# DENOISING FOR SPECTRAL COLOUR IMAGES

**Sneha .U[1], Liji Samuel.[2]**

[1]M.Tech, Computer Science & Engineering, Sree Buddha College of Engineering
Elavumthitta, Kerala, India, 689625
[2]Assistant Professor of Computer Science & Engineering, Sree Buddha College of Engineering
Elavumthitta, Kerala, India, 689625

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**Abstract -** *The main purpose of this work is to compare the spectral decomposition of existing systems and color images, through various concepts used in different colors. This article describes the different techniques used in SCD to reduce image noise by improving noise, thereby reducing noise in color images. The proposed system is a spectral-based noise cancellation method that has been proposed for use in the field of remote sensing. Hyperspectral image noise using line spectral vector lines eliminates the correlation between spectral information in the local area. The vector is obtained by local spectral component decomposition followed by iterative filtering steps. Filtered line components and residual components have a significant effect on reducing noise and smoothing image results. In addition, using local spectral components helps achieve better results than the results of conventional independent methods. The main advantages are: not only suggestions. The perfect alignment of the image restores natural color images with greater contrast and improves image quality.*

***Key Words*: Spectral line, local spectralcomponent decomposition, denoising, hyper spectral image.**

## 1. INTRODUCTION

Image processing is a method of converting an image into a digital form and performing some operations on it to obtain an enhanced image or to extract some useful information from it. This is a type of signal distribution in which the input is an image, such as a video frame or a photo, and the output can be an image-related image or feature. Generally, an image processing system includes processing images as two-dimensional signals while applying a set signal processing method to them. It is one of the rapidly developing technologies that are applicable to all aspects of the business. Image processing is also a core area of research in the field of engineering and computer science [4]. Image processing usually refers to digital image processing. Image processing is the use of computer algorithms for image processing of digital images. As a subclass or domain of digital signal processing, digital image processing has many advantages over analog image processing [1]. Digital image processing allows the use of more sophisticated algorithms, so more complex performance can be provided in simple tasks, and methods can be implemented in an analog fashion. In particular, digital image processing is the only practical technology. Both types of methods are used in image processing is analog and digital image processing. Image processing simulation or visual techniques can be used for hard copies such as prints and photos. Image analysts use a variety of basic explanations when using these visual techniques. Image processing is not limited only to the areas that need to be studied, but also requires the knowledge of analysts. Associations are another important tool for image processing through visual technology.

Some digital experiments that denoise simple color images in a red-green-blue (RGB) color space will present photographs. The output is the last stage where the result can be changed, ie an image or report based on image analysis. The image may be considered to contain sub-images that are sometimes referred to as regions of interest, ROIS or just regions [1]. This concept reflects the fact that images often contain a collection of each object of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image Processes the operation of the selected area. In computer graphics, images are manually created from physical models of objects, environments, and lighting, rather than from natural scenes (eg, video or 3D whole body magnetic resonance scanning). Images have also gained wider scope [7]. The advantage is that image degradation due to the imbalance of spectral component correlations can be avoided. Improve image quality by reducing deterioration. This method is mainly used for hyperspectral images.

## 2. RELATED WORKS

Linear vector algorithms are used in this method. Denoising does not occur with higher power noise. It does not apply to all noise method. The proposed method comes from the idea that noisy RGB images tend to contain outliers away from the color line. The color line properties are very useful for decorative channels and have been applied to image denoising to reduce color changing artifacts in RGB images [1]. The purpose of this paper is to generalize the denoising method based on linear features to the features of the M-dimensional spectral line and demonstrate its effectiveness for multi-channel images. For hyperspectral images, the correlation between channels is also expected to be high due to the narrow spectral resolution. According to the line principle of the RGB image color line, the inter-channel correlation of the hyperspectral image is observed by drawing the local intensity distribution [10]. For different numbers of channels, it is verified that the ratio between the

maximum eigen value and the sum of all eigen values is high, which means that the channels are linearly related.
K. Shirai, M. Okuda, and M. Ikehara [1] proposed a method that has succeeded in reducing noise and blur, but did not draw sharp edges for intensity images, thus expanding the TV standard to handle color and other The vector value is a very natural picture. In applications where the image is viewed or interpreted by humans, color is a holistic factor. Therefore, color processing is important for recognition, segmentation, and the like. Moreover, intensity-based processing cannot detect the edge, ie, the color "jumps" rather than the edge of the intensity. By the way, humans are not good at detecting these edges. Any attempt to extend the scalar TV norm to vector values should retain at least two basic advantages: i) no penalties for edges, and ii) no rotation in image space. Moreover, in the case of scalars, it is also advisable to reduce the extension to the usual standard. There have been several attempts to extend the associated recovery techniques and edge detection to vector-valued images [10].

YQ.Zhao and J. Yang [2] proposed a new image denoising strategy based on them along an additional fourth dimension to generate a four-dimensional structure called a group where different types of data correlation existed. In different dimensions: Correlations along two dimensions of the block locally, temporal correlations along the motion trajectory, and non-local spatial correlations (ie, self-similarity) along the fourth dimension of the group. Collaborative filtering is then achieved by associating a four-dimensional separable transform and then transforming each group by puncturing and inverse transforming. In this way, collaborative filtering can provide estimates for each volume stacked in the group, then return it and adaptively aggregate to the original position in the video. The proposed filtering procedure addresses several video processing applications such as denoising, deblocking and enhancing grayscale and color data.

P. Blomgren and T. F. Chan [3] propose a method in several factors such as noise, blur, blocking, ringing and other acquisition or compression artifacts typically impair digital video sequences. The large number of practical applications Motivations involving digital video have inspired significant interest in restoring or enhancing solutions, and the literature contains a large number of such algorithms. Currently, the most efficient method of recovering an image or video sequence exploits the redundancy given by the non-local similarity between patches at different locations within the data. Algorithms based on this method have been proposed for various signal processing problems, mainly for image denoising. So far, the most effective image denoising algorithm known as BM3D relies on the so-called packet and collaborative filtering paradigm: First, two-dimensional image blocks that are similar to each other are stacked into a three-dimensional group (grouping), and then the group is transformed. Domain collapse (Collaborative filtering) performs filtering while providing separate estimates for each block of packets.

T.F. Chan, S.H. Kang and J. Shen [4] proposed to return the methods in these estimates to their respective locations and finally aggregate to produce the final denoised image. In doing so, BM3D exploits the non-local and local spatial correlation of natural images, exploiting the richness of their respective similar patches and the high correlation of image data within each patch. The BM3D filtering scheme has been successfully applied to video denoising of the V-BM3D algorithm and several other applications, including image and video super-resolution image sharpening and image deblurring. In V-BM3D, a group is a three-dimensional array of mutually similar blocks extracted from a set of consecutive frames in a video sequence. In denoising, performance does not necessarily increase with the number of spatially self-similar blocks in each group, but is always improved by using time redundancy. In addition, even if there is a fast motion, the similarity along the motion trajectory is much stronger than the non-local similarity existing within a single frame. Such transform leverages three types of correlation: local spatial correlation between pixels in each block of a volume, local temporal correlation between blocks of each volume and nonlocal spatial and temporal correlation between volumes of the same group.
Omer and M. Werman [5] proposed a method for increassing image quality more and more natural image statistics have been found to be useful for image recovery problems. In this paper, a noise reduction technique is proposed by using color line hypotheses for natural color images. Based on the color line model, an algorithm is proposed to analyze the local color statistics and restore the original image by increasing the color linearity of the local color blocks. The proposed method can cooperate with existing noise reduction methods to successfully improve the quality of perception and objective evaluation. First, using recent research in natural color image statistics, the statistics claim that the color of a local area generally forms a line in the color space. Based on the color line model, the effect of noise was analyzed. Secondly, a noise reduction method based on local color analysis of super pixels is proposed. The proposed method is simple and easy to cooperate with previous smoothing-based algorithms to further improve image quality.

A better pixel grouping strategy is to consider the image content. The size and shape of the grouping should be adjusted adaptively. Super pixel segmentation techniques are used to generate local patches. The segmented super pixels are almost the same size, and their shape is perfectly aligned with the image content. Adaptively retains the image structure and obtains better perceptual quality, as shown by the noise in the color line model, and then proposes noise reduction techniques by increasing the linearity of local color statistics. For local pixel grouping, using super pixel-based segmentation to achieve better quality in objective assessment, the proposed method is useful for natural image noise reduction. The proposed technique is simple and effective. It is expected that the proposed technology can also be extended to other natural image processing applications.

## 3. OVERVIEW

Local spectral component decomposition based on local distribution line features. The goal is to reduce noise on multi-channel images by exploiting linear correlation in the spectral region of the local region. First calculate the linear features on the spectral components of the M-channel image, called spectral lines, and then use this line to decompose the image into three components, a single M-channel image and two grayscale images. With decomposition, the noise is concentrated on both images, so the algorithm only needs to eliminate two grayscale images regardless of the number of channels. As a result, image degradation due to the imbalance of spectral component correlation can be avoided. Experiments show that this method improves image quality and reduces the degree of deterioration while maintaining a clear contrast. This method is particularly effective for hyperspectral images.

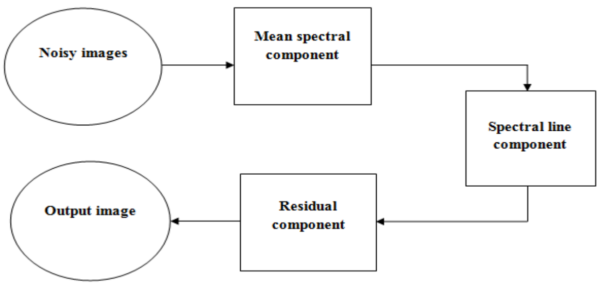


**Fig-3.1:** Basic Block Diagram

However, this method [3] has a lower level of competitiveness in terms of strong noise than other most advanced methods. A video denoising method called VBM3D is proposed, which is an extension of the single channel denoising method in which noise is reduced by using patches found in neighboring frames.

This feature is used in the channels of many image processing frameworks. This work accurately distinguishes one color from another by color lines. Starting from this idea, they implemented color line models for certain applications, namely segmentation, compression, color editing, and saturation color correction. In order to use natural image attributes: the smallest color change and the smallest corner point value [6]. Color line-based noise reduction techniques have also been introduced [4]. In the framework, the linear features on the spectral components of the M-channel image are first calculated, called spectral lines, and then the image is decomposed into three components using lines: a single M-channel image and two grayscale images. Therefore, this method produces better denoising performance than the conventional methods. The rest of this paper is organized as follows. In first demonstrate that the line property also holds for hyper spectral images. Then, proposed algorithm based on the spectral line property.

## 4. MODULES LINEAR FEATURE

First calculate the linear feature over the spectral component. It is called the spectral line. After colour images are decomposed into three components using this line. Mean spectrual component, Spectrual line component and residual components. Take this three component all the noise are concentrated on in this three component. Noise in this colour images are denoised in the case of advantage is improve the clarity of colour image. Using the mean spectral component $\boldsymbol{\mu}i$ and the spectral line vector $\mathbf{v}i$ decompose the original pixel $\mathbf{I}i$ to the three terms [9]. It begin with calculating the difference vector of the center pixel and the mean spectrum of the local window, $\Delta I_i = I_i - \mu_i$ Using the spectral line vector $\mathbf{v}i$ , the spectral line component $Di$ is calculated as the inner product of the normalized spectral line vector $\mathbf{v}i$ and $\mathbf{I}i$ , $Di$ = $v_i^T$ which is the component of $D_i$ $\mathbf{I}i$ . The direction of $\mathbf{v}i$, since $=||v_i|| =1$, Then, we calculate the difference between the two vectors $r_{i=} \Delta I_{i-D_i} v_i$. Finally, a residual component is derived from norm of the vector $\mathbf{r}i$ ,$N_{i=||r_i||}$ Note that the dimensions of the mean spectral component $\boldsymbol{\mu}i$ , the spectral line vector $\mathbf{v}i$ and residual vector $\mathbf{r}i$ are the same as the number of channels, that is M and the spectral line component Di and the residual component N$i$ are scalars. The main purpose of this decomposition is to concentrate noise, which is originally scattered in all the channels of an input image [6].

### 4.1 Mean spectral components

The Mean spectral components component $Di$ obtained in the previous step contains noise [1]. Fist it will taken an input image. Then it will extract three colour pixel from the image. Then take three value from corresponding pixels. That it is called as red, green and blue. The image is taken as different blocks then for each block corresponding values are taken and it is converted in a matrix form. Then it will find the sum by adding corresponding four pixels in each block. Then it will create the cell and it will divide sum into number of pixels. It is called as mean spectrual components. Consequently, denoising the spectral line components is required in the spatial domain. It refine the spectral line component by denoising it with BM3D [3]. Since iteratively apply BM3D, 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. To filter them adopt a two-phase denoising procedure. First apply the Geman McClure robust function [5] to reduce the noise with small intensities by the formula w$N_{i=} N_i^2$.

### 4.2 Residual component

The steps involved for selecting reliable pixels from image are as follows: It takes an input image. Calculate the mean value and sum of the pixels. It is based on the line feature of local distribution. To reduce the noise on multichannel by the linear correlation in the spectral domain of local region. First calculate the linear feature. Decompose the image into three components. To create the cell after apply the filtering method. The advantage is image deterioration due to the imbalance of the spectral component correlation can be avoided. Improve the image quality by reducing deterioration. This method is used mainly for hyper spectral images.

### 4.3 Recombination

Take the difference between input image and mean specutral component. After getting the result is called spectural line vector. Then find sum of the vector. This is called spectrual line component. This component is derived from the spectrual line component. Then dividing three component by using single value and final apply the geman macular robust function and also apply the filetering methods. The final step is recomposition of the resulting image from constituent components. The expected image can reconstructed. The steps involved for image integration to obtain output image are as follows: Take the difference between input image and Mean Spectral Component. To finds the sum of vector. This component is derived from Spectral line Component after reconstruct the noise reduction image.

## 5. COLOR-LINE PROPERTY

The concept of the color line is improve the image clarity by reducing the noise. The input image contains three channels. Finds the corresponding value of each pixels. Then getting the middle value is put on to that same position. Similarly find the mean value of all corresponding pixels. This is called mean spectrual component. Take the difference between the original image and mean spectrual component. Then find the maximum eigen value of the covariance matrix by using corresponding eigen vector. The result is called spetrual line vector [4]. The steps involved for selecting reliable pixels from image are as follows: It takes an input image. Calculate the mean value and sum of the pixels. It is based on the line feature of local distribution. First calculate the linear feature. Decompose the image into three components. To create the cell and apply the filtering method. The advantage is image deterioration due to the imbalance of the spectral component correlation can be avoided. Improve the image quality by reducing deterioration. This method is used mainly for hyper spectral images.

## 6. RESULT AND ANALYSIS

The experimental results of the proposed technique for spectral component decomposition for colour image based on spectral component decomposition are discussed in this section. An application is created using MATLAB application to implement this technique.

### 6.1 Result

The algorithm discussed above is implemented using MATLAB R2013a. In the proposed method implemented by using many modules and sub modules. The input image is a noisy image. These images are applied to first modules then calculate the linear feature of image. Final module reduce the noise and bm3d denoising method is applied on image. This model and selected pixels to obtain a high quality image as output.

**Fig-6.1: Noise image**

**Fig-6.2: Output image**

### 6.2 Discussion

These results prove that the proposed technique is used to improve the image quality. The input noisy image and output image can be taken with device having same resolution will produce high quality image. Also size of the input images depends on output image. The output is of good visual quality, although not always a better output because here combine noisy image. This image having some noisy artifacts. So output may contain little effect on this noise. The un-optimized MATLAB code takes 1-2 minutes to process an image (2592x1936).

### 6.3 Analysis

In this section analyses the quality of the output image. The quality of the output image depends on mainly two factors. The main two factors are:

1. Peak Signal to Noise Ratio (PSNR)

The PSNR blocks calculates the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and a compressed image. The metrics used to compare image compression quality. PSNR represents a measure of the peak error. To compute the PSNR, the block first calculates the mean-squared error using the following equation:. Then the block computes the PSNR using the following equation:

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right) \qquad (5.11)$$

where R is the maximum fluctuation in the input image data type.

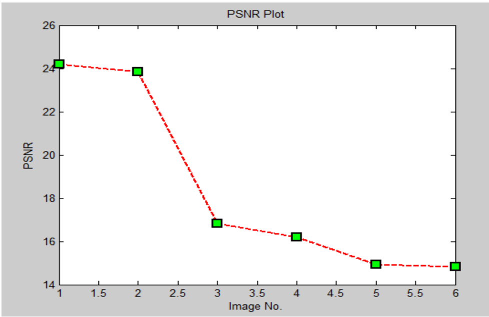


**Fig-6.3:** PSNR of Images

2. Mean Brightness Error(MBE)

This factor can be used to check the brightness of the output image. For that calculate the mean of noise image and output image. Then calculate the difference between the mean of noise image and output image. Reduce result from one.

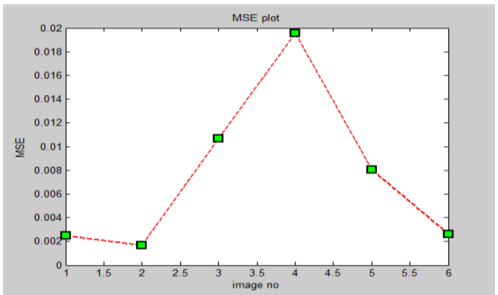


**Fig-6.4:** MBE of Images

## 7. CONCLUSION

A new denoising method based on the spectral line has been proposed for the remote sensing field. Hyperspectral image denoising using a spectral line vector field uses the correlation among spectral information in the local region. The vectors are obtained by local spectral component decomposition followed by iterative filtering steps. Filtering the spectral line component and residual component gives significant effects in reducing the noise and smoothing results the image. Moreover, the use of local spectral components contributes to achieving better results compared with the result of the stand-alone conventional method. It involve solving this computational complexity.

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## BIOGRAPHIES

**Sneha U** received Diploma in Computer Engineering from NSS Poly technic college Pandalam in 2012. She has received B.Tech from Sree Buddha College of Engineering, Ayathil in 2016. She is studying M.Tech in Sree Buddha College of Engineering, Ayathil.

**Liji Samuel** received B. Tech Computer Science from IHRD College of Engineering, Poonjar in 2009. She has received M.E from PSNA College of Engineering and Technology in 2011, She has been with Sree Buddha College of Engineering, Ayathil, as an Assistant Professor.