Analysis of Dimensionality Reduction Techniques for Hyperspectral Image Classification

[1]Sinduja.R, [2]Prof.S.Chidambaram and [3]Dr.A.Sumathi
[1]PG Scholar-M.E Communication Systems [2]Assistant Professor, [3]Prof & Head
Adhiyamaan College of Engineering, Hosur

Abstract-**Hyperspectral imagery utilized in remote sensing applications provides richer data concerning materials than multispectral imagery. The new larger information volumes from hyperspectral sensors gift a challenge for ancient process techniques. as an example, the identification of every ground surface picture element by its corresponding spectral signature remains tough as a result of the large volume of knowledge. standard classification strategies might not be used while not dimension reduction pre-processing. this is often as a result of the curse of spatiality, that refers to the very fact that the sample size required to estimate a perform of many variables to a given degree of accuracy grows exponentially with the quantity of variables. Principal part analysis (PCA) has been the technique of alternative for dimension reduction. However, PCA is computationally high-ticket and doesn't eliminate anomalies which will be seen at one arbitrary band. The high-dimensional nature of the information collected by such sensors not solely will increase procedure complexness however can also degrade classification accuracy. to deal with this issue, spatiality reduction (DR) has become a crucial aid to rising classifier potency on these pictures. Dimension reduction algorithms don't scale back the dimension of knowledge with the goal of reconstructing AN approximation to the initial signal. Instead, they ask for a minimal illustration of the signal that sufficiently retains the requisite data for prosperous unmixing within the lower dimension. Dimension reduction algorithms are designed to attenuate errors within the procedures performed within the lower dimension.**

I INTRODUCTION

Hyperspectral remote sensing image provides richer spectral data than multispectral imagery and has been wont to finely classify totally different ground materials.Compared with supervised classification, unattended classification for hyperspectral remote sensing mental imagery will discriminate totally different materials while not previous data. However, because of the matter of the "curse of dimensionality" in high dimensional areas, all of the size might not be relevant to a given cluster. Ground materials represent different spectral absorption and reflection options on different bands, thus totally different clusters will exist in numerous subspaces of the high-dimensional and distributed feature area.Classification is one among the foremost outstanding analysis areas in hyperspectral image process. Hyperspectral classification is employed in several applications together with town planning, mining and military call support. they supply priceless data concerning the composition of the article of the scene because of their high spectral resolution. the most goal of hyperspectral categoryification is that the assignment of every picture element to the right class. Hyperspectral classification accuracy extremely depends on coaching knowledge. to research this development, the classification ways ar used with totally different coaching knowledge and sample size. Moreover, the enhancements on classification performance by mistreatment spatial data with spectral data also are studied. the necessity of spatiality reduction for hyperspectral image classification is additionally detailed. This study is dedicated to analyzing hyperspectral classification with Absolute distinction, by-product distinction and Correlation Coefficiency algorithms. the primary issue is crucial the impact of various coaching knowledge choice technique on classification accuracy.

Another issue that's analyzed here is that the impact of spatiality reduction with Principal part Analysis. The image cube obtained by the imaging spectroscope of independent agency owned mobile Visible/Infrared Imaging spectroscope (AVIRIS) includes 224 spectral bands of 512 x 614 sized pixels1 and Hyperspectral Digital assortment Experiment(HyDICE) mobile sensing element contains 210 bands of 307 x 307 sized pixels . due to its high degree of spectral content , identification and classification of options, patterns and objects in these pictures ar cumbersome.Hyperspectral sensors have the flexibility to amass pictures in several slim spectral bands that ar found within the spectrum from visible, close to infrared, medium infrared to thermal infrared. Hyperspectral sensors capture energy in two hundred bands or a lot of which suggests that they unendingly cowl the reflective spectrum for every picture element within the scene
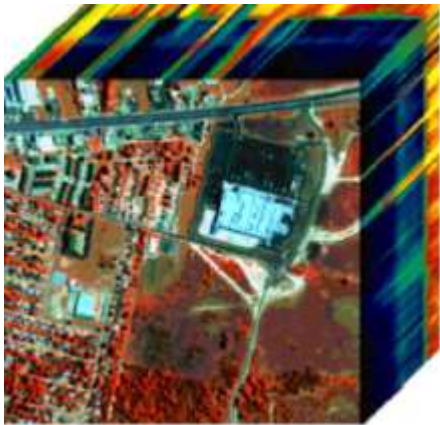
Fig.1 3D Image Cube

II DIMENSIONALITY REDUCTION TECHNIQUES

Higher dimensional data generally increases classification accuracy. However, according to Hughes phenomenon [4, 5], the required training sample size for classification grows exponentially as the number of spectral bands increase. Applications of hyperspectral image processing may require data volume or dimensionality reduction without loss of critical information. Dimensionality reduction also improves classification time.. To reduce training data size, reduction of the number of dimensions is required. Dimensionality reduction is also required to eliminate highly correlated bands. Here dimensionality reduction can be categorized as feature selection [6].

Feature selection methods are primarily based on eliminating bands that do not contribute to the hyperspectral image processing task. These methods simply eliminate the irrelevant and repetitive features to reduce the dimensionality from the original dimension M to N, where (N<M). There are different methods for feature selection [6,7]. These reduction techniques select features by their relevance for the task and lack of correlation between the features. They differ from each other by their feature selection methods. Feature selection is reducing dimension by eliminating highly correlated bands, the feature extraction uses maximal statistical dependency criterion to select features to eliminate.
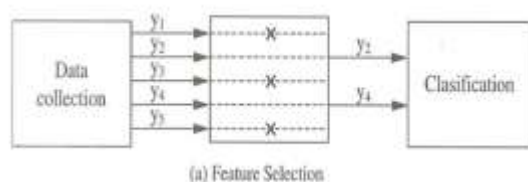

(a) Feature Selection

Fig 2 Feature Selection

Principal Component Analysis (PCA) is one of the common feature extraction algorithms. ISOMAP, Factor Analysis, Linear Discriminant Analysis, Sammon mapping, Local Linear Embedding are other methods that are used for dimensionality reduction. Mathematical explanation of PCA is given in [9] and [10]. After applying PCA, the number of principal components can be selected using the principal values generated.

These principal vectors can be used for classification. Total processing time is often significantly reduced with lower number of principal components [10]. Some of the bands suffer from a low signal to noise ratio (SNR) and do not contribute to the subsequent classification of pixels within the hyperspectral image. Users of hyperspectral images typically become familiar with individual images or sensors and often manually omit these bands before classification. Removal of these bands improves the classification performance of a well-researched hyperspectral test image by over 10% while reducing the size of the image from a data storage perspective by almost 30%.

A common method for displaying hyperspectral imagery is a 3-D image cube. The X-Y plane holds the spatial information and the Z-axis represents the spectral information in the file. As a result of spatial and spectral sampling, airborne hyperspectral imaging (HSI) sensors produce a three dimensional (3D) data structure with spatial-spectral components, referred to as a image cube.

In this paper the dimension reduction process in done using two parameters which are removal of low SNR bands and removal of Highly correlated bands. Block diagram for dimension reduction is shown below
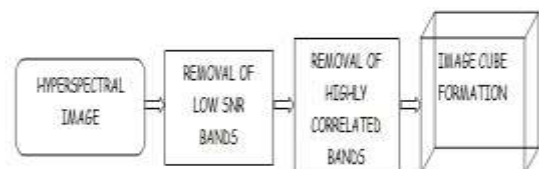

Fig 3 Block Diagram For Dimension Reduction

From the above shown block the process for dimension reduction for hyperspectral imagery can be explained. The hyperspectral image is taken so as to reduce the dimension using two parameters. Firstly the low SNR bands are removed from the image where the image consists of 210 bands. After removal of low SNR bands 210 bands are reduced to162 bands. The number of bands which are highly correlated reduces the accuracy. For this purpose the bands which are highly correlated are removed and the remaining bands are formed into a 3d image cube. Finally better performance and accuracy is obtained.

III HYPERSPECTRAL IMAGE DATASET

The classification results simulated below are based on the analysis of hyperspectral dataset namely Urban dataset. The Urban dataset was taken by Hyperspectral Digital Image Collection Experiment airborne sensor over Copperas Cove, an urban area in Texas.It collects data of 210 bands over a range 0.4-2.5 µm spectral region[10] at nominal spectral resolution of 3 nm.The portion used in experiments corresponds to 307 x 307 pixel subset of Urban dataset.The low signal to noise ratio (SNR) bands and water absorption bands were deleted prior to analysis. After discarding the image bands containing no information; 162 bands are used for classification. The image in RGB color composition is shown in Fig 2.It contains ten main classes such as Building A ,Building B,Road A ,Road B, Parking Area,Concrete, White Soil, Soil, Grass and Tree.The corresponding ground truth of HyDICE image is shown below.
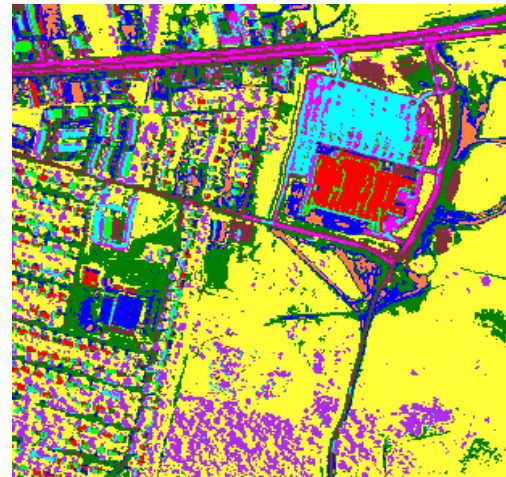

Fig 4 Hydice Image In RGB Color Composition

IV RESULTS

The fig 5 shows the Hyperspectral image which was classified without dimensionality reduction, where the processing steps are more,consumes more time and results with low accuracy. The fig 6 shown below is the hyperspectral image which resulted after dimension reduction with better accuracy, good performance also consuming less time.

Fig 7 represents the comparison between the two parameters Deduction of Low SNR Bands and Deduction of Highly Correlated Bands where the number of pixel in hyperspectral image gets reduced to get better accuracy which is shown in fig 8. Table 1 shows the exact values obtained during Dimension reduction and Classification Accuracy .

Fig 5 Classification Without Dimensionality Reduction

Fig 6 Classification After Dimensionality Reduction

Table 1

Comparision of Metrices

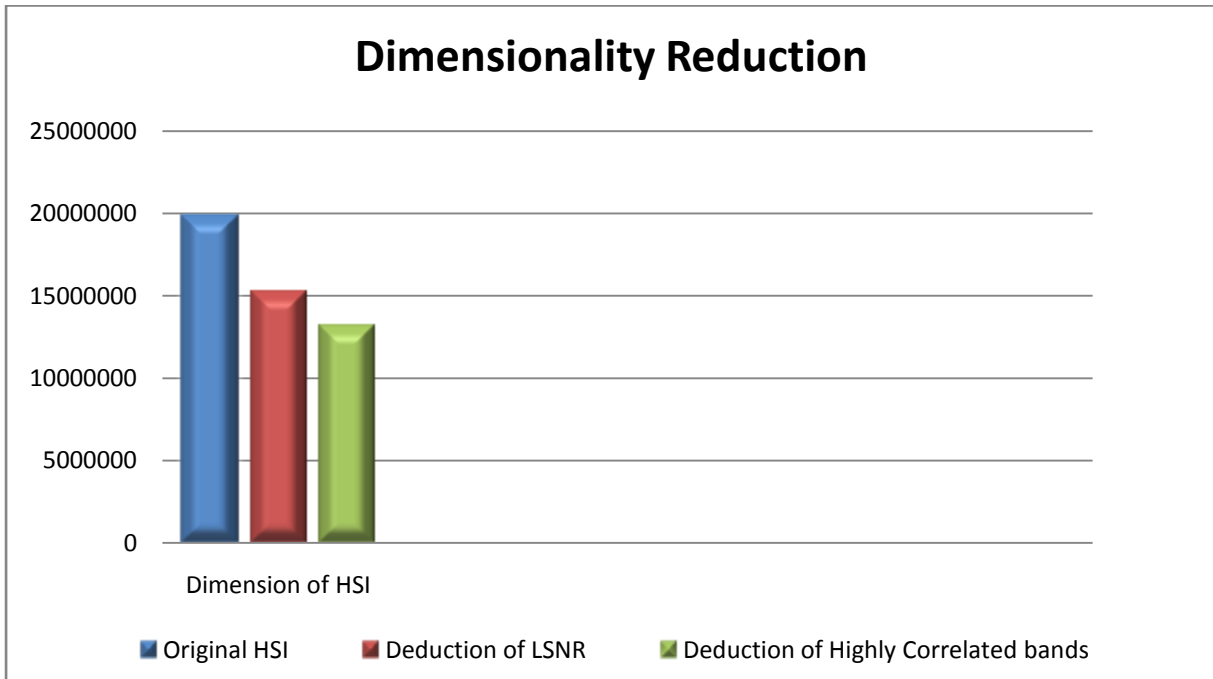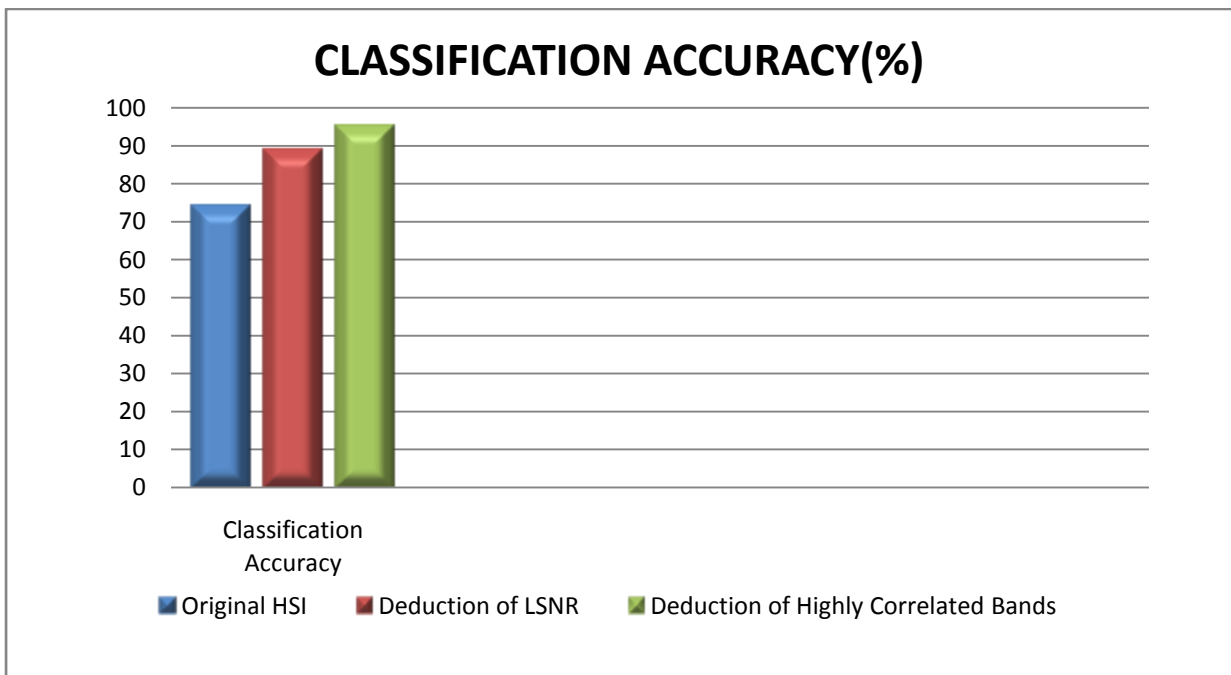|	Original HSI	Deduction Of LSNR	Deduction Of Highly Correlated Bands
Dimension Reduction	1,97,92,290	1,52,68,338	1,31,94,860
Overall Accuracy(%)	74	89	96

Fig 7 Dimensionality Reduction

Fig 8 Classification Accuracy

V CONCLUSION

Dimensionality Reduction techniques for HSI classification applications is investigated. HyDICE image dataset has been used for simulation to validate the results. The performance of classification before and after reduction of dimension of HSI is reported in terms of dimension and classification accuracy. It is concluded that the classification of HSI after dimension reduction outperforms well than the classification with original number of bands.

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