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A Review of Image Denoising Techniques in Different Domain

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Abstract: *The ultimate goal of image denoising from video is to improve the given image, which can reduce noise interference to ensure image quality. Image denoising is a problem of fundamental importance for enhancement of quality in image restoration and computer vision. Through denoising technology, image quality can have effectively optimized, signal-to-noise ratio can have increased, and the original image information can have better reflected. Image denoising is a vital preprocessing step for image based object detection, recognition, and tracking since high frequency image details are mixed with noise in most cases, most of the existing image denoising methods have difficult preserving the edge and texture information while thoroughly eliminating the noise. In this paper we review the different image denoising techniques.*

Keywords: - Image denoising, Transformation, Wavelet Transformation, Image Quality, Computer Vision.

Introduction

Image denoising is one of the basic tasks for the researchers dealing with image processing since there may occur distortions of images during the acquisition, processing, compression, transmission or reconstruction processes. Therefore, it is important to eliminate the noise from the images and increase the quality, or produce good estimates from noisy ones. Images are affected by noise during their acquisition and transmission. Therefore, the denoising process is necessary to achieve higher quality images. However, both edges of the image and noise are characterized by high frequencies; loss of edge information may become unavoidable as a result of the denoising process. Thus, recovered, denoised images, become blurrier or less denoised. Therefore, a wavelet threshold denoising technique, based on edge detection, can be used to preserve more edge information and enhance the quality of the denoised image. The image noise can be Gauss, Poisson, or particle noise. The visuality and processing of the image are both affected by the noise. Therefore, it is aimed to preserve the useful information of the image and to reduce the noise by the image denoising process. Since denoising is a preliminary process in the field of image processing, almost all researchers interested in image processing have dealt with this problem and therefore researches on this effect made significant progress. Spectrum distribution is used for the traditional image denoising algorithms. Image denoising is one of the most important applications in image processing. Using the knowledge that high frequencies characterize noise as well as edges, the denoising process and edge detection can be combined. Thus, deficiencies in commonly used denoising methods can be overcome. Although many denoising and edge detection methods are used today, different methods can be useful in different noise and image types. In the wavelet edge detection method, it is important to determine the appropriate threshold value while thresholding wavelet coefficients because noises are not clustered in a few wavelet coefficients. Therefore, if the threshold is not chosen high enough, the noise may not be reduced significantly. On the other hand, if it has a higher value, the better denoising performance will occur however it will result in blurred edges.

Noise is the unwanted energy which is mixed during the acquisition, transmission, and/or reconstruction of an image. Though the noise cannot be altogether eliminated, however, it can be reduced at acquisition time. Post-processing of acquired imagery using data processing algorithms is used to reduce its effects. In such applications, denoising is a major challenge for the researchers [8]. Denoising is an inverse ill-posed problem which is classically addressed by specifying a forward model and then inverts it for the unknowns. Recent developments are exploring the use of deep learning techniques for the denoising. Denoising is the fundamental step in medical image processing applications while doctors and medical practitioners most often rely on these processed images for the diagnosis. In particular, magnetic resonance imaging (MRI) and computed tomography (CT) scans are used to observe the internal structure as well as any defects like tumors or injuries present inside the body. Generally, MRI and CT images are affected by noise due to fluctuations in temperature of the scanner room, disturbance in the scanning machines and/or patient's movement during the image acquisition. Due to the noise, magnitude of the pixel/voxel values in the images/image stack are perturbed which leads to artifacts and loss of details in the images. It makes the diagnosis and disease prediction complicated. The main considerations involved in medical image denoising algorithms include: a) edges in the denoised image should be preserved, i.e., filtering performed for denoising should not blur out the finer details of imagery and while at the same time, b) the visual quality of the denoised image should be preserved and improved.

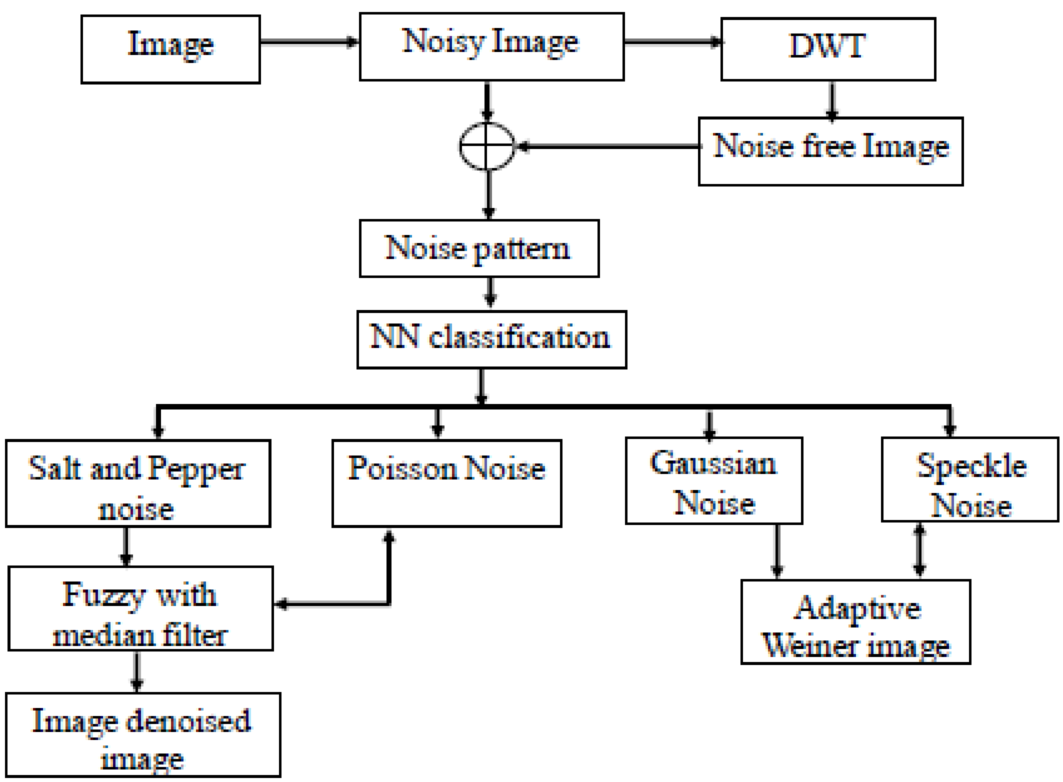

Figure 1: Designed system for noise pattern generation and image filtering using that information.

II. Literature Review

[1] In this study, two evolutionary computational algorithms namely SGOA and APSO are applied to denoising problem in gray scale images. For image denoising, linear filters are also ineffective against signal based noises. Similarly, image denoising algorithms based on spatial frequency filtering and wavelet transforms take a long time to create and are computationally complex. Image denoising and accuracy can be improved with increased efficiency if all of the above shortcomings in literary works are tackled. The proposed method distinguishes between noisy and noise-free pixels in the image, despite smoothing the data for filtering. After that, the noise-free image is created using the filtering window.

Hyperspectral images (HSI) are corrupted by a combination of Gaussian and impulse noise. Successful denoising of HSI data increases the accuracy of high-level vision operations like classification, target tracking and land-cover problem. On the one hand, the traditional approach of handling the denoising problem using maximum a posteriori (MAP) criterion is often restricted by the time-consuming iterative optimization process and design of hand-crafted priors to obtain an optimal result. On the other hand, the discriminative learning-based approaches offer fast inference speed over a trained model; but are highly sensitive to the noise level used for training. A discriminative model trained with a loss function which does not accord with the Bayesian degradation process often leads to sub-optimal results. In this paper [2], they design the training paradigm emphasizing the role of loss functions in neural network; similar to as observed in model-based optimization methods. Further, Bayesian motivated loss functions also act as priors to constrain the solution space to the types of noise observed in hyperspectral image acquisition process. As a result, loss functions derived in Bayesian setting and employed in neural network training boosts the denoising performance. Extensive analysis and experimental results on synthetically corrupted and real hyperspectral datasets suggest the potential applicability of the proposed technique under a wide range of homogeneous and heterogeneous noisy settings.

Haze reduces the contrast of an image and causes the loss in colors, which has a negative effect on the subsequent object detection; therefore, single image dehazing is a challenging visual task. In addition, defects exist in previous existing dehazing approaches: Pixel-based dehazing approaches are likely to result in insufficient information to estimate the transmission, whereas patch-based ones are prone to generate shadows. They both also tend to induce color deviations. Therefore, this study [5] proposes a novel method based on multi-scale wavelet and non-local dehazing. A hazy image is first decomposed into a low-frequency and three high-frequency sub-images by wavelet transform. Non-local dehazing and wavelet denoising are then employed on the low-frequency and high-frequency sub-images to remove the haze and noise, respectively. Finally, a haze-free image is obtained from the reconstruction of sub-images.

Deep convolutional neural networks (CNNs) for image denoising have recently attracted increasing research interest. However, plain networks cannot recover fine details for a complex task, such as real noisy images. In this paper, [6] they propose a Dual denoising Network (DudeNet) to recover a clean image. Specifically, DudeNet consists of four modules: a feature extraction block, an enhancement block, a compression block, and a reconstruction block. The feature extraction block with a sparse mechanism extracts global and local features via two sub-networks. The enhancement block gathers and fuses the global and local features to provide complementary information for the latter network. The compression block refines the extracted information and compresses the network. Finally, the reconstruction block is utilized to reconstruct a denoised image. The DudeNet has the following advantages: (1) The dual networks with a parse mechanism can extract complementary features to enhance the generalized ability of denoiser. (2) Fusing global and local features can extract salient features to recover fine details for complex noisy images. (3) A Small-size filter is used to reduce the complexity of denoiser.

[7] They introduce an image denoising algorithm which utilizes a novel online dictionary learning procedure together with patch ordering. The developed algorithm employs both the non-local image processing power of patch ordering and the sequential patch-based update of online dictionary learning. The patch ordering process exploits the similarities between patches of a given image which are extracted from different locations. Joint processing of the ordered set of image patches facilitates the non-local image processing ability of the algorithm. The algorithm starts with the extraction of a maximally overlapped set of patches from the given noisy image. Then, the extracted patches are reordered by using a distance measure, and the 3D ordered patch cube is formed. The ordered patch cube is used sequentially to update an over complete dictionary. In each iteration, firstly the present patch is denoised using sparse coding over the current over complete dictionary. Secondly, the over complete dictionary is updated using the current image patch, and the dictionary is passed to the next iteration.

X-ray acquisitions are beneficial in food contaminant analysis as they can detect both metallic and non-metallic objects. This paper considers the scenario of single-pixel hyperspectral X-ray acquisitions applied to a series of materials with different characteristics. They propose [11] a method that jointly applies a denoising operation and detects the analysed material in terms of a physical parameterisation. The proposed algorithm is based on a Convolutional Neural Network (CNN) trained with a multitask learning strategy using a custom loss function tailored to the problem at hand. Experimental results on metals and polymers show that the proposed method can also generalise to materials never seen at training time.

[12] Images are affected by noise during their acquisition and transmission. Therefore, the denoising process is necessary to achieve higher quality images. However, both edges of the image and noise are characterized by high frequencies, loss of edge information may become unavoidable as a result of the denoising process. Thus, recovered, denoised images, become blurrier or less denoised. Therefore, a wavelet threshold denoising technique, based on edge detection, can be used to preserve more edge information and enhance the quality of the denoised image. In this paper, a novel image denoising method, based on wavelet thresholding by using Otsu's threshold, has been proposed and the clarity of the image which has been handled with this method is superior to that currently achieved by the other wavelet thresholds. The obtained results show that the proposed method, in this paper, provides better performance compared to commonly used wavelet image threshold denoising methods in terms of the visual quality of the denoised image. In addition, when the edge detection and denoising processes are combined, the deficiencies of the commonly used denoising methods are eliminated and a better denoising effect has been achieved.

[13] Hyperspectral image (HSI) mixed noise removal is a fundamental problem and an important preprocessing step in remote sensing fields. The low-rank approximation-based methods have been verified effective to encode the global spectral correlation for HSI denoising. However, due to the large scale and complexity of real HSI, previous low-rank HSI denoising techniques encounter several problems, including coarse rank approximation (such as nuclear norm), the high computational cost of singular value decomposition (SVD) (such as Schatten p-norm), and adaptive rank selection (such as low-rank factorization). In this article, two novel factor group sparsity-regularized nonconvex low-rank approximation (FGSLR) methods are introduced for HSI denoising, which can simultaneously overcome

the mentioned issues of previous works. The FGSLR methods capture the spectral correlation via low-rank factorization, meanwhile utilizing factor group sparsity regularization to further enhance the low-rank property.

In this work, [14] they present Eformer- Edge enhancement based transformer, a novel architecture that builds an encoder-decoder network using transformer blocks for medical image denoising. Non-overlapping window-based self-attention is used in the transformer block that reduces computational requirements. This work further incorporates learnable Sobel-Feldman operators to enhance edges in the image and propose an effective way to concatenate them in the intermediate layers of our architecture. The experimental analysis is conducted by comparing deterministic learning and residual learning for the task of medical image denoising.

III. Image Discrete Wavelet Transformation

Various medical imaging modalities are used for diagnosis purposes and treatments. Magnetic resonance imaging (MRI) [1], X-ray, ultrasound, radionuclide, and optical are the most common of them. Modern medical imaging systems have many problems associated with visual data processing. Low informativeness of 2D and 3D images often does not contain enough information for highquality diagnosis is one of them. Multiple views combining the same organ solve this problem in practice. The resulting image is more informative and facilitates perception by both humans and machines, increasing diagnostics' accuracy. Modalities MRI, computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), and their hybrids CT/PET, CT/SPECT, CT/MRI, MRI/PET, MRI/SPECT are used for brain diseases diagnosis, for example. Such combinations provide the complete description of the organ anatomical structure and follow up the organ cell behavior [11]. Medical imaging systems produce increasingly accurate images with improved quality using igher spatial resolutions and color bit-depth. Such improvements increase the amount of information that needs to be stored, processed, and transmitted. This process is significant for 3D scanning technology. Medical imaging sets of 10-30 TB per patient are not unusual. Tomograph that registers images of 1196 by 500 pixels, 24 bits per pixel, and 20 frames per second creates a tomogram of about 20 GB in 10 minutes. The retina OCT results may require more than 40 GB. Virtual microscopy color image sets can often have a size exceeding 50 GB [20].

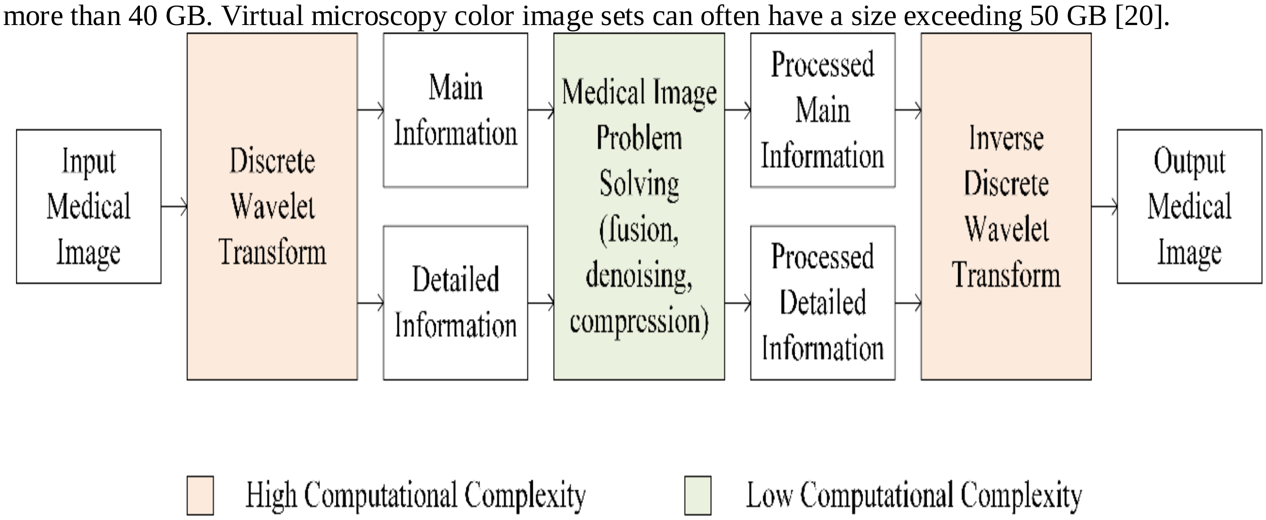

Figure 2: Medical image wavelet processing scheme [11].

Medical imaging mainly uses wavelets to solve three important problems: fusion, denoising, and compression of medical images. The authors [11] proposed an efficient colorful Fourier ptychographic microscopy reconstruction method using multi-resolution wavelet-based fusion. Wavelet fusion method and algorithm for the fusion of intravascular ultrasound and OCT pullbacks to improve the use of those two types of medical images. Wavelets technique is very popular denoising approach in mathematics and digital image processing area because of their ability to effective represent and analysis of data. The current wavelet approach applies a wavelet transform on images in a pyramid fashion up to the desired scale using the theory of multi resolution signal decomposition with the wavelet representation and the concept of embedded zerotree wavelet (EZW) based on the decaying spectrum hypothesis.

IV. Conclusion

With the development of science and technology and the need of work and life, the application of digital image filtering will be more and more extensive, and the requirements will be higher and higher. So far, there are still many new ideas and methods in denoising, and constantly enrich image denoising methods. Denoising is the low-level signal processing technique used to remove specific noise from noisy observation in order to improve the quality of signal analysis. In theory, the real noise can be defined as "the random error" which cannot be predicted and can only be recognized by probability and statistics. In this paper we review the various techniques related to image denoising techniques and in future need to enhance the image quality.

References

[1] V Mnssvkr Gupta, Kvss Murthy, R Shiva Shankar, “A Novel Approach for Image Denoising and Performance Analysis using SGO and APSO”, Journal of Physics: Conference Series, 2021, pp. 1-9.

[2] Hazique Aetesam, Suman Kumar Maji, Hussein Yahia, “Bayesian Approach in a Learning-Based Hyperspectral Image Denoising Framework”, IEEE Access, 2021, pp. 169335-169347.

[3] Subrato Bharati, Tanvir Zaman Khan, Prajoy Podder , Nguyen Quoc Hung, “A comparative analysis of image denoising problem: noise models, denoising filters and applications”, 2020, pp. 1-16.

[4] Tugba Ozge Onur, “ Improved Image Denoising Using Wavelet Edge Detection Based on Otsu's Thresholding”, Acta Polytechnica Hungarica, 2022, pp. 79-92.

[5] Wei-Yen Hsu, Yi-Sin Chen, “Single Image Dehazing Using Wavelet-Based Haze-Lines and Denoising”, IEEE Access, 2021, pp. 104547-104559.

[6] Chunwei Tian, Yong Xu, Wangmeng Zuo, Bo Du, Chia-Wen Lin, David Zhang, “Designing and Training of A Dual CNN for Image Denoising”, IEEE 2020, pp. 1-12.

[7] Ozden Colak, Ender M. Eksioglu, “On the Fly Image Denoising using Patch Ordering”, Preprint submitted to Elsevier, 2020, pp. 1-10.

[8] Swati Rai, Jignesh S. Bhatt, S. K. Patra, “An unsupervised deep learning framework for medical image denoising”, IEEE 2020, pp. 1-22.

[9] K. Chithra, D. Murugan, “Comparative Analysis of Image Denoising Techniques for Enhancing Real-Time Images”, International Journal of Computer Engineering & Technology, Volume 9, 2018, pp. 250–259.

[10] Yuya Onishi, Fumio Hashimoto, Kibo Ote, Hiroyuki Ohba, Ryosuke Ota, Etsuji Yoshikawa, Yasuomi Ouchi, “ Anatomical-Guided Attention Enhances Unsupervised PET Image Denoising Performance”, , pp. 1-29.

[11] Nicolo Bonettini, Carlo Andrea Gonano, Paolo Bestagini, Marco Marcon, Bruno Garavelli, Stefano Tbaro, “Multitask learning for denoising and analysis of X-ray polymer acquisitions”, IEEE 2020, pp. 1-5.

[12] Shruti Bhargava Choubey, Abhishek Choubey, Durgesh Nandan, Anurag Mahajan, “Polycystic Ovarian Syndrome Detection by Using Two-Stage Image Denoising”, Article in Traitement du Signal · August 2021, pp. 1217-1229.

[13] Yong Chen, Ting-Zhu Huang, Wei He, Xi-Le Zhao, “Hyperspectral Image Denoising Using Factor Group Sparsity-Regularized Nonconvex Low-Rank Approximation”, IEEE Transactions On Geoscience And Remote Sensing, 2021, pp. 1-16.

[14] Achleshwar Luthra, Harsh Sulakhe, Tanish Mittal, Abhishek Iyer, Santosh Yadav, “Eformer: Edge Enhancement based Transformer for Medical Image Denoising”, 2020, pp. 1-8.

[15] Bin Zhou, Biying Zhong, Jun Feng, “A Skewness Fitting Model for Noise Level Estimation and the Applications in Image Denoising”, ISAEECE 2021, pp. 1-7.

[16] Kanggeun Lee, Won-Ki Jeong, “ISCL: Interdependent Self-Cooperative Learning for Unpaired Image Denoising”, IEEE Transactions On Medical Imaging, 2021, pp. 1-12.

[17] Madhu Golla, Sudipta Rudra, “A Novel Approach of K-SVD-Based Algorithm for Image Denoising”, IGI Global, 2019, pp 354-357.

[18] Rui Lai, Yiguo Mo, Zesheng Liu, Juntao Guan, “Local and Nonlocal Steering Kernel Weighted Total Variation Model for Image Denoising”, Symmetry 2019, pp 1-16.

[19] Zhenhua Gan, Fumin Zou, Nianyin Zeng, Baoping Xiong, Lyuchao Liao, Han Li, Xin Luo, Min Du, “Wavelet Denoising Algorithm Based on NDOA Compressed Sensing for Fluorescence Image of Microarray”, IEEE access, 2018, pp 13338-13346.

[20] Arundhati Misra, B Kartikeyan and S Garg “Wavelet Based SAR Data Denoising and Analysis”, IEEE, 2014, Pp 1087-1092.