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Research Article

Dimensionality Reduction of Hyperspectral Data – A Case Study

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Abstract: At present hyperspectral image investigation has become main exploration territory in remote sensing. Hyperspectral sensors are capable of detecting a wide spectrum of electromagnetic spectrum from Ultraviolet, Visible and Infra-Red and produce images with hundreds of continuous bands, in the form of a image cube. Processing of these high dimensional hyperspectral images using conventional image processing techniques such as classification, recognition etc., without reducing dimensionality is a very tedious task. Hence in this research dimensional reduction was considered using PCA, Incremental PCA, truncated SVD and their fitness to various datasets was discussed in this paper.

Keywords: Hyperspectral imaging, Dimensionality reduction, PCA, IPCA, SVD

1. Introduction

Nowadays remote sensing can be performed with the help of low cost unmanned aerial vehicles and corresponding on board light weight airborne sensors as payloads. Recent significant developments in the hyperspectral imaging systems made possible to capture images in hundreds of spectral bands in a single acquisition [1]. Hyperspectral images usually consist of the spectral bands such as ultraviolet (0.2-0.4 µm), visible (0.4-0.7 µm), NIR (0.7-1 µm), and SWIR (1-4 µm). This increased spatial resolution helps in examining land surfaces and identifying different materials. Hyperspectral images have a wide range of uses in a variety of fields, including Food Processing [2], Medical Investigation [3], Agriculture [4] etc. Illness prediction, water stress, pest attack on fields is generally carried by manual inspection from ground. Feature identification from aerial imagery depends on the reflected or emitted spectral characteristics of the electromagnetic spectrum from the target surface. These spectral signatures can be inferred through spectral variations, change in polarization, temporal variations, and thermal inertia. HSI, gather and process the information obtained from the entire electromagnetic spectrum. By means of each pixel's spectrum in the image, HSI finds objects, identifies materials, or detect the processes. As a result, HSI collects data from a wide number of spectral bands and creates a hyperspectral data cube. A hyperspectral remote sensing image provides high spectral resolution and the ability to distinguish slight variations in ground cover. The high dimensionality of hyperspectral images, on the other hand, introduces unique challenges in the advancement of data analysis methods. As a consequence, dimensionality reduction using feature extraction methods is required without affecting the original data. [4] Dimension reduction, in other words, is the transformation from a high order dimension to a lower order dimension.

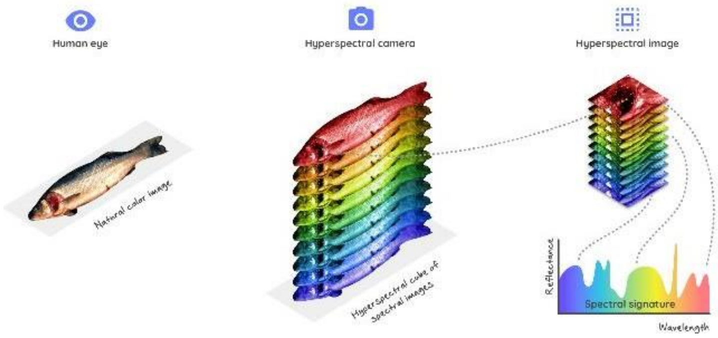


Figure 1. Interpreting an RGB image with Hyperspectral Image

A hyperspectral image has thousands of bands, leading to increased spectral resolution and fine spectral data. Classification of these pixels is an important task in real time applications. High dimensionality of HSI is a challenge to the classification problems. Dimensionality reduction process is shown in Fig.2 is an effective method for reducing the amount of high-dimensional data while retaining as much usable detail as possible. It helps in classifying the whole image by reducing the redundant features. There are many datasets with various spectral and spatial resolutions are available are shown in Fig.3.

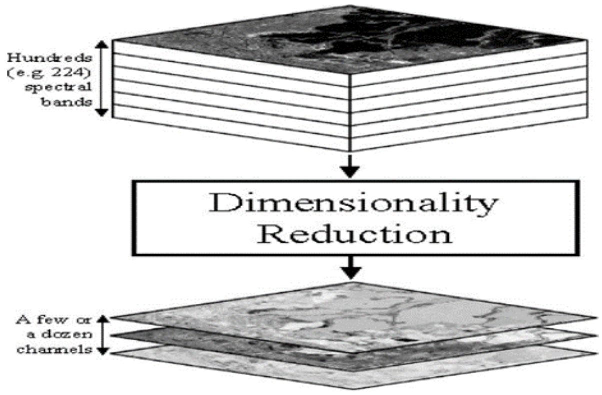
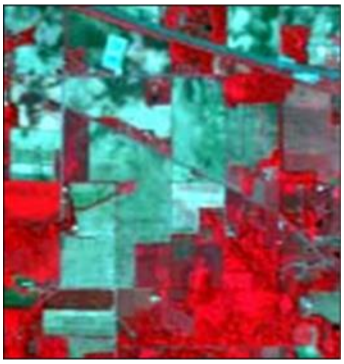


Figure 2. Dimensionality Reduction [8

(a) False Color Image of Washington DC Mall

(b) Pavia University



(c) False color image of Indian Pines

Figure 3. Images of three datasets

This article was further structured as follows. Section I covers the introduction and need of dimensionality reduction. Section II focuses on the literature survey in dimension reduction. Section III outlines the approaches that have been suggested for dimensionality reduction. Section IV discusses the findings, and Section V wraps up the document.

2. Literature Review

The spectral resolution of hyperspectral images is high compared with the conventional RGB images. Hyperspectral imaging sensors actively collect data in hundreds of spectral bands varying from visible to near infrared radiation. The significant benefit of lowering the dimensions is that it requires less physical space to save the hyperspectral images. The main objective of the research reducing the dimensions of the hyperspectral images without losing the significant information. The section presents some of the works done by the various authors.

Huiwen Zeng et al. [5] used pruning methods to reduce the dimension of hyperspectral images. They used XOR mapping to classify the target and clutter in a hyperspectral image. Principle Component Analysis (PCA) is one common feature extraction algorithms. Other common dimensionality reduction algorithms include Isometric Maping (ISOMAP), Factor Analysis, Linear Discriminant Analysis (LDE) etc.

PCA [6, 7] was useful to select the number of principal components. Lower the principle components, lesser the time taken to process the classification. Lori Mann Bruce et al., [8] proposed a wavelet-based approach for extracting hyperspectral features. The accuracy of the Discrete Wavelet Transform (DWT) based feature extraction process was higher than the traditional feature extraction techniques. The main drawback with DWT is, it is a lossy compression hence only approximation band is retained after wavelet transform.

Charles M. Bachmann et al., [9] proposed the Isometric Mapping (ISOMAP), which can provide optimal solution for dimension reduction. Jinya Su et al.,[10] experimented with the performance of PCA algorithm along with SVM classifier. Feature selection and feature extraction are often used to reduce the scale of the training dataset. In a hyperspectral image some of the bands suffer from low signal to noise ratio (SNR) which can be omitted before classification. In [11], Sindhuja. R et al., removed low SNR bands and highly correlated bands. By removing these bands dimension of the image is being reduced.

Ufuk Sakarya in [12] examined the role of global and local patterns in classification of hyperspectral image. This paper investigates a full global-local LDA (CGLDA) for dimension reduction. Linear Discriminant Analysis (LDA) is mostly concerned with the global geometrical configuration of data points. This paper concentrated on integrating local and global characteristics to minimize the dimension of hyperspectral images. Jinn-Min Yang [13] proposed a nonparametric feature extraction algorithm known as Nonparametric Fuzzy Feature Extraction (NFFE) in which the fuzzification procedure is carried to estimate the end members. In [14] fractal method-based dimensionality reduction was proposed where both spectral and spatial information are analyzed. For efficient dimensionality reduction, a mixture of principal component analysis (PCA) and linear discriminant analysis (LDA) is proposed in [15]. In this method the advantages of both the methods are combined and both the properties are preserved. Aloke Datta et al., in [16] proposed PCA and Incremental PCA based dimensionality reduction in hyperspectral images. Modified version of PCA named Incremental PCA has been discussed in this paper. Incremental PCA has the same properties as that of PCA.

When class knowledge already is identified, certain supervised band selection methods may be used. Various optimization-based band selection techniques are also used for reducing the dimensions of hyperspectral images. Genetic algorithms (GA) [17], Particle Swarm Optimization (PSO) [18], and Ant Colony Optimization (ACO) [19], [20] techniques were tested. Filter based band selection methods which uses discrimination measures like Mahalanobis Distance [21], artificial immune system was proposed in [22] which was used to identify the optimal bands which can be remained in hyperspectral images.

3. Methods and Materials

3.1. Principal Component Analysis (PCA)

The goal of dimensionality reduction in hyperspectral images are feature collection and feature extraction. By reducing the dimension of the hyperspectral image, one can preserve most of the variance in the dataset and it handles multicollinearity by eliminating unnecessary functions. In general, dimensionality reduction is accomplished in two ways. One method is to hold only the most important variables from the initial dataset. The other method is to find a reduced number of new variables.

Principal Component Analysis (PCA) is a method that removes the most non - overlapping principal components, and aids in the extraction of a new collection of variables from a wide set of known variables. The PCA approach first computes the dataset's covariance matrix and then finds the eigenvectors and eigenvalues of the data matrix. Few eigen vectors whose eigen values are sufficient to form a transformation matrix are selected and the dimensions of the data are reduced.

An image is generally represented as

$$y_i = [y_1, y_1, \dots \dots, y_N]_i^T \tag{1}$$

for all possible pixel values $y_1, y_1, \dots \dots, y_N$ at a pixel location. The dimension of the vector for a hyperspectral image is proportional to the number of hyperspectral bands. The aim of PCA dimensionality reduction is to reduce the bands in the hyperspectral image let us say B to b where b << B. Here B has different responses over different wavelengths. The principal components are derived in such a manner that the first principal component describes the most variance in the dataset, the second component attempts to explain the residual variance, and the third component tries to explain the variance that the first two components do not explain. In PCA, an eigen vector represents a direction or axis and the corresponding eigenvalue represents variance. Higher eigenvalues show the higher the variance along that eigenvector.

3.2. Incremental Principal Component Analysis (IPCA)

If the dataset is too large to fit in memory, Incremental Principal Component Analysis (IPCA) is used instead of principal component analysis. It computes a low rank estimate for the input data using a fixed amount of memory regardless of the number of data samples. While it is based on the input data attributes, memory use can be controlled by adjusting the number of components.

When a new data point appears, incremental dimensionality reduction techniques update the lower dimensional representations incrementally. Since the update only concerns a small subset of the larger dataset, computing complexity and processing requirements can be lowered. Several criteria, including the number of measurements of the data, the number of data points processed, the number of data points accumulated for the next download, and the number of principal components to be used. The biggest benefit of IPCA is that it just holds the most important singular vectors and projects the data in a smaller size.

The objective function for determining the geometric transformation or the correct approach is as follows:

$$Minimize\ \|c(P' + v\tau^T)R - P\|^2 \qquad (2)$$

Whereas P and P` are product of number of dimensions (d) and the no. of principal components (p) to provide the first p principal component values of d data points from the previous and current PCA results. $\tau$ is a (p x 1) a vector that converts data points of P` with v, while $v = (1\ 1\ \dots 1)^T$ is a (d x 1) vector. The uniform scale element is described by c

3.3. Truncated Singular Vale Decomposition (SVD)

Singular Value Decomposition (SVD) is one method for reducing the dimension of a dataset. SVD is given

$$X = UDV^T \qquad (3)$$

It is defined as the sum of two orthogonal matrices U and V and a diagonal matrix D. The dimensions of one orthogonal matrix are the same as the dimensions of the input matrix. The diagonal matrix is also a square matrix, as is the other matrix (V). The final reduced SVD is given as

$$X_{mXn} = U_{mXk} D_{kXk} V_{kXn}{}^T \qquad (4)$$

4. Experimental Results and Discussions

Experiments are conducted to assess the efficacy of the PCA, Incremental PCA, and SVD approaches on three hyperspectral remotely sensed representations of the datasets namely Indian Pines, Pavia University and DC Mall.

4.1. Datasets

The data sets lead to the Indian Pines test site in northwestern Indiana, a flight campaign over Pavia University in Northern Italy, and the Washington DC Mall in Washington, DC, respectively. Indian Pines data was collected by an AVIRIS sensor over the Indian Pines test site in northwestern Indiana, and it contains 145*145 pixels and 224 spectral bands. The ROSIS sensor obtained the Pavia University database during a flight campaign over Pavia, Northern Italy, and this data consists of 103 spectral bands with a resolution of 1096*1096. As a result, the datasets used in this analysis were Indian Pines Data Set (145 x 145 x 200), Pavia University Data Set (610 x 610 x 103) and Washington DC Mall Data Set (307 x 1280 x 191). In addition to the above-mentioned datasets, other hyperspectral images acquired by the IMS – 1 satellite of 64 bands, removing the bands corrupted by atmospheric noise combined to 17 bands are also used.

4.2. Performance Measures

The exhibition of the techniques was looked at by utilizing level of aggregate eigenvalues of head segments of PCA, Incremental PCA and Truncated SVD are taken as the boundary at different PC's. This work is implemented in Python language over Spyder platform on Dell Core i5 laptop.

In addition to the mentioned datasets, two datasets from ISRO's Bhuvan website are also used for conducting the study of dimensionality reduction. These hyperspectral data consist of 17 bands and these Bhuvan datasets are named as Bhuvan_6 and Bhuvan_5, respectively. Table 2 shows the performance comparison of the three algorithms on the datasets collected from ISRO's Bhuvan website. The table also includes computational time taken to reduce the number of components.

Tables 1 & 2 shows the number of principal components and the cumulative percentage of eigenvalues and computational time of the three datasets and Bhuvan datasets. Number of segments are arbitrarily chosen dependent on the quantity of groups present in the info picture.

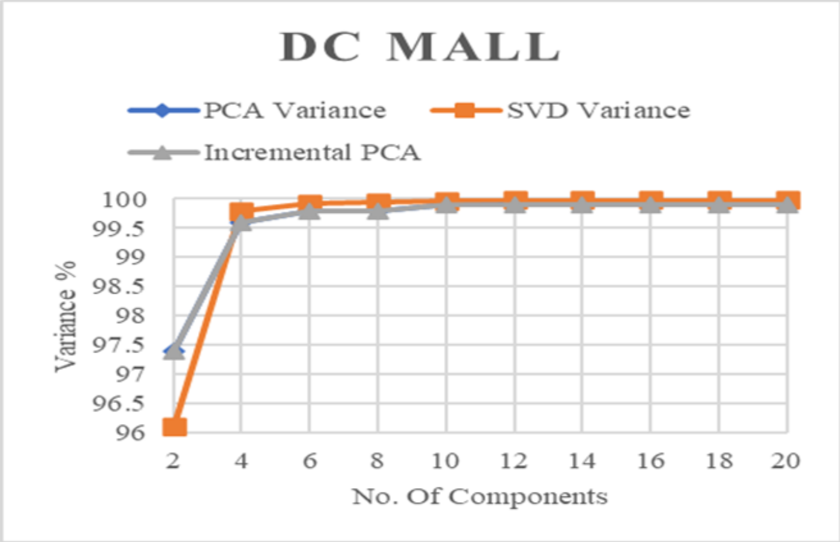
Table.1. Performance Comparison of PCA, Truncated SVD and IPCA for three Datasets

Dataset Name	**No. of PC's**	**% Cum. Eigen Values**		
		PCA	**SVD**	**IPCA**
DC Mall	2	97.42	96.12	97.4
	4	99.63	99.82	99.6
	6	99.81	99.93	99.8
	8	99.84	99.95	99.8
	10	99.91	99.96	99.9
	12	99.93	99.98	99.9
	14	99.95	99.99	99.9
	16	99.95	99.99	99.9
	18	99.96	99.99	99.9
	20	99.96	99.99	99.9
Indian Pines	2	92.0	87.9	92.0
	4	94.3	94.6	94.1
	6	95.5	96.0	95.1
	8	96.3	96.9	95.9
	10	96.9	97.5	96.6
	12	97.4	98.0	97.1
	14	97.8	98.3	97.6
	16	98.1	98.6	98.1
	18	98.4	98.9	98.2
	20	98.5	99.0	98.4
Pavia University	2	94.4	95.8	94.4
	4	99.1	99.1	99.1
	6	99.5	99.5	99.5
	8	99.7	99.7	99.7
	10	99.8	99.8	99.8
	12	99.8	99.8	99.8
	14	99.8	99.8	99.8
	16	99.9	99.9	99.9
	18	99.9	99.9	99.9
	20	99.9	99.9	99.9

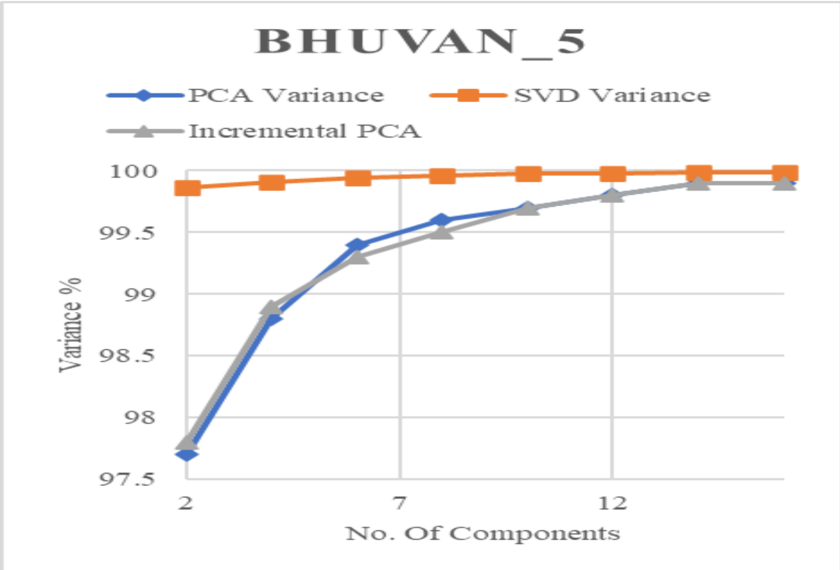
Table.2 Performance Comparison of PCA, Truncated SVD and IPCA for Bhuvan Datasets

Dataset Name	**No. of PC's**	**% Cum Eigen Values**		
		PCA	**SVD**	**IPCA**
Bhuvan_5	2	97.7	99.8	97.8
	4	98.8	99.9	98.9
	6	99.4	99.9	99.3
	8	99.6	99.9	99.5
	10	99.7	99.9	99.7
	12	99.8	99.9	99.8
	14	99.9	99.9	99.9
	16	99.9	99.9	99.9
Bhuvan_6	2	97.8	99.8	97.8
	4	98.8	99.9	98.9
	6	99.3	99.9	99.3
	8	99.5	99.9	99.5
	10	99.7	99.9	99.6

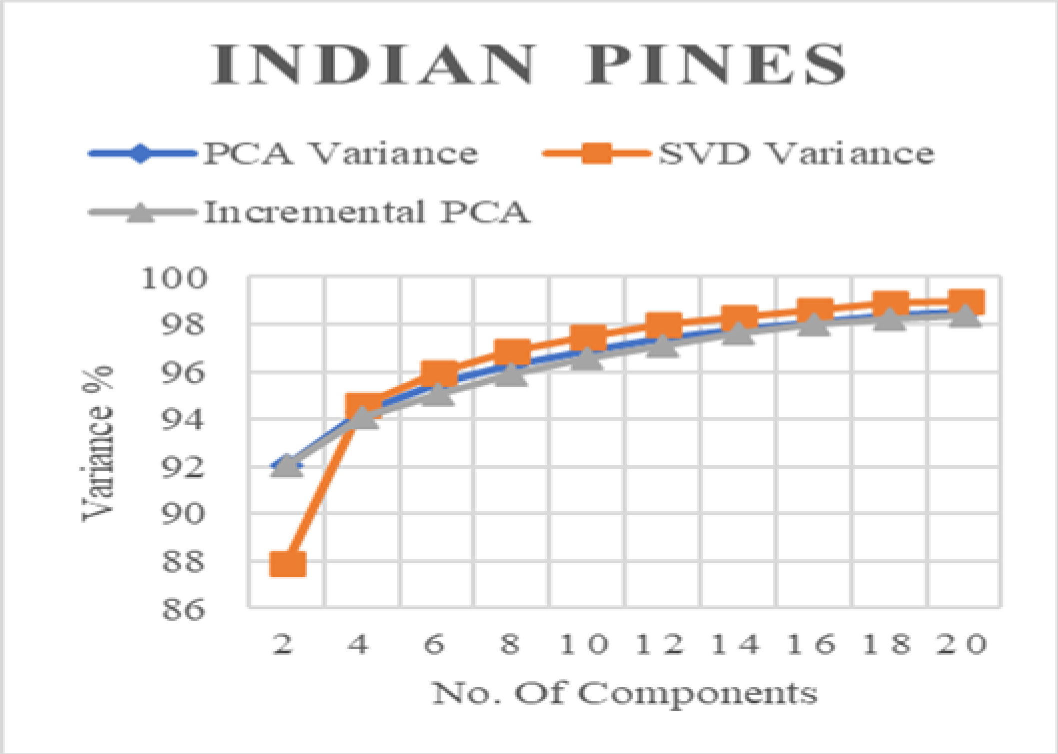
	12	99.8	99.9	99.7
	14	99.9	99.9	99.8
	16	99.9	99.9	99.9



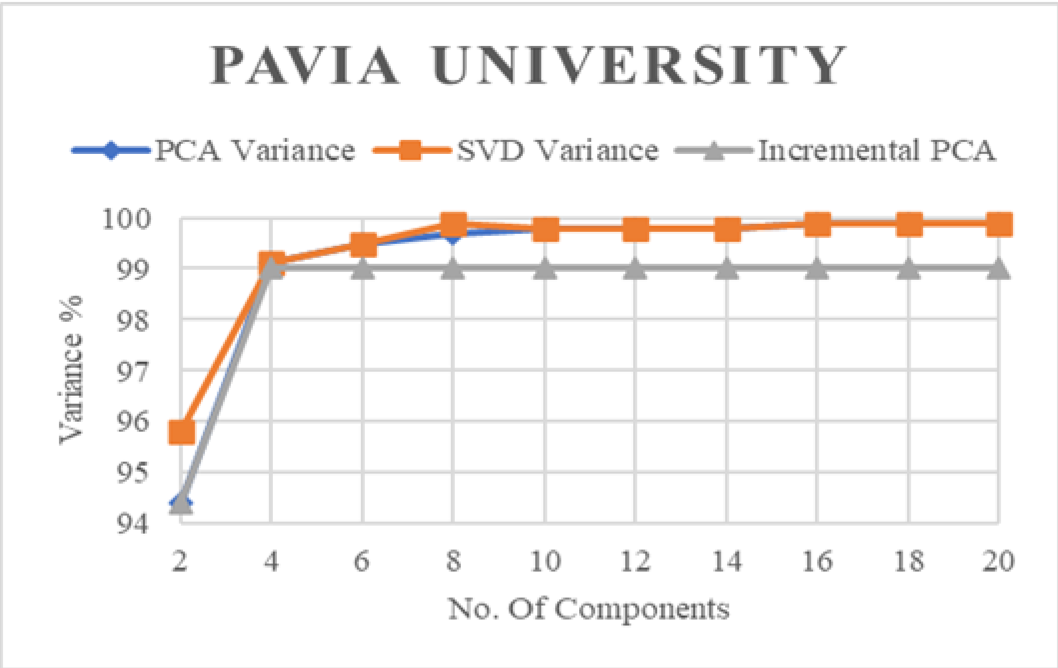
(a) DC Mall Dataset



(a) Bhuvan_5 Dataset

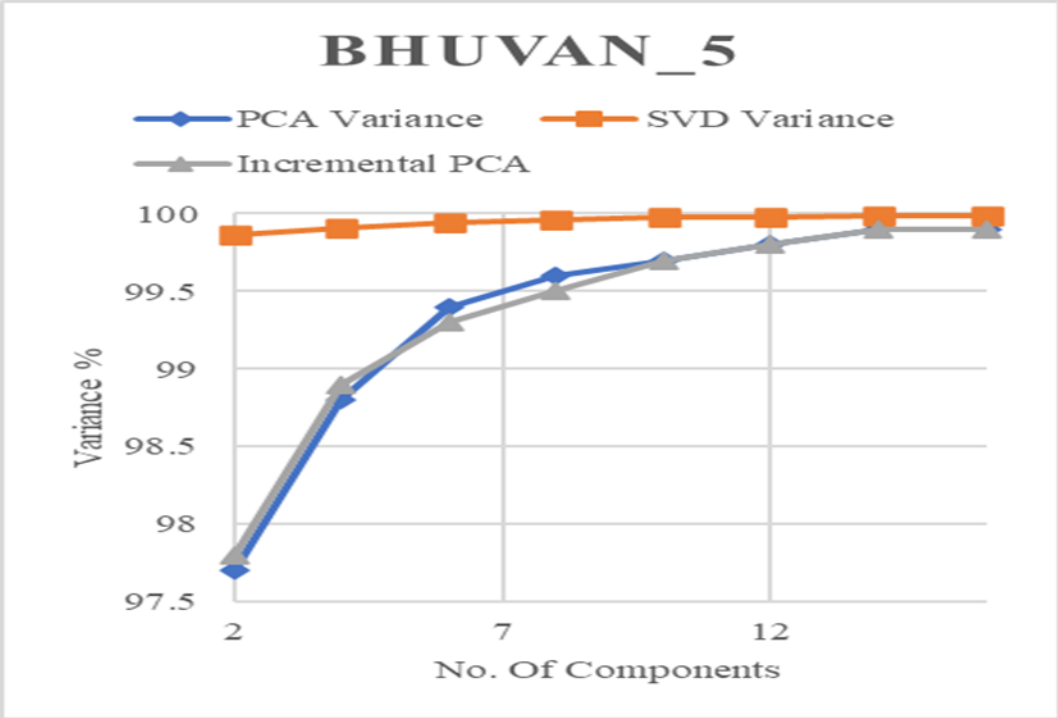


(b) Indian Pines Dataset

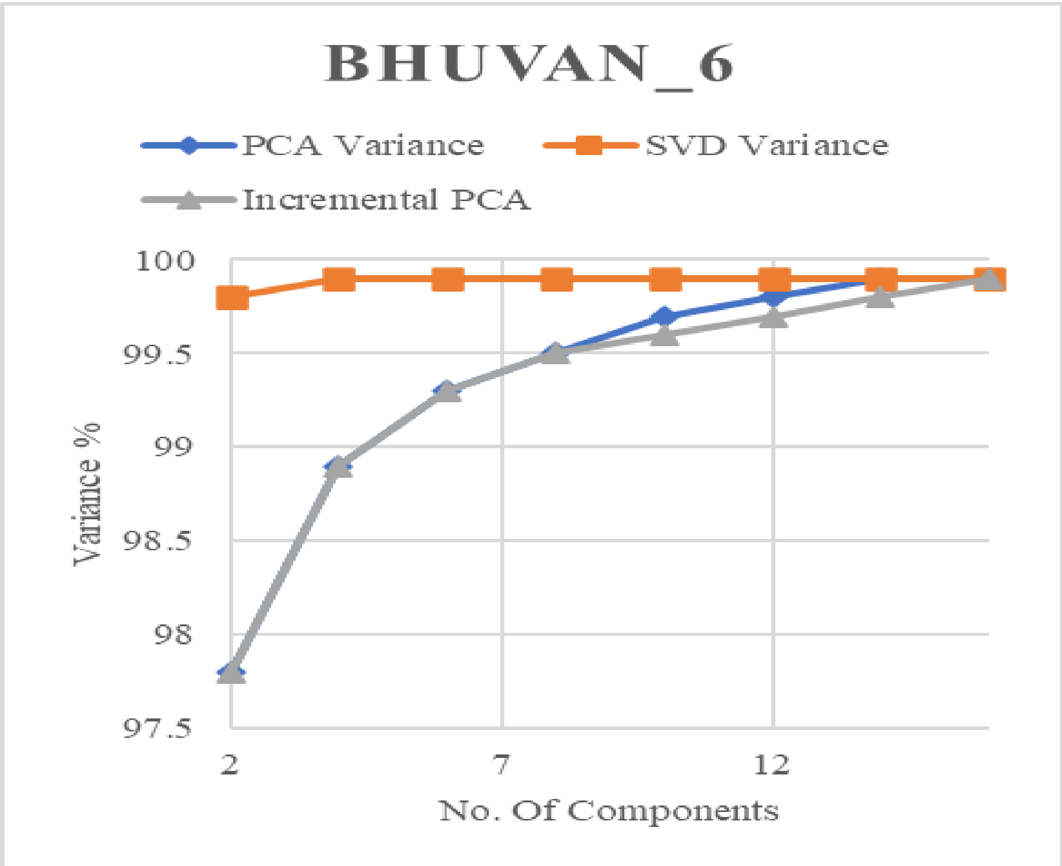


(c) Pavia University Dataset

Figure 4. (a)-(c) addresses the representation of trial consequences of three datasets like DC Mall, Indian Pines and Pavia University separately for the better understanding.



(a) Bhuvan_5 Dataset



(b) Bhuvan_6 Dataset

Figure 5. (a), (b) indicates the graphical representation of the ISRO Bhuvan datasets.

In this work percentage cumulative PCs is measured by varying PCs. It was observed that in case of DC Mall at PC=4, percentage cum. PCs reached 99. In case of Indian pines, it was varying from 88 to 99 and variation is 94 to 99 with respect to Pavia University. In case of Bhuvan datasets, cum. PCs varying from 98 to 100. All three algorithms and working well for four PCs.

5. Conclusion

In this paper dimensionality reduction of hyper spectral datasets was carried out using PCA, Incremental PCA and SVD methods. All the above-mentioned dimensionality reduction techniques were efficient in reducing the data with the step of PCs. With increasing number of components, the cumulative eigenvalues percentage is also increased. PCA is more suitable for linear data. Incremental PCA works well in case of non-linear data. Truncated SVD is outperformed the Incremental PCA and PCA.

PCA, Incremental PCA and SVD based dimension reduction for hyperspectral images has been presented in this paper. All the above-mentioned dimensionality reduction techniques were efficient in reducing the data. With increasing number of components, the cumulative eigenvalues percentage is also increased. Selecting the spectral bands is crucial for reducing the dimensionality of a hyperspectral image. DC mall and Pavia University are working with PC is equal to four. From the results it can be understood that SVD outperforms the remaining two algorithms PCA and Incremental PCA. SVD performs well only if the number of principal components is four. SVD is working well Bhuvan datasets with PC less than two.

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