D(X) = \frac{(b-a)^2}{12} \]

1.4.6 pulse (salt and pepper) noise
Salt and pepper noise (salt-and-pepper noise) is a black and white bright and dark noise [2] produced by image sensors, transmission channels, etc. Salt and pepper noise is a kind of noise caused by signal pulse intensity. Salt and pepper noise is generally caused by image cutting. The most commonly used algorithm to remove salt and pepper noise is the median filtering algorithm.

2. Traditional Image Denoising Methods
At present, the most suitable image denoising algorithms are generally divided into two categories; one is the spatial pixel feature denoising algorithm, the other is a transform-domain denoising algorithm. First, the former is processed directly in the image control, while the latter is processed [3] in the middle of the image transform domain.

2.1. Spatial pixel feature denoising algorithm
Spatial pixel feature denoising algorithm performs disposal processing in image space, and its representative algorithm is a non-local uniform algorithm (Non-Local Means)[4,5,6]. This algorithm uses redundant information in natural images to de-noise. It uses the whole image to reduce the noise, and takes the image block as the unit to find the similar region in the image, then carries on the average operation to this region position, finally removes the high image noise. The effect is perfect. The non-local uniform denoising method makes full use of the redundant information in the image. This method has a good denoising effect and can keep the image details as much as possible.
The non-local uniform algorithm's basic idea is that the unified non-local algorithm's basic idea is to use the weighted average of pixels in the image with a similar domain structure layout to find the estimated value of the current pixel.

The non-local average algorithm needs to judge the similarity between pixels in the whole image range. When processing a pixel point, it is necessary to calculate the similarity between the image and all image pixels. Although the non-local average algorithm has a good denoising effect, it is too complicated and time-consuming, leading to the algorithm not being good enough.

2.2. The variable domain denoising algorithm
The denoising method of image transform domain is transformed by process mathematics. First, the signal is separated from the noise in the transform domain, and then the noise is filtered out, then the noise-free signal is left. The image transform-domain denoising algorithm experiences a series of process changes, transforms the image from the spatial domain to the transform domain, uses the frequency as the segmentation condition, divides the noise into three kinds of frequency noise: high, medium and low. Then the transform domain method separates different noise. The inverse transform is then performed to transform the image from the transform domain to the original space domain and eliminate the image noise. Many types of image transform domain methods; the most commonly used method is the wavelet atrophy method.

Wavelet atrophy is generally divided into two categories: the first type is threshold shrinkage, which first sets the coefficient more minor than the threshold to zero, then retains the wavelet coefficient more significant than the threshold, then maps the threshold function to obtain the estimation coefficient. The second type is proportional shrinkage, which evaluates the degree of noise pollution and provides various measurement methods to determine the proportional [7] of atrophy.

2.3. BM3D denoising algorithms
BM3D image denoising algorithm is a kind of algorithm that uses both non-local denoising algorithm and transform domain denoising algorithm. It is the best traditional denoising algorithm [10]. The Algorithm flowchart [9] is shown in figure 5.

The following is the resulting diagram of the algorithm experiment. After the final estimation, the BM3D algorithm removes the [8] of the original noise significantly.

Figure 5. BM3D Flowchart.
2.4. Shortcomings of traditional methods
BM3D image denoising algorithm is the best traditional algorithm at present. Compared with the non-local average algorithm, it has less noise and can restore more details of the image. However, the complexity of the BM3D algorithm is too high, which affects the algorithm’s practicability.

The shortcomings of the traditional image denoising algorithm are apparent. In the test stage, complex optimization methods must be involved, parameters need to be set manually, and a model can only deal with one denoising task. Because of its flexible structure and strong self-study ability, deep learning technology can solve traditional algorithms’ shortcomings.

3. Image Denoise Based on Deep Learning
The traditional denoising algorithm usually finds out the rule from the noise image first and then carries on the corresponding denoising processing. However, if the noise image itself cannot find the rule, it is challenging to complete the denoising task. Using depth learning technology and using clear images of other similar contents, the network structure is used [11] in denoising tasks.

The following introduces several excellent deep learning denoising architectures proposed in recent years.

3.1. REDNet-based structure
The image denoising model uses the same size as the output image. The image segmentation model, such as convolution and deconvolution symmetric structure based on jump layer connection, is used to optimize the Euclidean distance loss one by one.

Applying CNN, image denoising as a regression model:

\[
\arg\min_{\theta} \sum_i L(f_{\theta}(\hat{x}_i), y_i)
\]  \tag{9}

the \( f \) is the CNN model, the \( x \) is the noisy sample, and they are the no-noise sample. \( L \) is a loss function [12].

The noise-free sample \( y \): is deduced by noise signal \( x \). The noise-free sample is

\[
\hat{x} \sim p(\hat{x} | y_i)
\]  \tag{10}

The following is a classic residual network, as shown in figure 7 below:
First, the input is convolved to extract the feature characteristics. After many convolutions, the effect of noise is reduced. Then, the extracted image feature is deconvolution, and then the image is restored. Because the image features used in deconvolution have been filtered, the noise reduction effect is achieved. With the deepening of the network level, there will be a problem of gradient disappearance. The shallow and deep links in the network can be used as data signal forming pathways to solve gradient disappearance by jumping links. These skipped connections pass image details from the convolutional layer to the deconvolution layer, recovering the original image. With huge capacity, a single model can be used to deal with different levels of noise.

### 3.2. DnCNN -based structure

Residual learning can effectively reduce the whole network's weight so that the network does not need to record too many image details; it only needs to learn the difference between the input image and the label image; that is, residual learning can also effectively solve the gradient disappearance problem.

DnCNN model is an end-to-end CNN gaussian denoising network [13], in the field of information processing, the amount of change of learning signal is often simpler than learning the original signal. The DnCNN model does not directly output the noisy image but predicts the residual image. The network uses residual learning strategies to remove potentially clean images from noisy images, speed up the training process, and improve denoising performance. Figure 8 below shows the network structure of the DnCNN model:

### 3.3. CBDNet based structure

The residual network model is a blind denoising model; that is, the noise level is not predicted, and the CBDNet model is a real image non-blind denoising framework [14]. The framework uses a noise approximation subnetwork to estimate the noise level and then, together with the original input graph, inputs a denoising model based on the hop-layer link. Because non-blind denoising is sensitive to underestimating noise level and performs well for overestimating noise level, the noise reduction effect is perfect when the noise estimation network's noise estimation network is more extensive than the actual noise level.

The image noise model plays a crucial role in reducing noise in real images with noise through a deep convolution neural network. CBDNet model is closer to the real noise model, which also
considers the noise associated with the signal and the camera processing pipeline's noise. CBDNet model consists of two parts: noise estimation subnet and non-blind noise elimination subnet. Both synthetic and real noise images are used for training CBDNet. Experimental results show that the CBDNet model significantly affects asymmetric learning compared with the previous method. Figure 9 below shows the network structure of the CBDNet model:

Figure 9. CBDNet Network Structure of the Model.

3.4. **GAN based structure**

One of the critical points in applying depth learning to denoising problems is acquiring real noisy and noise-free paired images, but because the simulation data set is often not accurate enough, it is a perfect way to generate real noise [15,16,17] based GAN generating adversarial networks.

A key point in applying deep learning to the denoising problem is acquiring real noisy and noise-free paired images. However, since the simulation data set is often not real enough, it is an excellent method to generate real noise based on the generation of countermeasure network GAN. The generative model GAN has a natural advantage in capturing noise distribution. GCBD (GAN) method uses GAN to collect noise from real noisy images and obtain real pair images for training noise reduction model models. Using real noise images and noise-free images is the key to apply depth learning to noise problems. Based on GAN and other unsupervised models, it has a broad application prospect. Figure 10 below shows the structure of the generated adversarial network:

Figure 10. Network structure diagram of the GAN model for generating confrontation network.

3.5. **Noise2Noise based structure**

Getting noisy pictures and clear pictures is very expensive. Noise2Noise[18] frame can train a good denoising model only using noisy images and can achieve a good denoising effect by using multiple noisy images in the same scene. Using machine learning and a basic signal reconstruction algorithm, the noise signal can be reconstructed into a pure signal so that the initial signal can be reconstructed only in the unlabeled noise signal without pure sampling. Moreover, the performance exceeds the use of clean data.
3.6. **Horizontal comparison of several denoising architectures**

In fact, with time, there are more and more kinds of deep learning denoising networks. A new denoising method is often proposed to improve and upgrade the existing methods and solve the problems that the existing methods can not solve. Image noise is irregular, randomly generated, and the denoising methods of different categories of images are different. Therefore, denoising is also a complicated process. A denoising network can not solve all the problems, but they have different partial emphasis.

Below is a horizontal comparison of several deep learning denoising networks listed in this article, and the comparison results are shown in Table 1.

| Table 1. Comparison of Denoise Network Architecture. |
|------------------------------------------------------|
| **REDNet** | **DnCNN** | **CBDNet** | **GAN** | **Noise2Noise** |
| Lead author | Xiao-Jiao Mao | Chunhua Shen | KaiZhang | Wangmeng Zuo | Shi Guo | Zifei Yan | Jingwen Chen | Jiawei Chen | Jaakko Lehtinen; Jacob Munkberg |
| Time of submission | 2016 | 2017 | 2019 | 2018 |
| Scope of application | Processing denoising and super-resolution image repair tasks | Processing familiar image denoising task is blind denoising. | Mainly deal with real noise in reality. | Handling cases where only a small number of samples can be provided | Handling cases where a clear image can not be created for the training set |
| Advantages | The advantage of treating high-grade noise is noticeable. | Gauss denoising with unknown noise level can be processed | The effect of removing real noise is obvious | Can significantly save the time of image rendering | No noise images as labels still perform denoising tasks. |

4. **Summary and Outlook**

This paper first summarizes the basic theory of image noise elimination, introduces the concept and characteristics of image noise, and then enumerates several common image noise. Then, several traditional image noise removal algorithms are introduced, and the shortcomings of traditional denoising algorithms are analyzed. After that, several image denoising models based on depth learning are introduced and summarized. Finally, the enumerated denoising architecture is compared horizontally.

The characteristics of these image denoising methods based on depth learning are as follows: CNN research is pervasive, but it is challenging to restore texture [19]. GAN can be used to eliminate image noise without data, but the GAN training stage's instability needs more in-depth research [20]. Noise2Noise structure can accomplish denoising tasks only by using the noisy image without paired training set, and the denoising effect is not inferior to or even better than that.

Current deep learning methods also face many challenges: Deeper networks need to occupy more memory. Deep denoising networks are challenging to train real noise images stably. There is no standard model of noise images. Real noise images are not easy to obtain other [21]. Based on the summary of the existing standard depth learning methods, it can be seen that depth learning has a wide range of application space in the field of image denoising. But at the same time, there are many challenges to be solved. Under the existing conditions, processing regular Gaussian noise has achieved great success, but it is still challenging to suppress its noise for problematic noise and irregular noise. How to effectively restore image clarity and image quality, improve image denoising efficiency, and reduce the cost of denoising are still the challenges that need to be solved in the future.
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References
[1] Yang, X.R., Kang, G., Ren, W.W. (2002) Analysis of Noise Characteristics of Digital Video Image [J]. Applied Testing Technology., 2:29-30.
[2] Dong, J.Y., Zhang J.Y. (2003) a simple salt and pepper noise filtering algorithm [J]. Computer Engineering and Applications., 20:27-28.
[3] Fang, L., Zhang P. (2010) A Review on the Research of Classical Image Denoising Algorithm [J]. Industrial Control Computers., 23:73-74.
[4] Buades, A., Coll, B., Morel, J.M. (2005) A non-local algorithm for image denoising[C]. In: IEEE Computer Society Conference. San Diego. pp. 60-65.
[5] Jose, V.M., Jose, C.C., Lull, J.J., (2008) denoising using Non-Local Means[J]. Medical Image Analysis., 12:514-523.
[6] José, V.M., Pierrick, C., Luis, M.B. (2010) Adaptive non-local means denoising of MR images with spatially varying noise levels.[J]. Journal of Magnetic Resonance Imaging Jmri., 31:192-203.
[7] Li, G.X. (2006) A Study on Image Wavelet Denoise Based on Wavelet Shrinkage Method [J]. Journal of Remote Sensing., 5:697-702.
[8] Dabov, K., Foi, A., Katkovnik, V., Egiazarian, K. (2007) Image Denoising by Sparse 3-D Transform-Domain Collaborative Filtering. In: IEEE Transactions on Image Processing. Liege. pp. 2080-2095.
[9] Djurovi, I. (2016) BM3D filter in salt-and-pepper noise removal[J]. EURASIP Journal on Image and Video Processing., 1:1-11.
[10] Huang, M., Huang, W.Q., Li J.B. (2014) Research on Parameters Based on BM3D Image Denoising Algorithm [J]. Industrial Control Computers., 10:99-101.
[11] Feng, Y.N. (2019) Research and optimization of image denoising algorithm based on deep learning [D]. Chongqing University.
[12] Mao, X.J., Shen, C., Yang, Y.B. (2016) Image Restoration Using Very Deep Convolutional Encoder-Decoder Networks with Symmetric Skip Connections[J]. 16:2802-2810.
[13] Zhang, K., Zuo, W., Chen, Y. (2017) Beyond a gaussian denoiser: Residual learning of deep CNN for image denoising[J]. IEEE Transactions on Image Processing., 26: 3142-3155.
[14] Guo, S., Yan, Z., Zhang, K. (2019) Toward convolutional blind denoising of real photographs[C]. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Long Beach. pp. 1712-1722.
[15] Chen, J., Chen, J., Chao, H., et al. (2018) Image blind denoising with generative adversarial network-based noise modelling [C]. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. Salt Lake City. pp. 3155-3164.
[16] Guo, S. (2019) A Study on Real Camera Image Denoise Based on Convolutional Neural Network [D]. Harbin Institute of Technology.
[17] Alsaiari.A., Rustagi.R., Alhakamy.A., Thomas.M.M., Forbes.A.G. (2019) Image Denoising Using A Generative Adversarial Network. IEEE 2nd International Conference on Information and Computer Technologies. Kahului. pp. 126-132.
[18] Lehtinen, J., Munkberg, J., Hasselgren, J. (2018) Noise2noise: Learning image restoration without clean data[J]. 36:1628-1643.
[19] Tian, C., Fei, L., Zheng, W. (2020) Deep Learning on Image Denoising: An overview. In: Neural Networks. Dubai. pp. 251-275.
[20] Da, Z. (2017) Research on improved algorithm of convolutional network in deep learning[D]. Southeast University of China.
[21] Xu, S.P., Liu, T.Y., Lin, Z.Y. (2019) A Technical Bottleneck and Research Prospect of Deep Convolution Neural Network Noise Reduction Model [J]. Chinese Journal of Image Graphics. 8:1207-1214.