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# Dimensionality Reduction of Hyperspectral Image Using Different Methods

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***Abstract*** *- The Hyperspectral images (HSI) are images obtained across the electromagnetic spectrum. Basically, images having a greater number of dimensions and complexity in processing and analyzing the data. As the number of dimensionalities increases, its accuracy gets decreases. Hence it is necessary to reduce the dimensionality by applying a pre-processing step. This HSI is widely used in industries and technology like remote sensing, seed viability study, biotechnology, environment monitoring, food, pharmaceuticals, medical diagnose, forensic, thin films, oil, and gas. There are different methods to reduce the dimensionality of these images like Principal component analysis (PCA), Weighted sparse graph-based (WSG), Curvilinear component analysis (CCA), Fractal based, Independent component analysis, Empirical mode and wavelets, Embedding, Band selection, Component analysis, Neighbourhood.*

***Keywords*** *- Hyperspectral image; Dimensionality reduction; different methods to reduce the dimensionality; principal component analysis.*

## I. INTRODUCTION

The Hyperspectral images deal with the high data set, and only the first few bands contain the information. These spectral bands are 3D most of the time, with two dimensions which represent pixel of spatial location (samples and lines), and 3rd dimension, which represents the reflectance of its spectral bands [1]. The HSI sensors are used to collect some information from images by different bands. Hyperspectral images are 3D in dimension with 100 bands, but regularly we can observe only three bands; they are red, green, and blue [2]. Each one of the pixels has a unique signature with different material. It contains 100 bands, relatively few of them explain the information. For such reason, HSI is important to mapped to lower dimensionality. This evidence is called dimensionality reduction of Hyperspectral images. The spectral width of HSI is about 5-10nm, which nearly a contiguous band.

The HSI brings some new capabilities and difficulties along with its processing as well as analysis. This processing difficulty is because of so many bands. The increase in spectral bands will cause a large amount of data involved in it. Hence it increases processing time as well as complexity.

There are various methods to reduce dimensionality, and PCA is one of the most used. In PCA, an image has more attributes, and it is used to remove those attributes with the help of algorithms. In a weighted sparse graph, it should have some information clubbed together to become noiseless, and hence it's useful in image processing. Curvilinear component analysis usual method where linearity very important for is maximum information. For linearity, CCA uses PCA on orthogonal projection to get its linearity, and for further experimental values independent component is very important. In fractal-based, both spectral and spatial characteristics are considered to the reduction of dimensionality. In the ICA method, the virtual dimension (VD) is introduced for the dimension to be preserved. The matrix is initialized by endmember, which is extracted from maximum distance. MNF means minimum noise fraction is used to process the data for the reduction of complexity. Finally, PCA is used to reduce the dimensionality that is measured by experimental results. In empirical mode and wavelets, both of these are used to get reduced dimensionality of the original data. Wavelet is a filter applied to get the noiseless pattern in EMD and wavelets. In embedding, it is based on RSI (robust spatial information). Robustness is taken in accountability of its complex operation on data. Basically, it can use spectral neighbors instead of its pixel distance.

In this paper, we are discussing different methods of dimensionality reduction of HSI. In this, I section introduction. Section II is Principal component analysis, and III is Weighted sparse graph-based, section IV is Curvilinear component analysis, V is Fractal based, VI section is Independent component analysis, VII is Empirical mode and wavelets, section VIII is Embedding, IX is neighboring based dimensionality reduction. X is the conclusion.

## II. Principal Component Analysis

The HSI has more dimensions, which causes more noise and attributes. In this algorithm, overfitting is one of a challenge to analysis the component. The overfitting means there are a greater number of pixel intensity to each pixel which increases its intensity. Here PCA is used to reduce the overfitting problem of hyperspectral images. It depends on views; likewise, we can reduce its dimension of HSI since this isn't exactly a machine learning algorithm but instead an unsupervised learning algorithm. Such that which actually helps to reduce the number of dimensions. Suppose we have a thousand number of features, then it is necessary to reduce the dimensionality for better accuracy by applying a machine learning algorithm [3].

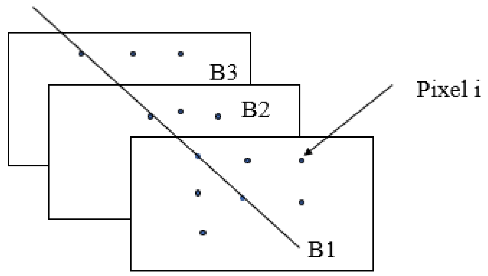


**FIG-1: Pixel vector in the principal component analysis [3].**

As the number of dimensions increases, it is a curse, and its accuracy gets impacted with the number of dimensions. If dimension increases, then accuracy gets lower. The principal component analysis is based on the statistical technique of linear transformation. This method gives a tool to process and analysis the data and its pattern, which is commonly used in image processing.

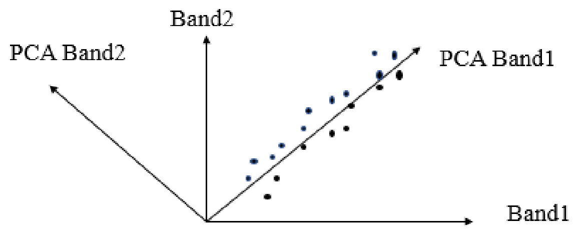


**FIG-2: Geometry of principal component analysis and PCA bands [3].**

Here the first step is to calculate the best fit line on the hyperspectral image. Then all the pixels on the line, this line considered as the principal component (PC). There are various PC lines that depend on the feature of the image. We need to select one component line such that the line has less variance as compared to other PC. The more variance means a greater number of information lost. The yields of this PC are about 70% correct classification rate. The images of HSI have more attributes or more features which causes to overfitting problem. The PCA algorithm used to reduce the overfitting problem depends on views likewise.

## III. Weighted Sparse Graph

The graph is mathematical data that represent so information about the pixel intensity, location, or pattern. Here we are discussing three techniques of sparse graph [4].

### *A. Based on Discriminant Analysis*

In this method, the graph will represent its location as well as its sparsity, but locality is more important than that of the sparsity. It must label all the samples represented on the graph by forcing them to a particular direction where the cluster with the best sample is presented. Then it is solved with the help of the eigenproblem statement. This experimental result gives a result of reduced dimensionality of hyperspectral images.

### *B. Based on Sparse Discriminant Embedding*

It basically deals with the technique called sparse preserving projection (SPP). The SPP ignores all the labeled samples of discriminant information, which can pay attention to its sparse structure. This can be classified as a sparse discriminant embedding (SDE). It utilizes all the merits of sparsity property as well as manifold structure. The SDE is an improved method of SPP. It can be further improved by achieving the feature of discriminant, where compactness can be boosted. This experiment of HSI shows the reduced technique of hyperspectral image.

### *C. Based on Semi-Supervised Local Fisher Discriminant Analysis*

This method was designed to deals with samples extended in it to realize between self and SPP. After this comparison of SPP and self, it offers very good discriminant ability and gives its location of that out of samples. Here that out-of information can be located. It means the noise of the graph is reduced, and good information is kept for further its process. This experimental result will give its reduced dimensionality of hyperspectral images.

## IV. Curvilinear Component Analysis

The dimensionality reduction of HSI is aimed to find some dimension reduction techniques depend upon the possibilities and maximum data extraction [5][6], [7]. Here, the linearity of the component is assumed with the help of PCA to perform linearity on orthogonal projection, for which can get the maximum variance of the image. Then Independent component analysis is used to compute linear projection for a particular subspace with statistically independent. It is limited for nonlinear data as the provided initial data. The dimension projection of the subspace is less as it is nearly equal to 2. This subspace is defined with a discrete parameter of nonlinear, and it should be related to the initial data of an algorithm.

The complete process of the algorithm as

1) Vector quantization.
2) Projection of the centroid.
3) Interpolation or extrapolation.

This algorithm is fast and flexible with only one parameter.

## V. Fractal Based

The dimensionality reduction of the HSI algorithm considering characteristics of spatial as well as spectral for its feature extraction. The spectral curve must be self-similar for the same object.

The process of dimensionality reduction can be explained below steps. Firstly, the image or the must be noiseless means noise removal is done. For this process, wavelet transform can be used to remove the noise. Before the inverse transform of wavelet, high-frequency data must be removed. This results in a noiseless spectral curve [8]. Secondly, the dimension of the fractal image to be calculated using filters. And it is designed to get the spectral curve.

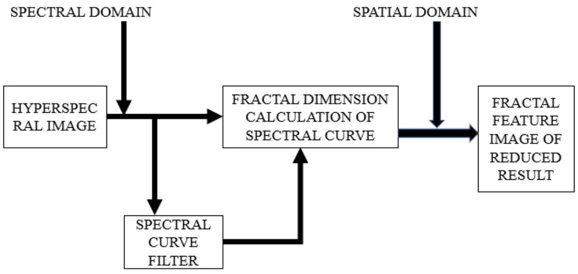


**FIG-3: Dimensionality reduction process using fractal analysis [6].**

Finally, the fractal dimension is used to reduce the dimensionality of HSI. Above, fig-3 gives a method to this process.

As below mentioned, fractal must be self-similarity for its dimension. But we consider fractal because of its crumple nature [9]. Above fig-4 feature, the dimension can be extracted by HSI data. Each dimension is considered to different pixel identity. Only those pixels considered have the majority of the information. This is called majority voting by using image segmentation. At the end of this result is considered for dimensionality reduction.

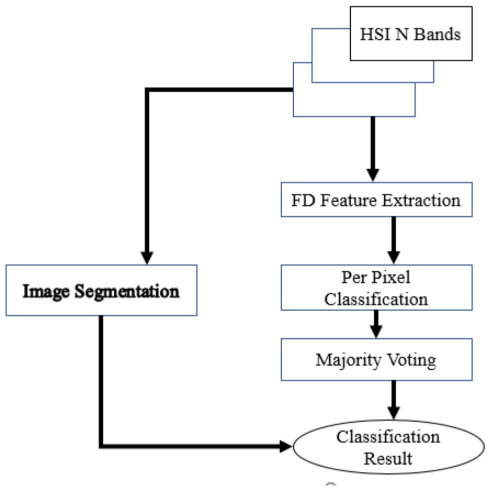


**FIG-4: block diagram of the process in the fractal analysis [9].**

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## VI. Independent Component Analysis

In the ICA method, the virtual dimension (VD) is introduced for the dimension to be preserved. The matrix is initialized by endmember, which is extracted from a maximum distance [10]. MNF means minimum noise fraction is used to process the data for the reduction of complexity. Finally, PCA is used to reduce the dimensionality that is measured by experimental results.

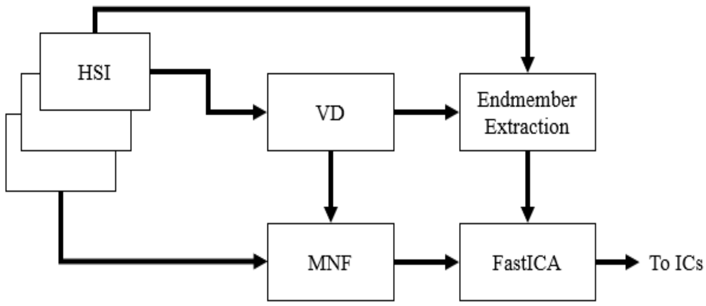


**FIG-5: Dimensionality reduction of HSI using FastICA [11].**

ICA is used to find linear decomposition data for its independent component [10]. Given by equation as

$$P=AX$$

Where P is a signal vector, A is a scalar matrix, and X is a source signal. Independent component is given as

$$Y = WP = WAX$$

Where Y is an independent component, basically, ICA is used to represent linearity that maximizes the measure of non-gaussianity. ICA mutual information vector is given by

$$I\ (Y, W) = \sum_i H(Yi) - H(Y)$$

Where H(Yi) and H(Y) are the predictability of random variables.

This predicted information is much better than the original information in terms of dimensionality.

## VII. Empirical Mode and Wavelets

There will be a limitation for filters such that wavelet transform is used to combine with a different signal. This will help us to achieve the signal with a better understanding. Here empirical mode decomposition has been proposed. The complex signal can be re-arranged so that the original data remains the same. This is called a decomposition process in empirical mode. The EMD is used to sort some spatial frequencies of the image. There are two methods of intrinsic mode function, and the first method extracts the images which have the highest spatial frequency.

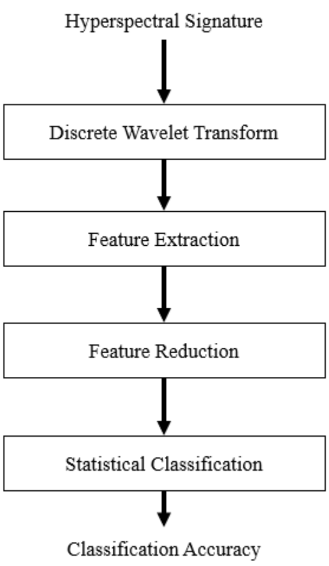


**FIG-6: The block DR is based on wavelet transforms [12].**

The second method stores the next values of their frequencies and so on [13]. There is a different condition for intrinsic mode function, which is given as first, the mode of differing at most by 1 for their zero-crossing and extreme point.

HSI provides high spectral data in terms of its resolution, and it is necessary to reduce its dimensionality for better accuracy. Here wavelet transform is used to extract the spectral feature and signature classification [8]. The dimensionality reduction process of HSI uses a hyperspectral signature. And it is used to get discrete wavelet transform for feature extraction. Further, it is reduced by using fisher's linear discriminant analysis. Then it will be measured by original information. The measurement of efficiency is called classification accuracy. This is given by above fig-6.

### VIII. Embedding Based

The dimensionality reduction method of locally linear embedding was proposed by Saul and Roweis. It is used to project high-dimensional data into lower dimensional with the non-linear concept. This concept deals with the nearest spectral pixel performance, and it will calculate the distance between other pixels and similarities. However, the HSI is considered with different spectral distances [14].

There are only a few processes to combine spectral information. The complexity is investigated by spatial information of the SI. Before measuring some similarities of the spectral band between any two patches, the neighbor of its pixel is sorted with respect to the similarities of any two pixels. To obtain the pixel distance is more robust so that it can be caused by the transformation of the geometric patch. The distance will remain the same for their pixels are mirrored or rotated. The neighboring spatial filter (SNF) proposed a noiseless calculation on spectral distance [15].

The final process of the classification is done by vector machine. Some of the machine vectors are introduced recently. Basically, attributes are removed from the image so that data can be measured for their dimensionality reduction. And the entire process is done by some filters and transformation.

### IX. Neighbourhood Based

The HSI image has a higher in its dimensionality; in this method, all pixels are very important to calculate. If there is a term neighbor, then distance matters [17]. So, calculating the distance between all points considering one to its center point.

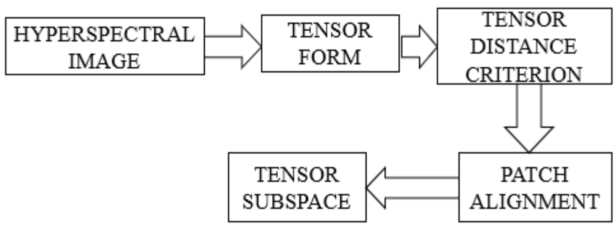


**FIG-8: Block diagram of Neighbour-based dimensional reduction of HSI [16].**

There are few steps to explain this method:

Step 1: Calculate the geometry of all pixels.

Step 2: Now, calculate the distance between all pair of neighborhood pixels.

Step 3: Choose the cluster head or center of the pixel with respect to the tensor distance.

Step 4: The alignment of the matrix is calculated.

Step 5: To calculate the least square value for the low dimensional projection.

The above steps to be followed to get low dimensionality of the hyperspectral image.

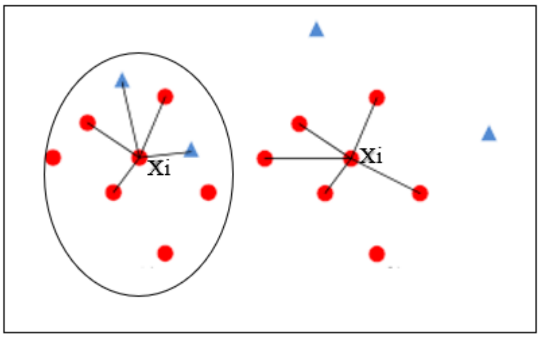


**FIG-9: Cluster head selection of neighborhood pixels [16].**

In the above figure, IX is the neighbor head such that other pixels are geometrically close to each other. The area which is considered to calculate the center is called a cluster.

## X. CONCLUSION

A hyperspectral image may contain hundreds or thousands of bands (or undescriptive channels) as compared to visible images having only three channels (Red, Green, and Blue) which drastically increases the spectral details, hence the ability to see the unseen in the former. For instance, hyperspectral images are used in identifying minerals which is impossible to achieve with the help of visible or multispectral images. But, due to the wide range of channels used in these images, it becomes very difficult to process these images. Dimensionality reduction plays a huge role in speeding up the processing and reducing the storage space of these images. Only relevant information is kept with important feature selection by implementing the algorithm until some specific criteria are met. Due to the existing trade-off between accuracy and complexity, the choice of an appropriate dimensionality reduction technique should be dependent on the variable and the situation at hand. The use of dimensionality reduction for hyperspectral images has paved the way for their application in various fields without any hesitation.

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