© 2017 IJSRSET | Volume 3 | Issue 5 | Print ISSN: 2395-1990 | Online ISSN : 2394-4099
Themed Section : Engineering and Technology

Multi-Channel Image Denoising In Local Spectral Component Decomposition

G. Shankara Bhaskara Rao
Associate Professor, Electronics & Communication Engineering, Sri Vasavi Engineering College, Tadepalligudem, Andhra Pradesh, India

BSTRACT

Based on the low image quality and effect of noise in the conventional methods, a method is implemented for local spectral component decomposition on the line feature of local distribution. The use of local spectral components contributes to achieving better results compared with the result of the stand-alone conventional method. The aim is to reduce noise on multi-channel images by exploiting the linear correlation in the spectral domain of a local region. By calculating a linear feature over the spectral components of an M-channel image, the image is decomposed into three components as a single M-channel image and the two gray scale images. By virtue of the decomposition, the noise is concentrated on the two images and thus the algorithm denoises only the two gray scale images, regardless of the number of channels. As a result, the image deterioration due to the imbalance of the spectral component correlation can be avoided. This method is especially effective for hyper spectral images. Hyperspectral image denoising using a spectral line vector field uses the correlation among spectral information in the local region. The vectors are obtained by the local spectral component decomposition followed by iterative filtering steps. Filtering the spectral line component and the residual component gives significant effects in reducing the noise and smoothing results in the image. The increase in noise power and the number of channels processed affects the complexity of achieving more accurate spectral line vector estimation. This denoising method based on the spectral line is used in remote sensing field. This method improves image quality with less deterioration while preserving vivid contrast.

Keywords: Denoising, Local spectral component decomposition, Gray scale image, Spectral line, Hyperspectral image.

I. INTRODUCTION

Digital image processing is an area characterized by the need for extensive experimental work to establish the viability of proposed solutions to a given problem. An important characteristic underlying the design of image processing systems is the significant level of testing & experimentation that normally is required before arriving at an acceptable solution. This characteristic implies that the ability to formulate approaches &quickly prototype candidate solutions generally plays a major role in reducing the cost & time required to arrive at a viable system implementation. The field of DIP refers to processing digital image by means of digital computer. The area of image analysis is in between image processing & computer vision. Digital image is composed of a finite number of elements, each of which has a particular location & value. The elements are called pixels. Vision is the most advanced of our sensor, so it is not surprising that image play the single most important role in human perception. However, unlike humans, who are limited to the visual band of the EM spectrum imaging machines cover almost the entire EM spectrum, ranging from gamma to radio waves. They can operate also on images generated by sources that humans are not accustomed to associating with image.

There are no clear-cut boundaries in the continuum from image processing at one end to complete vision at the other. However, one useful paradigm is to consider three types of computerized processes in this continuum: low-, mid-, & high-level processes. Low-level process involves primitive operations such as image processing to reduce noise, contrast enhancement & image sharpening. A low- level process is characterized by the fact that both its inputs & outputs are images. Mid-level process on images involves tasks such as segmentation, description of that object to reduce them to a form suitable for computer processing & classification of individual objects. A mid-level process is characterized by the fact that its inputs generally are images but its outputs are attributes extracted from those images. Finally higher- level processing involves "Making sense" of an ensemble of recognized objects, as in image analysis & at the far end of the continuum performing the cognitive functions normally associated with human vision.

Digital Image Processing is a component of digital signal processing .The area of digital image processing refers to dealing with digital images by means of a digital computer. Digital image processing has several advantages above analog image processing; it allows a considerably wider collection of algorithms to be apply to input data and can keep away from problems for instance the build-up of noise and signal deformation during processing. Digital Image Processing involves the modification of digital data for improving the image qualities with the aid of computer. The processing helps in maximize the clarity, sharpness of image and details of features of interest towards extraction of information & further analysis. Digital image processing is a very broad subject and it often involves the procedures which can be complex mathematically, but the central idea behind digital image processing is simple. The digital image is given as input into a computer and computer is programmed to change these data with the help of an equation or with series of equations and then store the values of the computation for each pixel or picture element.

The principal sources of noise in digital images arise during image acquisition and/or transmission. It can be produced by the sensor and circuitry of a digital camera or scanner. Noise degrades the image quality for which there is a need to denoise the image in order to restore the quality of image. Image noise means unwanted signal. It is random variation of color information and brightness in images, and is usually an aspect of electronic noises. It is an undesirable by-product of image capture that adds spurious and extraneous information. Many applications are now including the images in their methods, procedures, reports, manuals, data etc., to deal with their clients and image noise is the basic problem with these applications as it affects the data accuracy and efficiency level.

II. ALGORITHM

Multispectral images are often noisy in many situations because sensors have narrower spectral sensitivity functions and thus capture less light than normal RGB imaging devices. Whereas various applications, such as classification, target detection, spectral unmixing, and change detection need detailed and accurate spectral information and the noise due to, for example, thermal electronics and dark current, unavoidably contaminates the image acquisition process, which disrupts detailed spectral information and furthermore degrades its performance in the listed applications. Thus, denoising the images is a crucial phase in the preprocessing steps of these applications.

It is effective for image denoising methods to exploit inter-channel correlation as well as spatial correlation. Unlike channel-by-channel methods that tend to produce an imbalance of colors, nowadays many smoothing and denoising methods take inter-channel correlation into account to avoid color deterioration as shown by state-of-the-art denoising methods.

Similarly, it is expected that, for the hyper spectral image, exploiting the correlation in not only the spatial domain but also the spectral domain improves denoising performance because the hyper spectral images have high correlation between adjacent channels since they are retrieved from channels with a high spectral resolution. Channel-by-channel hyper spectral image denoising has a consequence in a low SNR because it ignores the spectral correlation. As an efficient feature to represent the inter-channel correlation of local regions, a color line is introduced in the field of color image processing. The color line is a linear cluster in the RGB color space that approximates the shape of color distribution in a local region. The feature is used to model the correlation among neighboring pixels as well as among the channels in many image processing frameworks. This work precisely distinguishes one color from another by its color line. From this idea, they implement a color-line model for some applications, i.e. segmentation, compression, color editing and saturated color correction. For demosicing, they also use natural image properties: least color variation and minimal corner value. It exploits the color-line pixel regularity of a single image to introduce a new dehazing method. It derives a local formation model that explains color lines in hazy scenes and uses it for estimating scene transmission.

Color-line-based noise reduction has also been introduced. It elaborate the color-line model with conventional filters, such as the bilateral filter and the nonlocal means filter, to improve their performance. It exploits the color correlation by minimizing a convex function with the LCNN. This method does not have denoising capability in itself, and its main purpose is to remove color artifacts. This method outperforms other RGB denoising methods, but its superiority in hyper spectral denoising is limited. The aim of this paper is to generalize the color line to the M -dimensional spectral line feature and introduce a methodfor local spectral component decomposition based on the spectral line.

In this framework, we first calculate a linear feature over the spectral components of an M -channel image, which we call the spectral line, and then using the line we decompose the image into three components: a single M -channel image and two gray scale images. By virtue of the decomposition, the noise is concentrated on the two images, and thus our algorithm needs to denoise only the two gray scale images, regardless of the number of channels. The method comes from the idea that noisy RGB images tend to contain outliers located away from the color line. The color-line property is very useful to decorrelate the channels and has been applied to image denoising to reduce discoloration artifacts in RGB images. The aim of this paper is to generalize the denoising method based on the line property to the M -dimensional spectral line feature and show its effectiveness for multi-channel images.

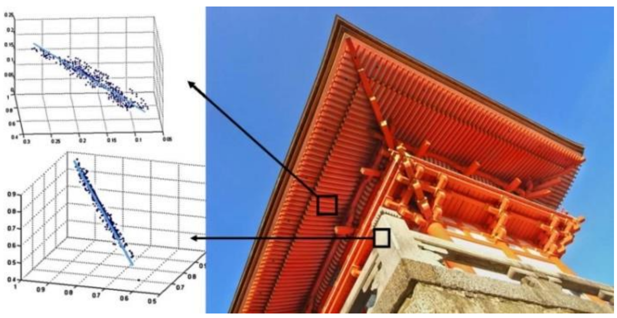


Figure 1. Color line for RGB image

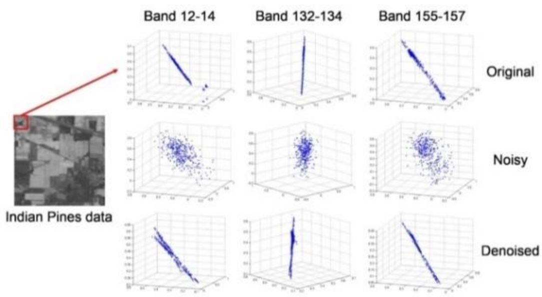


Figure 2. spectral line in hyper spectral images and the effect of denoising

In this regard, we exploit the property for denoising. We first extend the color line to more general multi-channels and call it the spectral line. We design a denoising method for multi-channel images based on the spectral line property. In the case of the multi-channel images, we consider the intensity distribution of M channels in every local region, which corresponds to the color distribution in RGB color images. The spectral line is found by applying PCA to the local window centered at a pixel. In our case, a noisy input is given, which may result in inaccurate line estimation. One possible solution to address this problem is to apply pre-denoising before PCA, but the quality of the resultant image heavily depends on the pre-denoising method. For example, weak denoising does not improve the accuracy of the line estimation.

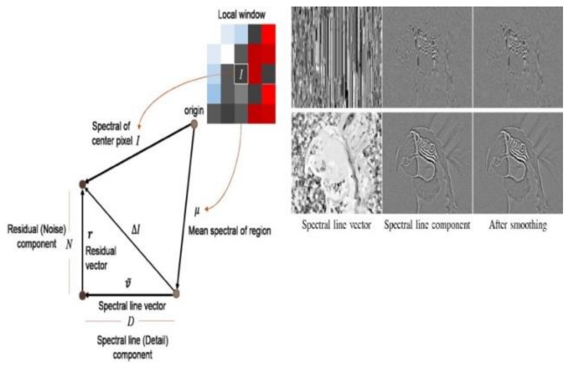


Figure 3. Local spectral component decomposition

The above figure indicates how the pixel of a local window is generalized. The principle lies in considering the spectral of center pixel of an image. It also defines the division of vector components.

Working Procedure:

Initially the noisy image is taken, which is previously added to the original image that leads to degrade the quality of the image. By considering this noisy one, the principal component analysis (PCA) is applied efficiently for each pixel and then spectral line vector estimation is done. The alignment of spectral line vector field gives the horizontal and vertical vector pixel formation. Through this, the vector field is divided into three components such as Mean spectral component, Spectral line component, Residual component.By dividing into these components is termed to be as local spectral component decomposition. The next step is followed by filtering process which is used to eliminate the noise present in these components. The mean spectral component is not filtered due to it is having vey less mount of noise. The remaining two components as spectral line and residual components are filtered by using Gaussian filtering method. After filtering the recomposition is done, which is a denoised one in order to get the original image quality

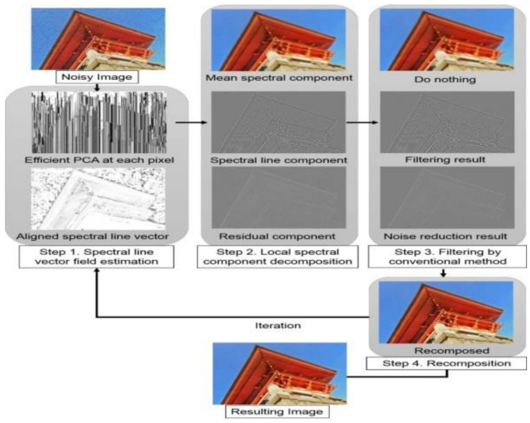


Figure 4. Flowchart of the algorithm

The whole procedure consists of following steps as:

Firstly calculate the local spectral distribution in a window centered at each pixel and find the principal component for each pixel by PCA. We define the spectral line vector as the principal component and a spectral vector field as an image that has the spectral line vector at each pixel. Then, we align the direction of each vector by changing the sign so that the neighboring vector directions become smooth, which improves the resultant image.

Using the spectral line vector, we decompose each pixel Ii(∈RM) of an M -channel image into the three components:

- ✓ Mean spectral component
- ✓ Spectral line component
- ✓ Residual component

The aim of the decomposition is to transfer noise only to the two components (spectral line and residual components). We assume that the noise is independent and zero-mean, and thus the mean spectral component tends to have little noise. Regardless of the number of channels, we only need to denoise the two components, which is especially effective for multi-channel images with M>3.

Next apply smoothing to the spectral line and residual components.

Finally reconstruct an image from the above components and the next iteration will be followed to perform the operation.

A. Spectral Line Vector Field:

1) Spectral Line Vector Estimation by PCA:

The spectral line vector is formulated as the eigenvector that corresponds to the maximum eigenvalue by using PCA.

2) Alignment of Spectral Line:

The resulting Eigen vector vi may have sign si with an ambiguity (si= +1 or − 1). The direction of the sign should vary smoothly in our framework otherwise the resultant image will have jaggy artifacts. To make the direction of the sign smoothly vary, we adopt the Jacobi relaxation method to determine the sign. For the vector direction alignment, the sign si should be set to fit the dominant direction of neighboring vectors by using the inner product as the criterion. To extend the pixel-wise flip to a larger region, a multi-resolution approach is used.

B. Filtering:

The spectral line component Di obtained contains the noise. Consequently, denoising the spectral line components is required in the spatial domain. We refine the spectral line component by denoising, and by applying iteration the denoising effect is adjusted not to be too strong. This procedure results in the filtered spectral line component Di. The residual component Ni contains a lot of weak noise. As for the mean spectral component μi , unlike the other components, there is no need to apply filtering because it has been already generated by averaging.

$$\boldsymbol{w(N_i) = \frac{N_i^2}{K + N_i^2}}$$

$$\boldsymbol{\widehat{N}_i = w(N_i)N_i}$$

C. Recomposition:

The final step is recomposition of the resulting image from its constituent components which is nothing but denoising the noisy image to achieve the quality of the original image.

Implementation:

According to the previous conventional methods, the noise is removed only for a particular extent but it has to be removed more to get the quality image. The previous used filters will remove the noise to only some level and here by using Gaussian filtering method the noise is eliminated to some more extent so that the quality of the image can be further improved. The implementation is done in the following steps such as:

- ✓ Considering the input image
- ✓ Performing Segmentation
- ✓ Applying different filter values to the image by using Gaussian filtering
- ✓ Decomposing the image
- ✓ Denoising the image
- ✓ Finally applying the extension median filter

The main criterion behind this project is to increase the peak to signal noise ratio (PSNR) of the image as compared to the noisy one. The PSNR must high for the denoised image as it indicates that the quality is improved and is similar to the original image. The PSNR value estimates the noise level in the particular image. By estimating this value, the percentage of quality of image is calculated.

Peak signal-to-noise ratio:

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs (e.g., for image compression). The signal in this case is the original data, and the noise is the error introduced by compression. The peak signal-to-noise ratio (PSNR) is calculated for every processed channel. Based on the PSNR value the image is preserved with more vivid contrast. When comparing compression codecs, PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. One has to be extremely careful with the range of validity of this metric; it is only conclusively valid when it is used to compare results from the same codec (or codec type) and same content. PSNR is most easily defined via the mean squared error (MSE).

Mean Squared Error:

The mean squared error (MSE) for our practical purposes allows us to compare the "true" pixel values of our original image to our degraded image. The MSE represents the average of the squares of the "errors" between our actual image and our noisy image. The error is the amount by which the values of the original image differ from the degraded image.

The proposal is that the higher the PSNR, the better degraded image has been reconstructed to match the original image and the better the reconstructive algorithm. This would occur because we wish to minimize the MSE between images with respect the maximum signal value of the image.

The mathematical representation of the PSNR is as follows:

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

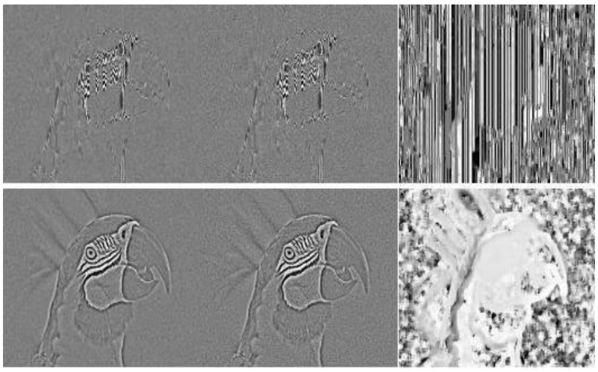
Where the MSE (Mean Squared Error) is:

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

Effect of Sign Flip:

First, to discuss the importance of sign flip before filtering, that emphasizes how it works on an image. The Jacobi relaxation used for the vector sign alignment significantly improves the performance by flipping the sign to the same direction as the local mean spectrum. Figure 7 shows the effect of the vector sign flip in our method. The top and bottom row show the results when the sign flip is not performed and performed, respectively. After PCA, the generated spectral line vectors are not smooth (top left). If we continue to the next steps without this procedure, the spectral line components and the filtered result are affected and fail to preserve the details. To avoid this problem, we use the Jacobi relaxation method for the spectral line vectors. As a result, the method can perform better as shown in the bottom images. The comparison of the final resultant images. The difference can easily be noticed in some regions of the image.

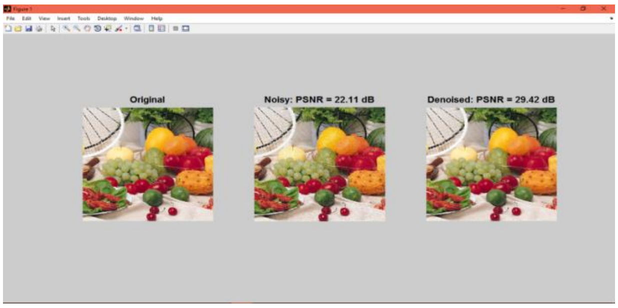
Spectral line vector Spectral line component After smoothing

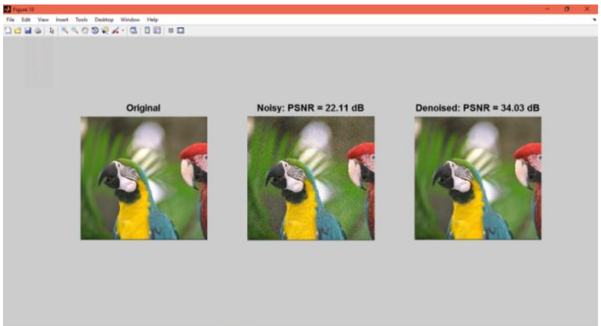


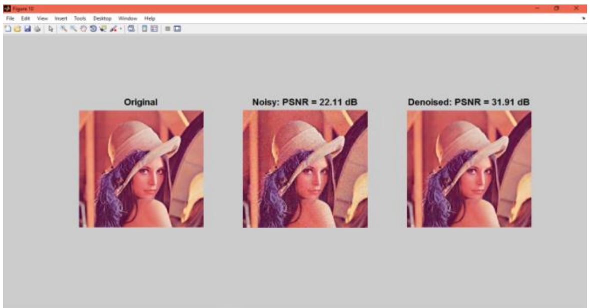
Spectral line estimation

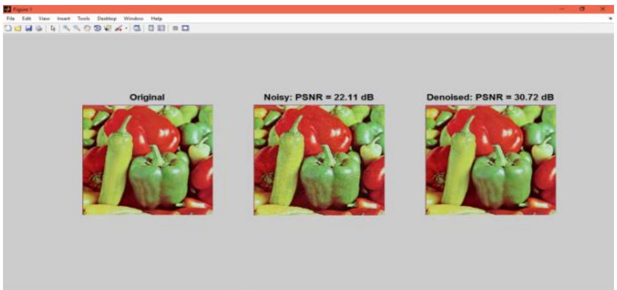
Original Image Sign-Flip Without Sign-Flip Sign – Flip

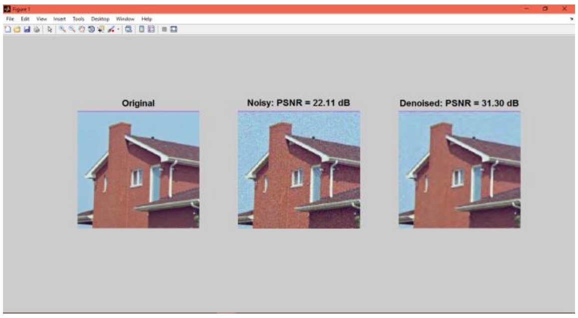
PSNR Values for images:

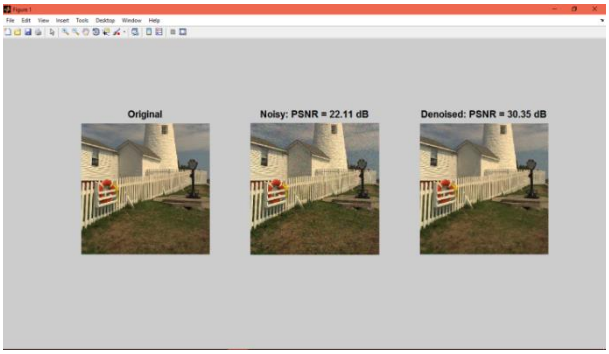












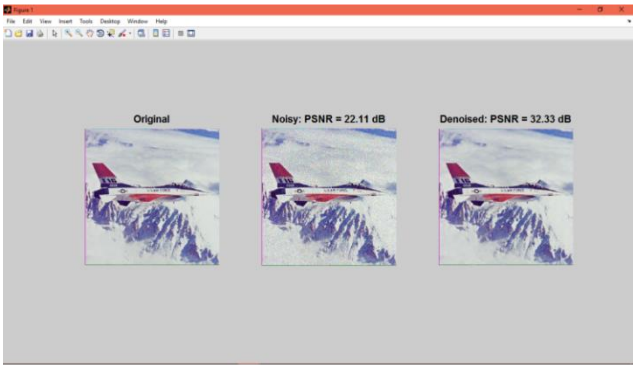


Table 1. Comparison of PSNR values

Image	**Noisy PSNR value**	**Denoised PSNR value**
Fruit	22.11	29.42
Lena	22.11	31.91
Lighthouse	22.11	30.35
Airplane	22.11	32.33
Parrots	22.11	34.03
House	22.1	31.30
Peppers	22.11	30.72

III. CONCLUSION

This paper provides an outline of digital image denoising techniques. Denoising image is a long standing problem for many image processing applications. Various systems are effectively and significantly benefit the solution of image recovery problems. The removal of noise is done by applying Gaussian filtering method. The Gaussian filter is used in this project for elimination of noise to the maximum extent. The noisy images were denoisedand the PSNR results were analyzed. The major role of this paper is to draw a picture of the state of the art of the image denoising techniques. The use of Gaussian filtering produces edges. By use of median filter this problem is reduced. This project tends to give an extension of the denoising technique is that by eliminating edges and providing texture to the image so that quality of the image can be improved to more extent. Future scope of this paper The noise is always a problem in the image processing even though it is eliminated, there is some percentage of noise in the image. There are many filters can be applied further to reduce noise based on the application and it extended more to eliminate it.

IV. REFERENCES

[1]. Mia Rizkinia, Tatsuya Baba, Student Member, Keiichiro Shirai,and Masahiro Okuda, "Local Spectral Component Decomposition for Multi-Channel Image Denoising," in IEEE Transactions on Image Processing, vol.25, NO. 7, July 2016

[2]. QiangGuo, Caiming Zhang, Yunfeng Zhang, and Hui Liu, "An Efficient SVD- Based Method for Image Denoising," IEEE Trans. Video Technology, vol. 51, no. 2, pp. 91-109, 2015

[3]. PriyamChatterjee, Student Member, IEEE, and PeymanMilanfar, Fellow, IEEE, "Patch-Based Near-Optimal Image Denoising," IEEE Trans.Image Processing, OL.21, NO. 4, APRIL 2012.

[4]. GM.VijaySubha.S.V,"Spatially Adaptive Image Restoration Method Using LPG-PCA And JBF ",IEEE Int. Conf.On Image Processing,, Mar. 2012.

[5]. A. Ravichandran, R. Chaudhry and R. Vidal, "Image Denoising Using Trivariate Shrinkage Filter in the Wavelet Domain and Joint Bilateral Filter in the Spatial Domain, " vol. 35, no. 2, pp. 342-353,October 2009.

[6]. Thierry Blu, Senior Member, IEEE, and Florian Luisier, "The SURE-LET Approach to Image Denoising", IEEE Transactions On Image Processing, Vol. 16, No. 11, November 2007

[7]. KostadinDabov,, Alessandro Foi, Vladimir Katkovnik, and Karen egiazarian, "Denoising by Sparse 3-D Transform Domain Collaborative Filtering EEE Transactions on Image Processing, vol. 12, no. 11 pp. 1338-1351, November 2005

[8]. P. J. Burt and E. H. Adelson, "The Laplacian pyramid as a compact image code," IEEE Trans. Commun., vol. 31, no. 4, pp. 532–540,Apr. 1983.

[9]. M. J. Black and A. Rangarajan, "On the unification of line processes,outlier rejection, and robust statistics with applications in early vision,"Int. J. Comput. Vis., vol. 19, no. 1, pp. 57–91, 1996.

[10]. D. Tschumperlé and R. Deriche, "Vector-valued image regularization with PDEs: A common framework for different applications," IEEE

[11]. Trans. Pattern Anal. Mach. Intell., vol. 27, no. 4, pp. 506–517,Apr. 2005.

[12]. C.-I. Chang, Hyperspectral Data Processing: Algorithm Design and Analysis. Hoboken, NJ, USA: Wiley, Mar. 2013.

[13]. A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms, with a new one," Multiscale Model. Simul., vol. 4, no. 2,pp. 490–530, 2005.

[14]. J. V. Manjón, P. Coupé, and A. Buades, "MRI noise estimation and denoising using non-local PCA," Med. Image Anal., vol. 22, no. 1,pp. 35–47, May 2015.

[15]. M. Maggioni, G. Boracchi, A. Foi, and K. Egiazarian, "Video denoising,deblocking, and enhancement through separable 4-D nonlocal spatiotemporal transforms," IEEE Trans. Image Process., vol. 21, no. 9, pp. 3952–3966, Sep. 2012