PLANTS CHANGE DETECTION IN FOREST AREAS BASED ON SATELLITE IMAGES USING KERNEL MNF

PROJECT REPORT

Submitted by

NIRMALA.K

Register No: 13MCO14

in partial fulfillment for the requirement of award of the degree

of

MASTER OF ENGINEERING

in

COMMUNICATION SYSTEMS

Department of Electronics and Communication Engineering

KUMARAGURU COLLEGE OF TECHNOLOGY

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APRIL 2015

BONAFIDE CERTIFICATE

Certified that this project report titled **"PLANTS CHANGE DETECTION IN FOREST AREAS BASED ON SATELLITE IMAGERY USING KERNEL MNF"** is the bonafide work of **NIRMALA.K [Reg. No. 13MCO14]** who carried out the research under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

ACKNOWLEDGEMENT

First, I would like to express my praise and gratitude to the Lord, who has showered his grace and blessings enabling me to complete this project in an excellent manner.

I express my sincere thanks to the management of Kumaraguru College of Technology and Joint Correspondent **Shri. Shankar Vanavarayar** for the kind support and for providing necessary facilities to carry out the work.

I would like to express my sincere thanks to our beloved Principal **Dr.R.S.Kumar Ph.D.,** Kumaraguru College of Technology, who encouraged me with his valuable thoughts.

I would like to thank **Dr.Rajeswari Mariappan Ph.D.,** Head of the Department, Electronics and Communication Engineering, for her kind support and for providing necessary facilities to carry out the project work.

In particular, I wish to thank with everlasting gratitude to the project coordinator **Ms.R.Hemalatha M.E.(Ph.D).,** Associate Professor, Department of Electronics and Communication Engineering ,for her expert counselling and guidance to make this project to a great deal of success.

I am greatly privileged to express my heartfelt thanks to my project guide **Dr.A.Vasuki Ph.D.,** Professor, Department of Electronics and Communication Engineering, throughout the course of this project work and I wish to convey my deep sense of gratitude to all teaching and non-teaching staff of ECE Department for their help and cooperation.

Finally, I thank my parents and my family members for giving me the moral support and abundant blessings in all of my activities and my dear friends who helped me to endure my difficult times with their unfailing support and warm wishes.

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LIST OF ABBREVIATIONS

CVA	Change Vector Analysis
DSM	Digital Surface Model
FIR	Far infrared
GLCM	Gray Level Co-occurrence Matrix
ICDA	Iterated Canonical Discriminant Analysis
IR-MAD	Infrared-Multivariate Alteration Detection
KMAF	Kernel Maximum Autocorrelation Function
KMNF	Kernel Minimum Noise Fraction Analysis
MAD	Multivariate Alteration Detection
MCVA	Modified Change Vector Analysis
MSS	Multispectral image
MIR	Middle infrared
NIR	Near infrared
PAN	Panchromatic image
PCA	Principal Component Analysis
RGB	Red Green Blue
SPCA	Selected Principal Component Analysis

CHAPTER 1

INTRODUCTION

Satellite images are captured using satellite sensors at different electromagnetic wavelengths. Whenever a particular range of frequency is captured, grid of pixels is created that constitute digital image by combining scanning in cross talk direction and platform motion along track direction. A pixel is created whenever sensor system electronically samples the continuous stream of data provided by scanning. Nowadays, a number of satellite images available from many earth observation platforms, such as SPOT, Landsat, IKONOS, QuickBird and OrbView. Moreover, due to the growing number of satellite sensors, the acquisition frequency of the same scene is continuously increasing. Remote sensing images are recorded in digital form and then processed by computers to produce image products useful for a wide range of applications. Satellite imagery provides an effective means of observing and quantifying the complexities of the surface of the earth. The technologies behind the application of this imagery are mature, yet evolving rapidly. They demonstrate excellent scientific tools in support of development and monitoring. Satellite imagery provides

- Information on land cover, land use, habitats, landscape and infrastructure
- A time series by acquiring images on multiple dates
- Capability to map and monitor change
- It gives you quantifiable information that is transparent and auditable
- Provides a good value for money method of mapping a wide range of our built and natural environment.

Digital change detection essentially comprises the quantification of temporal phenomena from multi-date imagery that is most commonly acquired by satellite-based multispectral sensors. The scientific literature reveals, however, that digital change detection is a difficult task to perform. Nevertheless, visual change detection is difficult to replicate because different interpreters produce different results. Furthermore, visual detection incurs substantial data acquisition costs. Apart from offering consistent and repeatable procedures, digital methods can also more efficiently incorporate features from the infrared and microwave parts of the electromagnetic spectrum. Renewable natural resources such as forests are continuously changing, where change is defined as "an alteration in the surface components of the vegetation cover" (Milne, 1988) or as "a spectral/spatial movement of a vegetation entity over time" (Lund, 1983). The rate of change can be dramatic and/or abrupt, as exemplified by large-scale tree logging, or subtle/gradual, such as growth of standing volume. Some forest cover modifications are human-induced, including deforestation for land-use conversion.

1.1. TYPES OF IMAGES

A. PANCHROMATIC IMAGE

A panchromatic image consists of only one band. It is usually displayed as a grey scale image, i.e. the displayed brightness of a particular pixel is proportional to the pixel digital number which is related to the intensity of solar radiation reflected by the targets in the pixel and detected by the detector. Thus, a panchromatic image may be similarly interpreted as a black-and-white aerial photograph of the area. The Radiometric Information is the main information type utilized in the interpretation. Panchromatic images are created when the imaging sensor is sensitive to a wide range of wavelengths of light, typically spanning a large part of the visible part of the spectrum. Here is the thing; all imaging sensors need a certain minimum amount of light energy before they can detect a difference in brightness. If the sensor is only sensitive (or is only directed) to light from a very specific part of the spectrum, say for example the blue wavelengths, then there is a limited amount of energy available to the sensor compared to a sensor that samples across a wider range of wavelengths. To compensate for this limited energy availability, multi-spectral sensors (the kind that create red, green, and blue near infrared images) will typically sample over a larger spatial extent to get the necessary amount of energy needed to 'fill' the imaging detector.

Fig1.1 Panchromatic Image

A panchromatic image extracted from Orbview3 satellite panchromatic scene at a ground resolution of 1 m. The ground coverage is about 6.5 km (width) by 5.5 km (height). The urban area at the bottom left and a clearing near the top of the image have high reflected intensity, while the vegetated areas on the right part of the image are generally dark. Roads and blocks of buildings in the urban area are visible. A river flowing through the vegetated area, cutting across the top right corner of the image can be seen. The river appears bright due to sediments while the sea at the bottom edge of the image appears dark.

Thus, multispectral band images will typically be of a coarser spatial resolution than a panchromatic image. There is a trade-off that is made between the spectral resolution (i.e. the range of wavelengths that are sampled by an imaging detector) and the spatial resolution. This is why commercial satellites like Ikonos and Geoeye will commonly provide three or more relatively coarse resolution multispectral bands along with a finer spatial resolution panchromatic band. Importantly, there exists a kind of compromise here in which you can combine the fine spatial resolution of a pan image with the high spectral resolution of multi-spectral bands. This is what is known as panchromatic sharpening and it is commonly used to compensate for the spectral/spatial compromise in satellite imaging.

B. MULTISPECTRAL IMAGE

A multispectral image is one that captures image data at specific frequencies across the electromagnetic spectrum. The wavelengths may be separated by filters or by the use of instruments that are sensitive to particular wavelengths, including light from frequencies beyond the visible light range, such as infrared. Spectral imaging can allow extraction of additional information the human eye fails to capture with its receptors for red, green and blue. It was originally developed for space-based imaging.

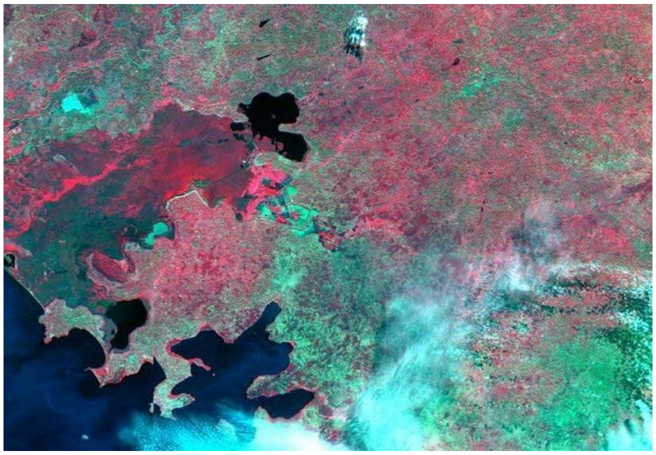


Fig 1.2 Multispectral image

Multispectral images are the main type of images acquired by remote sensing (RS) radiometers. Dividing the spectrum into many bands, multispectral is the opposite of panchromatic, which records only the total intensity of radiation falling on each pixel. Usually, satellites have three or more radiometers (Landsat has seven). Each one acquires one digital image (in remote sensing, called a 'scene') in a small band of visible spectra, ranging from 0.7 µm to 0.4 µm, called red-green-blue (RGB) region, and going to infrared wavelengths of 0.7 µm to 10 or more µm, classified as near infrared (NIR), middle infrared (MIR) and far infrared (FIR or thermal).

C. HYPERSPECTRAL IMAGE

Hyperspectral images collect and processes information from across the electromagnetic spectrum. The goal of hyperspectral imaging is to obtain the spectrum for each pixel in the image of a scene, with the purpose of finding objects, identifying materials, or detecting processes. Much as the human eye sees visible light in three bands (red, green, and blue), spectral imaging divides the spectrum into many more bands. This technique of dividing images into bands can be extended beyond the visible. In hyperspectral imaging, the recorded spectra have fine wavelength resolution and cover a wide range of wavelengths.

Fig 1.3 Hyperspectral image

Engineers build hyperspectral sensors and processing systems for applications in astronomy, agriculture, biomedical imaging, mineralogy, physics, and surveillance. Hyperspectral sensors look at objects using a vast portion of the electromagnetic spectrum. Hyperspectral cubes are generated from airborne sensors like the NASA's Airborne Visible/Infrared imaging Spectrometer (AVIRIS),or from satellites like NASA's EO-1 with its hyperspectral instrument Hyperion. However, for many development and validation studies, handheld sensors are used.

1.2 SATELLITE SENSORS

CARTOSAT-1 or IRS-P5 is a stereoscopic Earth observation satellite in a sun-synchronous orbit, and the first one of the Cartosat series of satellites. The satellite was built, launched and maintained by the Indian Space Research Organisation. Weighing around 1560 kg at launch, its applications will mainly be towards cartography in India. It was launched by Polar Satellite Launch Vehicle, serial number C6, on 5 May 2005 from the newly built Second Launch Pad at Sriharikota. Images from the satellite will be available from GeoEye for worldwide distribution. The satellite covers the entire globe in 1867 orbits on a 126 day cycle. Adjacent paths are covered with a separation of eleven days.

Cartosat-1 carries two state-of-the-art panchromatic (PAN) and Multispectral (MSS) cameras that take black and white stereoscopic pan image and coloured Multispectral pictures of the earth in the visible region of the electromagnetic spectrum. The swath covered by these high resolution PAN cameras is 30 km and their spatial resolution is 2.5 metres.

GEOEYE

GeoEye-1 satellite was launched September 6, 2008. The GeoEye-1 satellite has the highest resolution of any commercial imaging system and is able to collect images with a ground resolution of 0.41 meters (16 inches) in the panchromatic or black and white mode. It collects multispectral or colour imagery at 1.65-meter resolution or about 64 inches

DIGITAL GLOBE

Digital Globe's WorldView-2 satellite provides high resolution commercial satellite imagery with 0.46 m spatial resolution (panchromatic only). The 0.46 meters resolution of WorldView-2's panchromatic images allows the satellite to distinguish between objects on the ground that are at least 46 cm apart. Similarly Digital Globe's Quick Bird satellite provides 0.6 meter resolution (at NADIR) panchromatic images.

SPOT IMAGE

The 3 SPOT satellites in orbit (Spot 2, 4 and 5) provide images with a large choice of resolutions – from 2.5 m to 1 km. Spot Image also distributes multi resolution data from other optical satellites, in particular from Formosat-2 (Taiwan) and Kompsat-2 and from radar satellites (TerraSar-X, ERS, Envisat, Radarsat). Spot Image will also be the exclusive distributor of data from the forthcoming very-high resolution Pleiades satellites with a resolution of 0.50 meter or about 20 inches

RAPIDEYE

Rapid Eye's constellation of five satellites, launched in August 2008, contain identical multispectral sensors which are equally calibrated. Therefore, an image from one satellite will be equivalent to an image from any of the other four, allowing for a large amount of imagery to be collected (4 million km² per day), and daily revisit to an area. For Each travel on the same orbital plane at 630 km, and deliver images in 5 meter pixel size. Rapid Eye satellite imagery is especially suited for agricultural, environmental, cartographic and disaster management applications. The company not only offers their imagery, but consults with their customers to create services and solutions based on analysis of this imagery.

IKONOS

IKONOS is a commercial earth observation satellite, and was the first to collect publicly available high-resolution imagery at 1- and 4-meter resolution. It offers multispectral (MS) and panchromatic (PAN) imagery. The IKONOS launch was called “one of the most significant developments in the history of the space age”. IKONOS imagery began being sold on January 1, 2000.

LANDSAT

The first three satellites were identical and their payloads consisted of two optical instruments, a multispectral sensor (Multispectral Scanner or MSS) and a series of video cameras (Return Beam Vidicons or RBVs). The next two satellites (LANDSAT 4 and 5) were equipped with two multispectral sensors, i.e., a multispectral scanner (MSS) and a Thematic Mapper (TM). These mechanical sensors collected information in four spectral bands and over a 185 x 185km area. Since this instrument was developed after the three RBV cameras, these bands were numbered from 4 to 7. Landsat 3’s multispectral scanner included an additional spectral band in the thermal infrared band.

Among the different types of satellite images and the respective sensors are discussed in the introduction. Sensors used to capture panchromatic images and multispectral images are considered in this paper. As the panchromatic image is a gray scale iamge it has a difficulty in identifying forest changes and how it is used for the change detection process is discussed in the following chapters.

CHAPTER 2

LITERATURE SURVEY

The literature survey involves a study regarding various change detection techniques applied to the satellite images of forest areas. The images are observed at different time periods were examined using PCA, CVA and Multivariate alteration detection (MAD) in earlier times are discussed briefly. With refernce to the earlier methods of change detection techniques, the proposed method has an efficient result. And the earlier methods are discussed below.

2.1. CHANGE DETECTION TECHNIQUES USING REMOTELY-SENSED DATA

Change detection is the process of identifying differences in the state of an object or by observing it at different times. One of the major applications of remotely sensed data obtained from Earth-orbiting satellites is change detection because of repetitive coverage at short intervals and consistent image quality. There is a definite need for a change detector which will automatically correlate and compare two sets of imagery taken of the same area at different band display the changes and their locations to the interpreter. It has been suggested that a significant increase in speed can be achieved for image processing by representing only the changes rather than expose the human viewer to all of the information in both images. Comparative analysis of independently produced classifications for different dates and analysis of multi-temporal data. If an image I(x, y) contains light objects (change) on a dark background (no change), then these objects may be extracted by a simple thresholding technique, where T is the threshold value supplied empirically or statistically by the analyst. All the pixels which belong to the object (change) are coded 1, and the background (no change) is coded 0. If one wants to define more than one threshold one may use the technique of density slicing. In this, several objects of different pixel values are grouped into pre-defined slices. Image rationing In rationing two registered images from different dates with one or more bands in an image are rationed, band by band. The data are compared on a pixel by pixel basis this multivariate analysis technique is used to reduce the number of spectral components to fewer principal components accounting for the most variance in the original multispectral images. Principal component analysis of this data set should result in the gross differences associated with overall radiation and atmospheric changes appearing in the major component images and statistically minor changes associated with local changes in land cover appearing in the minor component images. When a forest stand undergoes a change its spectral appearance changes accordingly. The vector describing the direction and magnitude of change from the first to the second date is a spectral change vector. The decision that a change has occurred is made if the magnitude of the computed spectral change vector exceeds a specified threshold criterion. The direction of the vector contains information about the type of change, i.e. clear cut or re growth (Malila 1980). This method was applied to forest change detection in northern Idaho (Malila 1980) and in South Carolina (Colwell and Weber 1981). In this method, a multi-temporal Landsat data set is transformed into greenness and brightness data sets (Kauth and

Thomas 1976). The transformed data set is clustered using a spectral/spatial clustering algorithm called BLOB (Kauth **et al.** 1977).

The regression method using Landsat MSS band 2 produced the highest change detection accuracy followed by image rationing and image differencing. The various local pre processing techniques such as image smoothing, edge enhancement and standard deviation texture, when combined with the raw image, did not improve the change detection accuracy.The multispectral classification approach produced the lowest change classification accuracy.

2.2 KERNEL MAXIMUM AUTOCORRELATION FACTOR AND MINIMUM NOISE FRACTION TRANSFORMATIONS

Kernel versions of Maximum Autocorrelation Factor (MAF) and minimum noise fraction (MNF) analysis are discussed. The kernel versions are based upon a dual formulation also termed Q mode analysis in which the data enter into the analysis via inner products in the Gram matrix only. In the kernel version, the inner products of the original data are replaced by inner products between nonlinear mappings into higher dimensional feature space. Via kernel substitution also known as the kernel trick these inner products between the mappings are in turn replaced by a kernel function and all quantities needed in the analysis are expressed in terms of this kernel function.

In the dual formulation of PCA and MAF/MNF analyses the data enter into the problem as inner products between the observations. These inner products may be replaced by inner products between mappings of the measured variables into higher order feature space.The idea in kernel Orthogonalization is to express the inner products between the mappings in terms of a kernel function to avoid the explicit specification of the mappings. Both the Eigen value problem, the centring to zero means and the projections onto eigenvectors to find kernel scores may be expressed by means of the kernel function.

2.3 KERNEL METHODS FOR PATTERN ANALYSIS

Pattern analysis algorithms Identifying patterns in a finite set of data presents very different and distinctive challenges. We will identify three key features that a pattern analysis algorithm will be required to exhibit before we will consider it to be effective. Pattern analysis algorithms must be able to handle very large datasets. Hence, it is not sufficient for an algorithm to work well on small toy examples; we require that its performance should scale to large datasets. The study of the computational complexity or scalability of algorithms identifies efficient algorithms as those whose resource requirements scale polynomial with the size of the input. Any kernel methods solution comprises two parts: a module that performs the mapping into the embedding or feature space and a learning algorithm designed to discover linear patterns in that space. There are two main reasons why this approach should work. First of all, detecting linear relations has been the focus of much research in statistics and machine learning for decades, and the resulting algorithms are both well understood and efficient

Algorithms will be able to handle noisy data and identify approximate patterns. They should therefore tolerate a small amount of noise in the sense that it will not affect their output too much. We describe an algorithm with this property as robust.

2.4 LINEAR AND KERNEL METHODS FOR MULTIVARIATE CHANGE DETECTION

The iteratively reweighted multivariate alteration detection (IR-MAD) algorithm may be used both for unsupervised change detection in multi- and hyperspectral remote sensing imagery and for automatic radiometric normalization of multitemporal image sequences. Principal components analysis (PCA), as well as maximum autocorrelation factor (MAF) and minimum noise fraction (MNF) analyses of IR-MAD images, both linear and kernel-based (nonlinear), may further enhance change signals relative to no-change background. IDL (Interactive Data Language) implementations of IR-MAD, automatic radiometric normalization, and kernel PCA/MAF/MNF transformations are presented that function as transparent and fully integrated extensions of the ENVI remote sensing image analysis environment. The train/test approach to kernel PCA is evaluated against a Hebbian learning procedure. Matlab code is also available that allows fast data exploration and experimentation with smaller datasets. New, multi-resolution versions of IR-MAD that accelerate convergence and that further reduce no-change background noise are introduced. Computationally expensive matrix diagonalization and kernel image projections are programmed to run on massively parallel CUDA-enabled graphics processors, when available, giving an order of magnitude enhancement in computational speed.

Normalization as well as for kernelized versions of principal components, maximum autocorrelation factors, and maximum noise fraction transformations. Comparison with the kernel Hebbian algorithm indicates that the use of 1% sub-sampling for kernel methods will give satisfactorily reproducible results for the first five or six eigenvectors. We have also introduced new, multi-resolution variants of the IR-MAD algorithm, together with IDL and Matlab code.

2.5 MONITORING LAND-COVER CHANGES: A COMPARISON OF CHANGE DETECTION TECHNIQUES

Six change detection procedures were tested using Landsat Multi-Spectral Scanner (MSS) images for detecting areas of changes in the region of the Terminus Lagoon, a coastal zone of the State of Campeche, Mexico. The change detection techniques considered were image differencing, vegetative index differencing, selective principal components analysis (SPCA), direct multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison. The accuracy of the results obtained by each technique was evaluated by comparison with aerial photographs through Kappa coefficient calculation. Post-classification comparison was found to be the most accurate procedure and presented the advantage of indicating the nature of the changes. Poor performances obtained by image enhancement procedures were attributed to the spectral variation due to differences in soil moisture and in vegetation coverage between both scenes. Methods based on classification were found to be less sensitive at these spectral variations and more robust when dealing with data captured at different times of the year.

In single band analysis band 2 data proved to be superior to band 4 for detecting changes in land cover. The reason for the poor performance using band 4 data is to be found in the high infrared return from the herbaceous under storey in cleared areas which produces classifications errors

2.6. UNSUPERVISED CHANGE DETECTION IN SATELLITE IMAGES USING PRINCIPAL COMPONENT ANALYSIS AND *K*-MEANS CLUSTERING

In this letter, we propose a novel technique for unsupervised change detection in multi-temporal satellite images using principal component analysis (PCA) and k-means clustering. The difference image is partitioned into $h \times h$ non-overlapping blocks. S, $S \leq h2$, Ortho-normal eigenvectors are extracted through PCA of $h \times h$ non-overlapping block set to create an eigenvector space. Each pixel in the difference image is represented with an S-dimensional feature vector which is the projection of $h \times h$ difference image data onto the generated eigenvector space. The change detection is achieved by partitioning the feature vector space into two clusters using k-means clustering with $k = 2$ and then assigning each pixel to the one of the two clusters by using the minimum Euclidean distance between the pixel's feature vector and mean feature vector of clusters. Experimental results confirm the effectiveness of the proposed approach.

The proposed method uses $h \times h$ neighbourhood to extract feature vector for each pixel so that it automatically considers the contextual information. The proposed algorithm is simple in computation yet effective in identifying meaningful changes which makes it suitable for real-time applications.

2.7. REGION BASED FOREST CHANGE DETECTION FROM CARTOSAT-1 STEREO IMAGERY

This paper is aiming to improve the performance of DSM based change detection result by combining it with features from original Cartosat-1 imagery. In the first step, the initial regions are generated using mean shift segmentation of gray values from the co-registered CARTOSAT-1 imagery of 2008 and 2009. In the second step, the forest areas are extracted by analysing the forest cover rate and the mean height value of each region. The initial difference map is generated based on these results. The deforestation areas can be extracted by analysing the texture features and height differences in the difference map. The height variations are extracted using DSM (Digital surface model). To get more information about of the DSM quality, DSM accuracy analysis is done by comparing them with LiDAR data. The performance is evaluated by comparing the results with manual/visual inspection. Four groups of pixels are chose and compared in this test. The region based forest change detection method is relied on the following assumptions.

i). Unchanged objects have similar texture features;

ii). Unchanged objects have relatively low height changes.

iii). Changes will influence the texture features and height.

iv). Changed regions have lower similarity.

Based on these assumptions, this paper, two first order texture features and six Grey Level Co - occurrence Matrix (GLCM) based second order texture features are calculated based on both panchromatic data as well as n-DSM. These features will be used in the SVM classification. In order to get the initial difference map, we calculate the vegetation cover rate and mean height of each region. Because of the lack of multispectral information of Cartosat-1 imagery, the vegetation cover map cannot be generated with the common use of the multispectral based vegetation extraction method. By analysing the land cover characters around forest area, it can be seen that forest areas have relatively darker gray value than the grass areas. . The non-linear 3D co-registration is supposed to perform better than the linear shift, but need more time in calculation. In this paper, only one direction with shift window sizes are tested, more directions GLCM will be used to improve the texture feature based change extraction in further investigations.

Therefore the approach is aiming to combine the information from n-DSM to improve the detection efficiency and accuracy. it is worth noting that the co-registration is a necessary prerequisite for this evaluation and an essential task for this kind of change detection. The results achieved are quite promising, although some parts of the DSMs generated by stereo matching exhibit low quality height values. However by a combination with the original images efficient forest change detection can be performed, even to detect small changes at forest borders.

2.8 LINEAR AND KERNEL METHODS FOR MULTIVARIATE CHANGE DETECTION

The iteratively reweighted multivariate alteration detection (IR-MAD) algorithm may be used both for unsupervised change detection in multi- and hyperspectral remote sensing imagery and for automatic radiometric normalization of multitemporal image sequences. Principal components analysis (PCA), as well as maximum autocorrelation factor (MAF) and minimum noise fraction (MNF) analyses of IR-MAD images, both linear and kernel-based (nonlinear), may further enhance change signals relative to no-change background. IDL (Interactive Data Language) implementations of IR-MAD, automatic radiometric normalization, and kernel PCA/MAF/MNF transformations are presented that function as transparent and fully integrated extensions of the ENVI remote sensing image analysis environment. The train/test approach to kernel PCA is evaluated against a Hebbian learning procedure. Matlab code is also available that allows fast data exploration and experimentation with smaller datasets. New, multiresolution versions of IR-MAD that accelerate convergence and that further reduce no-change background noise are introduced. If the scenes were acquired under similar illumination conditions and if no ground reflectance changes whatsoever occurred between the two acquisitions, then the only differences between them would be due to random effects such as instrument noise and atmospheric fluctuation. From the central limit theorem, we would expect that the histogram of any linear combination of spectral bands would be very nearly Gaussian. In particular, the MAD variates, being uncorrelated, should follow a multivariate normal distribution with diagonal variance–covariance matrix. Since MAD variates associated with genuine changes will deviate more or less strongly from such a distribution, we expect an improvement of the sensitivity of the MAD transformation if emphasis is placed on establishing an increasingly better back- ground of no change against which to detect change. This can be done in an iteration scheme in which observations are weighted by the probability of no change, as determined in the preceding iteration, when the sample means and variance–covariance matrices for the next iteration are estimated, thus leading to the iteratively re-weighted MAD (IR-MAD) algorithm.

The effect of sub-sampling for kernel spectral transformations can be examined, in the case of kernel PCA, by comparison with the KHA method (Section3.1), which generates transformations on the basis of all of the pixel data. Fig. 4 compares the largest Eigen values for kernel PCA applied to a small Landsat7ETM+ image using a 1% subsample followed by diagonalization of the kernel matrix with those obtained from KHA. Fig. 5 compares the Eigen vectors (projection directions in nonlinear feature space) on the basis of scatter plots of principal component projections for sub sampling and KHA. Correlations begin to deteriorate at the fifth or sixth Eigen vector.

Comparison with the kernel Hebbian algorithm indicates that the use of 1% subsam- pling for kernel methods will give satisfactorily reproducible results for the first five or six eigenvectors. We have also introduced new, multi-resolution variants of the IR-MAD algorithm, together with IDL and Matlab code. This chapter briefly explains the earlier methods used for change detection analysis and with reference to the existing algorithm the proposed methodology explains the change detection using kernel minimum noise fraction analysis.

CHAPTER 3

CHANGE DETECTION

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times. Essentially, it involves the ability to quantify temporal effects using multi-temporal data sets. One of the major applications of remote sensed data obtained from Earth orbiting satellites is used for change detection because of repetitive coverage at short intervals and consistent image quality. The basic premise in using remote sensing data for change detection is that changes in land cover must result in changes in radiance values and changes in radiance due to land cover change must be large with respect to radiance changes caused by other factors. These other factors include differences in atmospheric conditions, differences in Sun angle and differences in soil moisture.

Change detection methods could be categorized as either supervised or unsupervised according to the nature of data processing. The former is based on a supervised classification method, which requires the availability of a ground truth in order to derive a suitable training set for the learning process of classifiers. The latter approach, which is adopted in this letter, performs change detection by making a direct comparison of two multitemporal images considered without incorporating any additional information. Forest management and observation are important and time-consuming tasks. Automatic inventory and monitoring of forest changes have drawn the interest of many agencies, particularly after wind breakage. Satellite data are a valuable data source from which change information can be efficiently extracted for large regions. However, automatically extracting changes from satellite images is not easy, particularly when forest changes are mixed with other changes. Forest change detection studies in remote sensing mainly involve the use of multispectral data. In the early stages, vegetation index differencing is one of the most important methods for forest change detection, as the vegetation covers can be well highlighted through band-by-band arithmetic calculation. In order to fully use change features from all channels, change vector analyses (CVAs).

3.1 CHANGE DETECTION TECHNIQUES

There are six different kinds of change detection methods are tested using Multi-Spectral Scanner (MSS) used in earliest systems. The change detection techniques considered were,

- Image differencing
- Vegetative index differencing
- Selective principal components analysis (SPCA)
- Direct multi-date unsupervised classification

- Post-classification change differencing and a combination of image enhancement and post classification comparison

3.1.1 IMAGE DIFFERENCING

In this method, registered images acquired at different times are subtracted to produce a residual image which represents the change between the two dates. Pixels of no radiance change are distributed around the mean, while pixels of radiance change are distributed in the tails of the distribution (Singh 1986). Two subtracted images were created for bands 2 and 4, respectively. Data transformations were concerned to these bands because they are considered to be the most useful for discriminating forest canopy and vegetation alterations. It is a method with the most extensive application that can be applied to a wide variety of types of images and geographical environments. It is generally conducted on the basis of gray values. The changed region and unchanged region is determined by selecting the appropriate threshold values of gray levels in the subtraction image. The gray value of the subtraction image shows the differences of corresponding pixels of two images. Its advantage is that in the subtraction image the threshold selecting operation needs to be applied only once. Choosing a suitable threshold value can best separate the areas of real change and the change areas due to random factors. The gray values of the subtraction image are often approximating a Gaussian distribution, the unchanged pixels are grouped around the average value and the changed pixels are in the two tails of the distribution. It is beneficial for collecting change information at areas such as the beach zones, estuaries and

Water channel ditches. It is widely used in detecting coastal environmental changes, tropical forests changes, temperate forests changes, and desertification and crop analysis.

3.1.2 VEGETATIVE INDEX DIFFERNCING

The NDVI of an area containing a dense vegetation canopy will tend to positive values (say 0.3 to 0.8) while clouds and snow fields will be characterized by negative values of this index. Other targets on Earth visible from space include free standing water (e.g., oceans, seas, lakes and rivers) which have a rather low reflectance in both spectral bands (at least away from shores) and thus result in very low positive or even slightly negative NDVI values, soils which generally exhibit a near-infrared spectral reflectance somewhat larger than the red, and thus tend to also generate rather small positive NDVI values (say 0.1 to 0.2). In addition to the simplicity of the algorithm and its capacity to broadly distinguish vegetated areas from other surface types, the NDVI also has the advantage of compressing the size of the data to be manipulated by a factor 2 (or more), since it replaces the two spectral bands by a single new field (eventually coded on 8 bits instead of the 10 or more bits of the original data). Also, the NDVI has tended to be over-used (if not abused) in applications for which it was never designed. The following subsections review some of these issues. Mathematically, the sum and the difference of the two spectral channels contain the same information as the original data, but the difference alone (or the normalized difference) carries only part of the initial information. Whether the missing information is relevant or valuable is for the user to judge, but it is important to understand that an NDVI product carries only a fraction of the information available in the original spectral reflectance data. Users of NDVI have tended to estimate a large number of vegetation properties from the value of this index. Typical examples include the leaf area index, biomass chlorophyll concentration in leaves, plant productivity, fractional vegetation cover, accumulated rainfall, etc. Such relations are often derived by correlating space-derived NDVI values with ground-measured values of these variables. This approach raises further issues related to the spatial scale associated with the measurements, as satellite sensors always measure radiation quantities for areas substantially larger than those sampled by field instruments. Furthermore, it is of course illogical to claim that all these relations hold at once, because that would imply that all of these environmental properties would be directly and unequivocally related between themselves.

The reflectance measurements should be relative to the same area and be acquired simultaneously. This may not be easy to achieve with instruments that acquire different spectral channels through different cameras or focal planes. Mis-registration of the spectral images may lead to substantial errors and unusable results.

Also, the calculation of the NDVI value turns out to be sensitive to a number of perturbing factors including

- **Atmospheric effects:**

The actual composition of the atmosphere (in particular with respect to water vapor and aerosols) can significantly affect the measurements made in space. Hence, the latter may be misinterpreted if these effects are not properly taken into account (as is the case when the NDVI is calculated directly on the basis of raw measurements).

- **Clouds:**

Deep (optically thick) clouds may be quite noticeable in satellite imagery and yield characteristic NDVI values that ease their screening. However, thin clouds (such as the ubiquitous cirrus), or small clouds with typical linear dimensions smaller than the diameter of the area actually sampled by the sensors, can significantly contaminate the measurements. Similarly, cloud shadows in areas that appear clear can affect NDVI values and lead to misinterpretations. These considerations are minimized by forming composite images from daily or near-daily images. Composite NDVI images have led to a large number of new vegetation applications where the NDVI or photosynthetic capacity varies over time.

- **Soil effects**:

Soils tend to darken when wet, so that their reflectance is a direct function of water content. If the spectral response to moistening is not exactly the same in the two spectral bands, the NDVI of an area can appear to change as a result of soil moisture changes (precipitation or evaporation) and not because of vegetation changes.

- **Anisotropic effects:**

All surfaces (whether natural or man-made) reflect light differently in different directions, and this form of anisotropy is generally spectrally dependent, even if the general tendency may be similar in these two spectral bands. As a result, the value of NDVI may depend on the particular anisotropy of the target and on the angular geometry of illumination and observation at the time of the measurements, and hence on the position of the target of interest within the swath of the instrument or the time of passage of the satellite over the site. This is particularly crucial in analyzing AVHRR data since the orbit of the NOAA platforms tended to drift in time. At the same time, the use of composite NDVI images minimizes these considerations and has led to global time series NDVI data sets spanning more than 25 years.

- **Spectral effects:**

Since each sensor has its own characteristics and performances, In particular with respect to the position, width and shape of the spectral bands, a single formula like NDVI yields different results when applied to the measurements acquired by different instruments. For these reasons, the NDVI should be used with great caution. In any quantitative application that necessitates a given level of accuracy, all the perturbing factors that could result in errors or uncertainties of that order of magnitude should be explicitly taken into account; this may require extensive processing based on ancillary data and other sources of information. More recent versions of NDVI datasets have attempted to account for these complicating factors through processing.

3.1.3 UNSUPERVISED CHANGE DETECTION TECHNIQUES

Unsupervised change detection techniques mainly use the automatic analysis of change data which are constructed using multitemporal images. The change data are generally created using one of the following:

1) Image differencing;

2) Normalized difference vegetation index;

3) Change vector analysis;

4) Principal component analysis (PCA); and

5) Image rationing

Several unsupervised change detection techniques have been proposed in the literature falling in these categories which use complicated data modelling and parameter estimation.

In the proposed work the given two panchromatic images at different times are selected and compared to analyse the change factor using Kernel function, the resultant data points are obtained as 3x3 neighbourhood matrix and the process is known as Kernelization. Feature extraction of two images is done to differentiate changes in few training vectors. The changes present one or more training vectors are grouped in single vector, it is processed recursively to generate the mask. The kernel minimum noise fraction output or region of interest of an input image is given as an input to the ICDA (Iterated Canonical Discriminant Analysis) is used to generate the change detection mask with very few training sets. As the name describes it repeatedly iterates the changes to find the maximum level of changes in the input data sets. And the algorithm used to enhance the dimensional features of the image is KMNF (Kernel Minimum Noise fraction)

3.1.4 SELECTIVE PRINCIPAL COMPONENT ANALYSIS (SPCA)

In the Selective Principal Components Analysis (SPCA), only two bands of the multi-date image are used as input instead of all bands. By using only two bands, the information that is common to both is mapped to the first component and information that is unique to either one of the two bands (the changes) is mapped to the second component (Chavez and Kwarteng 1989). Principal components are usually calculated from a variance± covariance matrix. The standardization of the covariance matrix into a correlation matrix by dividing by the appropriate standard deviation reduces all the variables to equal importance as measured by scale. Singh and Harrison (1985) compared standardized and un standardized PCA and reported substantial improvement of signal to-noise ratio and image enhancement by using standardized variables. Selective standardized principal components analysis was performed using bands 2 and 4.

3.1.5 DIRECT MULTI-DATE UNSUPERVISED CLASSIFCATION

The direct multi-date classification is based on the single analysis of a combined dataset of the two dates in order to identify areas of changes (Singh 1986). Classes where changes are occurring are expected to present statistics significantly different from where change did not take place and so could be identified. Unsupervised classification was carried out using the ISODATA method of the ERDAS software which uses spectral distance and iteratively classifies the pixels, the criteria for each class, classifying again, so that the spectral distance patterns in the data gradually emerge (ERDAS 1991).

3.1.6 POST-CLASSIFICATION ANALYSIS

The most obvious method of change detection is a comparative analysis of spectral classifications for times t1 and t2 produced independently (Singh 1989). In this context it should be noticed that the change map of two images will only be generally as accurate as the product of the accuracies of each individual classification (Stow *et al.* 1980). Accuracy of relevant class changes depends on spectral separability of classes involved. In the present study, Landsat MSS data of both dates were independently classified using the maximum likelihood classifier.

- **Combination image enhancement/post-classification analysis**

In this method, the change image produced through an enhancement procedure is recoded into a binary mask consisting of areas that have changed between the two dates. The change mask is then overlaid onto the date 2 image and only those pixels that were detected as having changed are classified in the date 2 imagery. A traditional post-classification comparison can then be applied to yield from-to change information. This method may reduce change detection errors and provides detailed from-to change information. The digital change detection techniques based on image enhancement, it was necessary to establish a thresholding level in order to define land cover change. All histograms were examined and the mean and standard deviation values for each dataset were calculated. Various standard threshold levels were applied to the lower and higher tail of each distribution in order to find the threshold value that produced the highest change classification accuracy. The relationship between change classification accuracy and threshold for a given transformed band was studied by generating change images for thresholds ranging from 0.25 to 2.00 standard deviations, at 0.25 standard deviation intervals. As a following step, thresholds every 0.1 standard deviation around the initial empirical maximum were tested. If the distributions are non-normal and functions of the standard deviations are used to delimit change from no change, the areas delimited on either side of the mode are not equal. Therefore, the error rates on either side of the mode are not equal. For this reason, an attempt was made to determine the two threshold boundaries using two independent steps. In order to establish the optimal threshold value applied to the lower tail of the distribution, pixels which value was lower than the threshold level L1 were considered as changed, pixels whose value ranged between the threshold level L1 and the mean M were classified in the no-change category and pixels whose value was higher than the mean were classified as no data. Various threshold levels were applied in order the find the threshold value that produced the highest change classification accuracy. A similar procedure was applied to determine the threshold value of the higher tail of the distribution L2. Most accuracy indices are biased and affected by the ratio between the number of reference data points of the change and the no-change category (Nelson 1983). Fung and Ledrew (1988) examined the use of different accuracy indices, including overall, average and combined accuracies and the Kappa coefficient of agreement to determine an optimal threshold level for changes detection images. They recommended the Kappa coefficient because it considers all elements of the confusion matrix.

3.2 PATTERN ANALYSIS ALGORITHM USED FOR CHANGE DETECTION

Pattern analysis deals with the automatic detection of patterns in data, and plays a central role in many modern artificial intelligence and computer science problems. By patterns we understand any relations, regularities or structure inherent in some source of data. By detecting significant patterns in the available data, a system can expect to make predictions about new data coming from the same source. In this sense the system has acquired generalisation power by '*learning'* something about the source generating the data. There are many important problems that can only be solved using this approach, problems ranging from bioinformatics to text categorization, from image analysis to web retrieval. In recent years, pattern analysis has become a standard software engineering approach, and is present in many commercial products. Early approaches were efficient in finding linear relations, while nonlinear patterns were dealt with in a less principled way.

3.2.1 Principal Component Analysis

This method is the nonlinear equivalent of standard PCA, and reduces the observed variables to a number of uncorrelated principal components. The most important advantages of nonlinear over linear PCA are that it incorporates nominal and ordinal variables, and that it can handle and discover nonlinear relationships between variables. Also, nonlinear PCA can deal with variables at their appropriate measurement level, for example, it can treat Likert-type scales Ordinals instead of numerical. Every observed value of a variable can be referred to as a category. While performing PCA, nonlinear PCA converts every category to a numeric value, in accordance with the variable's analysis level, using optimal quantification. In the social and behavioural sciences, researchers are often confronted with a large number of variables, which they wish to reduce to a small number of composites with as little loss of information as possible. This widely-used method reduces a large number of variables to a much smaller number of uncorrelated linear combinations of these variables, called principal components that represent the observed data as closely as possible. However, PCA suffers from two important limitations. First, it assumes that the relationships between variables are linear, and second, its interpretation is only sensible if all of the variables are assumed to be scaled at the numeric level (interval or ratio level of measurement). In the social and behavioural sciences, these assumptions are frequently not justified, and therefore, PCA may not always be the most appropriate method of analysis. To circumvent these limitations, an alternative, referred to as nonlinear principal components analysis, has been developed. PCA is classified into linear PCA and Non-linear PCA. The objective of linear PCA is to reduce a number of m continuous numeric variables to a smaller number of p uncorrelated underlying variables, called principal components that reproduce as much variance from the variables as possible. Since variance is a concept that applies only to continuous numeric variables, linear PCA is not suitable for the analysis of variables with ordered or unordered (discrete) categories. In nonlinear PCA, categories of such variables are assigned numeric values through a process called optimal quantification (also referred to as optimal scaling, or optimal scoring). Such numeric

Values are referred to as category quantifications; the category quantifications for one variable together form that variable’s transformation. Optimal quantification replaces the category labels with category quantifications in such a way that as much as possible of the variance in the quantified variables is accounted for. Just as continuous numeric variables, such quantified variables possess variance in the traditional sense. Then, nonlinear PCA achieves the very same objective as linear PCA for quantified categorical variables. In nonlinear PCA the optimal quantification task and the linear PCA model estimation are performed simultaneously, which is achieved by the minimization of a least-squares loss function. In the actual nonlinear PCA analysis, model estimation and optimal quantification are alternated through use of an iterative algorithm that converges to a stationary point where the optimal quantifications of the categories do not change anymore. If all variables are treated numerically, this iterative process leads to the same solution as linear PCA.

Nonlinear PCA has been developed as an alternative to linear PCA for handling categorical variables and nonlinear relationships. Comparing the two methods reveals both similarities and differences. To begin with the former, it can be seen that both methods provide Eigen values, component loadings, and component scores. In both, the Eigen values are overall summary measures that indicate the VAF by each component; that is, each principal component can be viewed as a composite variable summarizing the original variables, and the Eigen value indicates how successful this summary is. The sum of the Eigen values over all possible components equals the number of variables m. If all variables are highly correlated, one single principal component is sufficient to describe the data.

3.2.2 Change Vector Analysis

Change vector analysis (CVA) is a change detection tool that characterizes dynamic changes in multi-spectral space by a change vector over multi-temporal imageries. The basic concept of CVA is derived from image differencing technique. The CVA can overcome the disadvantages of 'type-one' approaches e.g., cumulative errors in image classification of an individual date and processing any number of spectral bands simultaneously to retrieve maximum change-type information. A number of CVA based change detection techniques have been developed to make change detection more accurate for identifying changed area. In this paper, we have implemented all major CVA based change detection techniques on three different data sets to investigate the accuracy of each technique on global basis. The concept of the traditional change vector analysis (CVA) involves the calculation of spectral change based on multi-temporal pairs of spectral measurements and relates their magnitudes to a stated threshold criterion. The computed change vectors comprise essential information in magnitude and direction. The two important reasons that make CVA a more level headed change detection technique than other techniques are: (a) it relies on entirely contiguous pixels; (b) it relaxes the requirement of training and ground truth data.

3.2.3 Improved change vector analysis (ICVA)

A semiautomatic threshold determination technique, called double-window flexible pace search

(DFPS) has been proposed in improved change vector analysis (ICVA). The

DFPS technique effectively determines the threshold value from change magnitude imagery. The succession rate criteria of DFPS has been used to evaluate the performance of each potential threshold value during one search process for identifying 'change' and 'no-change' pixels. In semi-automatic DFPS process, success rate (S_r) criteria is calculated from training sample of three different respective satellite data sets, according to the following equation to select the most optimal threshold value for change magnitude imagery.

$$S_r = \frac{I_c - O_C}{I_t} \qquad (1)$$

'I_c' represents number of transformed pixels inside an inner window sample, O_C represents number of transformed pixels in an outer window sample and I_t is the total number of pixels in inner training window sample.

3.2.4 Modified change vector analysis (MCVA)

Additional development in change vector analysis, has been made by modified change vector

Analysis (MCVA) technique which preserves the change information in the magnitude and direction of change vector as continuous data and provided the capability to execute '*n*' change indicator input bands, simultaneously. The overall result of MCVA is a feature space where Cartesian coordinates in a continuous domain are used to describe each change vector. A significant advantage of this technique is that change classification is now entirely on the continuous data domain which permits change descriptors to be used in common change categorization methods. The MCVA technique is simple to execute as compared to ICVA, because empirical technique has been used for the determination of threshold value instead of any semi/automatic procedure. The manual threshold determination technique depends on analyst's skill and effects the accuracy assessment.

3.2.5 Change vector analysis in posterior probability space (CVAPS)

All CVA based change detection techniques necessitate a consistent radiometric imagery because CVA is based on pixel-wise radiometric resolution. The requirement of reliable radiometric for image processing limits the application of CVA. Change vector analysis in posterior-probability space (CVAPS) relaxes the strict requirement of radiometric consistency in remotely sensed data while this requirement is a bottleneck of CVA. In CVAPS approach, the posterior probability is implemented by maximum likelihood classifier (MLC). Assuming that the posterior probability vectors of one pixel in time 1 and time 2 are ' P_a ' and ' P_b ', respectively. The change vector in a posterior probability space, ΔP_{ab}.

$$\Delta P_{ab} = P_b - P_a \tag{2}$$

CVAPS technique follows the semiautomatic DFPS approach for the selection of threshold value. In CVAPS algorithm direction of the change vector in a posterior probability space is determined by applying supervised classification. In CVAPS algorithm direction of the change vector in a posterior Probability space is determined by applying supervised classification. The binary image generated through CVAPS for three different data sets represented the 'change' pixels in white colour and 'no-change' pixels in black colour. The Accuracy is measured using kappa co efficient accuracy. The kappa accuracy for CVA is 0.40.

CHAPTER 4

PROPOSED METHODOLOGY

The existing project deals with the generation of change detection mask using some change detection methods. There are many types of change detection methods of multi-spectral image data. They can be classified as three categories: characteristic analysis of spectral type, vector analysis of spectral changes and time series analysis. In this chapter we will mainly talk about the method of time series analysis, whose aim is to analyze the process and trend of changes by monitoring ground objects based on remote sensing continuous observation data. We will follow up with three methods.

4.1 IMAGE SUBTRACTION

It is a method with the most extensive application that can be applied to a wide variety of types of images and geographical environments. It is generally conducted on the basis of gray values. The changed region and unchanged region is determined by selecting the appropriate threshold values of gray levels in the subtraction image. The gray value of the subtraction image shows the differences of corresponding pixels of two images. Its advantage is that in the subtraction image the threshold selecting operation needs to be applied only once. Choosing a suitable threshold value can separate the areas of real change and the change areas due to random factors. The gray values of the subtraction image are often approximating a Gaussian distribution, the unchanged pixels are grouped around the average value and the changed pixels are in the two tails of the distribution. The main disadvantage of this method is that it does not reflect changes in some categories. The value of subtraction image does not always show the change of the objects because of a variety of factors such as atmospheric conditions, the sun illumination, sensor calibration, and ground water conditions, and so on.

4.2 THE METHOD OF CHANGE DETECTION AFTER CLASSIFICATION

This method is the most simple change detection analysis technique based on the classification. Each image of multitemporal images is classified separately and after that we compare the classification result images. If the corresponding pixels have the same category label, the pixel has not changed, or else the pixel has changed. There are supervised classification methods and non-supervised classification methods. Non-supervised classification is also known as cluster analysis or point cluster analysis. The advantage of this method is that it does not only ascertain the spatial distribution of changes but also gives the nature of changes, in other words the information on the transition from one class to another. One shortcoming of this method is the high requirements for a reasonable classification of categories. Secondly, when the classification and change detection become two relatively independent processes, the amount of information may be reduced and the accuracy also. Finally, this method is sensitive to classification errors. Therefore, the accuracy of this method depends on the accuracy of the classification results. This method is not suitable for change detection of details of urban areas because of the generally low-resolution of multispectral images and the complex spectral characteristics of cities.

Surface model is to identify the height variation to detect the change variation in surface area. The image is decomposed into several parts feature extraction is done to identify changes in each and every neighbouring parts of the image. Each pixel is examined for changes with the other input image. Pixel contains variation is used to generate the change detection mask using ICDA. As from the above discussion it is clear that ICDA has better performance than the above mentioned classifiers.

4.3 DATA SETS DESCRIPTION AND EXPERIMENT DESIGN

In this paper, Change detection is analyzed with two different types of Data sets, the panchromatic images are obtained from satellite Orbview3, launched on an OSC launch vehicle from (Pegasus-XL) from VAFB, CA, USA. It can only acquire the panchromatic stereo images of 2.5m. If only panchromatic images are available, the Principal component analysis, Multivariate alteration Detection and IR-MAD which makes the change detection is a challenging hypothesis. The images are taken from van vihar, Bhopal, Madhya Pradesh. The latitude and longitude information is given as 23.2414N; 77.3741E. Karawai, East Aru Tengah, Kepulauan Aru Regency, Maluku, Indonesia the latitude and longitude is -5.503255N; 134.721933E.

Fig 4.1 Pan Image (2004)

Fig 4.2 Pan Image (2008)

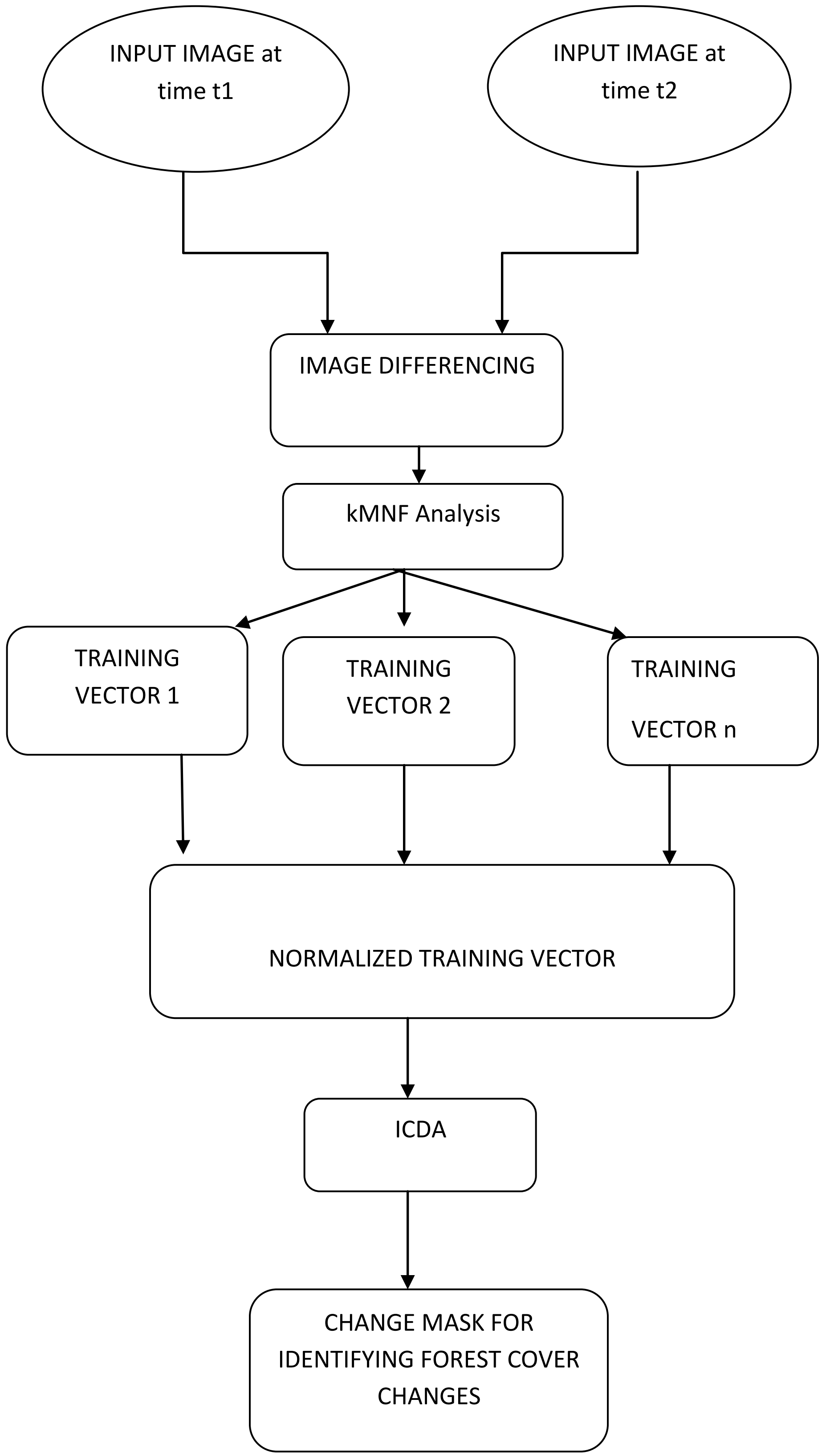


Fig 4.3 Flowchart for change detection analysis

As can be seen in the panchromatic images, this region is characterized by a typical mountainous forest area, with many shadow areas caused by steep terrain. The forest changes in this test area were caused by storms; thus, within only a one-year interval, many relatively large changes. The images are re-sampled to a GSD of 5m, which leads to an image size of 900 × 900 pixel. Change detection using Multispectral imagery is also discussed. Images are taken from OrbView space imaging satellite from Indian Space Research Organization. The Panchromatic and Multispectral images are analyzed using kernel minimum noise fraction. And the change detection map is generated using ICDA.

(A) CLUSTER ANALYSIS

Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar to each other than to those in other groups (clusters). It is a main task of exploratory data mining, and a common technique for statistical data analysis, used in many fields, including machine learning, pattern recognition, image analysis. Cluster analysis itself is not one specific algorithm, but the general task to be solved. It can be achieved by various algorithms that differ significantly in their notion of what constitutes a cluster and how to efficiently find them. Popular notions of clusters include groups with small distances among the cluster members, dense areas of the data space, intervals or particular statistical distributions.

(B) FEATURE EXTRACTION

Feature extraction a type of dimensionality reduction that efficiently represents interesting parts of an image as a compact feature vector. This approach is useful when image sizes are large and a reduced feature representation is required to quickly complete tasks such as image matching and retrieval. Feature detection, feature extraction, and matching are often combined to solve common computer vision problems such as object detection and recognition, content-based image retrieval, face detection and recognition, and texture classification. These above methods used to develop the training data sets for the change variations present in the second image. Thus by using ICDA it has various advantages such as

It requires very few training samples to generate the change detection map.

Due to transforming simple features into high dimensional features using KMNF it is possible to generate the mask even with one pixel.

When compared to the existing method, the proposed method has less false alarming. kMNF converts the simple change features into high dimensional features with use of digital

(C) KERNEL MINIMUM NOISE FRACTION (kMNF)

This paper introduces kernel versions of minimum noise fraction (MNF) analysis. The kernel versions are based upon a dual formulation also termed Q-mode analysis in which the data enter into the analysis via inner products in the Gram matrix only. In the kernel version, the inner products of the original data are replaced by inner products between nonlinear mappings into higher dimensional feature space. Via kernel substitution also known as the kernel trick these inner products between the mappings are in turn replaced by a kernel function and all quantities needed in the analysis are expressed in terms of this kernel function. This means that we need not know the nonlinear mappings explicitly. kernel MNF analyses handle nonlinearities by implicitly transforming data into high (even infinite) dimensional feature space via the kernel function and then performing a linear analysis in that space.

In linear minimum noise fraction (MNF) analysis, we consider multivariate measurements represented by the *n* by *p* data matrix ***X*** (one row per observation or pixel, one column per variable or spectral band) as being the sum of an uncorrelated signal X_S and noise X_N,

$$X = X_S + X_N \tag{3}$$

With uncorrelated signal and noise, the variance–covariance matrix of ***X***, Sx is equal to the sum of the variance–covariance matrices of the signal ***X***s and the noise ***X****N*,

$$S_X = S_S + S_N \tag{4}$$

- *NF* is defined as the ratio between the variance of the projected noise and the variance of the projected total

$$NF = \frac{a' S_N a}{a' S_S a} = \frac{aX_N X_N ' a}{a' \mathrm{X}' \mathrm{X} a} \tag{5}$$

Where X and X_N are column cantered. A regularised version of $1/NF$ is

$$\frac{1}{NF} = \frac{a' X' Xa}{a'[(1-\lambda) X'_N X_N + \lambda I]a} \tag{6}$$

Where **I** is the unit matrix.

The matrices **XX’** (the Gram matrix) and **XX$_N$** contain combinations of inner products of the rows of **X** only. Now, replace these inner products by inner products of nonlinear mappings of the originally measured variables into higher dimensional feature space and perform kernel substitution (the so-called kernel trick): replace the inner products by a kernel function to obtain

$$\frac{1}{NF} = \frac{b' K^2 b}{b'[(1-\lambda)K_N K'_N + \lambda K]b} \tag{7}$$

K_N is a kernelized version of the residual from a quadratic surface by 3x3 window.

We find the directions ***b*** by maximizing this Rayleigh quotient. kMNF variables can thus be calculated by multiplying the kernel matrix ***κ*** with each eigenvector from the Eigen value problem ink’***s*** represents a Kernelization of the entire image with the training data. In the change detection procedure, each observation with the training data is kernelized respectively before the multiplication

$$\text{KMNFi}=\kappa \text{bi} \tag{8}$$

To calculate one change image based on several kMNF variates, we norm these variates to unit variance, square them, and add them up.

$$\chi^2 = \sum_{i=1}^{m} \left(\frac{kMNf_i}{\sigma_i} \right)^2 \tag{9}$$

Pixels are characterised by high values are change pixels, whereas pixels with close to zero are no-change pixels.

4.4 PERFORMANCE OF CLASSIFIERS

There are three methods of classifier used in the existing methods they are

(i) Random forest

(ii) OSVM

(iii) K-means

RANDOM FOREST:

Random forests are a robust and powerful machine learning classifier, which is capable of processing large data sets. ICDA and OSVM require only sufficient number of training samples for change regions, whereas random forests needs samples for both change and no-change areas.

Accuracy of the random forest is close to ICDA but it requires large training set to evaluate the changes. It has to be mentioned that the random forests classifier builds decision trees randomly. Resultant output of the random forest classifier contains more false alarms compare to OSVM and ICDA.

OSVM (ONE CLASS SUPPORT VECTOR MACHINE)

Support Vector Machine (SVM) is a nonlinear classification method and has been successfully used in various fields such as image classification and disease prediction. OSVM tries to separate pixels belonging to one class from all other pixels. We use the OSVM implemented in LIBSVM, adopting a radial basis function kernel OSVM require only sufficient level of training samples for change regions,. As can be observed, the accuracy from OSVM is improving when more training samples are used. OSVM performs only slightly worse than ICDA, but it needs the whole test region to estimate proper parameters. The short comings with OSVM is that it has number of false negative pixels from OSVM

k-MEANS

K-means is an unsupervised classification method. The accuracy of k-means is closely related to the defined number of classes *k*. Accuracy of k-Means classifier is similar to ICDA but the result has false alarms.

(D) ICDA (Iterated Canonical Discriminant Analysis)

The idea in traditional CDA is to find projections in multi or hypervariate feature space, which give maximal separation between groups of the data. Here, we first use CDA with two groups based on a manually selected training area which then constitutes one of the two groups (one pixel is enough); the rest of the image is the other group. This gives rise to a potential problem: the rest of the image may contain regions that actually belong to the first group. To identify such regions and to update the training area, in a series of iterations, new training areas for the CDA are selected by automatically thresholding the canonical variate calculated in the previous iteration. Iterations stop when the canonical correlation stops improving

The KMNF output or the user defined region of interest of the image is given as an input to the ICDA technique. The rest of the image is the other group. This gives rise to a potential problem: the rest of the image may contain regions that actually belong to the first group. To identify such regions and to update the training area, in a series of iterations, new training areas for the CDA are selected by automatically thresholding the canonical variate calculated in the previous iteration. Iterations stop when the canonical correlation stops improving the proposed framework comprises two main steps: the kMNF-based change map generation and the production of the change mask based on ICDA. Therefore, two experiments have been designed in this part. In the first experiment, we generate the change maps by following the kMNF and parameter estimation approaches (hereafter referred to as kMNF-opti) described in Section II-B. The initial two-layer difference map used in this step results from the subtraction of the two panchromatic images and the two DSMs. Furthermore, the change maps resulting from image subtraction, DSM subtraction, and CVA are generated. These results are then compared with the reference change map in order to assess their accuracy. Accuracy of the change mask is verified using Kappa co-efficient accuracy measurement.

CLASSIFICATION METHOD	**MEAN**	**STANDARD DEVIATION**
K-means	0.3872	0.3872
Random Forest	0.1567	0.018
OSVM	0.0799	0.012
ICDA	0.5652	0.019

Table 4.1 Kappa statistics of Accuracy measurement for 50 pixels

The software used to build the change detection technique using high level language tool system known as MATLAB. MATLAB is a high-level language and interactive environment for numerical computation, visualization, and programming. Using MATLAB, you can analyze data, develop algorithms, and create models and applications. The language, tools, and built-in math functions enable you to explore multiple approaches and reach a solution faster than with spreadsheets or traditional programming languages, such as C/C++ or Java. We can use MATLAB for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

CHAPTER 5

RESULTS AND DISCUSSION

From the two given input images, change points are extracted using kernel minimum noise fraction. Where each pixels are kernelized using kernel or kernel trick. The generated training vectors are considered as a single training vector and given as an input to the Iterated Canonical Discriminant analysis. One class support vector machine, k-means classifier and Random forest are the Classifiers used in the earlier days have many false alarms. ICDA has reduced the false alarms compared to the above mentioned classifiers

5.1 PANCHROMATIC IMAGERY

The proposed framework comprises two main steps: the kMNF-based change map generation and the production of the change mask based on ICDA. Therefore, two experiments have been designed in this part. In the first experiment, we generate the change maps by following the kMNF and parameter estimation approaches (hereafter referred to as kMNF-opti) described in the initial two-layer difference map used in this step results from the subtraction of the two panchromatic images and the two DSMs. Furthermore, the change maps resulting from image subtraction, DSM subtraction, and CVA are generated. These results are then compared with the reference change map in order to assess their accuracy. The change mask obtained with each threshold value can be compared with the reference data thus, the true positive rate (Sensitivity) and false positive rate can be calculated. A larger area under the ROC curve indicates better quality of the change map. For a better display and comparison of these results, the 0.5% largest values are removed, and all the obtained values are linearly scaled from 0 to 1. Fig 3.7.4 shows that the change map obtained with kMNF-optic highlights the real forest changes better than CVA. The input images are obtained from satellite Orbview3, launched on an OSC launch vehicle from (Pegasus-XL) from VAFB, CA, USA. The Data sets used are from van vihar National park, Bhopal, Madhya Pradesh. The latitude and longitude information is given as 23.2414N; 77.3741E.

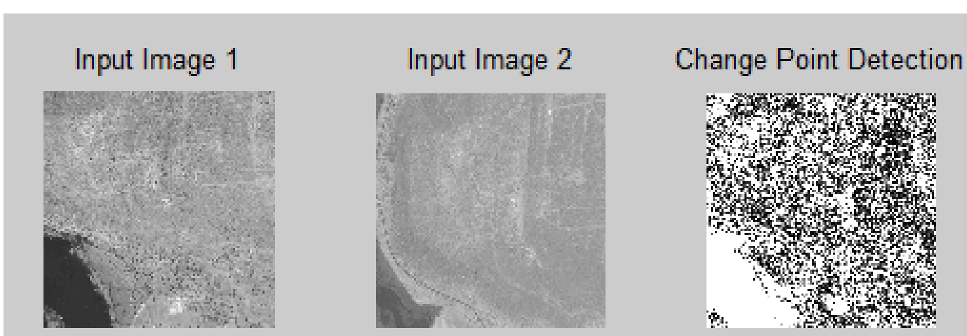
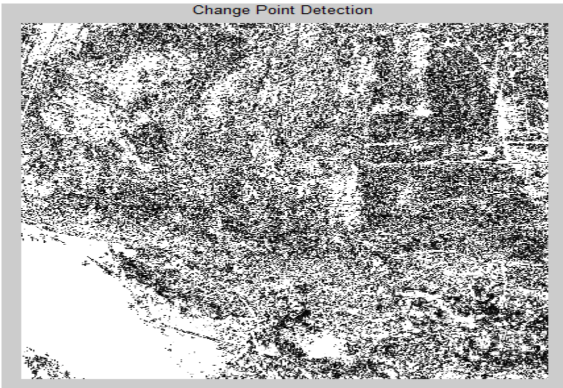
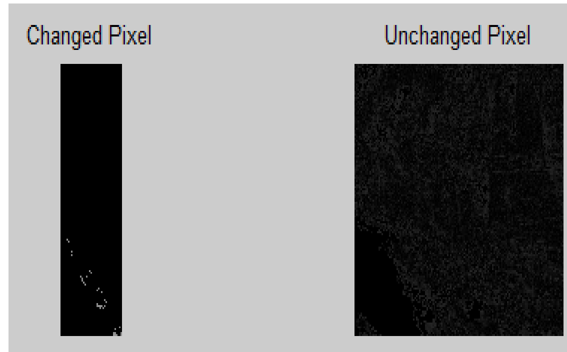


Fig 5.1 Extracted changes from the two given input images





(a) **(b)**

Fig 5.2 (a) shows change points from the two panchromatic images, (b) white pixels are considered as change pixels equal to '1' and black pixels indicate no change pixels considered as '0'

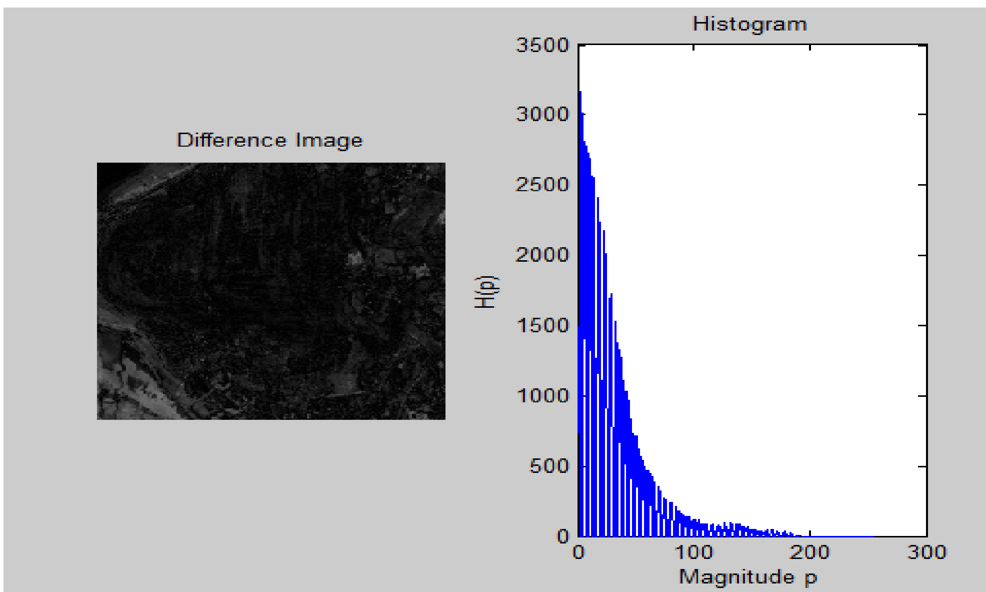


Fig 5.3 Histogram of a difference image from the two input images

The Fig 5.1 describes the two input images at two different years used for change detection analysis. The change detection point is displayed. Fig 5.2 shows the difference for changed pixels and unchanged pixels for the two input images. Fig 5.3 shows the Histogram graph for magnitued of pixel variation with respect to the intesity of pixel variation with refernce to the difference image

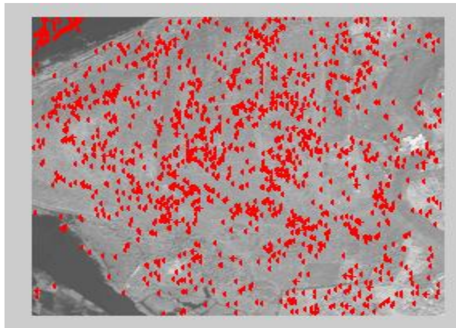
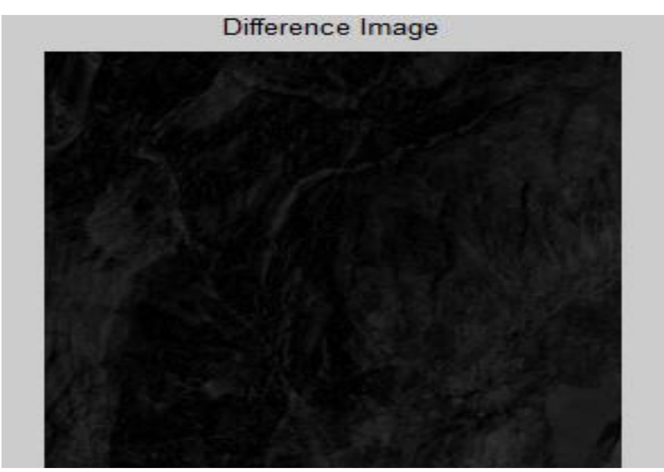


Fig 5.4 Obtained Change mask using ICDA

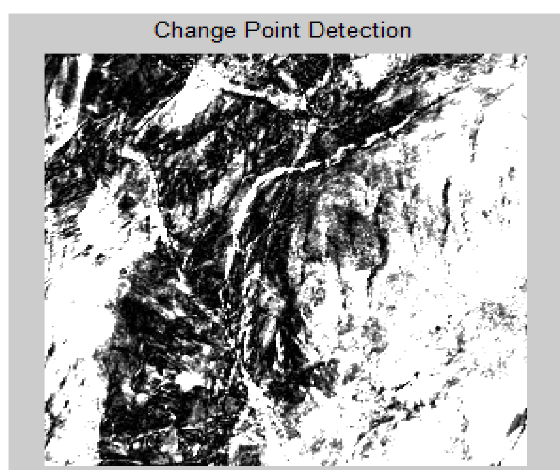
From the above figure the red points are indication the locations where changes present in the image. ICDA requires a fewer number of pixels it can generate a change mask with reference to the input image. False alarms are reduced when compared to the other classifiers such as OSVM, Random Forest and k means. Some panchromatic data sets are used for change detection and their difference image and change mask using kernel MNF are given below.

(a)

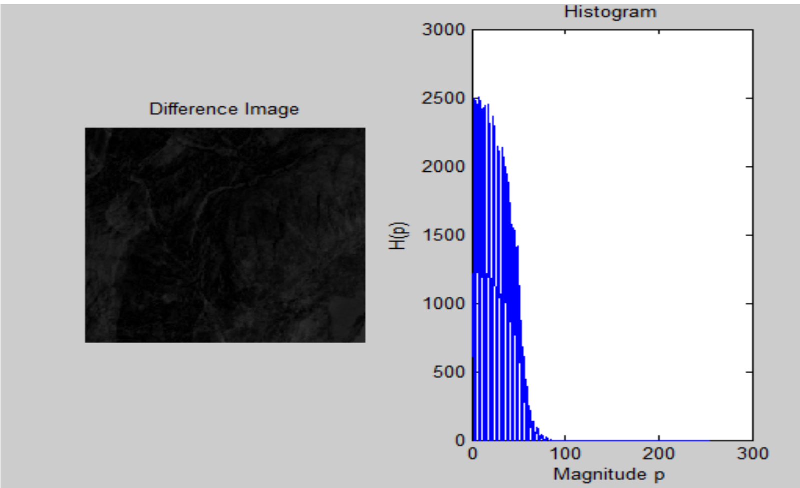
(b)



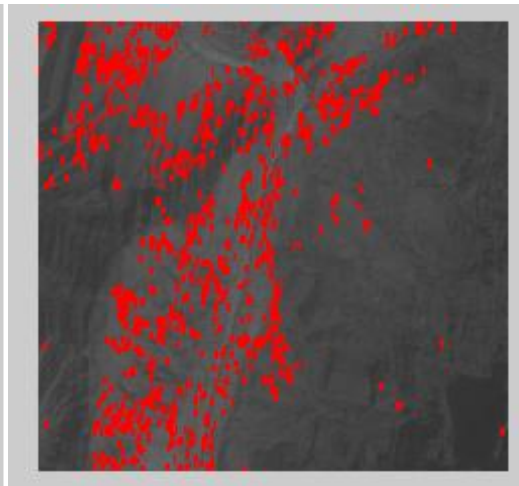
(c)



(d)



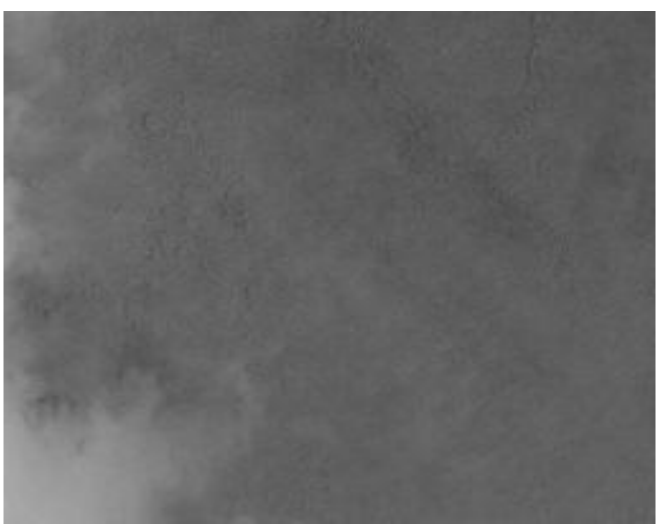
(e)



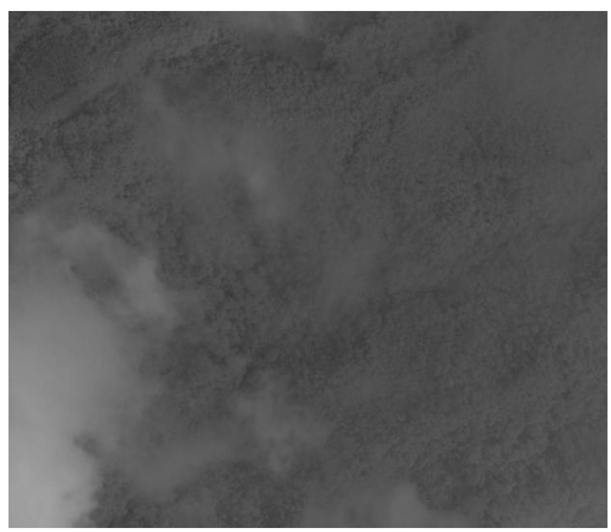
(f)

Fig 5.5 (a) Data from Gulf of Aden during the year 2006, (b) Data from Gulf of Aden during the year 2008, (c)Subracted difference image from the two input images at two different years, (d) Enhanced Change point detection using kernel MNF algorithm.

(e) Histogram variation of a difference image, (f) Change mask for the two input images.



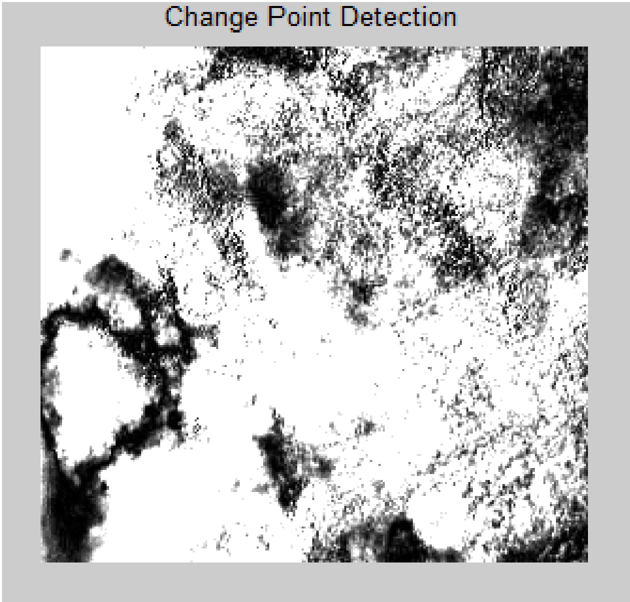
(a) During the year 2006



(b) During the year 2006

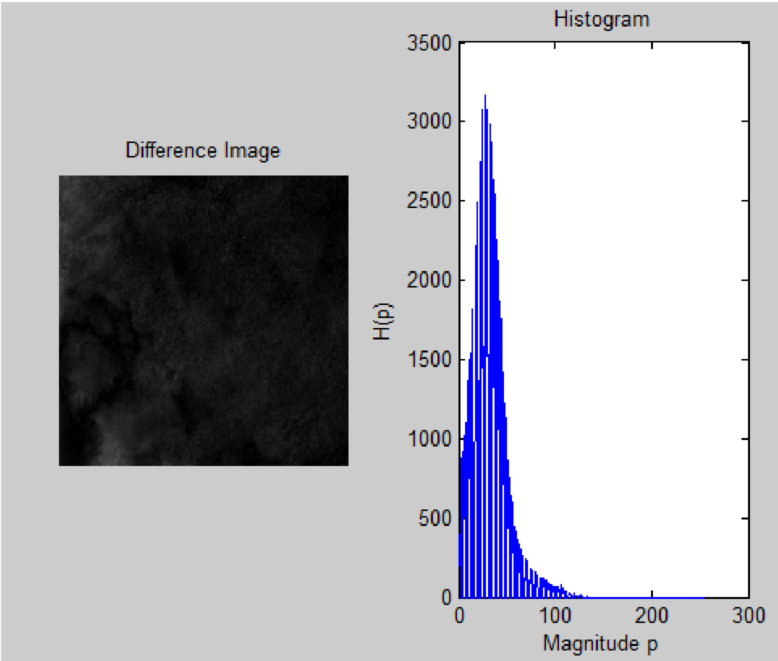
The above figure is an example given for panchromatic images obtained from Data set from North 6, Yemen taken during the year 2006 and 2008. Both the images are analysed using kernel

Minimum Noise fraction Analysis the changes features are extracted. The change mask is given in the fig 5.6 (f)

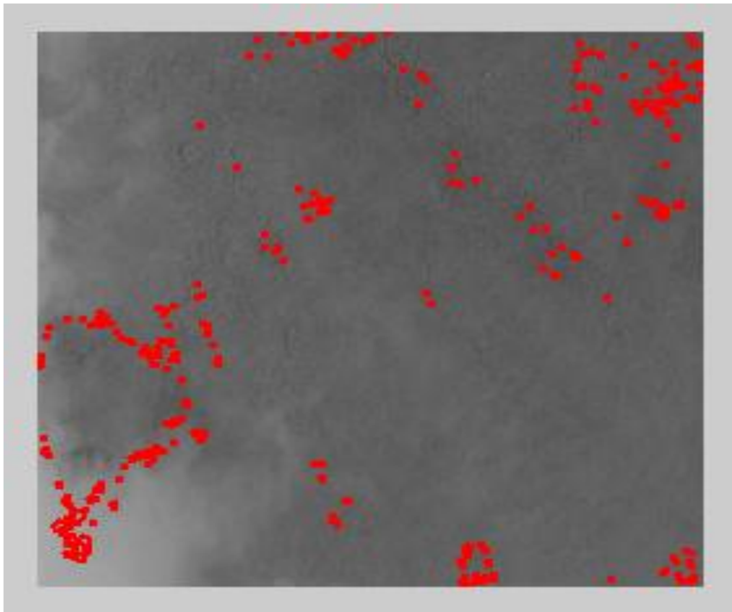


(c) Subracted difference image from the two input images at two different years

(d) Enhanced image of a difference image shows the white pixels are change region and black pixels are the no change region



(e) Histogram of the difference image

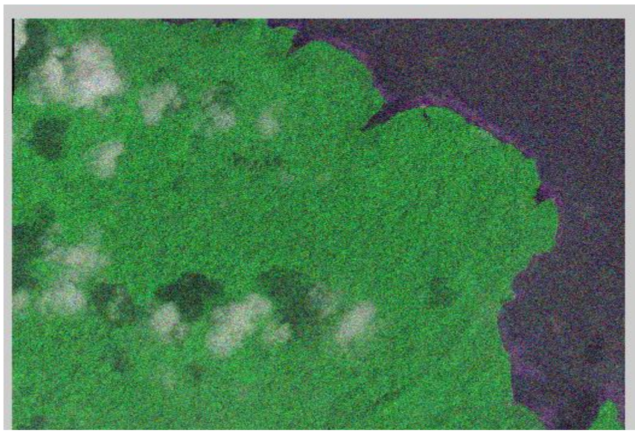


(f) Change mask from the obtained input images

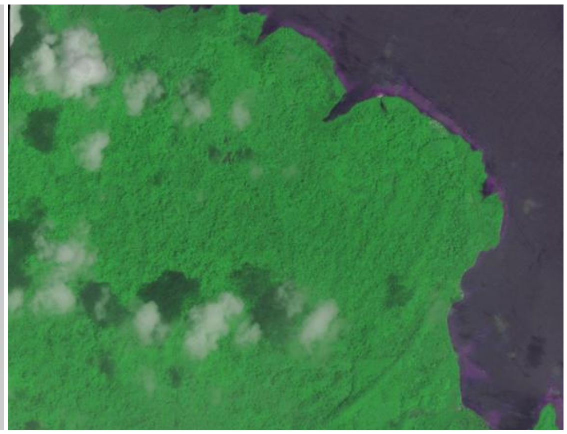
Fig 5.6 (a) Data set from North 6, Yemen taken during the year 2006, (b) Data set from North 6, Yemen during taken the year 2008, (c) Subracted difference image from the two input images at two different years, (d) Enhanced image of a difference image shows the white pixels are change region, (e) Histogram of the difference image, (f) Change mask from the obtained input images

5.2 Multispectral Imagery

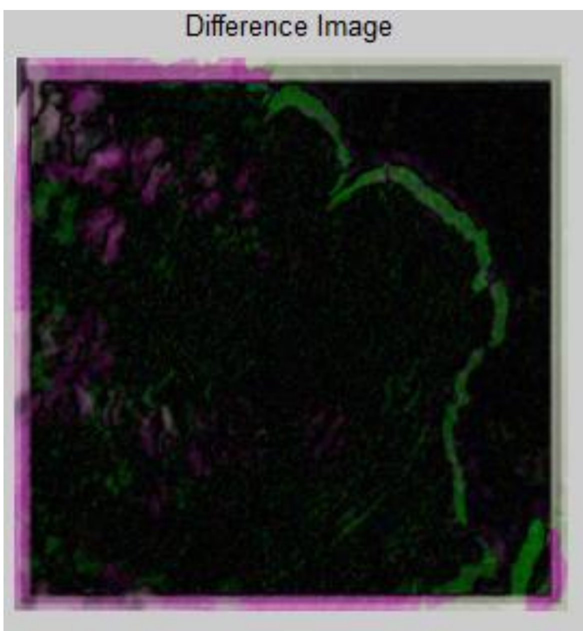
In this paper, it is given that change detection can also obtained from multispectral image. It is optically acquired in more than one spectral values or wavelength interval. Each individual image is of same physical area and scale but of a different spectral band. The two given input images are subtracted to obtain the basic difference between the two images, which is given as Subtraction of two images followed by Kernel minimum noise fraction is achieved; and it is a non-linear machine learning algorithm mainly used for pattern analysis and clustering and so on. It consists of the data to form a single cluster in the infinite feature space induced by the Gaussian kernel and determined the support vectors delimiting it. In the input space the support vectors are examined. In the kernel version the inner products of the original data are replaced by inner products between non linear mappings into higher dimensional feature space. The kernel substitution is also called as a kernel trick and these inner products between the mappings are replaced by kernel function; all the quantities in the mapping are replaced by a kernel function. From which it is clear that we do not know the non-linearity explicitly. kMNF analysis handles the non- linearity by implicitly transforming the data into higher dimensional feature space. Using the kMNF analysis clustering, centering and classification is performed the resultant.



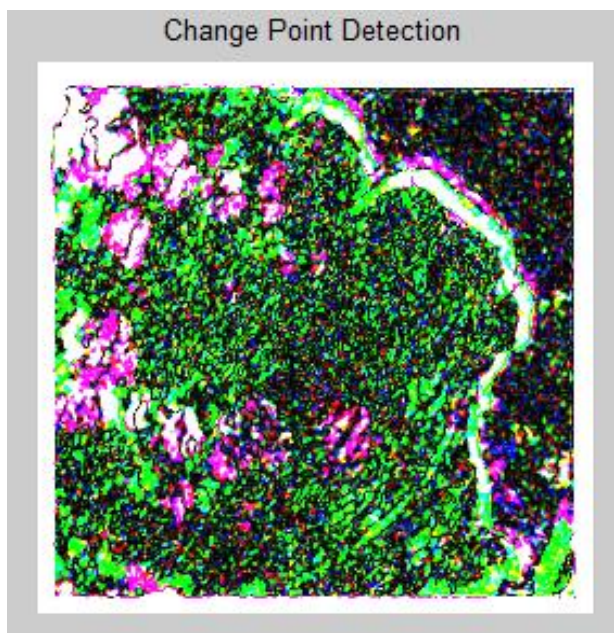
(a) During the year 2004



(b) During the year 2006

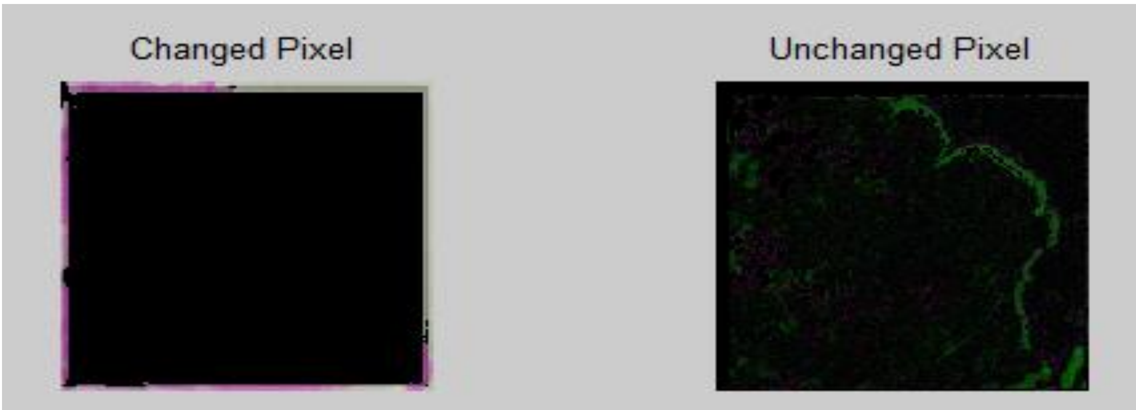


(c)

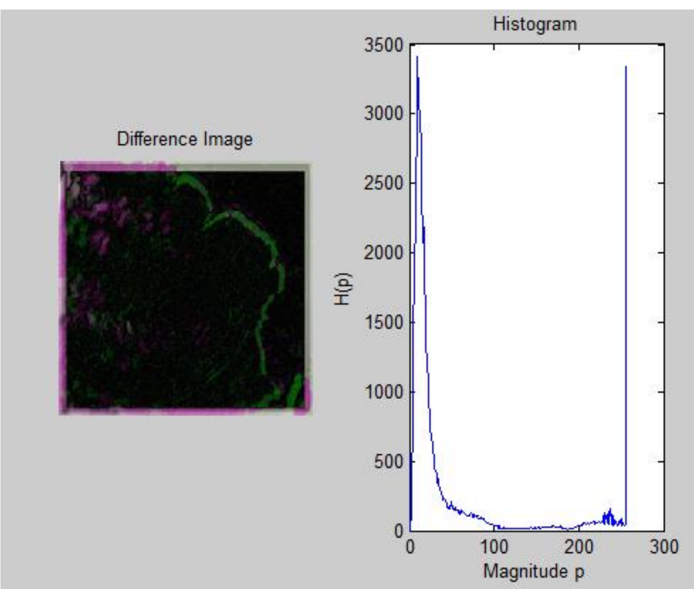


(d)

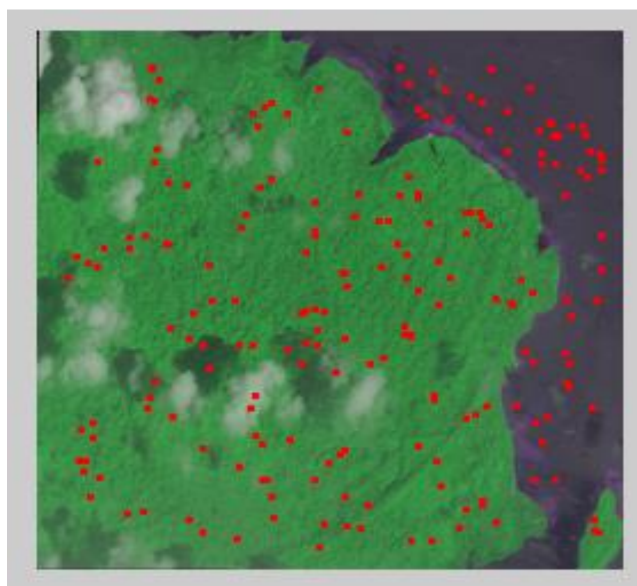
At different directions the training vectors are chosen by determining Eigen vectors. By clustering and Centering Process the different training vectors are clustered in a single training and used for change mask generation. Fig 5.7 (e), (f) illustrates the pixel change detection from the two input images. Training vectors are used to determine the changes in the desired direction.



(e) (f)



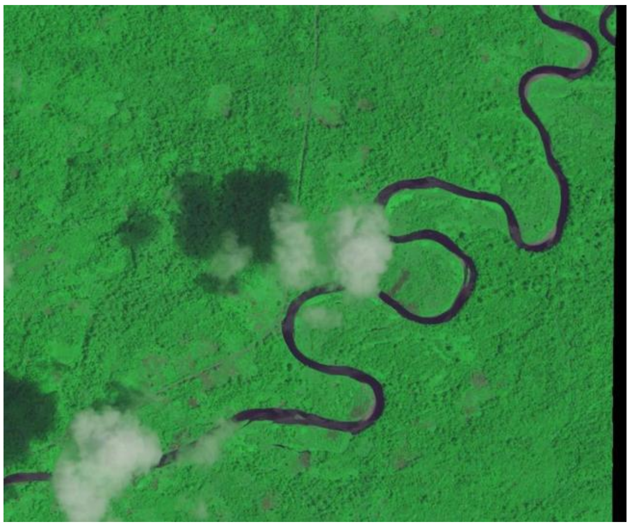
(g)



(h)

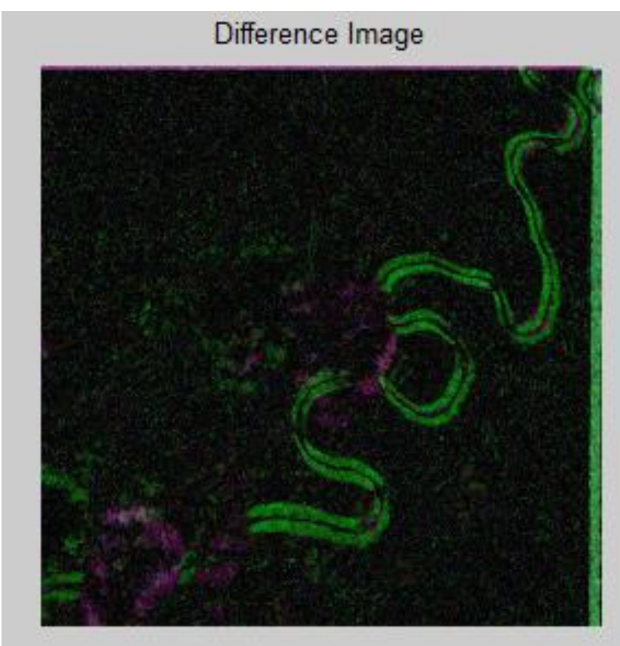
Fig 5.7 Karawai, East Aru Tengah, Kepulauan Aru Regency, Maluku, Indonesia taken during the year (a).2004 , (b). 2006, (c) Difference image from the two input images , (d) Enhanced change point detection obtained from the difference images, (e) Shows the changed pixels from the difference image, (f) shows the common pixels from the input images, (g) Histogram representation of a difference image magnitude of pixel versus intensity of pixels, (h) Change mask obtained from ICDA algorithm

The Fig 5.7 (h) shows the iterated output of ICDA. For each iteration the change features accuracy is also improved. When compare to the other classifiers like Random forest, k-means, and OSVM. ICDA provides more accurate change detection map generation with very few training sets**. T**he below given Data set is obtained from Autonomous Region of Bougainville, Papua, New Guinea during the year (2003 - 2006).

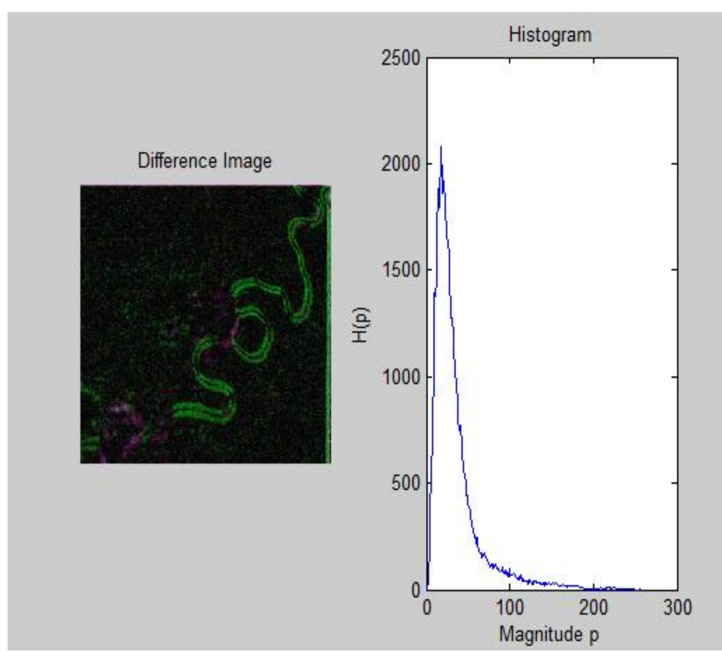


(a) Data set 1 (2003)

(b) Data set 2 (2006)

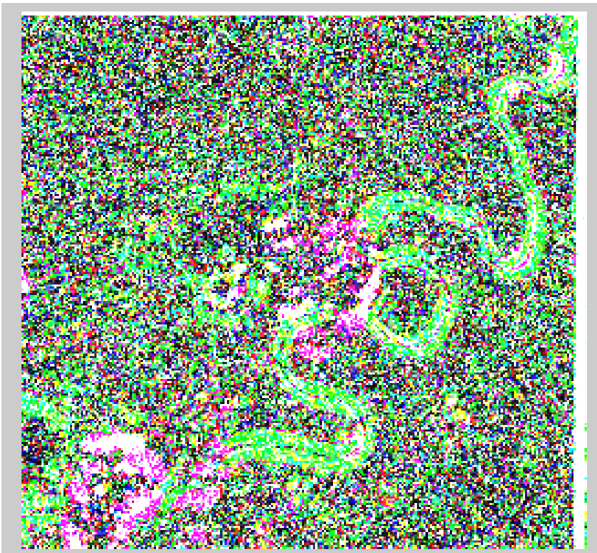


(c)

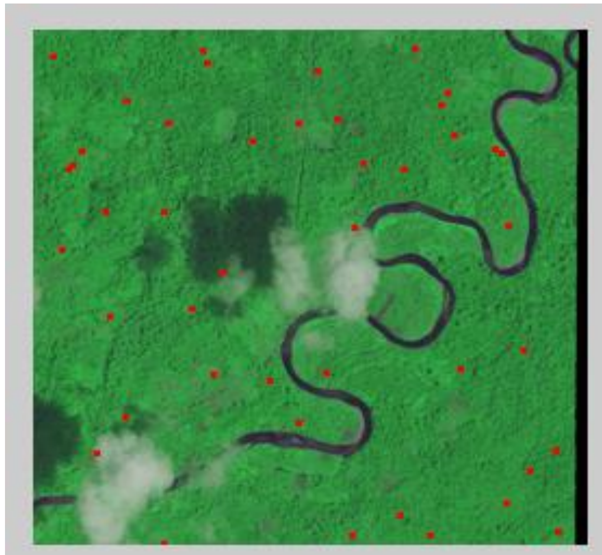


(d)

The Fig 5.8 (a),(b) is input multispectral images from North cascade Australia. This is used for kMNF analysis. Using image subtraction technique two input images are subtracted the resultant images are extracted for its change features in all direction by re-parameterization using kernel trick. Normalized training vector is used for change mask generation using ICDA.

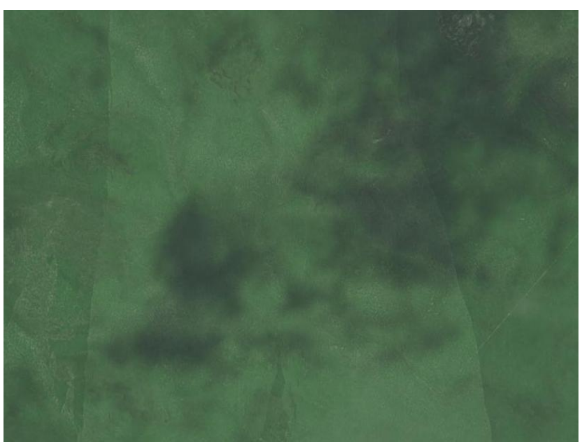


(e)

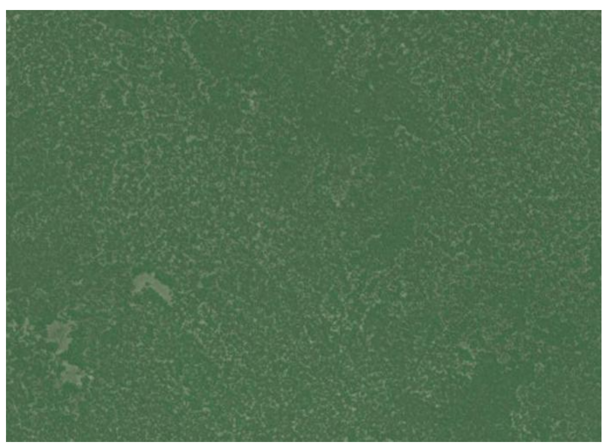


(f)

Fig 5.8 (a),(b) Two data sets obtained from Autonomous Region of Bougainville, Papua, New Guinea during the year (2003 - 2006), (c) Difference image , (d) Histogram of a difference image, (e) Enhanced change point detection image , (f) Obtained Change mask

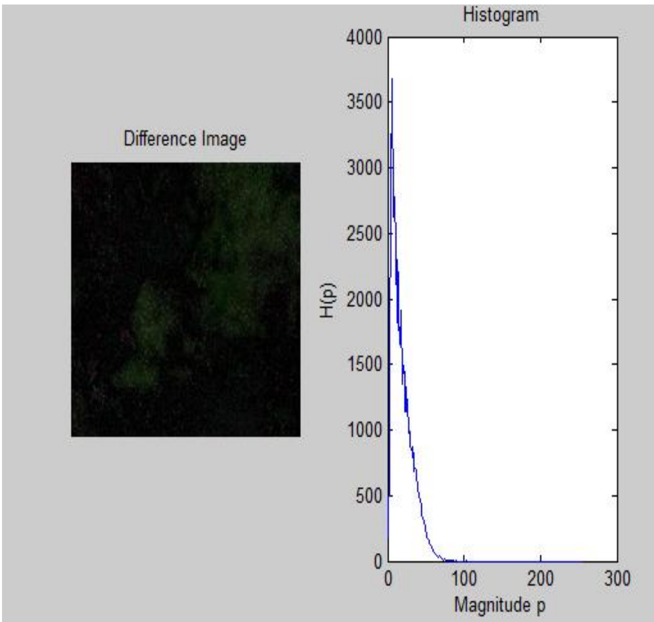


(a) Data set 1

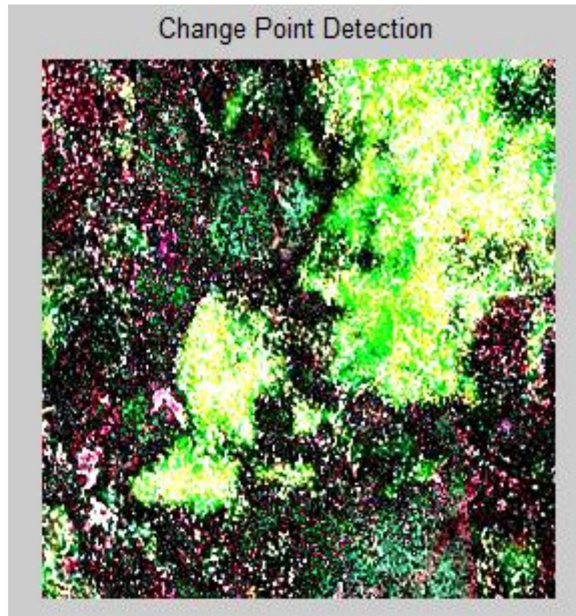


(b) Data set 2

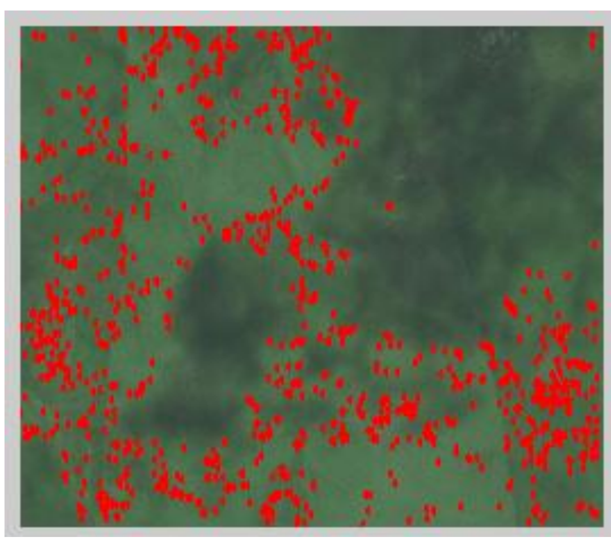
Fig 5.9 (a), (b) is the two multispectral images from North cascade Australia is used for change detection analysis which gives a change detection mask obtained better than the panchromatic images.



(c)



(d)



(e)

Fig 5.9 (a), (b) Two data sets from Cascades Road, North Cascade WA, Australia (2003-2006), (c) Histogram variation of a difference image , (d) Enhanced Change point detection, (e) Obtained Change mask

Change detection is an essential task in natural resource development and management. The proposed work is done for change detection in Multispectral images and panchromatic images using kMNF analysis. The resultant output shows accurate changes between the given inputs. The change detection method purely based on a intensity and segmentation method which will extract the changes from the given image. The images, used are [1200x1200] for panchromatic images and [1153x1153] for multispectral images. The data obtained are the uncompressed data. As the approach followed is intensity based one. Threshold values plays an important role for intensity variation by setting threshold values change features are estimated. In kMNF analysis which checks the neighbourhood pixels in array of elements in matrix to convert it to a kernel matrix. The kernel output is a training vector in a specified direction is given as an input to the ICDA method which generate the change mask locating the points where changes has been actually occurred in the resultant image. The change detection mask of the multispectral images shows better results when compared to the panchromatic image change detection.

CHAPTER 6

CONCLUSION

In this paper, change detection is worked for forest regions using different satellite images such as panchromatic and multispectral images. Images from two different periods as collected and analysed for both the panchromatic and multispectral images, and the two images are subtracted to collect the attributes of the change points. Kernel minimum noise fraction analysis is used to determine the change features in all direction as by using re-parameterisation technique. Change mask is presented using ICDA method with reference to the input image. From the obtained results, it is clear that the change detection in multispectral image is more accurate than the panchromatic image. The 2D change features are processed in a high dimensional feature space using kMNF analysis to highlight the change features. The kMNF value or region of interest is given as a input to the ICDA method to generate the change mask pointing the change areas in the resultant image. The main advantage of this method is it requires only a smaller number of pixels to generate the change features. As change detection is more helpful in many areas as this method can also be implemented for building change detection and snow/ice change detection on earth surface using Earth resource satellite areas.2-D change features were processed onto high-dimensional feature space based on the kernel trick, and the kMNF was successfully applied to highlight the real forest changes. Finally, the ICDA was adopted to automatically extract the forest change mask.

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[20] J. Tian, J. Leitloff, T. Krauß, P. Reinartz “Region based forest change detection from cartosat-1 stereo Imagery”

LIST OF PUBLICATIONS

JOURNAL

- Paper titled "**plants change detection in forest areas based on satellite imagery using kernel MNF**" has been selected in International journal of computer Application.

CONFERENCE

- Presented a paper titled "**plants change detection in forest areas based on satellite imagery using kernel MNF**" in **National Conference on Information Processing and Remote Computing** at PSG College of technology and PSG polytechnic college, Coimbatore.