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# PCA Based Classification of Relational and Identical Features of Remote Sensing Images

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**Abstract:** ***Principal Component Analysis (PCA) technique is useful in reducing dimensionality of a data set in order to obtain a simple dataset where characteristics of the original dataset that contributes most to its variance are retained. This method is to transform the original data set into a new dataset, which may better capture the essential information. Remote sensing images from orbiting satellites are gaining ground in recent years in inventory, mapping and monitoring of earth resources. These images are acquired in different wavelengths of the electromagnetic spectrum and therefore there exist correlation between the bands. The developed algorithm can not only reduce the dimensionality of remote sensing image but also extract helpful information for differentiating the target feature from other vegetation types more effectively. In this paper the usefulness and innovative of PCA in processing of multispectral remote sensing images have been tinted. It has been observed that PCA effectively summarize the dominant modes of spatial, spectral and temporal variation in data in terms of linear combinations of image frames. It provides maximum visual separability of image features thus improving the quality of ground truth collection and also turn to improving the image classification accuracy. Here, we propose a fast alternative to iterative PCA that makes it suitable for remote sensing applications while ensuring its theoretical convergence illustrated in the challenging problem of urban monitoring.***

**Keywords: PCA, KPCA, HPC, Covariance Matrix and Classification.**

## 1. Introduction

Principal Component Analysis (PCA) is a mathematical technique for reducing the dimensionality of a data set. Because digital remote sensing images are numeric, their dimensionality can be reduced using this technique. In multi-band remote sensing images, the bands are the original variables. Some of the original bands may be highly correlated and to save on data storage space and computing time is less and also correlated Eigen images by PCA. In addition to its use in this way, PCA can be used as a change detection technique in remote sensing. Principally, there are two ways PCA can be used in change detection.

- Independent data transformation analysis - in which multi-temporal remote sensing image data sets are spectrally, enhanced separately using PCA. Each image is separately classified for use in post classification change detection.
- Merged data transformation - in which all the bands from the n - dimensional multi-temporal image data set are registered and treated as a single *N* - dimensional data set as input to the PCA.

Principal Component Analysis (PCA) is a statistical technique used to reduce a set of correlated multivariate measurements to a smaller set where the features are uncorrelated to each other. The advent of satellite remote sensing with multispectral and hyper spectral images in digital format has brought a new dimension in inventory, mapping and monitoring natural resources of the earth. The multispectral (or multi band) images have been acquired in different parts of the electromagnetic spectrum retaining correlation between the bands. The innovative techniques of PCA have been incorporated as a special transformation in digital image processing of satellite images where N number of correlated

bands of the image data have been reduced to few uncorrelated bands. For example the LANDSAT satellite system provides seven band image data from which six bands are reduced to 3 bands using PCA and thereafter these three bands are used to create a false color composite where the visual interpretation for ground features is highly enhanced. The enhanced image is effectively used as a base for ground truth collection in supervised classification of land use and land cover, performing special tasks such as geologic interpretation etc. In this paper an attempt has been made to highlight the significance of PCA in processing of remote sensing images on the basis of evaluation process.

However, in many remote sensing applications acquiring ground truth information for all classes is very difficult, especially complex and heterogeneous geographical areas are analyzed. Actually, many other applications have turned to recognize one specific land-cover class of interest and to discriminate it from the other classes present in the investigated area. This formulation of the problem relaxes the constraint of having an exhaustive training set, but requires the availability of representative training data for the analyzed class and if possible, some training samples representative of other classes considered. Recently, high interest has been played to this approach through the fields of:

- Anomaly Detection - where one tries to identify pixels differing significantly from the background.
- Target Detection - where the target spectral signature is assumed to be known (or available from spectral libraries) and the goal is to detect pixels that match the target.
- One-class or Multi-class Classification - where one tries to detect one class or extend to multi class and others.

## 2. Evaluation of PCA in Remote Sensing Image Analysis

The innovative technique of Principal Component Analysis (PCA) has found wide use in digital processing of multispectral remote sensing images. PCA is used to enhance an image particularly in the land-cover classification of satellite images, where such images are used for increasing the interpretability of human observers and for improving the accuracy of the classification. In the field of remote sensing, especially in multispectral imagery, reduction of the dimensionality is a key point for image analysis to prevent from classification process. Many satellites collect correlated data from earth surface with different spatial, spectral and temporal resolutions.

A conventional principal component analysis is built on the basis of a statistical concept. The principal component analysis is to summarize data defined by many variants or various features into a few of principal components, so that the meaning of the data can be lost as little as possible and interpreted as well. A fuzzy concept can be employed to construct a principal component model which can deal with fuzziness, vagueness or possibility of system considered, which is named a fuzzy principal component analysis for fuzzy data. The fuzzy data is employed to deal with the possibility of the vague system and to analyze a real state of the concealed system under the image data. Therefore, the fuzzy principal component analysis for fuzzy data is built in terms of the possibility and evaluates all observed values as a possibility to measure the image performance.

A linear model to estimate the optimum number of principal components to use in such dimensionality reduction of this application. Remote sensing image produces large amounts of digital data which are collected into databases. The principal component analysis is applied to the hyper spectral image and then the integer wavelet transform is applied to the residual image to further concentrate the energy and reduce the entropy. The coding quality of the method is measured with the zero-order entropy and it is clearly lower than the other methods. The computation of the residual image through PCA is much faster than that through the vector quantization, which is typically very time consuming. Feature extraction of hyper spectral remote sensing image can be investigated using PCA which has shown to be a good unsupervised feature extraction. By mapping the image data into another feature space and using nonlinear function, Kernel PCA (KPCA) can extract higher order statistics. Using kernel methods, all computation are done in the original space, thus saving computing time. KPCA is used for the preprocessing step to extract relevant feature for classification is done with a back-propagation neural network on real hyper spectral remote sensing data from urban area.

This method was used to extract features that are uncorrelated in some feature space. Basically KPCA is used as feature extraction on hyper spectral data, which performed well in terms of accuracy. A nonlinear approach based on a combination of the fuzzy c-means clustering (FCMC), feature vector selection and principal component analysis (PCA) to extract features of multispectral images when a very large number of samples need to be processed. The PCA method has defects in the area of influenced and non-influenced attributes and it provides an effective solution to determine the value of knowledge rule in image information still remains a question. This method focuses on two crucial issues:

- The core attributes of the target categories in remote sensing image classification are systematically analyzed while eliminating surplus attributes rationally.
- The unique point of each attribute, which influenced the target categories, is successfully found. This is a crucial aspect and very helpful for the construction of decision rule.

Remote sensing image have become very widespread in recent years and the exploitation of this technology has gone from developments mainly conducted by government intelligence agencies to those carried out by general users and companies. There is a great deal too remote sensing data than meets the eye and extracting that information turns out to be a major computational challenge. For this purpose, high performance computing (HPC) infrastructure such as clusters, distributed networks or specialized hardware devices provide important architectural developments to accelerate the computations related with information extraction in remote sensing.

Automatic image classification is one of the fundamental problems of remote sensing research. The classification of urban areas in high-resolution images is even more challenging because many relevant objects are small and because at small ground sampling distance (GSD) fine important details become visible such that the spectral variation within one class increases. At the same time, remote sensing of urban areas is becoming more important. The classification process involves two steps: first, one has to derive features from raw observations in order to represent local radiometric properties. Then classification method which, given the previously extracted features, estimates the most likely land cover class has to be applied. Classifiers are nowadays well understood and there exists a advanced theory of statistical learning and classification, whereas the feature design still remains mainly an empirical process. In the present paper we empirically evaluate PCA methods for feature extraction from the remote sensing image. After the evaluation process, the different features are extracted and fed into a standardized classifier and then the output is compared to manually labeled ground truth to assess the classification accuracies.

## 3. Statistical Background of PCA

PCA is a mathematical method to applying the PCA in multispectral remote sensing images, each band is transformed into a linear combination of orthogonal common components with decreasing variations. The resulting components carry different information uncorrelated one to each other. The components will explain all of the variance contained in the original bands. The PCA in map algebra is used for several purposes:

- Transformation of the original bands to obtain new uncorrelated pseudo bands successively used in the classification process. The greatest amount of the variance in the original dataset can be explained with a lower number of components. The classification process is often improved with the use of these new bands.
- Object recognition of PCA method is used as classification methodology to improve the performance.

### 3.1 Band Transformation

The high correlation of original bands sometimes produces intense computational efforts and generates inefficient results. In Remote Sensing PCA is often used to compress the information content of n number of original image channels into a fewer number of transformed principal component images. The principal components are new uncorrelated bands obtained by linear combination of original data, retaining as maximum as possible the information present on the original data. Among all the PC bands, the first one contains the largest amount of information of the original dataset while, the last one contains noise. In this way, a classification using the first PCs can be better than one performed by means of the original dataset.

### 3.2 Object Recognition

This approach is typically used for remote sensing image, Eigen vectors are calculated on a training set of images, each one representing a sample of objects. In remote sensing applications, commonly the highest Eigen values are the most face-like of orthonormal basis vectors are called Eigen-faces. The Eigen vectors represent the distinctive features of an image and realize the space of the features: each image can be obtained as linear combination of Eigenvectors and projected on the feature space. In the recognition phase the components of one image on the feature space are calculated and compared with the principal features of other images. In this case, each image of the training sample set represents a remote, a classification system is defined each class is represented by a certain number of remote sensing images in the training sample set. For a successful classification, the classes have to be well separated by a set of principles features.

### 3.3 Classification

Remote sensing image classification is a very important process in many image vision applications, which involved in partitioning an image into isolated regions, such that each region shares common properties and represents a different object. Since image classification represents the interface between image pre-processing and image understanding. Assuming that the image features have been extracted, classification amounts to estimating for each possible class the probabilities that a certain pixel or a region belongs to that class. Following the main classification approaches are:

- Parametric generative class models which assume a simple parametric form of the classes in the feature space.
- Instance-based class models directly based on the examples given as reference data such as KNN (k-Nearest-Neighbor) algorithms.
- Discriminative classifiers which focus on the class boundaries such as linear discriminant analysis (LDA), Support Vector Machines (SVMs) and Random Forest classifier.

It is important to note that not all the classifiers are suitable for all sets of features. This is supported both not only by the literature in computer vision and machine learning but also by experiences with hyper spectral remote sensing data. We have also actively investigating object class detection and semantic labeling in images. It made significant progress mainly based on improved feature extraction and discriminative classification methods.

### 3.4 Image Features

The amount of energy measured by the sensor in different spectral bands i.e. the raw pixel values are the most obvious features. In particular cases useful features can be hand-crafted to represent a known physical effect (e.g. the normalized differential vegetation index NDVI). However one cannot expect that such simple relations exist for all the classes that one might want to extract spectral special and temporal features. Thus it should be useful to look at the pixel values in a certain neighborhood of a pixel. More sophisticated features are only occasionally used in remote sensing applications

### 3.5 Feature Learning

Feature learning aims to find a mapping, which optimally represents the data while suppressing noise. A standard method for that purpose is a linear projection on an orthogonal basis found with PCA basis. Since different images differ in their radiometric properties due to sensor characteristics and lighting effects, it seems reasonable that classification could benefit if one were to use features designed specifically for a given dataset. In the recent statistical learning, there are two complementary approaches to learn features from data. First, the simpler method generates a large set of potential features and then enforces the sparsity of the feature vector when learning the classifier such that only an optimal and sufficiently small subset is used for classification. Second, possibly more advanced method to select right features proceeds in a different way. The basic idea is to choose a general class of parametric functions that map pixel values to features.

### 3.6 Training Classifier

Features are well-known with respect to their spectral and physical characteristics which could be helpful to increase accuracy of classification. Moreover it is practical to consider various pre-classification transformations to distinguish categories from each other. As the unsupervised classification involves algorithm that examine the unknown pixels in an image and combined them into a number of classes based on the natural grouping or clusters present in the image values, consequently natural groupings in the data identified by plotting a scatter diagram regarding to original image and PCA image extracted for the most informative component. This is the technique for processing of multiband data make use of a two dimensional histogram where the data file values of one band have been plotted against the data file of another band.

## 4. Innovative Technique of PCA

A principal component analysis was performed to refine the spectral resolution and data redundancy. PCA is able to fulfil three objectives higher order polynomials:

- Fist, to ascertain the information content of each of multispectral band.
- Second, to identify the most informative bands.
- Third, transformation of the information content onto orthogonal axes increases spectral separability of certain adjacent classes.

Under the assumption of PCA finds the linear basis that is optimal in the sense that for a given number of basis vectors, it preserves the largest amount of the variance in the data.

### 4.1 Four Stage PCA Classification

The PCA approach for extracting image features is long-standing and widely used in remote sensing image. In our study, inherently performs feature selection and is known to handle well with spurious dimensions. The work can be divided into four stages can be summarized in the following table 1:

**Table 1:** Summary of four stage PCA classification

| Four Stage PCA Classification |
|---|
| **Stage 1: Pre-processing**<br>The remote sensing image dataset has been orthorectified in a selected coordinate system.<br>**Stage 2: Definition of Training and Control Samples**<br>An exhaustive number of samples based on a hierarchical classification terminology was the starting point for the PCA and for the assessment of the results.<br>**Stage 3: PCA Bands of Dataset Transformation**<br>Several transformations based on different training sample sets were performed and a thresholding of the resulting bands were carried out. The resulting image can be used as mask in the feature classification of the selected classes.<br>**Stage 4: Accuracy Assessment Method**<br>An evaluation of the accuracy during the thresholding phase was carried out. |

### 4.2 Graphical Representation of PCA

This paper is organized in the following four distinct sectors. The background and Pre-processing sector introduces the methodological approach used and it also provides a description of data orthorectification. The sample data set sector points out the necessary procedures to obtain a sufficient number of training samples that are prerequisites for a successful classification. Finally accuracy assessment sector to evaluate the different PC bands of results. The graphical representation of PCA is shown in the figure 1.

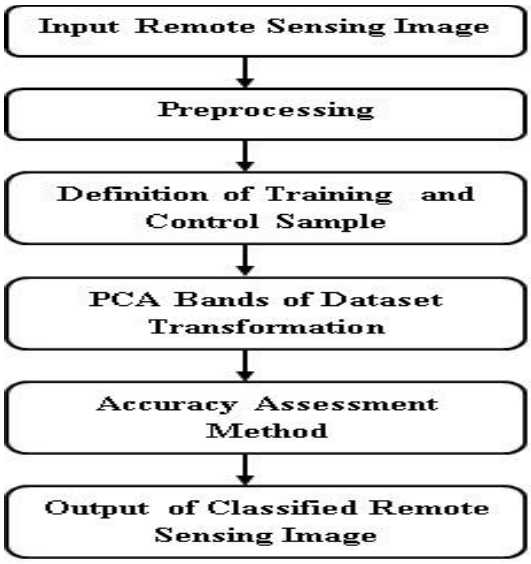



**Figure 1:** Graphical representation of the classification of remote sensing images using the PCA

### 4.3 Advantages

PCA has been widely used in pattern recognition and remote sensing application, mathematically establishes a new set of variables, which describe the variance in the original data set. The principal component is useful in providing maximum visual separability of image feature. Therefore, principal component analysis can be used in image classification to improve the accuracy.

- PCA is one of the most commonly adopted feature reduction techniques in remote sensing image analysis.
- It can not only reduce the dimensionality of hyper spectral remote sensing imagery but also extract helpful information for differentiating the target features
- A better approach is to reduce the data dimensionality while trying to maintain the most vital and useful information in the data set.
- In particular, PCA is simple, straightforward, easy to use and most importantly has been implemented in almost all available remote sensing image processing and analysis package.
- It is possible to use PCA as the fundamental frame work to develop an appropriate feature extraction system that is capable of collecting information most helpful to the discrimination of target classes.
- PCA system is specifically designed for identifying predetermined features from hyper spectral remote sensing imagery.
- PCA is efficient and usually yields satisfactory outcomes in extracting useful features.
- PCA for improve a better use with hyper spectral data is to accelerate the processing for better feature extraction.
- PCA is a statistical approach for image processing to decrease the number of correlated image bands and to increase the interpretability of components as combinations to multiple bands.

### 4.4 Schematic Diagram

Principal Component Analysis (PCA) is the general name for a technique which uses sophisticated underlying mathematical principles to transforms a number of possibly correlated variables into a smaller number of variables called principal components. In this paper we use the principal component analysis to select the best bands for classification, analyze their contents, and evaluate the correctness of classification obtained by using PCA images. The principal component analysis has been used in remote sensing for different purposes. Multispectral remote sensing PCA classification is a complex process of sorting pixels bands into a finite number of individual classes or categories of data. If a pixel band satisfies, a certain set of criteria, the pixel is assigned to the class that corresponds to those criteria. Thus an appropriate classification system and an adequate number of training samples are fundamentals for a successful classification. The schematic diagram of multistage PCA classification is shown in the figure 2:

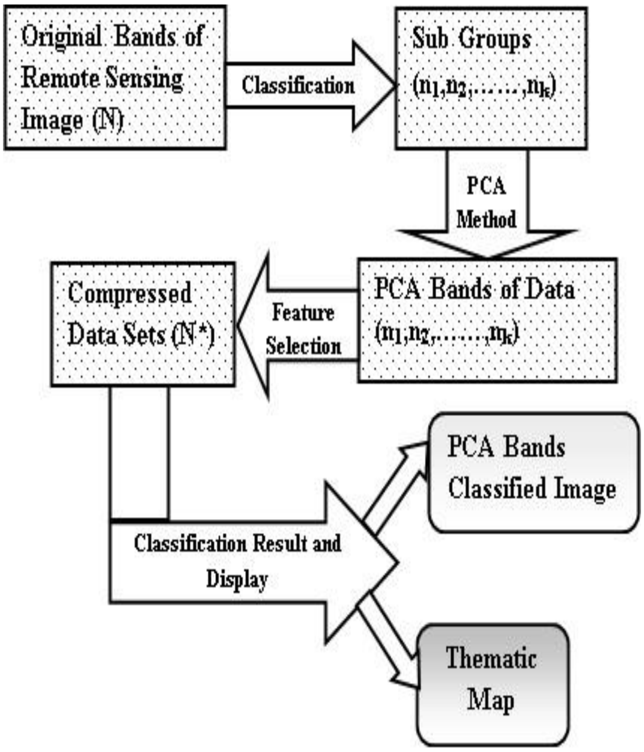



**Figure 2:** Schematic Diagram of Multistage PCA Classification

### 4.5 Methodology

The principal component analysis is based on the fact that neighboring bands of hyper spectral remote sensing images are highly correlated and often convey almost the same information about the object. In the process, the optimum linear combination of the original bands accounting for the variation of pixel values in an image is identified. The Classification of PCA technique is developed based on the following considerations.

**Table 2:** Algorithm for Innovative Technique of PCA

**Procedure: Innovative Technique of PCA**

**Step 1**
Each sample image is converted into row vector. A row vector can be constructed by concatenating each row with first in sequence. For a hyper spectral image with m rows and n columns matrix is converted into a single row l x mn vector X..

**Step 2**
The row vector matrix is constructed by combining together the row vectors of n remote sensing images. $X_i$ is a row vector of a sample image i, where i = l………n. First row vector of n images are combined to make a 2-D array of n images * training image pixels dimensions.

**Step 3**
The unbiased estimates of the mean vector and covariance matrix are given by an image pixel vector is calculated as:

$$m = 1/M \sum_{i=1}^{M} [\, X_1, X_2, \ldots\ldots\ldots, X_N \,]_i^{\,T}$$

with all pixel values $X_1$,$X_2$,......$X_N$ at one corresponding pixel location of the hyper spectral remote sensing image data. The dimension of that image vector is equal to the number of hyper spectral bands N.

**Step 4**
The covariance matrix of x is defined as:

$$CM(x) = E\{(x-E(x))(x-E(x))\}^T$$

where: E = expectation operator, T is superscript = transpose operation and CM = notation for the covariance matrix**.**

**Step 5**
The covariance matrix is approximated via the following calculation:

$$C_{MX} = 1/M \sum_{i=1}^{M} (X_i - m)(X_i - m)^T$$

**Step 6**
The PCA is based on the Eigenvalue decomposition of the covariance matrix, which takes the form of:

$$C_{MX} = RDR^T$$

where: D = DMat( $\lambda_1$, $\lambda_2 \ldots \lambda_N$) is the diagonal matrix composed of the Eigen values $\lambda_1$, $\lambda_2 \ldots \lambda_N$ of the covariance matrix $C_{MX}$, and R is the orthonormal matrix composed of the corresponding *N* dimension Eigen vectors $r_k$, (k=1,2,…, N) of $C_{MX}$ as follows: $R = (r_1, r_2, \ldots r_N)$

**Step 7**
The linear transformation function defined by:

$$L_i = R^T X_i \ (i = 1,2,\ldots,M)$$

is the PCA pixel vector and all these pixel vectors form the PCA bands of the original images. Such formed PCA bands have the highest contrast or variance in the first band and the lowest contrast or variance in the last band. Therefore, the first k factor of PCA bands often contain the majority of information residing in the original hyper spectral remote sensing images and can be used for more effective and accurate analyses because the number of image bands and the amount of image noises are reduced.

**Step 8**
The numbers of highest valued eigenvectors are then picked to make an image space from the resultant

covariance matrix $C_{MX}$. A set of rules are defined to classify the corresponding type of the matched remote sensing image features. At the time of each training image has attached related information is coded. Finally the remote sensing image is classified into specific type according to the specified rules.

### 4.6 Assessment of PCA With Other Techniques

The correlation matrix is related to the covariance matrix, and its elements are determined by:

$$Q_{ii} = V_{ij}/\mathrm{Sqrt}(V_{ii}V_{jj}) \quad (1)$$

Here, $V_{ij}$ are elements of the covariance matrix and $V_{ii}$ and $V_{jj}$ are the variances of the ith and jth bands of data. It describes the correlation between band and band . It has been observed previously that when the original bands are highly correlated, and PCA works efficiently. However, for poorly correlated data, there may be little change after the application of PCA. The PCA is conducted separately on each subgroup of image data. The major advantage of PCA technique is saving computation time but it is more significant. Let Z be the brightness vector for an image pixel with spectral bands. The PCA is defined as:

$$Z = A^{T}x \quad (2)$$

Where A is the matrix of normalized eigenvectors of the image covariance matrix and T denotes the transpose operation. PCA provides a new feature space and its first k components are the best choice of k linear functions for reconstructing the original data in the sense of minimizing mean square error of the lingering.

Most of the vision or image based applications, two basic steps involved in the image retrieval are feature selection or extraction and similarity measure calculation. Various classification techniques and algorithms are used for remote sensing image classification. Every technique provide with respective accuracy level. The desired results using innovative PCA are compared with the results of other technologies used for remote sensing image classification. Results show that PCA, relative to other statistical techniques is more accurate. The statistical techniques include fuzzy c-means, thresholding technique and SVM that give 84% to 86% accuracy. The proposed PCA technique provides higher accuracy up to 95.6%. The overall statistics about the innovative technique of PCA based remote sensing image classifier is better than other used techniques.

## 5. Experimental Results

In experiments were used remote sensing forestry test color images. Experiments were done in Matlab 7.6. Original number of bands in image was twenty, which was reduced to eight using PCA. Image after selection of bands and classification results are shown below:

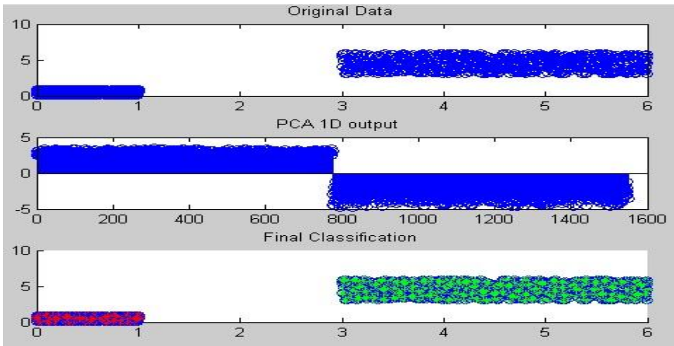



**Figure 3:** Project plotting of different random variances on to PCs features

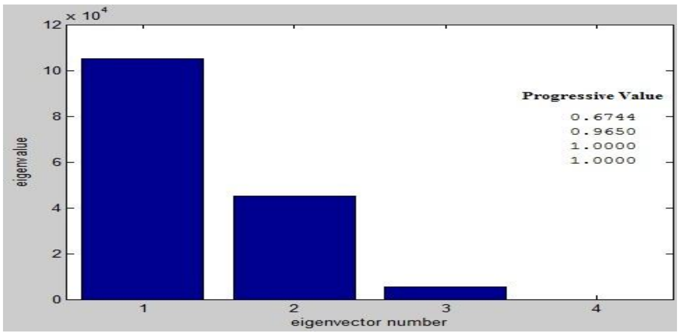



**Figure 4:** Eigen values of different random variance graph on to PCs features

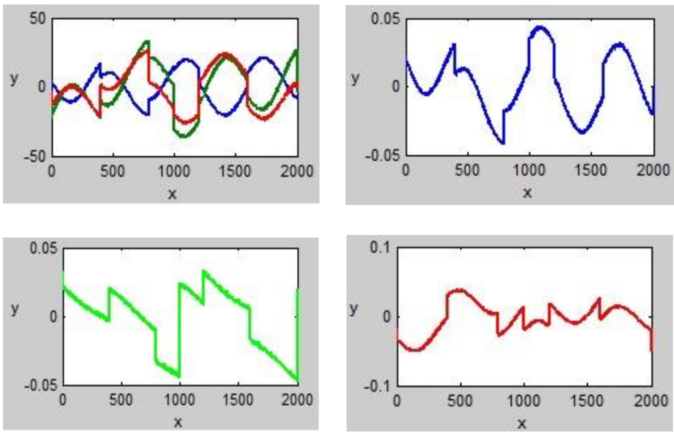
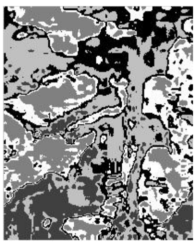
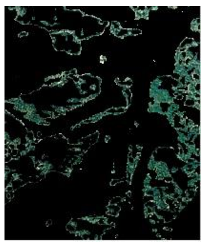


**Figure 5:** The separated signals plotted combined RGB, Blue, Green and Red PC bands from randomly mixed combination


Original Image


Case 1(Band 1)


Case 2(Band 2)

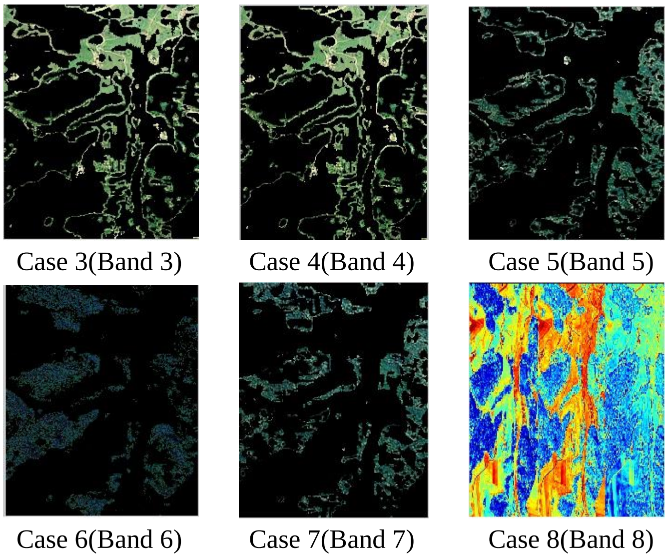



**Figure 4:** PCA classification results of all eight test cases

## 6. Conclusion

PCA is an efficient identifier in terms of time and provides a better accuracy in remote sensing image classification. A PCA based system provides the high speed processing with relatively better accuracy. PCA also easily handles a large number of image data due to its capability of reducing data dimensionality and complexity. PCA algorithm provides more accurate remote sensing image classification that infers better and concise results. This scheme is a practical and efficient method for dealing with hyper spectral remote sensing image data. It makes use of the block structure of the correlation matrix so that the PCA is conducted on data of smaller dimensionality. Therefore, computational load is reduced significantly.

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