A Brief Literature Review on Image Denoising Methodologies

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Abstract- Image denoising has turned into a basic advance 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 essential tasks in image processing for better analysis and vision. There are many types of noise which can decrease the quality of images. The Speckle noise which can be modeled as multiplicative noise, mainly occurs in various imaging system due to random variation of the pixel values. It can be defined as the multiplication of random values with the pixel value.

Images are a natural way for humans to think about spatial information, and dig- ital images are a natural representation of spatial data. Like all recorded signals, digital images are often corrupted by noise, increasing the difficulty with which human observers or computer algorithms are able to extract the useful underlying information. Although noise can be mitigated by improved image acquisition hardware, in some modalities, such as coherent imaging, the noise is an inherent part of the imaging process.

There are two main purposes for obtaining this estimate. First, the noise filtering can be performed as a pre-processing step for further machine analysis, such as scene segmentation, object detection, or visual tracking. Secondly, denoised images are easier to interpret by human observers, aiding in tasks such as classifying ice types in SAR images, or assessing arterial disease in ultrasound images.

Many researchers, proposed various denoising technique like Wavelet based thresholding, Wiener filtering etc. The Curvelet transform is a recently introduced as non-adaptive multi-scale transforms that is mainly popular in the image processing field.

Multiplicative noise or speckle noise occurred in various imaging systems due to random variation of pixel values. Although a number of restoration techniques were proposed in literature like Wiener filtering and Lee filtering to denoise such kind of noisy images, however these methods are not giving promising results in terms of PSNR, MSE and SNR.

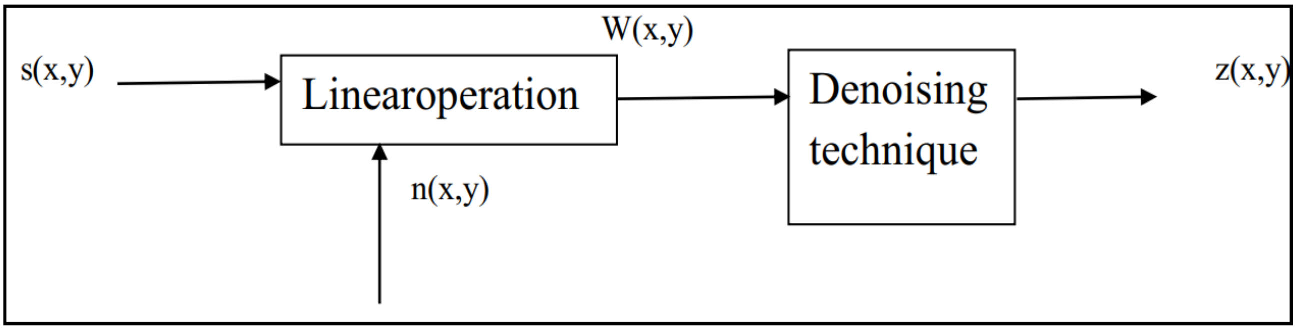

Fig. 1.1 Image denoising model.

In case of denoising the characteristic of the system as well as the type of noise is known beforehand. The image s(x,y) is blurred by the linear operations causing the noise n(x,y) to add or multiply with the image. The noisy image then undergoes a denoising procedure and produces the denoised image z(x,y). How close the image z(x,y) is to the original image depends on the noise levels and the denoising algorithm use.

Noise in image is caused by fluctuations in the brightness or color information at the pixels. Noise is a process which distorts the acquired image and is not a part of the original image. Noise in images can occur in many ways. During image acquisition the optical signals get converted into electrical which then gets converted to digital signal. At each process of conversion noise gets added to the image. The image can also become noisy during transmission of the image in the form of digital signals. The types of noises are

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

II. SPARSE REPRESENTATION

Sparse representation has received widespread attention because of its robust performance and wide range of applications. During the last decade, the theory of sparse representation has been used in various practical applications in signal processing and pattern recognition. It has also been used for compression, denoising, and audio and image analysis. In addition, dictionary learning and sparse representation have been used as powerful tools for recognition, classification and analysis of image and video data.

Generally, sparse representation is a technique for reconstructing a signal or image using the fact that signals can be presented by a set of basis elements. To build a robust and efficient recognition system, the number of training samples per subject (or object) is one of the main challenges. Recognition with a single training sample per subject (or object) , unless it is used along with a model, lacks information to predict the variations among different instances of the object. Furthermore, in many applications, several training samples per subject might be available, spanning different variations in illumination, pose or occlusion. In these cases, the features from each sample are extracted and used for the representation and classification of a query sample.

Sparse representations are intensively used in signal processing applications, like image coding, denoising, echo channels modeling, compression and many others. Recent research has shown encouraging results when the sparse signals are created through the use of a learned dictionary.

Theoretical developments of sparse signal representation have been interesting for researchers to use this powerful tool for computer vision and machine learning applications. Over the past decades, there have been many fundamental progresses in the field of machine learning. However, there are problems in dealing and processing of the high-dimensional data. During the last decade, a significant research effort has been devoted to find the compact or sparse representation for signals in order to process the large-scale data. Based on sparse representation theory, a signal can be decomposed into a linear combination of a few basic signals which is capable of representing the majority information conveyed by the target signal.

In fact, a sparse signal can be represented as a linear combination of a relatively few base elements in an over complete dictionary. To find sparse representations, there is a need to solve an under determined system of linear equations for sparsest solution. Sparse representation has recently found various applications in practical areas of signal processing and pattern recognition. Sparse signal representation has been used for compression, denoising and analysis of audio and image data.

a. Building the Dictionary

Sparse representation has been interesting for researchers in signal and image processing since many natural signals have a sparse or compressible representation in a variety of domains, such as Wavelet, discrete Sine transform (DST), discrete cosine transform (DCT) or Fourier domain. A sparse signal refers to a signal which admits a transform domain representation and most coefficients are zero.

b. Sparse Representation

In the theory of sparse representation, it is assumed that a feature vector of a test data from class i can be represented as a linear combination of the feature vectors of the training data from that class.

$$Y = \alpha_{I,1} + \alpha_{I,2} + \cdots \ldots \ldots + \alpha_{i,ni}\ V_{i,ni} \ldots \ldots \ldots \ldots \ldots (2.1)$$

where y ∈ R^m is the feature vector of the test data and the $\alpha_{i,j}$ values are the coefficients corresponding to the training data samples of subject i. A linear representation for the feature vector of the test data, y, can then be given as:

$$y = Ax \in R^m \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (2.2)$$

where x is the coefficient vector. Any x solving this system of equations gives a representation of y. Since A is a m by n, with m is more than 1, there are infinitely many such bfx's as the above system is under determined. By solving this equation for x, the class of the test data y can be identified. Note that in equation all the training data samples of a given subject are used to form a representation of the test data.

III. PRIOR WORK

SR. NO.	TITLE	AUTHORS	YEAR	APPROACH
1	Residual Correlation Regularization Based Image	G. Baloch, H. Ozkaramanli and R.	2018	New residual correlation based regularization for image denoising has

	Denoising,	Yu,		been reported in this work.
2	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
3	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
4	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
5	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
6	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
7	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.

G. Baloch, H. Ozkaramanli and R. Yu, [1] 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, [2] 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, [3] 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,[4] 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, [5] 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, [6] 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, [7] 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 factorisations. 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.

IV. PROBLEM STATEMENT

Image denoising is one of the most essential tasks in image processing. The need for image enhancement and restoration is encountered in many practical applications. For instance, distortion due to additive white Gaussian noise (AWGN) can be caused by poor quality image acquisition, images observed in a noisy environment or noise inherent in communication channels. Linear filtering and smoothing operations have been widely used for image restoration because of their relative simplicity. . In reality, real-world images have typically non-stationary statistical characteristics. They are formed through a nonlinear system process where the intensity distribution arriving at the imaging system is the product of the reflectance of the object or the scene of interest and the illumination distribution falling on the scene. The need for noise suppression without significantly degrading the edges and other high frequency components of the image has thus motivated the development of efficient noise mitigation techniques.

V. CONCLUSION

This examination work presents an extensive survey of literature on image denoising based on prior work. Image Noise is random variation of brightness or color in an image. It can be produced by any circuitry such as sensor, scanner or digital camera. Image noise is an undesirable signal, it's produce by image capturing device that add extra information. In many cases, it reduces image quality and is especially significant when the objects being imaged are small and have relatively low contrast. This random variation in image brightness is designated noise. This noise can be either image dependent or image independent.

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