IET Chennai and Vivekanandha College of Technology for women, Third International Conference on Sustainable Energy and Intelligent System (SEISCON 2012), VCTW, Tiruchengode, Tamilnadu, India on 27-29 December, 2012.

Assessment of Sparse Forest and Fire Detection using Threshold Watershed Algorithm

E. Menaka*, Dr. S. Suresh Kumar, P. Parameshwari***

*Department of Information Technology, Vivekananda College of Engineering for Women, Tiruchengode, Tamilnadu, INDIA.

**Principal,Vivekanandha College of Technology for Women, Tiruchengode, Tamilnadu, INDIA.

Email: menakaparthi80@gmail.com, nice.ssk@gmail.com

Keywords: *Watershed algorithm, Threshold watershed algorithm, Forest fire, Remote sensing.*

Abstract: *Fire, a natural disaster, has significant effects on ecosystems and plays a major role in deforestation, and it is a major source of trace gases, aerosol etc,. Remote sensing is a valuable data source to investigate different phases of fire management. Monitoring and management of forest fires is very important in tropical countries like India where 55 percent of the total forest covers is prone to fires annually causing adverse ecological, economic and social impacts. Studies on the impacts of tropical wildfires on the environment indicated Satellite remote sensing plays a key role in estimating loss of the forest cover and land cover change. in the existing watershed algorithm it encounters many problems such as over segmentation, poor detection of segmented areas. In the proposed system first compare pixel values with different threshold and convert pixels as dry. Apply watershed algorithm for the modified data. It is able to provide the information about sparse and high dry regions accurately and up-to-date, over wide areas, and repeatedly over the time.*

1. Introduction

Global forests cover about 33 million km2, with about one-third of that area classified as humid tropical forest; total gross forest cover loss (GFCL) during 2000–2005 was about 1 million km2, with about 27% of that loss occurring in humid tropical forests[1]. Remote sensing methods have been applied over a number of regions worldwide to detect and monitor forest fires. Monitoring fire and smoke simultaneously by remote sensing was suggested by[2]. The current satellite-based strategies for large-area burn assessment may be grouped into two categories: active fire (hotspot) detection and post-fire burn detection[3]. Fire influences global changes and tropical ecosystems through its connection to land-cover dynamics, atmospheric composition, and the global carbon cycle[4].

In India there is no comprehensive data to indicate the loss to forests in terms of area burned, values, and volume and regeneration damaged by fire[8]. The available forest fire statistics are not reliable because they under estimate fire numbers and area burned. The reason behind this is attributed to the fear of accountability. However, Forest Survey of India in a country-wide study in 1995 estimated that about 1.45 million hectares of forest are affected by fire annually. According to an assessment of the Forest Protection Division of the Ministry of Environment and Forests, Government of India, 3.73 million hectares of forests are affected by fires; annually in India.

The last few decades, however, have brought a significant increase in wild-fire activities in many areas of the world[5,6]. According to[7], every year fires affect an estimated 350 million hectares of land. These fires damage property and livelihoods and frequently result in loss of life. Fires in vegetation, forests, woodlands, and rangelands are a major and continuing threat to human life, health and livelihoods, and also to economic development and the environment.

One of the main reason for forest degradation is forest fire. Recently the forest fire was occurred in india on August 13, 2012, which was noticed near China Mayilaar on August 11, 2012, spread rapidly with a gusty wind assisting the flames to destroy dry bushes grown on three hectares at Mudanthurai area and another five hectares in Papanasam area. So the forest fire prevention is necessary to avoid majority of the forest degradation. The forest degradation results in many environmental disasters such as ozone depletion, poor rainfall, global warming etc,. Many existing techniques help to prevent the forest fire but no efficient forest fire detection techniques are rapid. So the research on this area is widely developing.

Land use and land cover change in the tropics has impacts on ecosystem, carbon stocks and carbon and energy fluxes. It become a focus of international attention through the United Nations Framework Convention on Climate Change program in reduced emissions from deforestation and forest degradation. According to[13], every year fires affect an estimated 350 million hectares of land. These fires damage property and livelihoods and frequently result in loss of life. Fires in vegetation, forests, woodlands, and rangelands are a major and continuing threat to human life, health and livelihoods, and also to economic development and the environment.

In this paper, the algorithm is used to find the dry areas based on the threshold of the image. The threshold helps to find the contrast image which is used to get the accurate value. Image thresholding is a pixel based technique in which an image is turned into a binary image in such a way that the objects of interest are separated from the background. The selection of an appropriate threshold value is usually based on image known properties and the background. The contrast between the objects may be poor and the illumination conditions may vary and cause artefacts that make the determination of appropriate threshold difficult.

Table 1: Survey of forest fire

Year	Place	Area Affected (in Sq.Km)	People Affected by Fire
1871	Peshtigo, Wisconsin	2,000 square miles	2,300
1943	Hamburg, Germany	3.2 square miles	21,000
1945	Dresden, Germany	4.6 square miles	135,000
1987	Argentina	-	1,52,752
1992	Nepal	-	50,000
1994	Indonesia	-	30,00,000
1998	Russia	-	1,00,683
2003	Portugal	-	1,50,000
2007	Macedonia	-	10,00,000
2007	United States	-	6,40,064
2007	Paraguay	-	1,25,000
2010	Russia	10000 ha	25,000

2. Literature Survey

In the image analysis and pattern recognition literature, there has been a great development of new methods for image labeling in recent years (image segmentation, clustering, and classification methods are identified as image-labeling algorithms). Unfortunately, owing to their functional, operational, and computational limitations, many labeling techniques, both supervised and unsupervised, have had a minor impact on their potential field of application.

The application of remote sensing is at present a significant method for forest fires monitoring[9], particularly in vast and remote areas. A thorough review of hotspot detection algorithms is presented in[10]. The AVHRR fire detection algorithm used in FireM3[11,12] was developed and tested specifically for boreal forest fires. More than 50% of small fires are undetected from MODIS in Brazil, Africa, and Eurasia[13–16]. In the U.S., the probability of small fire events undetected is more than 50% from the combination of Terra and Aqua MODIS (burned area < 1.05 km2), from Aqua MODIS (burned area < 1.95 km2), and from Terra MODIS(burned area < 3.34 km2) separately[17]. The detection rate varies with time period and location of samples[17].A new robust clustering algorithm called Detect Forest Fire using K Mediods[18] algorithm.

3. Study Area

3.1 Data Set

In the paper we use GeoEye-1's unsurpassed panchromatic image resolution of .41 meters of an object the size of home plate on a baseball field. Once a panchromatic image is collected by GeoEye-1, it must be resampled to .500-meter resolution according to our current operating license. After a multispectral image is collected at 500 feet resolution by GeoEye-1, it may be sharpened using information from the panchromatic mode. So that the final image is full-color with .50-meter resolution. TamilNadu State located in the south-eastern region of India has an area of 130,058 km21 with a population of approximately 62,405,679 people. Its population density is 480 people\km23, making it one of the most densely populated states. Its western region is mountainous due to the Western Ghats mountain range, whereas in the eastern region, plains stretch towards the Bay of Bengal. The climate in the western mountainous belt averages an annual temperature ranging from 20o to 24oC, while the plains area in the eastern region is semitropical and hot throughout the year with temperatures of around 30oC. The average annual rainfall is 925 mm. The rainy season is from October to December. It is affected by the north-eastern monsoons. Tamilnadu includes a Recorded Forest Area of 22.6 lakh ha. Covering 17.4% of geographic area of the State. However area under forest cover according to FSI is only 17.07 lakh ha covering 13.13% of the Geographic Area. Tropical dry Deciduous Forest covers an area of 12.23lakh ha constituting 54.30%, Tropical Thorn Forest covers an area of 5 lakh ha constituting 22.10%, Tropical Moist Deciduous Forest covers an area of 2.60 lakh ha constituting a percentage of 11.10%. The Biodiversity rich forest types are the Tropical Wet Evergreen Forest covering an area of 0.60 lakh ha constituting 2.67%,

Tropical Semi Evergreen Forest covering an area of 0.23 lakh ha constituting 1.01%, Subtropical Broad leaved Hill Forest covers an area of 1.14 lakh ha constituting 5.04%, the Tropical Dry Evergreen Forest which is a unique type of Tamil Nadu covers an area of 0.26 lakh ha constituting 1.16%, the mangrove forest covers an area of approximately 0.23 lakh ha constituting 1.01%. in this paper we applied sathyamangalam forest image.

4. Proposed System

The pre-fire scenario needs inputs on effective preparations and planning for managing and combating the fire. This process might stands at understanding of fire proneness / vulnerability and forest fire spread potential. These two parameters together reflect in the Fire Danger Rating (FDR). In this proposed method, the high parched area is pointed out for pre-fire precautions.

4.1 Watershed Algorithm

The watershed method was originally developed by Lantujeoul and is extensively described together with its many applications by Beucher and Meyer. Since its original development with gray-scale images it has been extended to a computationally efficient form (using FIFO queues) and applied to color images. The watershed segmentation techniques are one of the most advanced tools offered by image processing for segmentation of images. A recent and most comprehensive review of various watershed algorithms is presented and it has various drawbacks.

Some important drawbacks also exist, and they have been widely treated in the related literature. Among them the most important are as follows.

- **Over segmentation:** From the conclusion of the watershed algorithm it results as segment the image as a very small area. This is not useful for most of the application. So the reduction of small region is essential in many applications. Thus the proposed threshold watershed algorithm provides the exact segmentation of the image. It results in high accuracy of the image processing.
- **Sensitivity to noise:** To achieve high accuracy in the image processing result the noise should be removed. The actual watershed algorithm is very sensitive to noise. Te noise such as clouds, mist etc., can change the result dramatically. This will result in poor image analysis. So, the filters should be used to eliminate the noise by estimating the gradient. Anisotropic filters have been used to minimize this problem [21], [22].
- **Poor detection of significant areas with low contrast boundaries:** If the signal to noise ratio is not high enough at the contour of interest, the watershed transform will be unable to detect it accurately. Furthermore, the watershed transform naturally detects the contours with higher value between markers, which are not always the contours of interest. A clear example is white matter-gray matter surface detection, where the proximity of other, higher contrast surfaces such as gray matter-CSF or CSF-bone will make the task difficult for the plain watershed transform.
- **Poor detection of thin structures:** When the watershed transform is applied on the gradient image, the smoothing associated with gradient estimation, together with usual approach of storing gradient values only at the image pixel positions rather than with sub-pixel accuracy, make it difficult to detect thin catchment basin areas. Often this is critical for successful segmentation of medical images.



Fig. 1: Watershed with thin structures.

The watershed transform presents some advantages.

- The watershed lines always correspond to the most significant edges between the markers. So this technique is not affected by lower-contrast edges, due to noise, that could produce local minima and, thus, erroneous results, in energy minimization methods.
- Even if there are no strong edges between the markers, the watershed transform always detects a contour in the area. This contour will be located on the pixels with higher contrast.

The unions of all the regions form the entire image region.

4.2 Threshold Watershed Algorithm

The Threshold watershed algorithm is mainly used to detect the dry areas. The modified watershed algorithm detects the dry areas for the prevention of forest fire. It helps to preserve forest and avoids deforestation. In the forest the forest fire area are marked as red based on the evaluation of the pixels in the image.

To improve the image contrast the threshold level of the image is fixed. It helps to find the dense forest so it will be easy to identify the dry area.

The main advantage of the threshold watershed algorithm is exact segmentation of the dry area whereas in the watershed algorithm it is not possible. So it results in poor detection of the dry areas in the forest. But in the threshold watershed algorithm the it produces the best result then the actual watershed algorithm.

The threshold watershed algorithm works as follows:

- Read the satellite image
- Preprocess the image



Fig. 2: Original Image

- Find the different threshold value for the image, based on the image quality and characteristics.

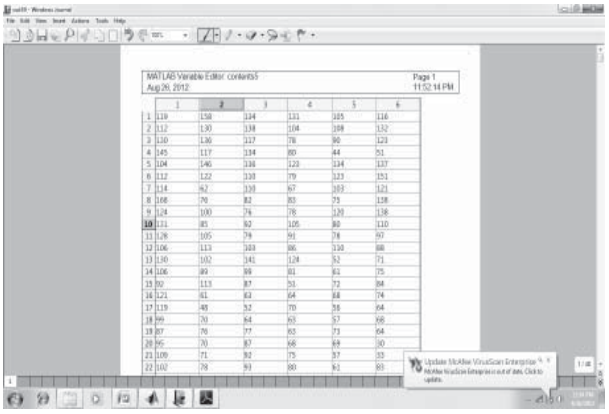


Fig. 3: Image Pixel Value

- Compare image pixel value with threshold, if it is greater than the threshold; assign the region as dry.

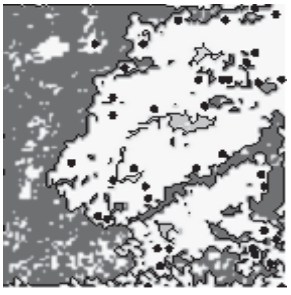


Fig. 4: Threshold Image

- Apply watershed for the above image.



Fig. 5: Output of Threshold Watershed Segmentation

- Finally compare the segmented region of threshold watershed with watershed algorithm.

The proposed method gives better solution than existing watershed algorithm which is best suitable for dry forest segmentation.

5. Expremental Result

Columns (a) and (b) in Fig. 2 show different sets of two satellite images as the input images and are individually used in our simulation experiments. Column (a) and (b) of Fig. 3 presents the processed image of dry pixel of each experiment. Column (a) and (b) of Fig. 4 presents the existing watershed algorithm result with over-segmentation. Column (a) and (b) of Fig. 5 shows the Threshold watershed algorithm result with the exact dry region segmentation of the forest area.

6. Conclusion

In the proposed system the accuracy of detection of sparse forest is very high when compared to the existing may algorithms. Due to the robustness and the accuracy of the proposed system it helps to detect the forest fire region from sparse region very easily. Using this algorithm, the Forest Fire Management (FFM) can possible to decrease the forest fire in all types of the forest. In the proposed system where the major disadvantage of the existing system i.e, over segmentation has been avoided and accuracy of the result. In the future the unsupervised detection of forest fire evaluation will be developing. It helps to the environment scientist easy to evaluate the forest fire and dry areas.



Fig. 6(a): Original Image



Fig. 6(b): Original Image

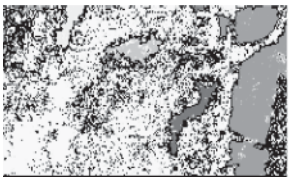


Fig. 7(a): Processed image of dry pixe

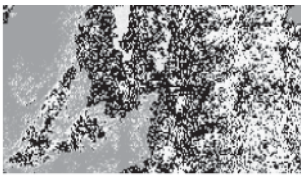


Fig. 7(b): Processed image of dry pixe

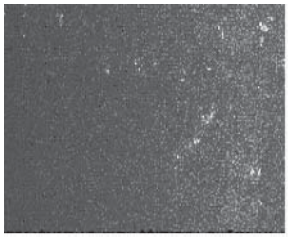


Fig. 8(a):Result of watershed



Fig. 8(b):Result of watershed



Fig. 9(a): Result of threshold watershed



Fig. 9(b): Result of threshold watershed

References

[1] M. C. Hansen, S. V. Stehman, and P. V. Potapov, "Quantification of global gross forest cover loss," Proc. Nat. Acad. Sci. USA, vol. 107, no. 19, pp. 8650–8655, May 2010.

[2] Y. J. Kaufman, C. J. Tucker, and I. Fung, "Remote sensing of biomass burning in the tropics," J. Geophys. Res., vol. 95, pp. 9927–9939, 1990.

[3] R. H. Fraser and J. Cihlar, "Hotspot and NDVI differencing synergy: A new technique for burned area mapping over boreal forest," Remote Sens. Environ., vol. 74, pp. 362–379, 2000.

[4] T. Jeffrey et al., "Validation of MODIS active fire detection products derived from two algorithms," Earth Interactions, vol. 9, p. 1, 2005.

[5] J. Pinol, J. Terradas, and F. Lloret, "Climate warming, wildfire hazard and wildfire occurrence in coastal eastern Spain," Climatic Change, vol. 38, pp. 345–357, 1998.

[6] J. Pierce and G. Meyer, "Long-term fire history from alluvial fan sediments: The role of drought and climate variability and implications for management of RockyMountain forests," Int. J.Wildland Fire, vol. 17, pp. 84–95, 2008.

[7] R. Wright, L. Flynn, H. Garbeil, A. Harris, and E. Pilger, "Automated volcanic eruption detection usingMODIS," Remote Sens. Environ., vol. 82, pp. 135–155, 2002. pp. 84–95, 2008.

[8] Meisner, B. N. Correlation of National Fire Danger Rating System Indices and Weather Data with Fire Reports. Forest Fire Laboratory, Pacific Southwest Research Station, Riverside: USDA Forest Service; 1993; Final Report, Interagency Agreement No. R500A.2002.

[9] D. Stojanova, P. Panov, A. Kobler, S.Dzeroski, and K. Taskova. Learning to Predict Forest Fires with Different Data Mining Techniques. In D. Mladenic and M. Grobelnik, editors, 9th International multiconference Information Society (IS 2006), Ljubljana,Slovenia, 2006.

[10] V. Cuomo, R. Lasaponara, and V. Tramutoli, "Evaluation of a new satellite- based method for forest fire detection," Int. J. Remote Sens., vol. 22,pp. 1799–1826, 2001

[11] Z. Li, S. Nadon, J. Cihlar, and B. Stocks, "Satellite-based mapping of Canadian boreal forest fires: Evaluation and comparison of algorithms," Int. J. Remote Sens., vol. 21, pp. 3071–3082, 2000.

[12] Z. Li, R. Fraser, and A. Khananian, "Remote sensing of forest fires in boreal ecosystem from space," in Proc. SPIE—Remote Sensing for Earth Science, Ocean, and Sea Ice Applications, vol. 3868, G. Cecchi, E. T. Engman, and E. Zilioli, Eds., Florence, Italy, Sept. 20, 1999, pp. 228–231.

[13] W. Schroeder, E. Prins, L. Giglio, I. Csiszar, C. Schmidt, J. Morisette, C. Justice, and D. Morton, "Validation of GOES and MODIS active fire detection products using ASTER and ETM+ data," Remote Sens. Environ., vol. 112, no. 6, pp. 2711–2726, May 2008.

[14] J. Morisette, L. Giglio, I. Csiszar, and C. Justice, "Validation of the MODIS active fire product over Southern Africa with ASTER data," Int. J. Remote Sens., vol. 26, no. 19, pp. 4239–4264, 2005.

[15] J. Morisette, L. Giglio, I. Csiszar, A. Setzer, W. chroeder, D. Morton, and C. Justice, "Validation of MODIS active fire detection products derived from two algorithms," Earth Interactions, vol. 9, p. EI 141, 2005, Paper No.9.

[16] I. Csiszar, J. T. Morisette, and L. Giglio, "Validation of active fire detection from moderate-resolution satellite sensors: The MODIS example in Northern Eurasia," IEEE Trans. Geosci. Remote Sens., vol. 44, no. 7, pp. 1757–1764, Jun. 2006.

[17] T. J. Hawbaker, V. C. Radeloff, A. D. Syphard, Z. Zhu, and S. I. Stewart, "Detection rates of the MODIS active fire product in the United States," Remote Sens. Environ., vol. 112, no. 5, pp. 2656–2664, May 2008

[18] A Gnana Baskaran and Dr.K.Duraiswamy " an efficient approach to detect forest fire using k-mediods algorithm" Journal of Global Research in Computer Science, Volume 2, No. 7, July 2011.

[19] G. P. Asner, M. Keller, R. Pereira, and J. C. Zweede, "Remote sensing of selective logging in Amazonia—Assessing limitations based on detailed field observations, Landsat ETM+, and textural analysis," Remote Sens. Environ., vol. 80, pp. 483–496, 2002, (2002b).

[20] E. N. Broadbent, G. P. Asner,M. Peña-Claros,M. Palace, andM. Soriano, "Spatial partitioning of biomass and diversity in a lowland Bolivian forest: Linking field and remote sensing measurements," Forest Ecol. Manage., vol. 255, no. 7, pp. 2602–2616, Apr. 2008.

[21] United Nations Framework Convention on Climate Change, Report of the Conference of the Parties on Its 13th Session, Part Two: Action Taken by the Conference of the Parties at Its 13th Session, pp. 3–8, 2007. [Online]. Available: http://unfccc.int/2860.php