Identification Of The Difference Between The Images Using Segmentation Method

R.Kalai selvi[1]

[1]Research Scholar, Raja Doraisingam Govt. Arts College, Sivagangai.
(Email:tkalaiselvi86@gmail.com)

Dr.N.Sujatha[2]

[2]Assistant Professor, Department of computer science Raja Doraisingam Govt. Arts College,
Sivagangai, Tamil Nadu, India.

ABSTRACT

The satellite images were main source for the identification of the resources.The analysis of the forest resources were more helpful in the identification of the reliable sources.The differences in the region can be identified be segmenting the images and comparing the segmented portions in the images.The segmentation of the images were done based on color based clustering.The color based clustering identifies the regions in the images that are having similar colors.The clustered regions were then compared and then differences were measured.The difference regions were then compared and performance is compared.Statistical region modelling process is employed for the region based clustering in the images. The statistical region modelling make sure that the images were clustered based on the differences in the intensities in the images which is made to further enhance the performance. Finally the change percentage in the images were also measured which shows that the process can be used for calculating the remote sensing data using SAT images. The comparison of the process is employed based on the difference between the clusters in two images. The distance value is compared with the overall size of the images in order to find the change detection percentage in the image.

Keywords : Clustering, Color Masking, Edge Detection, Image segmentation, Satellite Image, SRM Algorithm.

I. INTRODUCTION

The most widely used unsupervised change detection scheme includes three fundamental steps: pre - processing, comparison and analysis.

- The *pre - processing stage* includes normalization of the available multi temporal remote sensing images (i.e., co-registration, radiometric correction, geometric correction, atmospheric correction, etc.), so that they can be used in the subsequent stages.
- In the *comparison step*, the multispectral remotely sensed images taken over the same geographical area at different times are compared using suitable mathematical operators like, single band differencing, vector differencing, rationing, etc. Change vector analysis (CVA) based difference image generation scheme is a popular technique. In the CVA - based scheme the difference image is generated by analyzing the magnitude of the spectral change vectors obtained from vector difference of each pair of corresponding pixels.
- The *analysis step* is aimed at producing the final change detection map.

II.PREPROCESSING

Image pre-processing is done prior to extraction of features from the image. The features are then extracted using suitable schemes. These features are then classified using appropriate classifying algorithm. In this paper, we discuss various image processing techniques and three feature extraction schemes that were used for our analysis. Algorithm is based on a model of image generation which captures the idea that grouping is an inference problem.

This provides us with a simple merging predicate, and a simple ordering in merges which, with high probability, both suffers only one source of error, and achieves with high probability allow error in segmentation. It can be reliably approximated by very fast segmentation algorithm, SRM, which from our experiments tends indeed to satisfy our goal of image segmentation. Experiments display the ability of the approach to cope with significant noise corruption, handle occlusions, and perform scale-sensitive segmentation's.

III.CLUSTERING

The region statistics. Moreover, we show that this statistical interpretation comes along with several implications. Firstly, one can derive extended versions of the Mumford-Shah functional including more general distribution models. Secondly, it leads to faster implementations. Finally, thanks to the analytical expression of the smooth approximation via Gaussian convolution, the coordinate descent can be replaced by a true gradient descent.

The inclusion of statistical region-based information into the deformable model is done using region descriptors, which are defined in terms of the negative algorithm of a Probability Density Function (PDF) associated to the region. The estimation of the PDF for each region, involves the definition of the features that characterize the image inside the different regions. Fig(4).

In fact, the estimated PDF can be considered as a conditional PDF P(x|f)where x is the point in the image domain and f is the vector of features used to describe the image in the estimation process.

In most previous attempts the estimation of the PDF for region descriptors are based on two main assumptions: image intensity is the most discriminant regional descriptor, and the statistics of image intensity can be described using parametric estimators of the PDF. In particular, PDFs are usually modeled from the intensity values using a Gaussian Mixture Model (GMM) with parameters estimated via the Maximum Likelihood principle.

However, we argue that the use of up to second order information could provide better approximations for the different regions as, besides intensity, local geometrical information is introduced for region characterization and therefore, improve the segmentation.

IV.SEGMENTATION

Image segmentation refers to the process of partitioning a digital image into N number of parts. The images are segmented on the basis of set of pixels or pixels in a region that are similar on the basis of some homogeneity criteria such as color, intensity or texture, which helps to locate and identify objects or boundaries in an image.

In terms of mathematical formula, Image segmentation divides a digital image f(x, y) into continuous, disconnect and non empty subsets, from these subsets higher level information can be easily extracted. Practical applications of image segmentation include object identification and recognition, facial recognition, medical image processing, criminal investigation, airport security system, satellite images, quality assurance in factories.

Due to the importance of the image segmentation, large number of algorithms has been proposed but the selection of the algorithm purely depends upon the image type and the nature of the problem.

A.SEGMENTATION BASED ON EDGE DETECTION

The intensity data of an image only provides partial and uncertainly information about the location of edges. Edge detection technique is finding pixel on the region boundary. This method attempts to resolve image segmentation by detecting the edges or pixels between different regions that have rapid transition in intensity are extracted and linked to form closed object boundaries.

The result is a binary image. One source of uncertainly comes from the existence of noise introduced in the imaging process and later in the transmission and sampling process. The other source of uncertainly comes from fact that any measurement device is imperfect and their results are only partial observation. This means that edge detection methods are generally ill-posed, i.e. they are under-constrained and so may not have unique solutions.

The easiest way to detect edges in an image is to look for places in the image where the intensity changes rapidly, using one of these criteria: Places where the first derivative of the intensity is larger in magnitude than some threshold. Places where the second derivative of the intensity has a zero crossing. Edge detection [ ] technique is one of the structural techniques of the image segmentation technique. Based on theory there are two main edge based segmentation methods- gray histogram and gradient based method [2].In the edge approach, the edges are identified first, and then they are linked together to form required boundaries.

Edge detectors have different operator for detection of edge such as soberly operator, Laplace operator, canny operator, LOG (Laplacian of Gaussian) operator and so on. Edge detection method require a higher image quality so its need to reduce or remove the noise.

B.SEGMENTATION BY SRM ALGORITHM

SRM is a recent color image segmentation technique based on region growing and merging. The method models segmentation as an inference problem, in which the image is treated as an observed instance of an unknown theoretical image, whose statistical (true) regions are to be reconstructed.

Fig2. Color Masking. The advantages of this method include its simplicity, computational efficiency, and excellent performance without the use of quantization or color space transformations. Let I be an observed image that contains |I| pixels, each of which is comprised of R, G, B color channel values belonging to the set {0, 1, …, g − 1} (where g = 256 for 24-bit RGB images with 8 bits per color channel). I is an observation of a true image I* in which pixels are perfectly represented by a family of distributions from which each of the observed color channel is sampled.

Fig3 The optimal statistical regions in I* share a homogeneity property such that inside any statistical region and given any color channel, the statistical pixels have the same expectation, whereas the expectations of adjacent statistical regions differ in at least one color channel. I is obtained from I* by sampling each statistical pixel for observed RGB values. The color channel values for every pixel in I* is replaced by a set of Q independent random variables, which take on values from (0, g/Q). It is to be noted that the Q parameter can be used to quantify the statistical complexity of I*, the generality of the model, and the statistical difficulty of the problem. Higher values of Q result in finer segmentation and thus the generation of more regions. Like other region growing algorithms, SRM is based on two major components; a merging predicate and the order followed in testing this predicate.

V.DIFFERENCE IDENTIFICATION

Farming seems to be practiced moderately, occupying 25% of the total classes. This may be due to the fact that the city is just moving away from the rather traditional setting where farming seems to form the basis for living. Apart from this, the time of the year in which the area was imaged which happens to fall could also be a major contributing factor to the observed classification, contributing to the high percentage of waste land and the low percentage of forest land.

Fig 5.Change detection analysis encompasses a broad range of methods used to identify, describe and quantity differences between images of the some scene at different times or under different conditions many of the tools can be used independently or in combination or in combination as part of a change detection analysis.

changes taking place at the texture level which preserve the mean value will not be detected by the mean ratio detector. This remark invites a more accurate analysis of the local statistics of the images to be compared. n the absence of texture, it is known that the radar intensity follows a Gamma distribution. In the presence of texture, the local statistics can deviate from the Gamma distribution.

For instance, if the texture is modeled by a Gamma distribution with a shape parameter, the resulting intensity distribution follows a K-law.

VI.CHANGE PERCENTAGE CALCULATION

Fig6.This module calculate the difference between pixels percentage. Comparing this pixels result find the change percentage calculation.

The difference image is interesting since the noise level in this type of imagery is additive and hence taking the difference between image at time t1 (denoted to as I1) and the image at time t2 (I2) gives a valid change measure. This kind of difference measure may be applied directly on the radiometrical value of the pixels.

VII.PERFORMANCE ANALYSIS

The performance of resultant image highest accuracy level. The accuracy of the process is measured by comparing the resulting on the average calculation and the difference between the data. The proposed method has much similarity with the original change percentage with the original change percentage measured from the original statistcal data. The comparision of the process can be employed based data collected.

A. METHODOLOGY

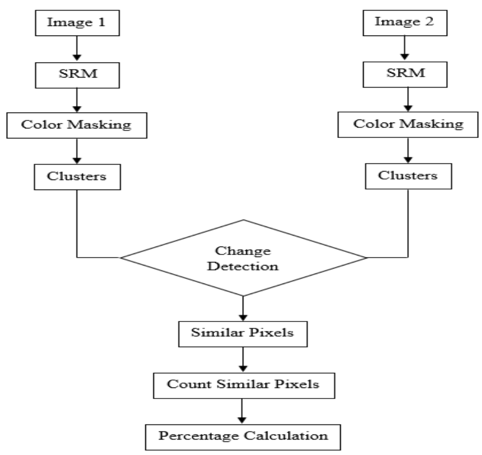


IMAGE1-1984 & IMAGE2-2014

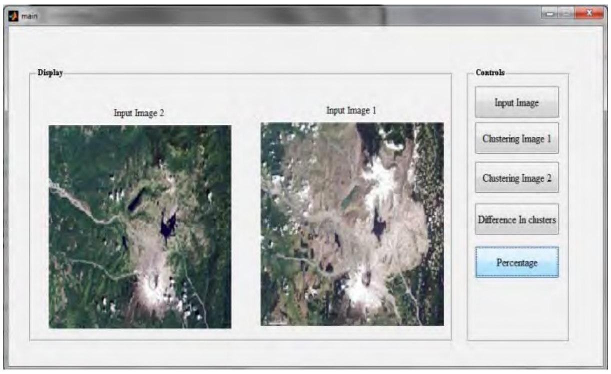


Fig1. Image1 1979 & Image2 2015 The year of change

Fig2. Color Mask in Image1 & Image2

Fig3. Labeled Mask in Image1 & Image2

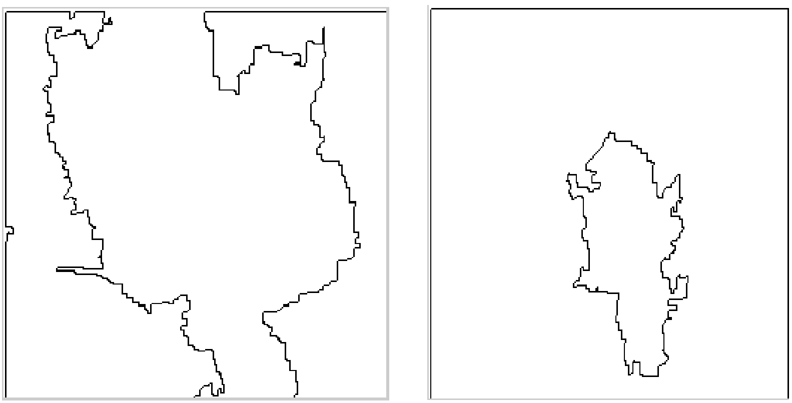


Fig4. Edge Detection in Image1 & Image2

Fig5. Change Detection in Image1 & Image2

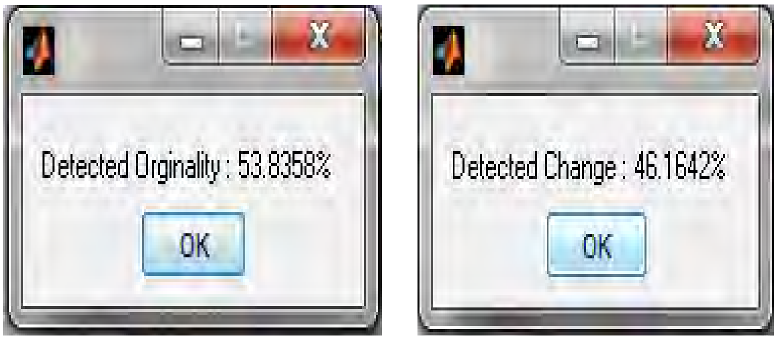


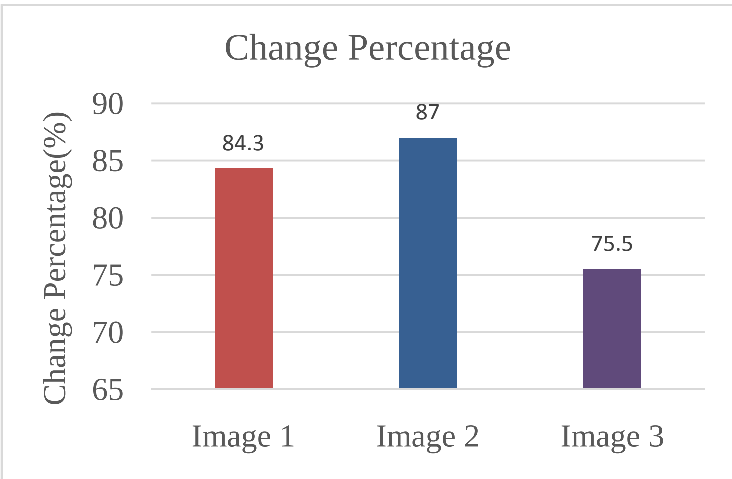
Fig6. Change Percentage in Image1 & Image2

B.TABLE

Satellite Images	Year	Change Percentage (%)
Image 1	2000 – 2002	84%
Image 2	1979 - 2015	87%
Image3	1990 – 1992	75%

A table showing the obtained Change Percentage value for existing and the proposed method for different images tested.

C.CHART



Dataset were collected from Mexico and Island of Sardinia, Italy

- Image 1 - an area of Mexico on 18th April 2000 and 20th May 2002.
- Image 2 - an area of Recovery at Mt. St. Helens
  On June17, 1979 and July 6, 2015
- Image 3 - an area of Italy in March 1990 and July 1992

MATLAB

- The name MATLAB stands for matrix laboratory.
- MATLAB is a software program that allows us to do data manipulation and visualization, image analysis, calculations, maths and programming.
- It can be used to do very simple as well as very sophisticated tasks.

Study Area

The devastation of the May 1980 eruption of Mt. St. Helens and the gradual recovery of the surrounding landscape is documented in this series of satellite images from 1979—2015.

The 1980 eruption of Mt. St. Helens — which began with a series of small earthquakes in mid-March and peaked with a cataclysmic flank collapse, avalanche, and explosion on May 18 — was not the largest nor longest-lasting eruption in the mountain's recent history. But as the first eruption in the continental United States during the era of modern scientific observation, it was uniquely significant.

In the decades since the eruption, Mt. St. Helens has given scientists an unprecedented opportunity to witness the intricate steps through which life reclaims a devastated landscape. The scale of the eruption and the beginning of reclamation in the Mt. St. Helens blast zone are documented in this series of images captured by NASA's Landsat series of satellites between 1979 and 2015. The older images are false-color (vegetation is red) because earlier Landsat satellites could not "see" blue light. To make a photo-like satellite image, you need red, green, and blue wavelengths of light.

The May 18 eruption began with an earthquake that caused the northern flank of the mountain to collapse, producing the largest landslide in recorded history. The avalanche buried 14 miles (23 kilometers) of the North Fork Toutle River with an average of 150 feet (46 meters)—but in places up to 600 feet (180 meters)—of rocks, dirt, and trees. In subsequent years, the river re-carved a shallow, braided path through the buried valley.

When the mountain collapsed, it was like uncorking a bottle of champagne: hot rocks, ash, gas, and steam exploded upward and outward to the north. The outward blast spread volcanic debris (gray in the images) over 230 square miles (600 square kilometers) and blew down 4 billion board-feet of timber. A raft of dead trees drifts around Spirit Lake throughout the image series. All around the southern half of the mountain, volcanic mudflows (lahars) poured down rivers and gullies.

Not surprisingly, the first noticeable recovery (late 1980s) takes place in the north western quadrant of the blast zone, farthest from the volcano. It is another decade (late 1990s) before the terrain east of Spirit Lake is considerably greener. By the end of the series, the only area (beyond the slopes of the mountain itself) that remains conspicuously bare at the scale of these images is the Pumice Plain.

Ground surveys, however, have found even this seemingly barren area is coming back to life: the first plant to re-appear was a prairie lupine, which can take nitrogen—a critical plant nutrient—straight from the air rather than from the soil. These small wildflowers attract insects and herbivores and they catch blowing leaves and other organic matter. The dead plants and insects, the windblown organic matter, and the droppings of herbivores slowly create pockets of soil on the volcanic deposits. This process is underway on the Pumice Plain, even though it is not yet visible from space.

VIII.CONCLUSION

Change detection may be done either in supervised or in unsupervised manner. Relevance of unsupervised techniques is more than supervised ones for this problem as in most of the cases we do not have the ground truth information. We can view unsupervised change detection problem as a clustering problem where the task is to discriminate the data into two groups changed and unchanged Before performing the change detection between two multi- temporal images, a certain degree of pre-processing is needed because of co-registration error, radiometric and geometric errors. After pre-processing, the multitemporal images are taken as input and compared pixel by pixel to generate another image, called the difference image (DI), using different spectral bands.

IX.REFERENCES

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