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Optimal Methods for Image Denoising: A Survey

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Abstract- Noise is significant part of real world system. No system is ideal and every perfect system still has some part of noise. Removal or better to say reduction of effect of these noises from the affected system is called denoising. Image denoising has turned into advanced level in processing of images and eliminating undesirable noisy information from the image. The image denoising algorithms need to mitigate the undesirable noisy components and keep all the applicable features of the image. The image denoising algorithms need to tradeoff between the two parameters i.e. powerful noise elimination and preservation of image data. Images play a very important role in many fields such as astronomy, medical imaging and images for forensic laboratories. Images used for these purposes have to be noise free to obtain accurate results from these images. This examination work presents an extensive survey of literature on image denoising based on Residual Correlation Regularization.

Keywords- Image Denoising, Residual Correlation Regularization, Image Processing, sparse representation, Dictionary learning.

I. INTRODUCTION

Image denoising is one of the most basic errands in image handling for better examination and vision. There are numerous kinds of noise which can diminish the nature of images. The Speckle noise which can be displayed as multiplicative noise, for the most part happens in different imaging framework because of random variety of the pixel esteems. It tends to be defined as the increase of random qualities with the pixel esteem.

Images are a characteristic path for people to consider spatial data, and burrow ital images are a characteristic portrayal of spatial information. Like every single recorded signal, digital images are regularly ruined by noise, expanding the trouble with which human eyewitnesses or PC calculations can separate the helpful fundamental data. Despite the fact that noise can be relieved by improved image securing equipment, in certain modalities, for example, rational imaging, the noise is a natural piece of the imaging procedure.

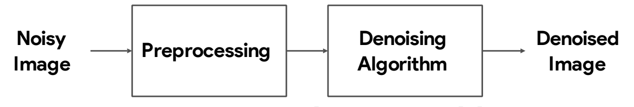

Fig. 1.1 Image denoising model.

There are two fundamental purposes for acquiring this gauge. To start with, the noise sifting can be proceeded as a pre-preparing step for additional machine examination, for example, scene division, object identification, or visual following. Also, denoised images are simpler to decipher by human onlookers, helping in assignments, for example, arranging ice types in SAR images, or evaluating blood vessel infection in ultrasound images.

Numerous specialists, proposed different denoising procedure like Wavelet based thresholding, Wiener filtering and so forth. The Curvelet change is an as of late presented as non-versatile multi-scale changes that is for the most part famous in the image handling field.

Multiplicative noise or speckle noise happened in different imaging frameworks because of random variety of pixel esteems. Albeit various rebuilding strategies were proposed in writing like Wiener filtering and Lee filtering to denoise such sort of uproarious images, anyway these techniques are not giving promising outcomes as far as PSNR, MSE and SNR.

If there should arise an occurrence of denoising the trait of the framework just as the sort of noise is known beforehand. The image s(x,y) is obscured by the direct activities causing the noise n(x,y) to include or increase with the image. The loud image at that point experiences a denoising system and produces the denoised image z(x,y). How close the image z(x,y) is to the first image relies upon the noise levels and the denoising calculation use.

Noise in image is brought about by vacillations in the splendor or shading data at the pixels. Noise is a procedure which twists the procured image and isn't a piece of the first image. Noise in images can happen from numerous points of view. During image securing the optical signals get changed over into electrical which at that point gets changed over to digital signal. At each procedure of change noise gets added to the image. The image can likewise get loud during transmission of the image as digital signals. The sorts of noises are:

- Gaussian noise
- Salt and Pepper noise
- Shot noise (Poisson noise)
- Speckle noise

II. LITERATURE SURVEY

SR. NO.	TITLE	AUTHORS	YEAR	APPROACH
1	Enhancing Denoised Image Via Fusion With a Noisy Image	J. Yoo and J. Kim	2019	PCA coefficient and eigenvector are estimated in a alternate way, and are used for estimating the enhanced version
2	Residual Correlation Regularization Based Image Denoising,	G. Baloch, H. Ozkaramanli and R. Yu,	2018	New residual correlation based regularization for image denoising has been reported in this work.
3	Image guided depth enhancement via deep fusion and local linear regularizaron,	J. Zhu, J. Zhang, Y. Cao and Z. Wang,	2017	A deep residual network based on deep fusion and local linear regularization for guided depth enhancement
4	Penalizing local correlations in the residual improves image denoising performance	P. Riot, A. Almansa, Y. Gousseau and F. Tupin,	2016	A new variational approach defining generic fidelity terms to locally control the residual distribution using the statistical moments and the correlation on patches
5	Video super-resolution using joint regularization,	D. Chen, X. He, H. Chen, Z. Wang and Y. Zhang,	2016	Combine compensation-based TV (CTV) regularization term with multi-non-local low-rank (MNLR) regularization term in our algorithm
6	Incremental update of feature extractor for camera identification,	R. Li, C. Li and Y. Guan,	2015	A feature extraction method based on PCA denoising concept was applied to extract a set of principal components from the original noise residual
7	BM3D-based ultrasound image denoising via brushlet thresholding,	Y. Gan, E. Angelini, A. Laine and C. Hendon	2015	Present a brushlet-based block matching 3D (BM3D) method to collaboratively denoise ultrasound images
8	Quadtree Structured Image Approximation for Denoising and Interpolation,	L. McCrackin and S. Shirani,	2014	Reported a method of using a support vector machine (SVM) to select between multiple well-performing contemporary denoising algorithms for each pixel of a noisy image.

J. Yoo and J. Kim[1], Image denoising unintendedly removes the original information as well as noises. Especially, texture tends to be easily distorted and smoothed by denoising because it is not distinguishable from noise. In this paper, we propose a novel framework to enhance the denoised image. The lost information of the denoised image is restored by fusing it with a noisy input. The proposed fusion is done by cost optimization which includes two data terms (noisy and denoised), and sparsity constraint term which is adopted to effectively suppress the noise in the principal component analysis (PCA) domain. The fusing weight between noisy and denoised significantly depends on the local region characteristics. PCA coefficient and eigenvector are estimated in a alternate way, and are used for estimating the enhanced version. Experimental results show that the proposed method convincingly improve texture and structural information for an image.

G. Baloch, H. Ozkaramanli and R. Yu, [2] Patch-based denoising algorithms aim to reconstruct the clean image patch leaving behind the residual as contaminating noise. The residual should possess statistical properties of contaminating noise. However, it is very likely that the residual patch contains remnants from the clean image patch. In this examination, new residual correlation based regularization for image denoising has reported. The regularization can effectively render residual patches as uncorrelated as possible. It allows us to derive an analytical solution for sparse coding (atom selection and coefficient calculation). It also leads to a new online dictionary learning update. The clean image is obtained through alternating between the two stages of sparse coding and dictionary updating. The performance of the proposed algorithm is compared with state-of-the-art denoising algorithms in terms of peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and feature similarity index (FSIM), as well as through visual comparison. Experimental results show that the proposed algorithm is highly competitive and often better than leading denoising algorithms. The proposed algorithm is also shown to offer an efficient complement to the benchmark algorithm of block-matching and 3D filtering (BM3D) especially.

J. Zhu, J. Zhang, Y. Cao and Z. Wang, [3] Depth maps captured by RGB-D cameras are often noisy and incomplete at edge regions. Most existing methods assume that there is a co-occurrence of edges in depth map and its corresponding color image, and improve the quality of depth map guided by the color image. However, when the color image is noisy or richly detailed, the high frequency artifacts will be introduced into depth map. In this examination, reported a deep residual network based on deep fusion and local linear regularization for guided depth enhancement. The presented scheme can effectively extract the correlation between depth map and color image in the deep feature space. To reduce the difficulty of training, a specific layer of network which introduces a local linear regularization constraint on the output depth is designed. Experiments on various applications, including depth denoising, super-resolution and inpainting, demonstrate the effectiveness and reliability of our proposed approach.

P. Riot, A. Almansa, Y. Gousseau and F. Tupin, [4] In this work, address the problem of denoising an image corrupted by an additive white Gaussian noise. This hypothesis on the noise, despite being very common and justified as the result of a variance normalization step, is hardly used by classical denoising methods. Indeed, very few methods directly constrain the whiteness of the residual (the removed noise). A new variational approach defining generic fidelity terms to locally control the residual distribution using the statistical moments and the correlation on patches has reported in this examination. Using different regularizations such as TV or a nonlocal regularization, our approach achieves better performances than the L2 fidelity, with better texture and contrast preservation.

D. Chen, X. He, H. Chen, Z. Wang and Y. Zhang,[5] Video super-resolution (SR) is an inverse problem, and with this method, can reconstruct a high-resolution (HR) version of a low-resolution (LR) video sequence. Because regularization-based method can solve the pathological problem in super-resolution, so it is widely used. However, in many traditional regularization terms, only the intra-image correlation will be taken into consideration so that the redundancy between adjacent frames is not be utilized. In order to make full use of both inter-image correlation and intra-image correlation, combine compensation-based TV (CTV) regularization term with multi-non-local low-rank (MNLR) regularization term in our algorithm. Moreover, utilize a weight matrix to reduce the negative impacts which is caused by registration residuals in CTV, and the weight matrix is based on spatial information filtering and clustering. The experiments show that can get better results than the compared methods by the proposed algorithm in visual quality and objective effective evaluation.

R. Li, C. Li and Y. Guan, [6] Sensor Pattern Noise (SPN) is an inherent fingerprint of imaging devices, which has been widely used in the tasks of digital camera identification, image classification and forgery detection. In our previous work, a feature extraction method based on PCA denoising concept was applied to extract a set of principal components from the original noise residual. However, this algorithm is inefficient when query cameras are continuously received. To solve this problem, reported an extension based on Candid Covariance-free Incremental PCA (CCIPCA) and two modifications to incrementally update the feature extractor according to the received cameras. Experimental results show that the PCA and CCIPCA based features both outperform their original features on the ROC performance, and CCIPCA is more efficient on camera updating.

Y. Gan, E. Angelini, A. Laine and C. Hendon, [7] In this examination, reported a brushlet-based block matching 3D (BM3D) method to collaboratively denoise ultrasound images. Through dividing image into multiple blocks, group them based on similarity. Then, grouped blocks sharing similarity form a 3D image volume. For each volume, brushlet thresholding is applied to remove noise in the frequency domain. Upon completion of individual filtering, the volumes are aggregated and reconstructed globally. To evaluate our method, run our denoising scheme on synthetic images corrupted with additive or multiplicative noise. The results show that our method can achieve good denoising performance in comparison with existing methods. Our method is also evaluated on cardiac and fetal ultrasound images. Analysis on the contrast and homogeneity of the denoised images demonstrates the feasibility of applying our method to ultrasound images to improve image quality and facilitate further processing such as segmentation.

A. Scholefield and P. L. Dragotti, [8] the success of many image restoration algorithms is often due to their ability to sparsely describe the original signal. Shukla proposed a compression algorithm, based on a sparse quadtree decomposition model, which could optimally represent piecewise polynomial images. In this work, adapt this model to the image restoration by changing the rate-distortion penalty to a description-length penalty. In addition, one of the major drawbacks of this type of approximation is the computational complexity required to find a suitable subspace for each node of the quadtree. This issue is address by searching for a suitable subspace much more efficiently using the mathematics of updating matrix factorizations. Algorithms are developed to tackle denoising and interpolation. Simulation results indicate that beat state of the art results when the original signal is in the model (e.g., depth images) and are competitive for natural images when the degradation is high.

III. PROBLEM STATEMENT

Image denoising is one of the most fundamental assignments in image handling. The requirement for image improvement and rebuilding is experienced in numerous down to earth applications. For example, mutilation because of additive white Gaussian noise (AWGN) can be brought about by low quality image securing, images saw in a loud situation or noise natural in correspondence channels. Straight separating and smoothing activities have been generally utilized for image reclamation in view of their relative effortlessness. . As a general rule, true images have normally non-fixed factual attributes. They are framed through a nonlinear framework process where the force dispersion showing up at the imaging framework is the result of the reflectance of the article or the location of intrigue and the brightening conveyance falling on the scene. The requirement for noise concealment without fundamentally debasing the edges and other high recurrence segments of the image has accordingly roused the improvement of effective noise moderation strategies.

IV. CONCLUSION

This assessment work presents a broad overview of writing on image denoising dependent on earlier work. Image Noise is random variety of splendor or shading in an image. It tends to be delivered by any hardware, for example, sensor, scanner or digital camera. Image noise is an unwanted signal, it's produce by image catching gadget that include additional data. As a rule, it lessens image quality and is particularly significant when the articles being imaged are little and have moderately low difference. This random variety in image brilliance is assigned noise. This noise can be either image ward or image autonomous.

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