A Review on Application of Deep Learning for Image De-noising

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***Abstract*—With the explosion in the number of digital images taken every day, the demand for more accurate and visually pleasing images is increasing. However, the images captured by modern cameras are inevitably degraded by noise, which leads to deteriorated visual image quality.Image de-noising is mainly used as image pre-processing or post-processing to make the processed image clearer for subsequent image analysis and understanding. Therefore, work is required to reduce noise without losing image features (edges, corners, and other sharp structures). So far, researchers have already proposed various methods for decreasing noise. Each method has its own advantages and disadvantages. This paper presents a review of some noise models and significant work in the area of image de-noising.**

***Keywords*-Additive White GaussianNoise, Image de-noising, Sparserepresentation.**

I. Introduction

Due to the physical limitations inherent in various recording devices, images become subject to the manifestation of random noise during image acquisition. Noise can be understood as a fundamental distortion of the signal that hinders the process of displaying images and extracting information. Image noise removal is a fundamental foundation of image analysis and processing, so any advancements in image noise reduction help strengthen our understanding of basic image processing and statistics [1]. With the massive increase in the generation of digital images, often captured in atmospheric / low light conditions, image restoration methods have become indispensable tools in today's age of computational analysis. Of the many types of noise that predominate in different types of images, additive white gaussian noise (AWGN), impulsive (salt and pepper) noise, quantization noise, Poisson noise, and speckle noise are the most common discussed in literature [2]. AWGN mainly occurs in analog circuits during image acquisition and transmission. The prevalence of other types of noise such as quantization noise, impulsive noise, speckle noise, and Poisson noise occurs mainly due to manufacturing errors, bit errors and insufficient number of photons during image acquisition. A wide variety of digital images are available that provide valuable information in various application areas such as medical imaging, remote sensing, military and surveillance, robotics and artificial intelligence. The contamination of these images irrevocably destroys the interpretation of the image. Therefore, image noise-reduction methods are widely used in medical imaging, remote sensing, military and surveillance, biometrics and forensics, industrial and agricultural automation.

A. Objectives and Motivation

Image de-noising is to remove noise from a noisy image, so as to restore the true image. However, since noise, edge, and texture are high frequency components, it is difficult to distinguish them in the process of de-noising and the de-noised images could inevitably lose some details. Overall, recovering meaningful information from noisy images in the process of noise removal to obtain high quality images is an important problemnowdays.

The de-noising methods find optimalsolutions to reconstruct the de-noised image. However, such methods usually involve time-consuming iterativeinference. On the contrary, the CNN-based de-noisingmethods attempt to learn a mapping function by optimizing a loss function on a training set that contains degraded-clean image pairs.

II. Related Works

A. Flashlight CNN Image De-noising

FlashLight CNN (FLCNN) is used to remove noise from the image. The proposed approach is based on deep residual networks and capture networks and is capable of using many more parameters than simple residual networks to remove noise from grayscale images corrupted by Additive White Gaussian Noise (AWGN). FlashLight CNN demonstrates the state of the art in quantitative and visual comparison with current image de-noising methods[1].

B. Dilated Residual Convolutional Neural Networks for Low-Dose CT Image De-noising

Convolutional neural network model for de-noising low-dose CT images, inspired by a recently introduced compound residual network for the dissemination of SAR-DRN (synthetic flat radar) images. Specifically, stack normalization is added to some SAR-DRN levels to adjust SAR-DRN for noise suppression on low-dose CT scans. In addition, a pre-processing level and a post-processing level are added to improve the reception range and reduce the computation time. Furthermore, the loss of perception is used in conjunction with the MSE in the training phase, so that the proposed de-noising model can preserve the finer details of the de-noising images. Experimental results show that the proposed model can effectively denote low-dose CT images compared to some advanced methods [2].

C. *Unpaired Image De-noising*

Deep learning approaches in image processing predominantly resort to supervised learning. A majority of methods for image de-noising are no exception to this rule and hence demand pairs of noisy and corresponding clean images. propose method use a flow-based generative model to learn a prior from clean images. Then it is used to train a de-noising network without the need for any clean targets. [3].

D. *On the Numerical Distortion-Mutual Information Function of Image De-noising with Deep Convolutional Networks*

The Deep Convolutional NeuralNetworks (DCNN), models relates tuning hyperparameters such as a number of layers of DCNN. The Blahut-Arimoto algorithm is used to derive numerically distortion-mutual information function of image de-noising algorithm. The derived function is the distortion lower bound given the mutual information between the original image and the de-noised image. The noise environment is relied on the Poisson noise. The de-noised image qualities of different DCNN configurations are compared with the results from the numerical Blahut-Arimoto algorithm. The experimental results indicate that the DCNN models provide near optimal de-noised image qualities given mutual information, even though there are some rooms to further improve image de-noisingalgorithm [4]

E. *Image De-noising Algorithm Based on Incoherent Dictionary Learning*

In uncorrelated dictionary learning, the noisy image is divided into overlapping image blocks, and the image blocks are randomly extracted. The uncorrelated redundant dictionary is obtained by using uncorrelated dictionary learning technology. Finally, the sparse representation coefficients of each image block under the redundant dictionary are obtained by sparse coding algorithm, and the original image is restored by using the sparse representation coefficients. The experimental results show that the irrelevant redundant dictionary has a strong ability to express the texture information of the image. It cankeep the details and texture information of the image better and improve the visual effect [5].

F. *Low-Dose CT Image De-noising Using Cycle-Consistent Adversarial Networks*

Low-dose CT is actively pursued to reduce harmful radiation, but faces challenges of elevated noise in images. cycle-consistent adversarial networks (CycleGAN) is used toimprove low-dose CT image quality.Cycle-GAN can learn data distribution of organ structures from unpaired full-dose and low-dose images, i.e., there is no one-to-one correspondence between full-dose and low-dose images. This is an important development of learning-based methods for low-dose CT since it enables the model growth using previously acquired full-dose images and later acquired low-dose images from different patients. NIH-AAPM-Mayo Clinic Low Dose CT Grand Challenge data are used to test Cycle-GAN de-noising method. The results show that the proposed method not only achieves better peak signal-to-noise ratio (PSNR) for quarter-dose images than non-local mean and dictionary learning de-noising methods, but also preserves more details reflected by images and structural similarity index (SSIM)[6].

G. *Image De-noising Using Graph-Based Frequency Domain Low-pass Filtering*

By taking the image as a graph signal, construct a suitable underlying image to make the image relatively smooth, and combine the signal priori to image de-noising. Based on this idea, and combined with graph Laplacian matrix, a method of image low-pass filtering in frequency domain is proposed. Experiments show that the proposed method is effective in image de-noising, and superior to the traditional Wiener filtering and Gaussian filtering [7]

H. *Medical Image De-noising with Recurrent Residual U-Net (R2U-Net) base Auto-Encoder*

recurrent residual U-Net (R2U-Net) based autoencoder model is used for medical image de-noising which is applied for digital pathology, dermoscopy, Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) images de-noising tasks. The performance of R2U-Net based autoencoder model is also evaluated for Transfer domain (TD) between MRI and CT scan images. The experiments have conducted on different publicly available medical image datasets and shows promising de-noising results which can be applied in different medical imaging applications [8].

I. *U-Net for SPECT Image De-noising*

Single Photon Emitted Computed Tomography (SPECT) is characterized by low photon counts, which results in a high degree of image noise. In this work, deep learning-based image de-noising networks is applied to imaging modality. Four-layeredUNetis proposed for de-noising of SPECT images that was trained using data obtained from Monte Carlo simulations of XCAT phantoms. proposed network was able to increase image quality by a factor of 14.15 dB as measured with PSNR[9].

J. *An Effective Approach for Underwater Sonar Image De-noising Based on Sparse Representation*

an image de-noising approach based on sparse representation is used to remove the complex and severe noise from sonar image more effectively, To decompose and then reconstruct the sonar image on DCT dictionary with OMP is effective for additive noise removing. Logarithmic transformation was applied on the previous reconstructed image to make it adapt to sparse representation de-noising model. Experiments are provided to demonstrate the performance of the proposed approach. Results show that this method is efficient in removing additive and multiplicative noise from the sonar image and is also particularly appealing in terms of both de-noising effect and keeping details [10].

K. *Improved De-noising Auto-encoders for Image De-noising*

A deep de-noising auto-encoder has been proposed and shown excellent performance compared to conventional image de-noising algorithms. The statistical features of restored image residuals produced by De-noising Auto-encoders is used and propose an improved training loss function for De-noising Auto-encoders based on Method noise and entropy maximization principle, with residual statistics as constraint conditions. Experiments indicate that the Improved De-noising Autoencoders introduce less non-existent artifacts and are more robustness than other state-of-the-art de-noising methods in both PSNR and SSIM indexes, especially under low SNR[11].

L. *Image De-noising Based on A CNN Model*

CNN model is used in deep learning for image de-noising. Compared with traditional image de-noising methods, such as average filtering, Wiener filtering and median filtering, the advantage of using this CNN model is that the parameters of this model can be optimized through network training; whereas in traditional image de-noising, the parameters of these algorithms are fixed and cannot be adjusted during the filtering, namely, lack of adaptively.Thede-noising method based on a linear CNN model is implementing. The experimental results show that the proposed CNN model can effectively remove Gaussian noise and improve the performance of traditional image filtering methods significantly [12].

M. *Low-Dose CT Image De-noising Using a Generative Adversarial Network With Wasserstein Distance and Perceptual Loss*

Advanced image reconstruction from low dose CT data is required to improve diagnostic performance, which is a difficult problem due to its unfavorable nature. A new method of image noise removal is introduced, which is based on the Generative Adversarial Network (GAN) with Wasserstein distance and perceptual similarity. The Wasserstein distance is a key concept in optimal transport theory and promises to improve GAN performance. Perceptual loss removes noise by comparing the perceptual characteristics of a de-noised output with those of the basic truth in an established characteristic space, while GAN focuses more on the statistical migration of the noise distribution of the data from strong to weak. Thus, the proposed method transfers the knowledge of visual perception to the task of image de-noising and is capable not only of reducing the noise level of the image, but at the same time trying to retain critical information. Promising results were obtained in clinical CT imaging experiments[15].

TABLE 1 LITERATURE REVIEW

Researchers	**Method used**	**Type of Noise**
P. H. T. Binh	FlashLight CNN (FLCNN) based on deep residual networks	Additive White Gaussian Noise
N. Thanh Trung	Dilated Residual Convolutional Neural Networks for Low-Dose CT Image De-noising	Adjust SAR-DRN for noise suppression on low-dose CT scans
P. Kattakinda and A. N. Rajagopalan	Unpaired Image De-noising based on deep learning	It is used to train a de-noising network
W. Kumwilaisak	Deep Convolutional NeuralNetworks	Poisson noise
J. Li, J. Wang, and J. Li	Image De-noising Algorithm Based on Incoherent Dictionary Learning	-
Z. Li, J. Huang	Low-Dose CT Image De-noising Using Cycle-Consistent Adversarial Networks	Quarter-dose images
M. Liu and Y. Wei	Image De-noising Using Graph-Based Frequency Domain Low-pass Filtering	-
S. Nasrin, M. Z. Alom	Recurrent Residual U-Net (R2U-Net) base Auto-Encoder	Medical image De-noising
M. P. Reymann*et al*	Four-layered UNet	Imaging modality

III. APPLICATIONS OF IMAGE DE-NOISING

Image de-noising is fundamental image processing problem which finds applications in various fields of technology. With voluptuous growth of science and technology, scope of human action is expanding, creating higher demand of information which results in high resolution images [16][17]. The noise disturbs this information and image de-noising becomes increasingly important for subsequent image analysis. Image de-noising not only generates visually pleasant images, but also “uncovers”the corrupted information pixel for further image analysis and in- formation extraction. The process of image de-noising has left no area of application unaffected which includes medical imaging, biometrics, remote sensing, HVS (Human Visual System), military surveillance and infrared image de-noising.

A. *Medical Image De-noising*

Magnetic resonance imaging is used for the visualization of soft tissues of various organs of the body. MRI’s are invariably corrupted with various noise factors like variable field strength, radio frequency pulses or due to receiver bandwidth. The Computed Tomography is yet another form of imaging technologies which suffers from image degradation due to noise owing to the inherent problem of hardware restriction. Therefore, a lot of methods have been designed in order denoise the CT images [15].

B. *Underwater image de-noising*

Underwater laser imaging has been rapidly employed in order to acquire information regarding underwater regions. However, the image resolution degrades due to the corruption of acquisitions with noise due to watery medium. The major reasons of occurrence of noise in underwater imaging is attenuation and back scattering of laser waves by water resulting in poor image quality.

C. Remote sensing-image de-noising

Remotely sensed satellite images are invariably corrupted with noise either during signal transmission or acquisition. The removal of high frequency noisy components becomes inevitable in order to improve the visual appearance, extract and analyse the satellite imaging information. The exploitation of directional correlation in spatial and transform domain has been a common idea for image de-noising. However, the success of these methods largely depends on the amount of orientation correlation measurement.

D. SAR image de-noising

To despeckle the SAR (synthetic aperture radar) images, is one of the important research problems in the field of remote sensing. This imaging technology finds wide range of applications in military surveillance.

E. Infrared image de-noising

The infrared imaging technology is employed in order to capture the thermal radiation emitted by the metal objects and it finds extensive application in the night mode imaging and military surveillance. The infrared images are corrupted with Poisson noise due to low-light conditions and atmospheric perturbations

IV. CONCLUSION

In this paper, we studied image de-noising filtering technique that contributes an earnest effort in order to compare, classify and evaluate various image-de-noising methods. Extensive efforts by a huge number of researchers have generated a structural literature, which exhibits substantial progressive growth attained by a chain of sequential incremental improvements. While it is nearly impossible to cover all of them, we have covered each domain of image de-noising with several methods' representative of each category. The basic idea of image de-noising is edge preservation while getting rid of noisy pixels.

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