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# Research on Noise Suppression Algorithm for CMOS Image Sensors Based on Deep Learning

**Junren Shao**
*Guilin University of Electronic Technology, Guilin, Guangxi, China*

**Abstract: With the widespread application of CMOS image sensors, image noise has become an important factor affecting image quality, especially in low light or high ISO environments. As the key to improving image quality, noise suppression technology has become an important research direction in the field of image processing. Traditional noise suppression algorithms use filtering methods to smooth images. Although they can reduce noise to a certain extent, they often lead to the loss of image details and have limited processing capabilities for complex noise types. In recent years, noise suppression methods based on deep learning have developed rapidly. Through models such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and autoencoders, deep learning can more accurately identify and remove noise while effectively retaining image details, showing superior denoising performance than traditional methods. Although deep learning methods have shown excellent results in noise suppression, they consume large computing resources and have slow training and inference speeds. In summary, the application of deep learning in noise suppression has made significant progress and is playing an increasingly important role in image sensor technology.**

**Keywords: CMOS Image Sensor; Noise Suppression; Deep Learning; Convolutional Neural Network; Generative Adversarial Network**

## 1. Research Background and Importance

With the in-depth application of CIS in the field of smartphones, digital cameras, and security monitoring, the issue of image quality improvement has become one of the cores of the research. Particularly in conditions of low-light or high ISO, image noise is outstandingly highlighted. Noise not only affects the clarity and quality of the images but might also affect the accuracy in image processing and analysis. Therefore, noise suppression technologies have been playing an increasingly more important role in image processing. So far, traditional methods of filters and denoising algorithms that alleviate the problem of noises still have certain limitations when dealing with complex noises, especially in protecting image details. The rapid advance of deep learning in recent years has provided new ideas for noise suppression of images in particular [1]. According to some models like CNN, GAN, and autoencoder, deep learning technology has demonstrated much better performance than traditional methods in noise recognition and removal. Especially in a low-light environment, deep learning can retain the details of the image with noise removal.

Deep learning can find the noise pattern in images by training complex neural network models and perform denoising with more precision according to type and distribution. For example, CNNs enhance image quality by removing noise through hierarchical filtering operations without losing any image details. With an increase in deep learning, as part of the models, the impressive performance of GAN has enabled photo generation and restoration applications that give the best effects ever for high ISO noise and restoration of low-light images. Such application effects have helped bring the technological development of good-quality CMOS image sensors with different scenes [2].

Although the deep learning technology is noise-free, it still consumes a high level of computing resources with relatively slower training and inference speeds. Practical applications therefore develop how to reduce the computational complexity in ensuring denoising performance will be one of the essential investigation directions in the advanced area. Since optimization occurs at the deep learning model side with increasingly more effective algorithms and hardware acceleration technologies, deep learning noise suppression technology will probably become one of the key future technologies in the field of image sensors [3].

## 2. Noise Characteristics of CMOS Image Sensors

### 2.1 Working Principle of CMOS Image Sensors

In simple terms, CMOS sensors are semiconductor devices that convert light signals into electrical signals. Basically, the working principle utilizes the photoelectric effect as shown in Figure 1: every photodiode in the detecting array detects external light with the generation of corresponding charge. Each photodiode, so-called a pixel, will accumulate charge within the exposure process, thereafter converted into voltage signals to be amplified and read by the CMOS circuit. Each pixel of the image sensor normally includes a photodiode and a charge transfer device, like a MOSFET. The photosensitive element converts the incoming light energy into charge, which is then transferred to the charge amplifier for readout. Finally, the signal output from the image sensor is further processed to form a digital image [4].

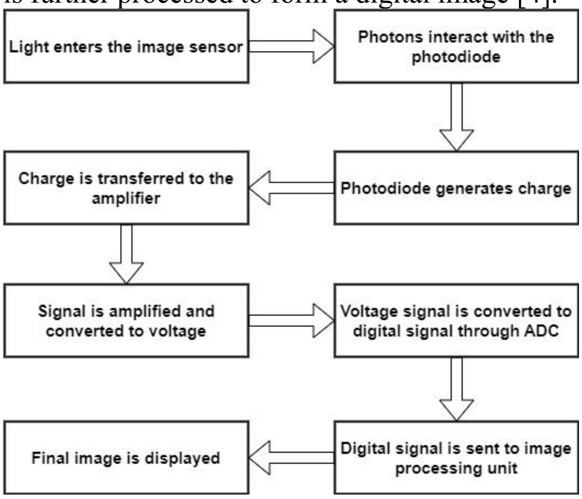


**Figure1. Working Principle of CMOS Image Sensor**

### 2.2 Noise Types in CMOS Image Sensors

In operation, during the workings of the CMOS image sensor, not only effective light signals are collected but various noises are also introduced that eventually affect the quality of the image. The main types of noise in CMOS image sensors include:

① Readout noise: the noise produced in the sensor internal circuit in the course of reading the image signal. The sources of such a component are usually an amplifier and the sampling circuit. Usually, the readout noise shows up at high frequencies and can barely be differentiated from the real signal.

② Thermal noise includes thermal noise and dark current noise: Owing to the temperature effect in the working of the CMOS sensor, the noises are proportional to the temperature. Thermal noise is produced by thermal motion of carriers in semiconductor materials; this kind of noise is increased with the rise in temperature. Dark current noise is independent of light, which is generated by thermal excitation of carriers in the photosensitive element.

③ Weak light noise: Light noise results from the uneven response of the sensor to weak light signals or changes in light. Under weak light, random fluctuations in the process of reading out easily take effect.

④ Quantization noise: In the ADC process, the discretization of the image signal leads to quantization noise. The amplitude of the quantization noise is related to the resolution of the ADC. The lower the resolution, the more significant the quantization noise.

### 2.3 Impact of Noise on Image Quality

The presence of noise will significantly affect the quality of the image and cause image distortion. The impact of noise is mainly reflected in the following aspects:

***Reduced signal-to-noise ratio (SNR)***

Noise will result in the amplitude of the signal being smaller than that of noise, thus reducing the SNR. This reduction in SNR will directly impact the contrast and detail performance of the image. SNR can be calculated by the following formula:

$$\mathrm{SNR} = \frac{P_{\mathrm{signal}}}{P_{\mathrm{noise}}} \tag{1}$$

Among them, $P_{\mathrm{signal}}$ is the power of the signal, and $P_{\mathrm{noise}}$ is the power of the noise. In the case of large noise, the SNR value is low and the image quality is significantly reduced.

***Relationship between noise characteristics and denoising***

Different noise statistical characteristics have a different influence on the design of image processing algorithms. Take Gaussian noise, for instance; it takes on the characteristics of a uniform distribution. Poisson noise is more suitable for methods of nonlinear filtering. Thus, understanding the distribution characteristics is very important in designing effective algorithms for noise suppression. Let the signal and noise for a certain pixel be expressed as follows:

$$I_{\text{observed}} = I_{\text{signal}} + N_{\text{noise}} \quad (2)$$

Among them, $I_{\text{observed}}$ is the observed image signal, $I_{\text{signal}}$ is the real signal strength, and $N_{\text{noise}}$ represents the noise. The goal of the noise suppression algorithm is to recover the real signal from the observed signal.

## 3. Application of Deep Learning in Noise Suppression

### 3.1 Overview of Deep Learning

Deep learning generally refers to a class of machine learning that is characterized by the use of deep neural network models for feature learning and pattern recognition. It embodies the core idea of automatic learning of appropriate feature representations from large-size data for solving a target task by building a deep neural network. In recent years, deep learning with the growth of computational power and data volume has achieved many things in a lot of areas, and most importantly in image and speech processing, with which the traditional methods are bypassed.

Deep learning, through its multi-layer network structure, simulates the way neurons work in the human brain. To put it another way, each layer performs a non-linear transformation of the input with the help of an activation function and extracts features step by step at high levels. The most commonly used deep learning models are CNN, RNN, and GAN.

### 3.2 Application of Deep Learning in Image Processing

Deep learning now ranges from a wide area of applications in image processing, including image classification, target detection, image segmentation, image super-resolution, and image generation among others. Probably, the most important contribution that it has provided is the capabilities of automatic learning of effective feature representations from raw-image data instead of hand-designed features [5].

In the course of suppressing image noise, deep learning methods can capture the characteristic distribution of both noise and signals using the large-scale image datasets during the image processing to effectively get rid of noise. Also, as compared to traditional picture processing approaches-mean filtering, middle filtering among others-deep learning captures more complex forms of noise patterns and rich high-level features of pictures for noise suppression. The advantages of deep learning in image processing mainly reflect in the following points:

① Feature learning automatically: There is no need for hand-design of complex feature extraction procedures, since the neural network can automatically learn an effective feature through hierarchical learning.

② Strong Representation Capability: Along with deep structures, it grants the capability to deep learning models for learning complex features and patterns from data effectively.

③ Speed in processing: According to the accelerated operation by GPU, it is possible for the training and inference in the case of large-scale images.

### 3.3 Noise Suppression Method Based on Deep Learning

Deep learning-based noise suppression typically adopts the CNN architecture that automatically learns noise features through a hierarchical structure of a deep network and effectively separates noise from signals. While doing this, the ultimate goal of training the network is to optimize the parameters of the network by minimizing the loss function for the purpose of restoring a clean image.

***Loss function***

$$L(\theta) = \tilde{a}\left[\| \hat{I} - I \|^2\right] + \lambda \cdot \Omega(\theta) \quad (3)$$

Among them, $L(\theta)$ is the loss function, $\hat{I}$ is the denoised image, $I$ is the original noise-free image, $\Omega(\theta)$ is the regularization term, and $\lambda$ is the regularization parameter. By minimizing the loss function, the network parameters can be optimized to maximize the denoising effect.

Besides, the convolutional neural network design can further utilize the ResNet structure, enhancing the performance of denoising. The residual network avoids the vanishing gradient problem by introducing jump connections and enhances the training capability of the network. The loss function of the residual network is usually expressed as:

*Residual network loss function*

$$L_{\mathrm{res}} = \| \hat{I} - (I + F(x)) \|^2 \tag{4}$$

Among them, $F(x)$ represents the residual term, $x$ is the input image, $I$ is the original image, and $\hat{I}$ is the denoised image. With this structure, the network can better restore the details and textures in the image.

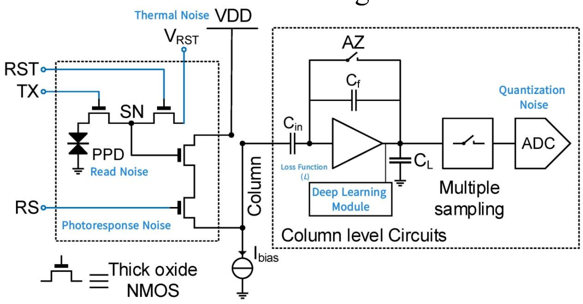


**Figure 2. Schematic of CMOS Image Sensor with Integrated Deep Learning for Noise Suppression**

Below is Figure 2, showing how it integrates deep learning into noise suppression processing in the CMOS Image Sensor. Capture and conversion of light to electrical signals in a Pixel Array happen after different nosing like Read Noise, Photo-response noise, Thermal Noise, and Quantization Noise. Signals are first gained and processed columnwise via Column-Level Circuitry for input into this Deep Learning Module. This module, though internally a simplification of complex architecture, understands the characteristics of the noise itself through advanced learning algorithms employed in it and adapts to mitigate it. And the Loss Function is one of the important components in training this model for further noise suppression. The sampled output in this module, and digitizing it through ADC, finally presents much cleaner image signals. It embeds deep learning to improve the signal-to-noise ratio while keeping the details of the image, which is a huge plus in comparison with the traditional methods of noise suppression.

## 4. Overview of Noise Suppression Algorithms for CMOS Image Sensors

### 4.1 Traditional Noise Suppression Algorithms

Most of the traditional noise suppression algorithms are based mostly on different filtering techniques in order to reduce the impact of noise by performing either local or global processing on the image. Some of the commonly used traditional methods are mean filtering, median filtering, Gaussian filtering, and wavelet transform. Mean filtering smooths the image by calculating the local average of pixel values, thereby reducing noise [6]. However, this technique also blurs edges and details within the image. Median filtering replaces the original pixel value by calculating the median of the pixel values in the local neighborhood of the image. It can effectively suppress salt and pepper noise but has a poor suppression effect on Gaussian noise. Therefore, Gaussian filtering can be used to smooth the image and remove some noise by weighting the Gaussian function on neighboring pixels and is applicable to those image scenes containing Gaussian noise. In particular, wavelet transformation can separately extract different frequency noises and signals and has an obvious effect on removing multiscale noises from images [7]. While the traditional approaches show their excellent performance for simple noises, they are less flexible in the presence of complicated types of noise and generally fail to preserve a high quality of details at a high noise level.

### 4.2 Noise Suppression Algorithm Based on Deep Learning

In recent years, deep learning-based noise suppression algorithms have gradually become hotspots. Deep learning methods can automatically learn noise characteristics and signal characteristics in images by training a large number of data, thus suppressing noise more accurately. The most commonly used deep learning model is the convolutional neural network, which can effectively learn the spatial features of an image. By constructing a number of convolutional layers and pooling layers, the noise information can be step-by-step extracted from the low-level to the high level, until noise is suppressed at last [8]. Moreover, recently, GAN has become a popular method applied to the denoising technique of the image. GAN tries to generate a realistic picture with a noise-free object through adversary training between a generator and a discriminator. Other models have also been proposed for image denoising, such as deep autoencoder (Autoencoder) and residual network (ResNet), which learn low-dimensional representation and introduce residual structure, respectively, thereby further improving the denoising effect. Compared with traditional methods, deep learning-based noise suppression algorithms can handle various complex noises much better and perform well in the processing of details and structures [9].

### 4.3 Evaluation and Comparison of Noise Suppression Algorithms

In other words, the primary factors to estimate the effectiveness of these algorithms, denoising and computing, represent two fundamental sides of noise-suppressing methodology. That is why evaluation in relation to denoising should reflect various sides like SNR, PSNR, and SSIM of the image. Among the given methods, the PSNR or Peak Signal-to-Noise Ratio plays a role as a frequently applied index, evaluating performance that would allow making some conclusion. If this value increases, so will the image quality. SSIM comprehensively considers the similarity of images in terms of structure, brightness, and contrast, and it is able to reflect the human visual perception effect much better. For computational efficiency, conventional noise suppression algorithms are normally high in computational efficiency due to the fact that the algorithm complexity is very low and can be conducted in real time. Although noise removal methods based on deep learning algorithms can perform well, their training generally requires high computational resources and is associated with low inference speed [10]. Several acceleration methods have been proposed in recent years to deal with this problem, such as network pruning, quantization technology, and knowledge distillation, which aim to improve the computational efficiency of the deep learning denoising algorithms. In general, deep learning algorithms perform better in recovery against complex noise and in the restoration of details but still face challenges such as some processing speed and consumption of resources. Traditional algorithms have advantages in computational efficiency and real-time performance, considering that when dealing with complex noise, a little is lacking.

## 5. Conclusion

With the continuous advancement of CMOS image sensor technology, the improvement of image quality has gradually become a research focus, especially in noise suppression. Noise is a key factor affecting the image quality of CMOS image sensors, especially in low light and high ISO settings, the noise problem is more serious. Although traditional noise suppression algorithms have improved image quality to a certain extent, they are often unable to effectively retain image details due to their limited adaptability to complex noise. The deep learning-based method can retain image details to the greatest extent while denoising by automatically learning the noise and signal features in the data, especially under high noise levels, showing superior performance.

It can be said that with the invention of models like CNN, GAN, and autoencoders, deep learning has done much in noise suppression. In fact, such deep learning methods are much more effective for noise suppression as compared to the traditional methods and hence, they can separate noise from the signal much more precisely, improving the signal-to-noise ratio, peak signal-to-noise ratio, and structural similarity of the images with a high margin. However, deep learning methods also have some problems, such as large computing resource needs during training and slow inference speeds, limiting their application in real-time processing. In the future, research should aim at how to optimize the computation efficiency of deep learning models, combining the advantages of traditional methods to further improve noise-suppression algorithm performance in various application scenarios. With advanced deep learning technology combined with effective computation methods, the noise suppression algorithms will have greater potential in the application of CMOS image sensors and promote image processing technology to higher precision and higher efficiency.

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