Multi-temporal Satellite Image Analysis Using Unsupervised Techniques

C.S. Arvind[1], Ashoka Vanjare[2], S.N. Omkar[3,*] J. Senthilnath[2], V. Mani[2], and P.G. Diwakar[3]

[1] Telibrahma Convergent Communication Pvt Limited, Bangalore
[2] Department of Aerospace Engineering, Indian Institute of Science, Bangalore
[3] Director, Earth Observation System, Indian Space Research Organisation, Bangalore
csarvind2000@gmail.com, omkar@aero.iisc.ernet.in

Abstract. This paper presents flood assessment using non-parametric techniques for multi-temporal time series MODIS (Moderate Resolution Imaging Spectro radiometer) satellite images. The unsupervised methods like mean shift algorithm and median cut are used for automatic extraction of water pixel from the image. The extracted results presents a comparative study of unsupervised image segmentation methods. The performance evaluation indices like root mean square error and receiver operating characteristics are used to study algorithm performance. The result reported in this paper provides useful information for multi-temporal time series image analysis which can be used for current and future research.

Keywords: MODIS satellite images, unsupervised image segmentation techniques, performance evaluation indices.

1 Introduction

Multi-temporal time series analysis of satellite images plays an important role to determine the land surface change detection [1]. The change detection study helps in surface analysis [2]. The NASA's MODIS satellite sensor has been considered as potential for multi-temporal image analysis because due to regular availability and open source. MODIS data provides excellent land and water discrimination along with wide area coverage [3]. The features like river, road network and vegetation are to be extracted and analysed, so this helps researchers to develop tools for analysing the surface changes occurred between different dates of imaging and it is useful in hydrological application such as flood assessment [4,5].

The researchers are continuously developing both supervised and unsupervised classification techniques for flood assessment. Rajiv Kumar Nath et al. [6] has worked on different remote sense data for flood assessment. The researchers have used supervised methods for flood application but performance limitation exists due to the extent and accuracy of the available and collected ground truth data. So in this context, several researchers are working towards unsupervised techniques.

* Corresponding author.

N. Meghanathan et al. (Eds.): Advances in Computing & Inform. Technology, AISC 177, pp. 757–765.
springerlink.com © Springer-Verlag Berlin Heidelberg 2013

R. Brakenridge et al. [3] have used unsupervised ISODATA method for flood risk analysis. An unsupervised or clustering technique automatically assigns each pixel to respective spectral clusters without manual intervention. It has a property of grouping individuals in the population and grouping of individuals is an outcome of partitioning of the data sets (i.e. mutually non-overlapping groups of the input datasets). But only a few unsupervised image segmentation methods like self organizing and K-means [] have been explored in flood assessment applications.

In this paper, unsupervised image segmentation methods like mean shift and median cut are used to extract non-linear features (river networks) from MODIS band-2 image [3] and the obtained results are verified with the ground truth data. Our investigation is in using unsupervised methods for low resolution MODIS satellite images in identifying water image pixels and thus identifying flooded places from satellite image. The results of image segmentation helps in separating water and non-water bodies so it will be useful in identifying flooded and non-flooded places from the extracted image.

Organization of the paper is as follows, in section -2, the study area description is presented; section-3 presents problem formulation, section-4 image processing methods are given. Section-5 gives the results and discussions. In the section-6, conclusion of this paper is presented.

2 Study Area

In this section, the study area chosen is Krishna and Tungabhadra rivers regions which flow in south India [] and area coverage is about 3, 13,568 sq mtrs2. During September-2009 rivers received heavy rainfall which caused river flooding so we have used MODIS (MOD09Q1) Terra Surface Reflectance 8-Day L3 Global 250 mtrs2 satellite images [3] because of wide coverage. Three different dated images like before (march-2009), during (September-2009) and after (November-2009) are considered in this study.

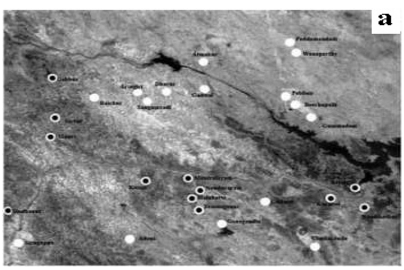

Fig. 1. Shows map of flooded (indicated by black dots within white dots) and non flooded places (indicated by white dots) which are used for flood assessment study.

3 Problem Formulation for Image Segmentation

This section explains problem formation for image segmentation. Segmentation problem involves the partitioning of a given image into a number of homogeneous segments and finally union of two neighbouring segments yields heterogeneous segments.

$$L = \{0, 1, 2, 3 \ldots\ldots\ldots\ldots L_m\}$$

be the set of the intensities of the image and

$$N_{mxn} = \{q = (z, w) \in S : | x - z | \le \lfloor m/2 \rfloor, y - w \le \lfloor n/2 \rfloor \tag{1}$$

$$S = \{(x, y)\} \quad 1 \le x \le N_c \quad 1 \le y \le N_r \tag{2}$$

are spatial co-ordinates of the pixel in N_r rows and N_c column image. The mxn neighbourhood of the pixel p=(x, y) over the S is given by

$$N_{mxn} = \{q = (z, w) \in S : | x - z | \le \lfloor m/2 \rfloor, y - w \le \lfloor n/2 \rfloor\} \tag{3}$$

Where: m and n are odd and $\lfloor . \rfloor$ Denotes the largest integer not greater that its argument.

The partition of an image is given by S

$\Delta_{k*}(S) = \{R_1, R_2 \ldots . R_{k*}\}$ for the natural number K^* such that

$$S = \bigcup_{k=1}^{k*} R_k$$

$$R_i \cap R_j = \varnothing$$

$\forall i, j \in \{i, 2 \ldots\ldots K*\}$ and $R_i \cap R_j = \varnothing \; \forall i, j \in \{i, 2 \ldots\ldots K*\} \; for i \ne j$

$for \cdot i \ne j$

$R_i \forall i \in \{1, 2 \ldots . K*\}$

$R_i \forall i \in \{1, 2 \ldots . K*\}$ is connected component.

$X(p)=C_m$ is a constant and C_m and C_n are not equal if R_m and R_n are adjacent.

The two regions are adjacent if they share a common boundary, i.e. if there is at least one pixel in one region, such that is 3x3 neighbourhoods contains at least one pixel belonging to the other region. According to the problem formulation the output of the image segmentation is represented by $\Delta_{k*}(S)$ and it is assumed that small pixel neighbourhoods contain either one (homogeneous) or two (heterogeneous) regions.

4 Image Processing Methods

Image filtering is applied to remove the clutters from the image. This noise reduction helps in preserving elongated river networks and thus helps to extract river features and group the similar water image pixels. Progressive median filter [7] is used to remove speckles.

4.1 Image Segmentation Methodology

Image segmentation is used to extract river networks by grouping the similar water image pixels. So to achieve this we have used non parametric mean shift and median cut methods.

Mean shift method (MS): MS is a popular non-parametric method based on kernel density estimation [8]. Initially both filtering and segmentation method is carried out on the image. This helps for identifying non-linear river network feature in the image. Initially arbitrary point is chosen in the feature space and move towards locally maximal density. The mean is shifted based on the weighted average and it is iteratively done to identify the similar pixels. Gaussian kernel is used for local point of convergence. Mean shift is carried-out in the two steps: a) Filtering and b) Segmentation.

In image filtering, the kernel density estimation is calculated using the similar image pixels which are given by:

$$\hat{f}(X) = \frac{1}{n h_i^d} \sum_{i=1}^{n} k \, \| \frac{(X - X_i)}{h_i} \|^2 \quad \ldots \tag{4}$$

The data points X_i, i=1, 2, 3.....n are in the d-dimensional space R^d, the kernel density estimation at the location x can is calculated using the bandwidth parameter h_i (where $h_i>0$). The kernel k is a spherically symmetrical kernel bounded which satisfies

$$K(x) = c_{k,d} k(\| x \|^2) > 0 where : \| x \| \leq 1 \tag{5}$$

where: The normalization constant $c_{k,d}$ definitely makes the k(x) integrates to 1 and k(x) is called the kernel profile. By assuming derivative of the kernel profile k(x) existed and g(x) =-k'(x) as the kernel profile.

The kernel G(x) is defined as $G(x) = c_{k,d} k(\| x \|^2)$

The gradient of equation is used to prove the property of kernel profile;

$$m_G(X) = c \frac{\nabla \hat{f}_k(x)}{\hat{f}(x)} \tag{6}$$

$where : m_G(X)$ is the mean shift vector, C is a positive constant and which gives the location x. Mean shift vector computed with kernel G is proportional to the normalized density gradient estimate obtained with the kernel K. The mean shift vector is defined as:

$$m_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i g\left(\frac{\| x - x_i \|^2}{h}\right)}{\sum_{i=1}^{n} g\left(\frac{\| x - x_i \|^2}{h}\right)} - x \tag{7}$$

Mean shift vector thus points toward the direction of maximum increase in the density. The mean shift procedure is obtained by successive computation of the mean shift vector and translation of the kernel G(x) by the mean shift vector. Finally, it converges at a nearby point where the estimate has zero gradients and iterative equation is given by:

$$y_{i+1} = \frac{\sum_{i=1}^{n} x_i g(\| \frac{x - x_i}{h} \|^2)}{\sum_{i=1}^{n} g(\| \frac{x - x_i}{h} \|^2)} \quad (8)$$
$$j = 1, 2, 3 \ldots n$$

Initial position of the kernel is chosen as one of the data point's x_i. Usually, the local maxima / modes the density is the convergence points of the iterative procedure. The mean shift technique is based on unsupervised clustering. It is unsupervised as there is no information indicating the correct group, for example, for most image extraction problems there are no pixels marked as being part of a specific object. It iteratively shifts the mean of a pixel resulting in the pixel being drawn to a local point of convergence.

MEDIANCUT (MC): Median cut is a segmentation algorithm based on colour quantisation [9]. The colour quantization is a technique in computer graphics in order to find the best colour palette with the least differences between the original image and the quantized one. The colour quantisation is used as colour clustering algorithm of the satellite images in this paper. Pre-quantization precision, calculating the cutting position based on variance and searching reversely the colormap, significantly promotes both the speed and quality of the colour quantization. The median cut quantization algorithm is developed by Heckbert [9] and it is based on colour distribution of original image. The basic idea is to let each entry in the representative color set, Y, represent approximately the same number of pixels in the original image. Median Cut is carried out in three steps: a) representing image as cube of colours, b) sorting along axis and c) splitting based on median (carry out iteratively).

```
Median cut(image(x,y), level)
  {
        Image(x,y) : is the input image
        Level: box size (4, 6, 12, 32)
       //representing image as cube
       //create a colormap using image cube
      //sort along axis
     // splitting based on median (as reference)
     // adaptive partitioning
     //merging the similar groups
   }
```

Median cut algorithm constructs colour histogram based on the original image. The algorithm mainly performs a color reduction which reduces the number of possible of unique colors so storage and computation time is reduced. From the color histogram list L is constructed from non-zero entries. The RBG color value and corresponding histogram count is determined. Smallest box and largest box determined and sorted from smallest to largest using component as the sort key. The ordered list is spitted at based on median image pixels in order to create two sub lists. The entry is traversed until k such lists are formed. For each iteration, one of the previously constructed sub lists is selected for list splitting and the list is chosen with most pixels. Finally, representative set is created by computing the average color of each list.

5 Results and Discussions

In this section, two segmentation methods are used to extract the river network across the Krishna River from the March 2009 image and November image as shown in Fig. 3 and 4. The extracted region is overlaid on original image and verified with ground truth data. From figure-3, the extraction of the river network's can be seen and the same region is overlaid on the original image to verify the precision of extraction [11, 12] and it is measured using RMSE value.

We have used Root means square error (RMSE) parameter is used to verify the extracted image with ground truth image. RMSE is the statistical measure for varying magnitude quantity. The value near to zero is better extraction result.

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N} E_k^2} \tag{9}$$

Where: E_k is the difference between the ground truth data and algorithmically segmented image and N is the number of the pixels in the image

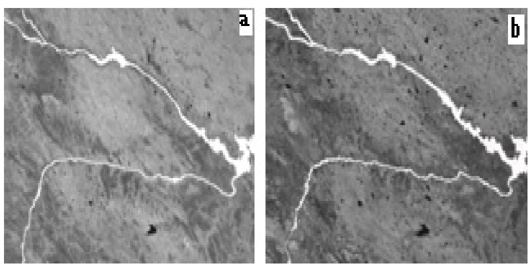

Fig. 2. Ground truth image for the a) March 2009 and b) November 2009 month

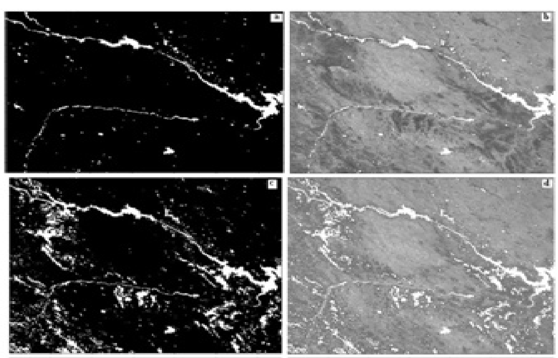

Fig. 3. (a) and (b) before flooded image March month using mean sift method for extraction and overlaying Fig-3.(c) and (d) median cut extraction and overlaid.

RMSE value between mean shift extracted March month image and ground truth image is 0.26.

RMSE between median cut extracted March month image and ground truth image is 0.37.

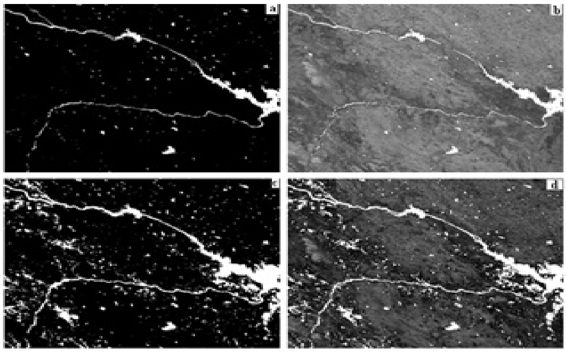

Fig. 4. (a) and (b) after flooded image November month using mean sift method for extraction and overlaying Fig-4.(c) and (d) median cut extraction and overlaid.

For the month of November month, mean sift extracted and ground truth is 0.27 and Median cut extracted and ground truth is 0.38

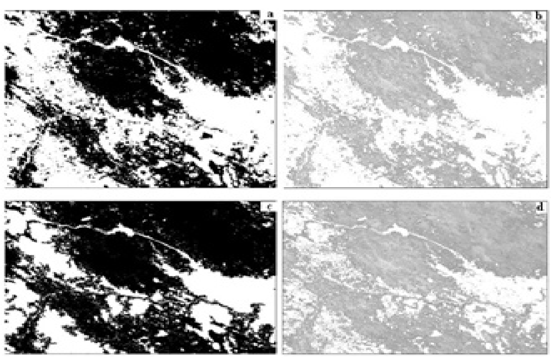

Fig. 5. (a) and (b) During flooded image September month using mean sift method for extraction and overlaying Fig-4.(c) and (d) median cut extraction and overlaid.

For the month of September 2009 image, mean shift and median cut are applied and extracted. But for during flooded image the extraction is verified using Receiver of characteristic parameters (ROC).

Receiver Operating Characteristics: ROC [10] consists of parameters like TP, TN, FP and FN which are calculated for the during flooded images for validation of the algorithmic performance [10].

In, during flooded images the ROC parameter is applied to locate the flooded places and distinguish flooded places from non-flooded places:

(a) Sensitivity or True Positive (TP) - A place which is positive according to the ground truth data and also according to the computed result is a True Positive (TP).
(b) Specificity or True Negative (TN) - A place which is negative according to the ground truth data and also according to the computed result is a True Negative (TN).
(c) False Positive (FP) - While the place which is positive according to the computed results but negative according to the ground truth data is a False Positive (FP).
(d) False negative (FN) - While the place which is negative according to the computed result but positive according to the ground truth data is a False Negative (FN).
The total number of flooded places – 12, Non-flooded places-16 and the total places verified -28.

These parameters are very helpful in order to determine the comparison of algorithms performance which is shown in the below table-1.

Table 1. Shows ROC parameter applied to September 2009 image in order to determine the flooded and non-flooded places

	ROC PARAMETERS	
Mean shift	TP	11
	TN	11
	FP	3
	FN	3
	ROC PARAMETERS	
Median cut	TP	11
	TN	12
	FP	3
	FN	2

6 Conclusion

We have used ROC parameter in order to identify the flooded cities. So from the table, mean shift performs better than median cut in identified the flooded places correctly. Also RMSE value of mean shift segmentation is less than median cut which proves a better extraction algorithm.

Acknowledgments. This work is supported by the Space Technology Cell, Indian Institute of Science and Indian Space Research Organization grant.

References

[1] Walkey, J.A.: Development of a change detection tool for image analysis. MS thesis. University of Wisconsin-Madison (1997)

[2] Bhavsar, P.D.: Review of remote sensing applications in hydrology and water resources management in India. Advances in Space Research 4(11), 193–200 (1984)

[3] Brakenridge, R., Anderson, E.: Modis-based flood detection, mapping and measurement: the potential for operational hydrological applications. NATO Science Series, 1, Volume 72, Transboundary Floods: Reducing Risks through Flood Management, 1, pp. 1-12

[4] Veronique, P., Zhou, Z., Songde, M.A.: A Framework for flood assessment using satellite images. IEEE International Geoscience and Remote Sensing, IGARSS 2, 822–824 (1998)

[5] Michael, S.A.: Multi-temporal Remote Sensing for mapping and monitoring Floods an approach involves validation of the KAFRIBA. Kafueu Flats. Zimba, Master Thesis (2007)

[6] Nath, R.K., Deb, S.K.: Water-Body Area Extraction from High Resolution Satellite Images-An Introduction, Review, and Comparison. International Journal of Image Processing (IJIP) 3(6), 265–384 (2010)

[7] Wang, Z., Zhang, D.: Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images. IEEE Transactions on Circuits and Systems—ii: Analog and Digital Signal Processing 46(1) (January 1999)

[8] Comaniciu, D., Meer, P.: Mean shift analysis and applications. In: The Proceedings of the Seventh IEEE International Conference on Computer Vision (1999)

[9] Heckbert, P.: Color image quantization for frame buffer display. In: Proceeding SIGGRAPH 1982 Proceedings of the 9th Annual Conference on Computer Graphics and Interactive Techniques. ACM SIGGRAPH Computer Graphics, vol. (16-3) (July 1982)

[10] Fawcett, T.: An introduction to ROC analysis. Pattern Recognition Letters 27, 861–874 (2006)

[11] Gonzalez, R.C., Woods, R.E.: Digital Image Processing, 3rd edn. Prentice Hall, Upper Saddle River

[12] Lillesand, T., Kiefer, R.W., Chipman, J.: Remote Sensing and Image Interpretation