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A Survey of Multispectral Image Denoising Methods for Remote Sensing Imagery Applications

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Abstract
In contrast with the conventional RGB or gray scale images, the multispectral images tends to convey more faithful representation for real world scenes to enhance the performance of many tasks entail with computer vision, object extraction, detection and quantification, tagging operations and image segmentation. High fealty of color reproduction is possible by using multispectral images of visible spectrum than the normal RGB systems due to attainment of limited information conveyed by RGB images. While capturing, the MSIs are certainly corrupted by various noises which may be due to limitations in equipment, scanty bandwidth and loss of radiant energy. Formulating a novel mathematical description of deep learning based denoising model is a complex research question and many researchers specified different algorithms or methods for denoising of MSI. Many researchers have suggested its use with the application of neural network as a sparse coding of noisy patches. Moreover, these allow various algorithms to amend itself for a task using machine learning algorithm. However, in general practice, a multispectral image is always encountered by various noises. In this study, we presented the past techniques specified for the noise influenced MSI. The survey describes the overview of past techniques and their advantages in comparison with each other.

Keywords: *Multispectral images, Deep learning based denoising model, Sparse coding, Machine learning algorithms.*

I. PROBLEM IDENTIFICATION

The MSIs become prevalent for research advances in the fields of remote sensing, fluorescence microscopy, astronomical imaging and geo tracking activities. During data acquisition most of the multispectral images are corrupted, which makes the resulting image lack in quality. The setup used for MSI imaging consists of an array of sensors with specified frequency bands of light. As the devices involve physical measurements, the captured images get influenced by various sources of noise. The multispectral sensors achieve imagery data in the form of hundreds of spectral bands.

The recorded imagery data can be represented in linear algebraic form as:

$$\hat{f} = f + \eta$$

Where f is the actual signal, η is the additive noise in the pixel wise form and $\hat{f}$ is the recorded imagery data in pixel wise manner.

Moreover in the past, various algorithms have been formulated to resolve the denoising of MSI. This method tends to provide the best estimate of the noise free image from the recorded noisy image. However this leads to heavy processing with additional requirements of employing thresholding techniques for denoising, which in turn is a forbidding task. Further some of the essential data of the original image is lost in extract of the noise free image signal. The main theme of this study is to provide a survey of various automated and non automated denoising methods of Multispectral images persuasively.

II. INTRODUCTION

Noise is an ineluctable part of most real world multispectral images and it is a notable that good denoising leads to improvement in performance of various image processing steps of classification, identification and segmentation. The noise may emanate in the formation or transmission processes. By linear frequency distortion, blocking artifacts and noise the images may be corrupted by degradation. Basically there are three types of noises that encounter the images: additive, impulse and speckle or multiplicative noises. MSI is a digital means for detection of thermal signature, remote sensing and terrain analysis. It is frequently used as a realistic proxy for mapping applications [1-7]. Thus in the study we précis several denoising algorithms concerned to multispectral images using several sparse coding, Deep learning based techniques for which its consummation are measured based on the denoised output image and computational workload, which helps the users for segmentation, detection and classification. The properties such as directivity and shift invariant of multispectral images have also discussed. During the study the database of multispectral image is used for MSI imagery [8-9].Multispectral images cannot directly identify the features of image by visual inspection. So the remote sensing data need to be classified first, escort by various image processing techniques which helps the user to understand the image features. Such classing is a compound task which includes precise validation of training samples rely on the classification algorithm used [10-11]. These methods can be grouped in to two ways: supervised classification which makes use of training samples and unsupervised classification which does not require any prior knowledge to stratify the features of the image. The selection of the training samples and biased selection will badly affect the performance of classification, so expert knowledge is very important in supervised classification where as in unsupervised classification grouping or clustering of pixel values are observed followed by setting a threshold for embracing the number of classes in the image. The finer the threshold, the more the classes. So in unsupervised classification inferred information about the classes is not required. In image processing, MSIs are most commonly used for remote sensing applications. Several images in the visual and non-visual range from several frequency bands are usually taken by satellites. For example LANDSAT 5(land satellite) produces 7 band images with wavelengths ranges from 450nm to 1250 nm.

III. TAXONOMY OF IMAGE DENOISING METHODS

The following listed methods are mostly implemented and extensively used for various applications of multispectral images denoising.

1. Filtering techniques based on parameterization of recorded signal and general arguments.
2. Techniques employing internal & global statistics of the image.
3. Techniques based on general arguments of recorded signal confined to internal statistics of the image.
4. Techniques:
   - Based on nonlocal group wise spectrum.
   - Based on nonlocal multitask sparse learning.
5. PCA-LPG algorithm
6. Patch based low rank approximation model.
7. Tensor based denoising approach.
8. Deep learning based denoising algorithm.

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From the above specified methods, each of the techniques is the sifting of one or the other and some are even used in amalgam to be used in peculiar areas. Thus in this aspect of denoising, the performance of the approach is well improved when it is implemented with one or decorous over a chain of axioms for the given multispectral image data, which indeed hold true; however, it also gives rise to certain problem of making too many assumptions which makes the denoising of the image more complex, which in turn degrades the performance and increases the computational cost of denoising. The problem in such statistical methods is the tradeoff between the variance and the bias. Most of the popular algorithms rely on the internal statistics of the image.

IV. FILTERING

The filtering is a principal operation to be performed for various processing applications of signal, image and video. The filtering based denoising methods rely on general arguments which vary drastically for all types of multispectral images and even for the digital signals.

The various filtering techniques include:

- Adaptive median filtering
- Mean filtering
- Wiener filtering
- Adaptive wiener filtering
- Bilateral filtering [12]
- Anisotropic diffusion [13]
- Fuzzy two-step filter
- Vector bilateral filtering [14]

Such methods do not require any preprocessing technique for performing computational operation of denoising and hence the speed of the system will be in general. But these methods are ancillary to the task oriented algorithms. Adaptive median filtering [15] is used for the removal of impulse noise from highly corrupted images, which consists of two steps. The first step is to locate the pixels affected with impulse noise which is based on the intensity values of the pixel and the step is to process the noise affected pixels to produce the noise free output by using median filtering. Fuzzy two step filter [16] is for impulse noise removal from color images which includes two phases: fuzzy detection based on the computation of fuzzy reasoning and fuzzy gradient values, iterative fuzzy filtering method. For providing a good tradeoff between the edge degradation and noise removal for multispectral images, a vector bilateral filtering is used. In this the filtering problem is posed as a nonlinear and minimization of stein's unbiased risk estimate. It provides a better denoising performance on MSI when compared with several other methods. A wiener filter [17-18] is used to de-noise the Gaussian noise from the satellite image based on an adaptive cuckoo search algorithm. The 2D finite impulse response estimates the original image and the window weights. To get the minimum Mean Square Error (MSE), the window weights are adjusted between the filtered output and the desired image. Here, the optimized filter weights are assigned by the cuckoo search algorithm. This ensures the least MSE compared to other Meta-heuristic systems.

V. ALGORITHMS APPLYING GLOBAL IMAGE STATISTICS

There are few methods which depend on global statistics of the image which rely on some general assumptions about the images. The extraction of general statistics is achieved by training of noise affected pixels which in turn requires a dictionary of neat imagery patches and thus the neighboring pixels function is related by Markov random fields. The methods based on this or which exploits the statistics of the image i.e., wavelet basis or lack of pixels in frequency domain give empiric finer performance which require computation proviso of formulating the denoised pattern.

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The methods of such approach include:

- Wavelet based methods
- Learning filter based methods

In the field of RS and GIS, mapping use for planning and decision support, land possession satellite images are widely used. Identifying and denoising the noise within the remote sensing images is a challenging task for the researcher. The wavelets are basically used to get quality denoised images. The multispectral images are often encountered by noise due to radiometric noise, atmospheric scattering and absorption which reduces the visual quality by affecting the structural information and blur the edges which limit the accuracy of noise detection step. When compared to general filters to get fine resolution, the wavelet is the best choice.

The wavelet based methods include:

- Wavelet based trivariate shrinkage filter
- Rational- dilation wavelet transform
- Bayesian wavelet based denoising method

Wavelet based trivariate shrinkage filter [19-20] is an efficient method for removing Gaussian noise from the noisy image. In this the wavelet coefficients are modeled as trivariate normal distribution then by using maximum a posteriori (MAP) estimator a trivariate shrinkage filter is derived. Basically they are affected by edge ringing and low frequency noise. This filter produces the efficient output by preserving the image details at low cost with good PSNR value and good visual quality. Rational- dilation wavelet transform [21-22] is used to denoise the remote sensing images which are widely used in environmental and social tasks with rich texture. This transform enhances the sampling rate in both frequency and spatial domain. This method preserves more features of the image with less spectral distortion compared with other denoising methods. Bayesian wavelet based denoising method [23] is used for multi component images which makes use of a prior model for evaluating the wavelet coefficients called Gaussian scale model(GSM) model and uses a noise free image as a extra prior information.

VI. ALGORITHMS APPLYING INTERNAL STATISTICS

There are few methods which depend on the statistics found in the image itself. The algorithms developed on this depend on the basis of patches. Block matching and 3D filtering is one of the futuristic methods of this type of application. Based on the locally sparse representation in transform domain, an image is denoised by using BM3D [24] denoising method. The process involved in grouping and filtering procedure in BM3D is known as Collaborative filtering.

The basic steps involved in this method are:

- Finding of similar image patches to a given image patch
- Grouping of similar image patches in a 3D block
- Linear transformation of 3D block
- Shrinkage of transform coefficients
- Inverse 3D transformation

The basic steps that are involved in this BM3D method are grouping, linear transformation, collaborative filtering, aggregation or inverse transformation. This method involves non local filters [25] and transforms domain [26] methodologies. This is widely adopted for gray scale images but a color image or a multispectral image conveys more faithful information for real world scenes. Hence directly applying this to every channel or spectral band fails to produce satisfactory results. So the solution for this sort of problem is specified in two ways. The first strategy is performing the denoising on each channel independently by transforming the original image into a less correlated color space and the second is to jointly characterize the color bands for better spectral correlation. As the method works only on the internal statistics, so it provides a better performance over other denoising techniques. Several algorithms have also proposed based on combining internal and

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global statistics for providing better performance and good computational speed when large number of patches related with the multispectral images having super resolution [27].

VII. IMAGE DENOISING FOR OTHER TYPES OF NOISE

High heterogeneity of the noise is the main issue in MSI denoising. The MSIs are typically encountered by non-stationary noises with different levels of noise for different channels. The undesired information that contaminates an image is called noise. The basic aim of denoising is to retain the features of the image from the noise. The different types of noise are:

- Stripe noise
- Mixed Poisson- Additive white Gaussian noise

STRIPE NOISE

The stripe noise is the one which greatly reduces the imaging quality and further limits the accuracy of subsequent processing in multispectral remote sensing images. The devices that are used for sensing the multispectral remote sensing images are push-broom and cross-track imaging devices. Due to relative gain or offset difference in response of the detectors the stripes are caused. The most common strip noise that can be removed easily is the periodic stripe. There are three types of methods to remove the stripe noise. The first approach is the digital filtering technique which may use wavelet analysis, low pass filter and a Fourier-wavelet combined filter. This kind of approach is useful for destriping periodic stripes and is easy to implement. The second approach is to detect the stripe lines first and then apply interpolation methodology to remove the stripes. The third approach for destriping the stripes is based on the digital numbers (DNs) for every detector. The stripes can be removed by rectifying the distribution of the stripes to a reference distribution, such as histogram matching and moment matching [28]. To remove the non-periodic stripes radiometric equalization [29] based method was used. To enhance the smoothness of solution for both spatial and spectral dimension, the multispectral image is treated as a spatial-spectral volume and proposed an anisotropic spectral-spatial total variation model [30].

MIXED POISSON-GAUSSIAN NOISE

Even though there are various types of noises but additive white Gaussian noise (AWGN) is mostly considered in image denoising. In poor light environment, the amount of noise that is introduced to the original signal is characterized by the stochastic nature of the signal itself, in such case a mixed Poisson-Gaussian distribution noise model is considered and several denoising methods had been proposed [31]. There are several methods to reduce the regular AWGN noise [32].

VIII. OTHER TECHNIQUES OF DENOISING

Nonlocal group wise spectrum

In nonlocal group wise spectrum [33], similar patches are grouped into 3D blocks by sparse collaborative filtering that includes five processes: grouping, transform, thresholding, inverse transform, and aggregation. Grouping is the collection of similar patches into a single group. Some of the grouping techniques include K means clustering [34], fuzzy clustering [35], and self-organizing maps [36]. After grouping, transform is applied to each group. The soft or hard thresholding applied to the transform coefficients lessens or attenuates the noise in the image. Finally, inverse transform gives the estimates of the grouped blocks and each block are returned to their respective original position.

Nonlocal multitask sparse learning

To deliver reliable information, the spectrum of each pixel in the image of a scene is obtained which is the primary goal of multispectral imaging. This method simultaneous uses the spatial and spectral sparsity of the MSI. This method includes two phases: patch grouping for retaining nonlocal self similarity across spatial domain and the high correlation of MSI in spectrum is characterized by multitask sparse learning [37-39]. The methods band wise KSVD and band wise BM3D are the denoising methods for 2D images which do not consider the correlation of MSI across the spectrum which obtain low Peak signal to noise ratio(PSNR) and Structural similarity(SSIM).

PCA-LPG algorithm

The Principal component analysis with Local pixel grouping [40] is an efficient image denoising method. For the preservation of image features, the training samples are selected from the local window by using block matching based local pixel grouping. The local structure patterns cannot be realized by using fixed wavelet basis, thus the wavelet based methods cannot produce that much visual quality. So as to overcome that the PCA-LPG method is proposed which consists of two stages. The first stage generates the initial estimation of the image by removing the most of the noise in the image and the stage produces more refined output of the first stage which increases the performance of the denoising strategy.

Patch based low rank approximation model

The patch based low rank approximation model [41] is very effective method which make use of spatial redundancy to improve the image denoising performance. The multidimensional correlation for data is exploited by using low rank tensor approximation with Laplacian scale mixture modeling. This method is widely used in applications where the edge sharpness needs to be preserved.

Tensor based denoising approach

Tensor based denoising methods are used to restore the 3D image from noise. The Weighted Tensor Rank 1 (WTR1) [42-43] decomposition model is used for non-local image de-noising. The de-noising approach groups similar patches in a matrix form and then group them in a 3D stack. After the formation of the stack it is then converted into rank 1 tensor by WTR1 de-noising. Finally, the weights are determined by the low-rank approximation and the estimated similar patches are aggregated.

Deep learning based denoising algorithm

It is required that certain assumption in association with the processing of the prior information of the signal is must to enable the denoising method for effective operation and performance with supplement of knowledge in to it. This can be achieved by the combination of machine learning with statistical data. The prior information in the sense makes different meaning based on the usage. In one shot it may refer to the lack of wavelet coefficients and at other shot it may refers to the distribution based coefficients. This sort of approach can be used in various image restoration tasks for better results.

Formulating a mathematical model of learning based denoising is a hard research question. Many have formulated its use with the aid of neural network as sparse coding of noisy patches [44-46]. Deep learning [47] methods have importance in image denoising. Deep learning methods of various types deals with the noise have large differences. Discriminative learning are used for estimating Gaussian noise and optimization based methods are used for estimating the real noises. The Convolutional neural networks (CNNs) are used for estimating the additive white noisy images, real noisy images, hybrid noisy images and blind denoising. Convolutional Neural Network (CNN)[48] is used to reduce the noise level in the image with a fast and flexible solution. The CNN comprises of three layers that

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perform different operations. Initially, the noisy image is reshaped into four sub-images. In order to sustain the dimension of the feature maps untouched, zero padding is employed after convolution. For the input with different dimensions, the patch-based technique is used for de-noising the image. Since this method performs de-noising on sub-images, the efficiency is improved with faster response. Also, the memory load is reduced by the introduction of sub-pixel and sub-sampling convolution.

IX. CONCLUSION

In this paper, we have presented an effectual comprehensive study of various denoising methods for multispectral images which are used for wide range of applications. These studies have covered the supervised and unsupervised techniques for image denoising of multispectral or multiband images, while keeping the computational complexity at nominal. With the increase of high noisy image, the image processing needs more techniques to improve the quality of the image. We hope our study will support the other researchers to ubiquitous look and compare their methods with several past techniques which help them to find the highlights of the past studies and also give them adequate study and opportunity to eliminate the challenges posed in the back methods and which in turn finally improves their denoising framework.

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