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Region Based Hyper spectral Image Scene Changed Detection for Fusion Images using Histogram Equalization

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Abstract:
Segmentation and scene changed detection of high resolution imagery is a challenging problem due to the fact that it is no longer meaningful to carry out this task on a pixel-by-pixel basis. Image analysis requires a segmentation step to distinguish the significant components of the image, i.e., the foreground from the background. As a step prior to image classification the quality of the segmentation is of significant importance. High-resolution satellite image classification using standard per-pixel approaches is difficult because of the high volume of data, as well as high spatial variability within the objects. One approach to deal with this problem is to reduce the image intricacy by dividing it into homogenous segments prior to classification. This has the added advantage that segments can not only be classified on basis of spectral information but on a host of other features such as neighborhood, size, texture and so forth. Segmentation of the images is carried out using the region based algorithms such as marker-based watershed transform. This paper presents an efficient method for image segmentation based on a multi-resolution application of a marker-based watershed segmentation algorithm. After the segmentation, the contains classified object represented by various colour maps. The system used method has ability for effectively solves the problem of isolated and random distribution of pixels inside regions but also obtains high edge accuracies. The simulated results will be shown that better image classification from satellite land cover images and its performance will be evaluated in terms of sensitivity and cluster efficiency.

Keywords: cluster efficiency, Homogenous segments, Marker-based watershed transform.

1. INTRODUCTON:-

Image Fusion is the process of combining relevant information from two or more images into a single image. The fused image should have more complete information which is more useful for human or machine perception. The resulting image will be more explanatory than any of the input images.

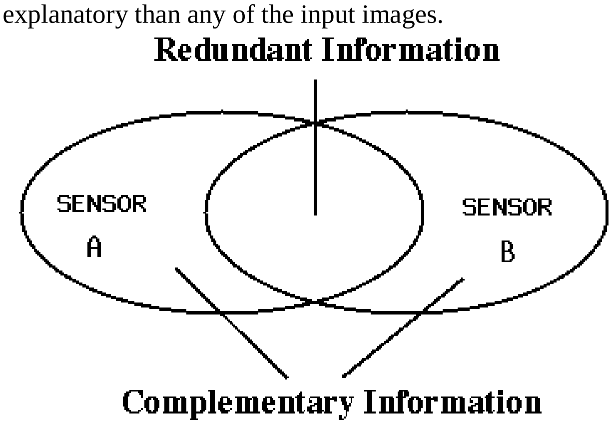

Figure.1. Basic diagram of image fusion

The input images are fused here to get more complementary information and also some common redundant information. Fusion methods are:

- linear superposition
- nonlinear methods
- optimization approaches
- artificial neural networks
- image pyramids
- wavelet transform
- generic multiresolution fusion scheme

Change detection techniques for space borne SAR data have not yet been fully explored. Change detection techniques for SAR data can be divided into several categories, each corresponding to different image quality requirements. In a first category, changes are detected based on the temporal tracking of objects or stable image features of observable geometrical shape. Absolute calibration of the data is not required, but the data must be rectified from geometric distortions due to differences in imaging geometry or SAR processing parameters, and the accurate spatial registration of the multidate data is essential. Combining information captured from multiple sensors has become very popular in many signal and image processing applications. Two reasons are there in the case of earth observation. The first one is that the fusion of the data produced by different types of sensors provides integral which overcomes the limitations of a specific kind of sensor. The other reason is that, often, in operational applications, the user does not have the possibility to choose the data to work with and has to use the available archive images or the first acquisition available after an event of interest. This is particularly true for checking applications where image registration and change detection approaches have to be implemented on different types of data. A **multispectral image** is one that seizures 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 derivation of added information the human eye fails to seizure with its receptors for red, green and blue. It was originally developed for space-based imaging. Multispectral images are the main type of images acquired by remote sensing (RS) radiometers. A **Hyperspectral image** assembles 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. **Panchromatic images** are single band images generally displayed as shades of gray. Thus, intensity of the images may not be visible clearly here. So we are using Multi and Hyper spectral images to get the clear view of the images.

2. LITERATURE SURVEY ANALYSIS:-

A. Recent Advances In Techniques For Hyperspectral Image Processing.

Imaging spectroscopy, also known as hyperspectral imaging, has been converted in less than 30 years from being a sparse research tool into a commodity product available to a broad user community. Currently, there is a need for standardized data processing techniques able to take into account the special properties of hyperspectral data. In this paper, we provide an influential view on recent advances in techniques for hyperspectral image processing. Our main focus is on the design of techniques able to deal with the high dimensional nature of the data, and to integrate the spatial and spectral information. Performance of the discussed approach is evaluated in different analysis scenarios. To satisfy time-critical constraints in specific applications, we also develop efficient parallel implementations of some of the discussed algorithms. Combined, these parts provide afinest snapshot of the state-of-the-art in those areas, and offer a thoughtful perspective on future potentials and emerging challenges in the design of robust hyperspectral imaging algorithms [21].

B. Multitask Remote Sensing Data Classification.

Many remote sensing data processing problems are inherently constituted by several tasks that can be solved either individually or jointly. For instance, each image in a multitemporal classification setting could be taken as an individual task. Here, the relation to previous acquisitions should be properly considered because of the nonstationary behavior of temporal, spatial, and angular image features which gives rise to distribution changes. This phenomenon is known as *covariate shift*. Additionally, when labeled data are scarce or expensive to obtain, the small sample-set problem arises, which makes solving the problems independently in each domain difficult. Multitask learning (MTL) aims at jointly solving a set of prediction problems by sharing information across tasks. This paper introduces MTL in remote sensing data classification. The proposed methods alleviate the data set shift by imposing cross-information in the classifiers through matrix regularization. We consider the support vector machine (SVM) as the core learner and two different regularization schemes: 1) the inclusion of relational operators between tasks and 2) the pair wise Euclidean distance of the predictors in the Hilbert space. These methods rely on simple and intuitive modifications of the kernel used in the standard SVM. Experiments are conducted in three challenging remote sensing problems: cloud screening from multispectral images, land-mine detection using radar data, and multitemporal and multisource image classification. The pair wise method consistently outperforms standard independent and aggregate approaches by about +2% to 4% in all problems at no additional cost. Also, the solutions found give us information about the distribution shift among tasks[23].

C. Object Based Image Analysis For Remote Sensing.

Remote sensing imagery needs to be transformed into tangible information which can be utilized in conjunction with other data sets, often within widely used Geographic Information Systems (GIS). As long as pixel sizes remained mostly coarser than, or at the best, similar in size to the objects of interest, emphasis was placed on per-pixel analysis, or even sub-pixel analysis for this conversion, but with increasing spatial resolutions different paths have been followed, aimed at deriving objects that are made up of several pixels. This paper gives an overview of the development of object based methods, which aim to depict readily usable objects from imagery while at the same time combining image processing and GIS functionalities in order to utilize spectral and theoretical information in an integrative way. The most common approach used for building objects is image segmentation, which dates back to the 1970s. Around the year 2000 GIS and image processing started to grow together immediately through object based image analysis (OBIA - or GEOBIA for geospatial object based image analysis). In contrast to classic Landsat resolutions, high resolution images support several scales within their images .The pixel paradigm is an inauguration to show cracks and the OBIA methods are making considerable progress towards a spatially accurate information extraction workflow, such as is required for spatial planning as well as for many monitoring programmes[5].

D. Advances in Spectral–Spatial Classification of Hyperspectral Image.

Recent advances in spectral–spatial allotment of hyperspectral images are presented in this paper. Several techniques are investigated for combining both spatial and spectral information. Spatial information is derived at the object (set of pixels) level rather than at the conventional pixel level. Mathematical morphology is first used to derive the morphological profile of the image, which includes characteristics about the size, orientation, and contradiction of the spatial structures present in the image. Then, the morphological neighborhood is defined and used to derive additional features for arrangement. Classification is performed with support vector machines (SVMs) using the available spectral information and the extracted spatial information. Spatial post processing is next considered to build more homogeneous and spatially consistent thematic maps. To that end, three presegmentation techniques are applied to define regions that are used to adjust the preliminary pixel-wise thematic map. Finally, a multiple-classifier (MC) system is defined to produce relevant markers that are exploited to segment the hyperspectral image with the minimum spanning forest algorithm. Experimental conclusion conducted on three real hyperspectral images with different spatial and spectral resolutions and corresponding to various contexts are presented. They highlight the priority of spectral–spatial strategies for the accurate classification of hyperspectral images and validate the proposed methods [11].

E.Spectral–Spatial Hyperspectral Image Classification with Edge-Preserving Filtering.

The assimilation of spatial context in the classification of hyperspectral images is known to be an effective way in improving classification accuracy. In this paper, a novel spectral–spatial arrangement framework based on edge-preserving filtering is proposed. The proposed framework consists of the following three steps. First, the hyperspectral image is classified using a pixel wise classifier, e.g., the support vector machine classifier. Then, the resulting allocation map is represented as multiple probability maps, and edge-preserving filtering is conducted on each contingency map, with the first principal component or the first three principal components of the hyperspectral image serving as the gray or color guidance image. Finally, according to the filtered possibility maps, the class of each pixel is selected based on the maximum probability. Experimental results demonstrate that the proposed edge-preserving filtering based classification method can improve the arrangement accuracy significantly in a very short time. Thus it can be easily applied in real application [15].

3. EXISTING SYSTEM

3.1 DWT BASED IMAGE FUSION:

In the case of wavelet transform fusion all corresponding wavelet coefficients from the input images are combined using the fusion rule. Since wavelet coefficients having large absolute values contain the instruction about the salient features of the images such as edges and lines, a good fusion rule is to take the maximum of the absolute values of the corresponding wavelet coefficients. A more advanced area based selection rule is proposed. The maximum absolute value within a window is used as an activity measure of the central pixel of the window. A binary decision map of the same size as the DWT is designed to record the selection results based on a maximum selection rule. Rather than using a binary decision, the resulting coefficients are given by a weighted average based on the regional activity levels in each of the images' sub bands. The DWT fusion methods provides computationally efficient image fusion techniques.

Disadvantages of DWT:

The discrete Wavelet transform has poor directionality and also fails to represent curvilinear structures. The discrete wavelet transform (DWT) cannot capture curves and edges of images well. More reasonable bases should contain geometrical structure information when they are used to represent images. There are some major drawbacks in the wavelet transform. First, it doesn't provide shift invariance, and it does not capture the edges properly. Another major drawback in the wavelet transform is, it provides limited information along the horizontal, vertical and diagonal direction. The above said drawbacks are to be removed using some best transform like contour let transform.

3.2 Thresholding Segmentation:

The most straightforward method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image. The key of this method is to prefer the threshold value (or values when multiple-levels are selected). Several popular methods are used in industry including the maximum entropy method, Otsu's method (maximum variance), and k-means clustering. Recently, methods have been developed for thresholding computed tomography (CT) images. The key idea is that, unlike Otsu's method, the thresholds are derived from the radiographs instead of the (reconstructed) image.

3.3 HISTOGRAM EQUALISATION:

Histogram equalization is a method in image processing of contradiction adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the accessible data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower regional contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. The method is useful in images with backgrounds and foregrounds that are both bright or both dark. A key convenience of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the initial histogram can be recovered. The calculation is not computationally intensive.

Disadvantage of Histogram Equalization:

A disadvantage of the method is that it is extensive. It may increase the contrast of background noise, while decreasing the usable signal.

4. PROPOSED METHOD ANALYSIS:-

System Model:

Scene changed Detection for satellite image analysis based on,
Region Based detection

Methodologies

- Preprocessing: Contrast Limited Adaptive Histogram Equalization
- Region Based Contour Detection
- Watershed Segmentation
- Performance Evaluation(Cluster Efficiency and Accuracy)

4.1 Discrete Contour Transform

The contourlet transform uses a double filter bank structure to get the gentle contours of images. In this double filter bank, the Laplacian pyramid (LP) is first used to capture the point break, and then a directional filter bank (DFB) is used to form those point discontinuities into linear structures. The Laplacian pyramid (LP) decomposition only produce one bandpass image in a multidimensional signal processing, that can bypass frequency scrambling. And directional filter bank (DFB) is only fit for high frequency since it will leak the low frequency of signals in its directional subbands. This is the logic to combine DFB with LP, which is multiscale decomposition and remove the low frequency. Therefore, image signals pass through LP subbands to get bandpass signals and pass those signals through DFB to seizure the directional.

BLOCK DIAGRAM:

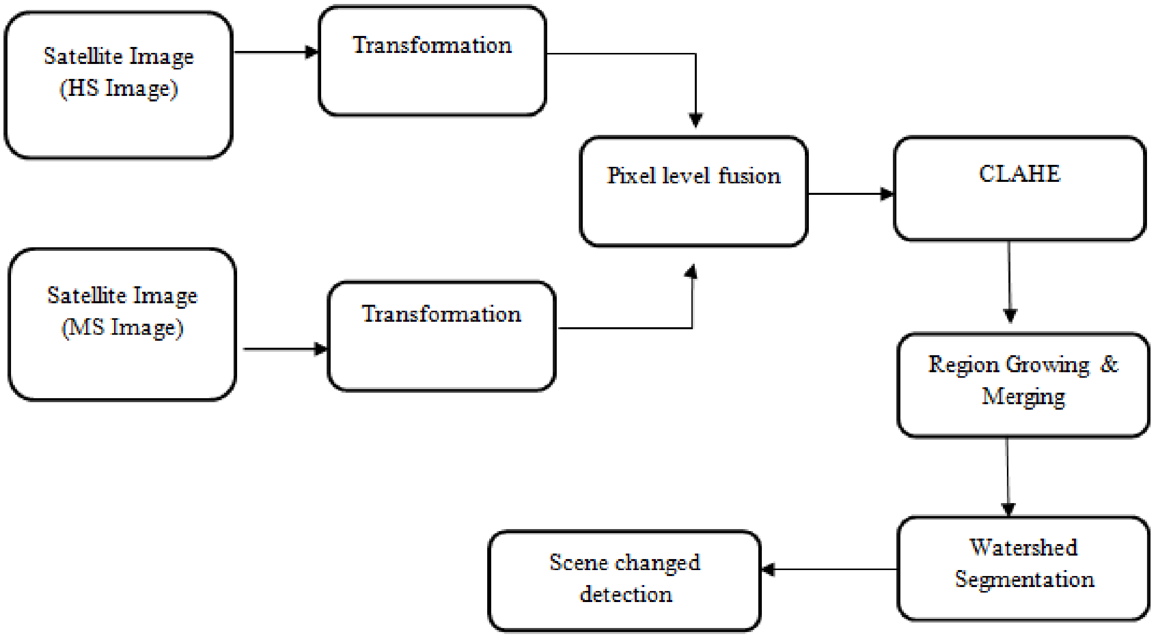

Figure.1. Block diagram

Information of image. This double filter bank structure of combination of LP and DFB is also called as pyramid directional filter bank (PDFB), and this transform is near the original image by using basic contour, so it is also called discrete contourlet transform.

ADVANTAGES OF CONTOURLET TRANSFORM

Different from the curvelet which is first developed in continuous domain and then is discretized for sampled data, contourlet transform (CT), introduced by Do and Vetterli, starts with a discrete- domain construction. This transform is more suitable for constructing multi-resolution and multi-directional expansions using non-separable Pyramid Directional Filter Banks (PDFB) with small redundancy factor. Contoured transform starts with a discrete domain construction. The contourlet is also deemed as a "true" two dimensional transform that can capture the intrinsic geometrical structure of an image. Two filter banks are employed to implement the contoured transform. The Laplacian pyramid is first used to capture the point discontinuities, and then a directional filter bank is used to link point discontinuities into linear structures. As the DWT, the contoured transform also has no shift invariant property because of the down-sampling operation. With a rich set of basis oriented at various directions and scales, contourlet can effectively capture the intrinsic contours and edges in natural images that set radiational multiresolution analysis methods are difficult to handle. Contourlet offers a much richer sub band set of different directions and shapes, whichhelps to capture geometric structures in images much more efficiently. The wavelet transform is good at isolating the discontinuities at object edges, but cannot detect the smoothness along the edges. Moreover, it can capture limited directional information. The contourlet transform can effectively overcome the disadvantages of wavelet. Contourlet transform is a multi-scale and multi-direction framework of discrete image. In this transform, the multi- scale analysis and the multidirection analysis are separating a serial way.

4.2 Region-based segmentation

The main idea of region-based segmentation is to compute local similarity and then optimize the segmentation over the whole image through a global criterion. For segmentation using intensity alone, local similarity is invariably some measure of how much the intensities of two pixels are alike. In this section, we describe how information about curvilinear continuity can be incorporated into the similarity measure between two pixels.

Watershed Segmentation Algorithm

The main goal of watershed segmentation algorithm is to find the "watershed lines" in an image in order to separate the distinct regions. To imagine the pixel values of an image is a 3D topographic chart, where x and y denote the coordinate of plane, and z denotes the pixel value. The algorithm starts to pour water in the topographic chart from the lowest basin to the highest peak. In the process, we may detect some peaks disjoined the catchment basins, called as "dam". Before describing the steps of watershed, we previously define some parameters.

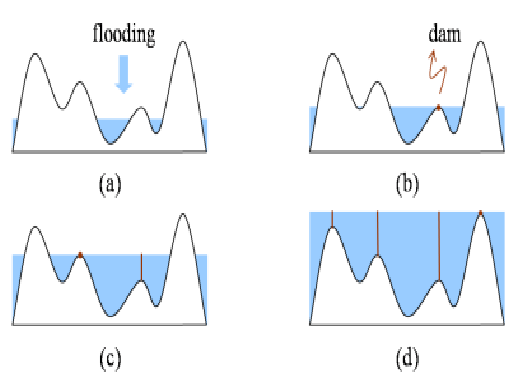

Figure.2. Watershed Segmentation Algorithm

Let M1, M2, …, MR sets denoting the coordinates in the regional minima of an image g(x, y), where g(x, y) is the pixel value of coordinate (x, y). Denote C(Mi) as the coordinates in the catchment basin associated with regional minimum Mi . Finally, let T[n] be the set of coordinates (s, t) for which g(s, t) < n and show as

$$T[n] = \{(s,t) | g(s,t) < n\}$$

Then the process of watershed algorithm is discussed as below [1]. Step1. Find the minimum and maximum pixel value of g(x, y) as min and max. Assign the coordinate of min into Mi. The topography will be flooded in integer flood increments from n = min +1. Let Cn(Mi) as the coordinates in the catchment basin associated with minimum Mi that are flooded at stage n.

Step2. Compute

$C_n\ (M_i)$=C (M_i)∩ $T[n]$

If) i(∈) x y C M , (and , Cn(Mi) = 1 at location (x, y); otherwise][∈) x y T n , (Cn(Mi) = 0. Then let C[n] denote the union of the flooded catchment basins at stage n:

$$C[n] = \bigcup_{i=1}^{R} C_n\ (M_i)$$

4.3 Contrast Limited Adaptive Histogram Equalization

Contrast Limited AHE (CLAHE) differs from ordinary adaptive histogram equalization in its contrast limiting. This feature can also be applied to global histogram equalization, giving rise to contrast limited histogram equalization (CLHE), which is rarely used in practice. In the case of CLAHE, the contrast limiting procedure has to be applied for each neighbourhood from which a transformation function is derived. CLAHE was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to. This is achieved by limiting the contrast enhancement of AHE. The contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function. This is proportional to the slope of the neighbourhood cumulative distribution function (CDF) and therefore to the value of the histogram at that pixel value. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4. It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins.

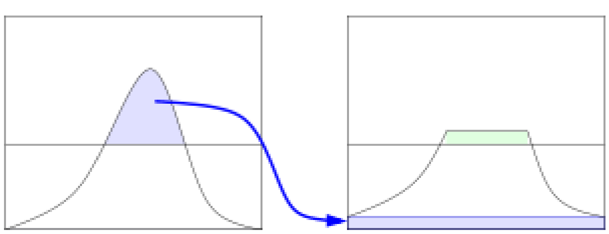

Figure.3. histogram bins

The redistribution will push some bins over the clip limit again (region shaded green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution procedure can be repeated recursively until the excess is negligible.

4.4 ADVANTAGES OF PROPOSED SYSTEM

CLAHE was developed to prevent the over amplification of noise that adaptive histogram equalization can give rise to. CLAHE, through able to increase contrast more than other techniques. It introduces large changes in the pixel gray levels. CLAHE may lead to introduction of the processing artifacts and effect of decision making process.

5. CONCLUSION:

In this paper, we discussed different image fusion levels, current state of art of image fusion in remote sensing, different image fusion methods and image fusion evaluation parameters. Concluding remarks for all these sections are organized as follow:

• Image fusion methods obtain more accurate and reliable image information by eliminating redundancy.

• Analysis of some researchers shows that different image fusion methods suits different applications.

• The pixel level fusion has been extensively researched for different approaches, since it gives comparatively better quality of fused results; but at the expense of more time consumption.

• For evaluation of image fusion algorithms, there is no standardized reference hence common practice followed is to test the algorithms on more number of datasets and to use optimum fusion strategy depending on application.

• Along with the objective evaluation, many times it is reported that the fused result should be subjectively evaluated based on visual characteristics.

6. RESULTS:

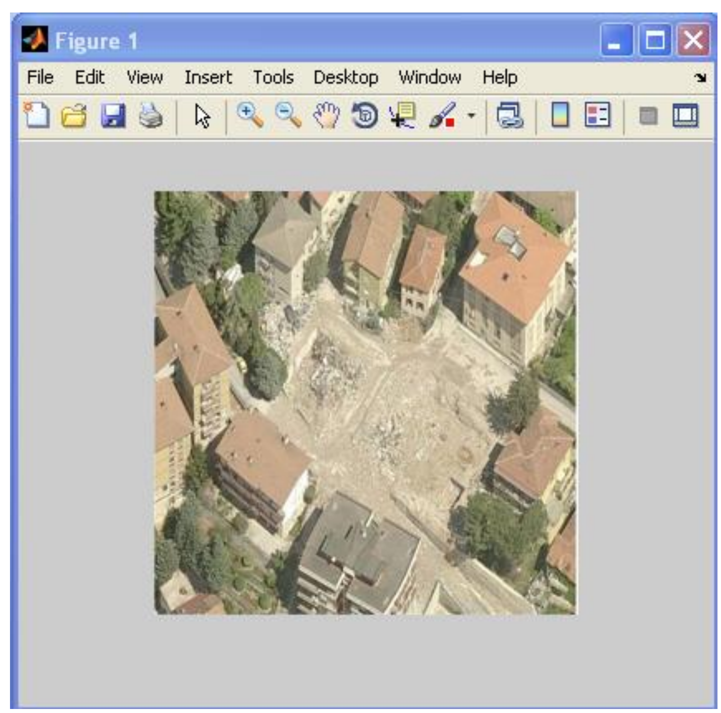

Figure.4. Source image

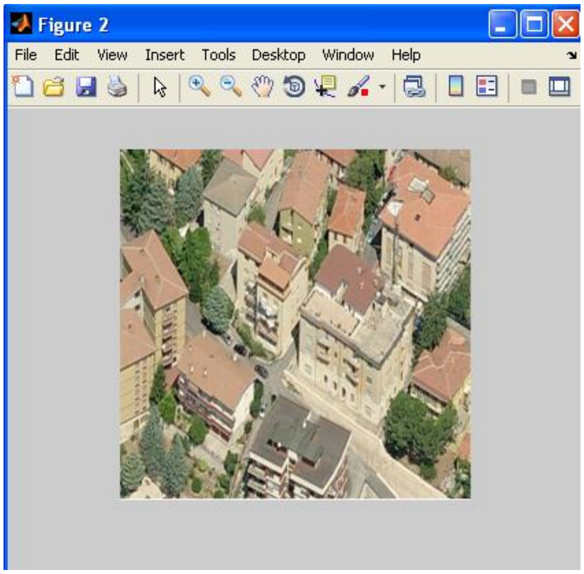

Figure.5. Source image

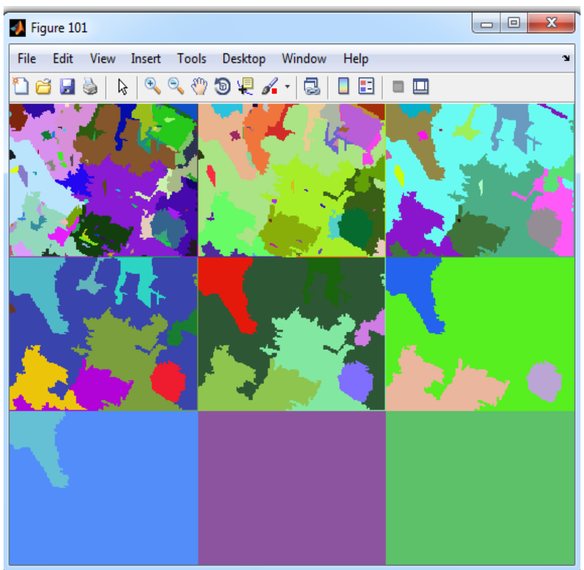

Figure.6. Fused image

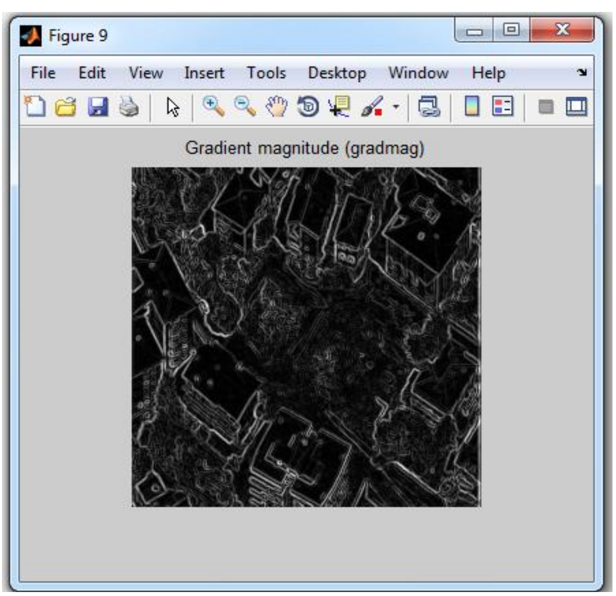

Figure.7. Gradient magnitude

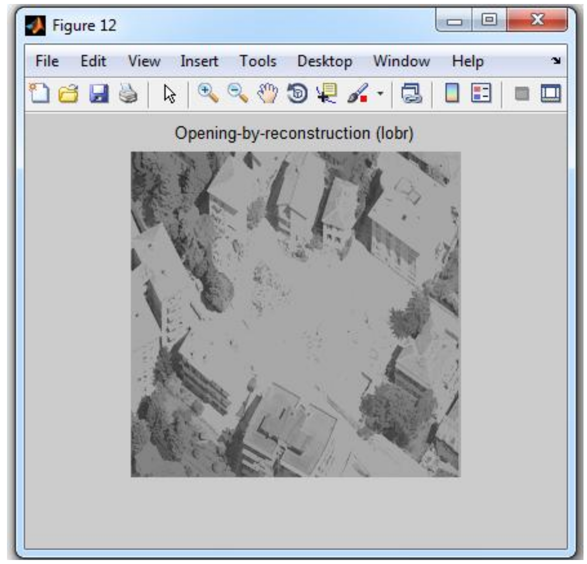

Figure.8. Fused image

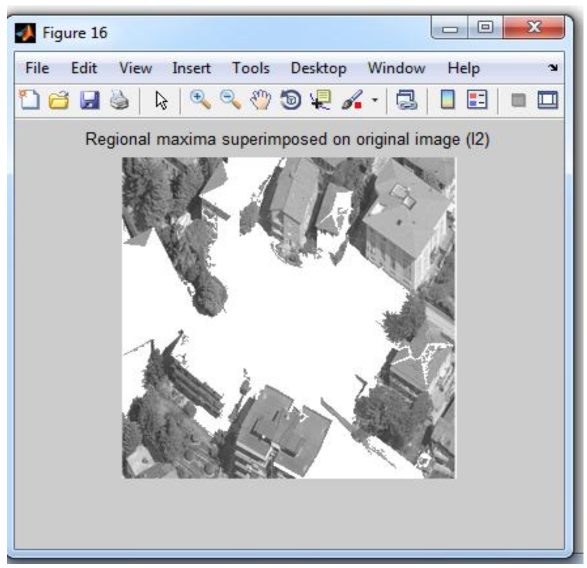

Figure.9. Super imposed image with inner information.

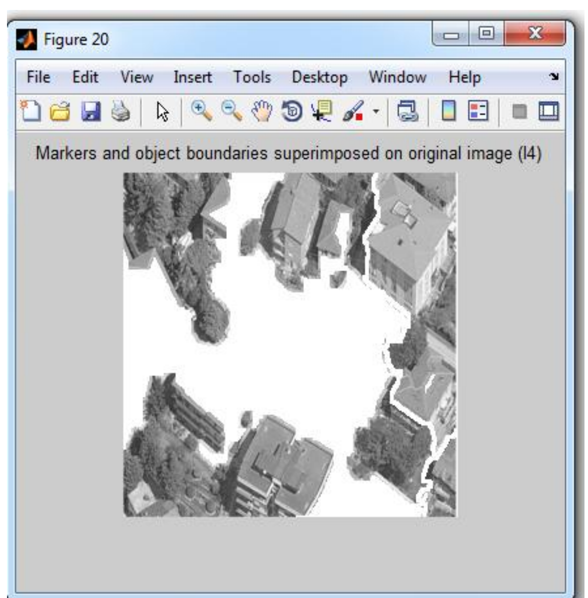

Figure.10. Super imposed image of marker and object boundaries.

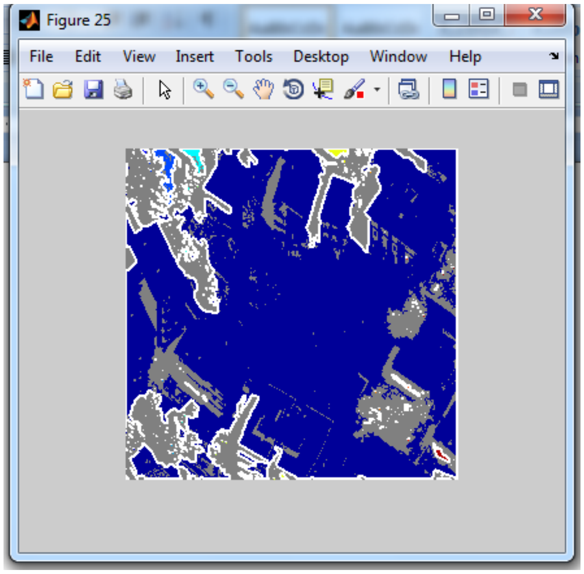

Figure.11. Change detected image

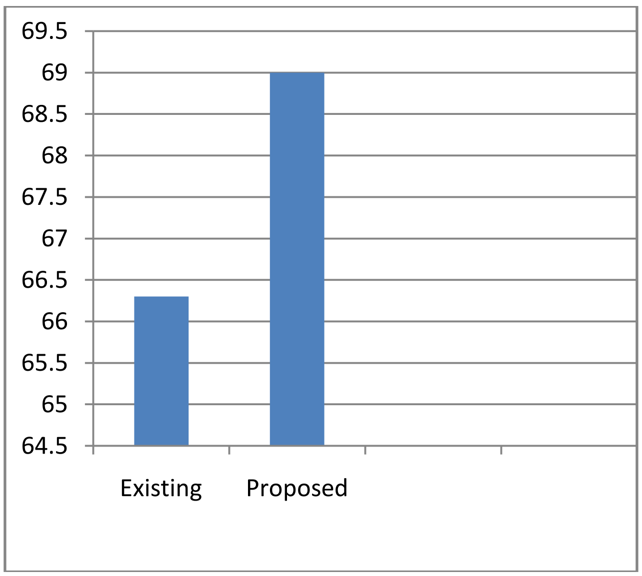

Figure.12. Performance Analysis Graph

6. REFERENCES:

[1].Amin Zehtabian, Student Member, IEEE, and Hassan Ghassemian, Senior Member, IEEE, "Automatic Object-Based Hyperspectral Image Classification Using Complex Diffusions and a New Distance Metric".

[2].A. Plaza et al., "Recent advances in techniques for hyper spectral image processing," Remote Sens. Environ., vol. 113, no. S1, pp. 110–122, Sep. 2009.

[3].M. Fauvel, Y. Tarabalka, A. Benediktsson, J. Chanussot, and J. C. Tilton, "Advances in spectral–spatial classification of hyperspectral images,". Proc. IEEE, vol. 101, no. 3, pp. 652–675, Mar. 2013.

[4].X. Kang, S. Li, and J. A. Benediktsson, "Spectral–spatial hyperspectra limage classification with edge-preserving filtering," IEEE Trans. Geosci. Remote Sens., vol. 52, no. 5, pp. 2666–2677, May 2014.

[5].Z_GIS Centre for Geoinformatics and Department for Geography and Geology, University of Salzburg, Hellbrunner Street 34, A-5020 Salzburg, Austria, "Object based image analysis for remote sensing".

[6].S. Bernabe, P. R. Marpu, A. Plaza, M. Dalla Mura, andJ. A. Benediktsson, "Spectral–spatial classification of Multispectral images using kernel feature space representation," IEEE Geosci. Remote Sens. Lett., vol. 11, no. 1, pp. 288–292, Jan. 2014.

[7].P. Ghamisi, J. A. Benediktsson, G. Cavallaro, and A. Plaza, "Automatic framework for spectral–spatial classification based on supervised feature extraction and morphological attribute profiles," IEEE J. Sel. Topics Appl.Earth Observe. Remote Sens., vol. 7, no. 6, pp. 2147–2160, Jun. 2014.

[8]. R. Gaetano, G. Masi, G. Poggi, L. Verdoliva, and G. Scarpa, "Marker controlled watershed-based segmentation of multiresolution remote sensing Images," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 6,pp. 2987–3004, Jun. 2015.

[9].P. Zhang, M. Li, Y. Wu, and H. Li, "Hierarchical conditional random fields model for semisupervised SAR image segmentation," IEEE Trans. Geosci. Remote Sens., vol. 53, no. 9, pp. 4933–4951,Sep. 2015.

[10].H. Akcay and S. Aksoy, "Automatic detection of geospatial objects using multiple hierarchical segmentations," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 7, pp. 2097–2111, Jul. 2008.

[11].Mathieu Fauvel, Yuliya Tarabalka, Member IEEE, Jo´n Atli Benediktsson, Fellow IEEE, Jocelyn Chanussot, Fellow IEEE, and James C. Tilton, Senior Member IE, "Advances in Spectral–Spatial Classification of Hyperspectral Images"

[12].M. Pedergnana, P. R. Marpu, M. Dalla Mura, J. A. Benediktsson, andL. Bruzzone, "A novel technique for optimal feature selection in attribute profiles based on genetic algorithms," IEEE Trans. Geosci. Remote Sens., vol. 51, no. 6, pp. 3514–3528, Jun. 2013.

[13].A. Zehtabian, H. Ghassemian, A. Nazari, and M. Gribaudo, "Adaptive restoration of multispectral datasets used for SVM classification," Eur. J.Remote Sens., vol. 48, pp. 183–200, Jun. 2015.

[14]. A. P. Witkin, "Scale-space filtering," in Proc. 8th Int. Joint Conf. Artif. Intell., Karlsruhe, Germany, 1983, pp. 1019–1021.

[15]. Xudong Kang, Student Member, IEEE, Shutao Li, Member, IEEE, and Jón Atli Benediktsson, Fellow, IEEE, "Spectral–Spatial Hyperspectral Image Classification With Edge-Preserving Filtering".

[16].P. Perona and J. Malik, "Scale-space and edge detection using anisotropic diffusion," IEEE Trans. Pattern Anal. Mach. Intell., vol. 12, no. 7, pp. 629–639, Jul. 1990.

[17].S. V. Forero and V.Manian, "Improving hyperspectral image classification based on graphs using spatial

preprocessing," in Proc. IEEE IGARSS, 2008, vol. 3, pp. III-656–III-659.

[18]. P. D. Long and P. T. Cat, "Image ramp edge enhancing and denoising by complex nonlinear diffusion using cellular neural network," in Proc. 7th Asian Control Conf., 2009, pp. 1509–1514.

[19].Y.Wang and R. Niu, "Hyperspectral urban remote sensing image smoothing and enhancement using forward-and-backward diffusion," in Proc.Urban Remote Sens. Event, 2009, pp. 1–5.

[20]. S. Bettahar and B. Stambouli, "An efficient PDE framework for satelliteimage classification," Revue Energies Renouvelables, vol. 13, no. 3, pp. 369–377, 2010

[21].Antonio Plaza a,□ , Jon Atli Benediktsson b, Joseph W. Boardman c, Jason Brazile d, Lorenzo Bruzzone e,Gustavo Camps-Valls f, Jocelyn Chanussot g, Mathieu Fauvel g,b, Paolo Gamba h, Anthony Gualtieri i,j,Mattia Marconcini e, James C. Tilton i, Giovanna Trianni h, "Recent advances in techniques for hyperspectral image processing".

[22].E. Nadernejad, H. Hassanpour, and H. MiarNaimi, "Image restoration using a PDE-based approach," IJE Trans. B, Appl., vol. 20, no. 3, pp. 225–236, Dec. 2007.

[23].Jose M. Leiva-Murillo, Member, IEEE, Luis Gómez-Chova, Member, IEEE, andGustavo Camps-Valls, Senior Member, IEEE, "Multitask Remote Sensing Data Classification".

[24].H. Hassanpour, A. Zehtabian, and S. J. Sadati, "Time domain signal enhancement based on an optimized singular vector denoising algorithm," Digit. Signal Process., vol. 22, no. 5, pp. 786–794, Sep. 2012.

[25].P. Ghamisi, J. A. Benediktsson, and M. O. Ulfarsson, "Spectral–spatial classification of hyperspectral images based on hidden Markov random fields," IEEE Trans. Geosci. Remote Sens., vol. 52, no. 5, pp. 2565–2574, May 2014.

[26].P. Ramzi, F. Samadzadegan, and P. Reinartz, "Classification of hyperspectral using an Ada Boost SVM technique applied on band clusters," IEEE J. Sel. Topics Appl. Earth Observe. Remote Sens., vol. 7, no. 6, pp. 2066–2079, Jun. 2013.