AN ENHANCED CONTEXTUAL ALGORITHM FOR FIRE DETECTION USING MODIS DATA

F. Parto and M.R. Saradjian

Surveying Engineering Dept., College of Engineering, University of Tehran, Tehran, Iran
Fateme_Parto@yahoo.com , sarajian@ut.ac.ir

KEY WORDS: Fire, Fire Detection, MODIS, Change Detection, Remote Sensing, Environment management

ABSTRACT:

Fire detection algorithms mainly rely on hot spot detection using thermal infrared (TIR) channels with fixed or contextual threshold. The use of MODIS for fire detection has recently been preceded. This work presents a new method based on combination of Giglio (2003) method and change detection of two consecutive MODIS images.
The principle of the approach is to detect fires by comparing the observed brightness temperature of the pixel with the expected temperature during fire conditions. The expected temperature is modelled by series of observations. A thresholding algorithm is used to prevent false alarms. A change detection algorithm on two thermal images of consecutive days is used to improve the efficiency of the method.
The proposed method was applied on two case studies. Results show that both fires were detected correctly and in one case there was only one false alarm. The detected fires were validated with ground data collected by FRWMO in Iran. The result show that joint Giglio and change detection method leads to detection of fires appropriately with minimum false alarms.

1. INTRODUCTION

Many forest fires have occurred in recent years due to effect of climate change and draught. Therefore, fire detection in real-time is a necessity to avoid large scale losses. Remote sensing is a fast technique for monitoring and detecting forest fires on a large scale such as country or state. The Moderate Resolution Imaging Spectroradiometer (MODIS) imagery for fire detection has been used for more than a decade.
This work presents a new method based on combination of Giglio (2003) method and change detection of two consecutive MODIS images. The principle of the approach is to detect fires by comparing the observed TOA brightness temperature of the pixel with the expected temperature during fire.

2. DATA AND PREPROCESSING

The images at the time of fire events have been downloaded from the Earth Observing System Data Gateway, Land Processes Distributed Active Archive Centre (DAAC). The data are MODIS Level 1B Radiance product (MOD02/MYD02) and geolocation data set (MOD03/MYD03).
Another dataset of MOD02 and its MOD03 images close to the time of fire events were downloaded for change detection.
The fire events information of two fires in Iran was provided by The Forests, Range and Watershed Management Organization (FRWMO) in Iran for validation and testing.
MOD03 was used for direct georeferencing of the MOD02 images. The maximum error of georeferencing within images was 135 meter.
Atmospheric correction was performed using Flash software.
Proposed algorithm by Wen (2008) is used to correct the ‘‘bowtie’’ effect.

3. METHODOLOGHY

Since MODIS instrument onboard Terra and Aqua began collecting data in February 2000 (Terra) and June 2002 (Aqua), satellite fire detection capability has been improved using two 3.96 μm channels. Many authors (Dozier, 1981; Giglio et al., 2003; Langaas, 1993; Lasaponara et al., 2003) have focused on fire detection based on theoretical analysis, fixed threshold method, or contextual algorithms.
Kaufman et al (1998) placed different thresholds for night and day fires. Giglio et al (2003) improved some aspects of the MODIS original algorithm. This enhanced contextual fire detection algorithm was recently used for MODIS version 4 fire products, in which the sensitivity to small, cool fires increased. This algorithm achieved significantly lower false alarm rates by using several solar reflectance channels to reject false alarms, and by adjusting the potential fire threshold and contextual thresholds in the earlier version of the MODIS contextual algorithm. Contextual algorithms use dynamic thresholds, relying on the contrast between a potential fire pixel and its background pixels (Flasse and Ceccato, 1996; Giglio et al., 2003; Justice et al., 1996; Kaufman and Justice, 1998; Kaufman et al., 1998; Boles, 2000) to detect fires. These algorithms are more flexible and effective in variable surface conditions than fixed threshold approaches (Flasse and Ceccato, 1996; Li et al., 2001). The MODIS contextual fire detection algorithm which has been designed for operational global fire monitoring, presents some weaknesses for regional fire detection including fixed thresholds for identifying potential fire pixels; the assumption of a similar non-fire background nearby fire pixels; the effects of reflected solar radiation; the impact of undetected fires in the valid background pixels; problems caused by solar zenith angle and scan geometry; and the influence of atmospheric optical thickness. When applied to regional active fire detection, small, cool fires are often times missed due to special regional wild land fire patterns and environmental factors (Martin and Boyce, 1993; Stanturf et al., 2002). In

addition, small, cool fires exhibit different characteristics depending on biome, amount of fuel burning, time of day, fire-line, season, geographic region, and view geometry (Giglio et al., 1999).
Reflected solar radiation around 4 μm channels demonstrate high brightness temperature on bare soil, exposed rock, senescent or sparse vegetation, desert, tropical dry savannah. Therefore, temperate selection of fixed thresholds leads to a risk of omitting fire grassland. It is also the reason for sun glint effect over small bodies of water surface, coastline, wet soil and cirrus clouds, and misleading lower values on uneven forested areas (Csiszaret al., 2003; Giglio et al., 2003; Giglio et al., 1999; Lasaponara et al., 2003; Wang 2006). The MODIS contextual algorithm is composed of three basic parts including preliminary thresholds to identify potential fire pixels, contextual tests to confirm fires among the potential fire pixels and thresholds to reject false alarms. In the first part, the selection of fixed thresholds is subtle as an over-high setting runs a risk of omitting fire pixels. Meanwhile, an over-low setting causes more noise in deriving the parameters of the background pixels (Li et al., 2001) and generates more false alarms. The MODIS version 4 contextual algorithm employs fixed thresholds globally to identify potential fire pixels. For global applications, the preliminary thresholds cannot be set low enough to detect most small fires that can be physically detected for regional concern. Therefore, it needs improvement for fire monitoring and management at the regional scale (Li et al., 2001).
The second part of the MODIS algorithm determines valid neighbouring pixels for every potential fire pixel, which will be used to derive the background parameters designed to set the remaining dynamic thresholds. The separation of fire pixels and non-fire background pixels becomes ambiguous with increasing background temperature caused by the presence of undetected background fires, seasonal change and certain surface types. This can directly affect the performance of the contextual algorithms. Giglio et al. (1999) excluded the eight pixels surrounding the potential fire pixel from the processing window in order to take out the fire contaminated background pixels. Due to the above reasons contextual algorithms were adjusted by Wang (2007) by changing thresholds for identifying potential fire pixels, tuning the type of background pixels and the size of the background window.

4. PROPOSED METHOD

This regional fire detection algorithm is designed to reduce false alarm using change detection between brightness temperatures of two consecutive days.
In the proposed algorithm, according to the maximum sensitivity, MODIS 4μm and 11μm channels are used for detection of pixel fires in images. These channels are denoted by T4 and T11, respectively. The MODIS instrument has two 4μm channels, numbered 21 and 22, both of which are used by the detection algorithm. Channel 21 saturates at nearly 500K and channel 22 saturates at 331K. Since the low-saturation channel (22) is less noisy and has a smaller quantization error, T4 is derived from this channel whenever possible. However, when channel 22 saturates or has missing data, it is replaced with the high saturation channel to derive T4. T11 is computed from channel 31 which saturates at approximately 400K for the Terra MODIS and 340K for the Aqua MODIS. Channel 32 is used for cloud masking. Brightness temperature for this channel is denoted by T12. The 250m resolution red and near-infrared channels, aggregated to 1 km, are used to mask clouds, waters and computing NDVI.

In this algorithm by using water mask base on NDVI and applying dilation, using fire mask according to difference between two consecutive images and detecting change in temperature, applying bare soil mask and omitting stage of false alarm rejection in Giglio algorithm (2003), high accuracy and minimum false alarms have been achieved.

4.1 Cloud, Soil and Water Masking

The cloud detection approach adopts the technique used in the MODIS contextual algorithm (Giglio et al., 2003). The low potential fire threshold, which is used in the following step, introduces cloud edge false alarms. So, dilation and closing morphological operations were applied on the cloud mask to reject cloud edge and gaps.
For water mask, based on Marcos et al., (2004) pixels with NDVI < 0.05 are considered to be water. In Giglio fire detection algorithm some coastal false alarms occur when cooler water pixels are unknowingly included in the back ground window. For removing these errors it was assumed that in 1 km around the coastal area there wouldn't be fire, therefore dilation morphological filter was used to reduce the number of false alarms.
By assuming that fire wouldn't occur in bare soil, the normalized difference soil index was used to mask bare soil to reduce further false alarms.
MODIS data using the information from the channel 2 (NIR: 841-876 nm) and the shortwave infrared channels 5 and 6 (SWIR: 1230-1250 nm and 1628-1652 nm, respectively) were used to derive bare soil.

4.2 Background Fire Pixels Detection

In some cases, fire takes place between two or four pixels leading to increase in temperature of these pixels which are called background fire pixels. The background fire pixels are in turn defined as those having T_4>320K and ΔT>10K for daytime observations, or T_4>310K and ΔT>10K for night-time observations where $\Delta T = T_4 - T_{11}$.

4.3 Background Characterization

In the next phase of the algorithm, an attempt is made to use the neighboring pixels to estimate and model the radiometric signal of the potential fire pixel in the absence of fire. Valid neighboring pixels in a window cantered on the potential fire pixel are identified and used to estimate a background value. Within this window, valid pixels are defined as those that (1) contain usable observations, (2) are located on land, (3) are not cloud-contaminated, and (4) are not background fire pixels.
The window starts as a 3×3 pixel square ring around the potential fire pixel. Due to the triangular along-scan response of the MODIS instrument (Kaufman, Justice et al., 1998), the two along-scan pixels adjacent to the potential fire pixel are deemed unreliable and excluded from the background characterization. The ring is increased to a maximum of 21×21 pixels, as necessary, until at least 25% of the pixels within the window have been deemed valid, and the number of valid pixels is at least eight. The 21×21 pixel maximum size ensures that the background is sampled within 20 km of the potential fire pixel, a scale found empirically to be appropriate for preventing false alarms induced by an unrepresentative selection of background pixels.

If a sufficient number of valid neighboring pixels can be identified, several statistical measures are computed. These are $\overline{T_4}$ and δ_4, mean absolute deviation of T_4 for the valid neighbouring pixels; $\overline{T_{11}}$ and δ_{11}, the respective mean and mean absolute deviation of T_{11} for the valid neighbouring pixels; $\overline{T_{\Delta T}}$ and $\delta_{\Delta T}$, the respective mean and mean absolute deviation of ΔT for the valid neighboring pixels.

The mean absolute deviation was employed as a measure of dispersion rather than the standard deviation since it is more resistant to outliers (Huber, 1981). For contextual fire detection algorithms, this is highly desirable since contamination of the background window by undetected clouds, water, fires, and other sources is not uncommon.

4.4 Identification of Potential Fire Pixels

A preliminary assessment is used to eliminate obvious non-fire pixels. Those pixels that remain are considered in subsequent tests to determine if they do in fact contain an active fire.

A daytime pixel is identified as a potential fire pixel if T_4>310K, ΔT>10K, and $\rho_{0.86} < 0.3$.

For night-time pixels, the reflective test is omitted and T4 threshold is reduced to 305K. Pixels failing these preliminary tests are immediately considered as non-fire pixels.

4.5 Contextual tests

If the background characterization was successful, a series of contextual threshold tests are used to perform relative fire detection. These look for the characteristic signature of an active fire in which both the brightness temperature (T_4) and the brightness temperature difference (ΔT) depart substantially from that of the non-fire background. Relative thresholds are adjusted based on the natural variability of the background. The tests are:

$$\Delta T > \overline{\Delta T} + 3.5 \times \delta_{\Delta T} \qquad (1)$$

$$\Delta T > \overline{\Delta T} + 6 \qquad (2)$$

$$T_4 > \overline{T}_4 + 3 \times \delta_4 \qquad (3)$$

The original algorithm after detecting fire pixels applied some false alarm rejection. Then temporal change detection is applied between to MODIS image from two different days.

Change detection was applied on thermal bands between two consecutive days and those Pixels that their temperature increased more than 5K is selected as changed pixels. In the next step change mask was applied on detected fire image to eliminate false alarms.

5. RESULT AND DISCUSSION

Proposed algorithm was applied on two case studies and validated by data provided by The Forests, Range and Watershed Management Organization (FRWMO) in Iran. The information of two fires are listed in Tables 1.

Table 1. Fire events information from FRWMO

Date and Time	Lat	Long
Sep 04, 2006 9 am until 10 pm	56.96620	37.38968611
Nov 16, 2010	55.37178201	36.98014309

Each case is calculated using both the improved algorithm and the MODIS contextual algorithm. In both cases, fire events were detected correctly by the MODIS contextual algorithm (Figures 1 and 2).

By applying dilated water mask number of false alarms reduced from 4587 to 2868 and 587 to 452 in the two case studies, respectively.

By applying cloud mask number of false alarms reduced from 2868 to 2841 and 452 to 414 in the two case studies, respectively.

By applying change mask, number of false alarms reduced from 2841 to 16 and 414 to 58 in the two case studies, respectively.

Many false alarms were seen in boundary of deserts therefore bare soil mask to separate fires in grasslands and forests from bare soil false alarms was applied (Table 2).

Table 2. Effect of each mask on the number of false alarms (first and second lines are for the two case studies respectively)

Mask \ Number of false alarm	Before Applying	After Applying
dilated water mask	4587	2868
	587	452
cloud mask	2868	2841
	452	414
change mask	2841	16
	414	58
NDSI mask	16	1
	58	18

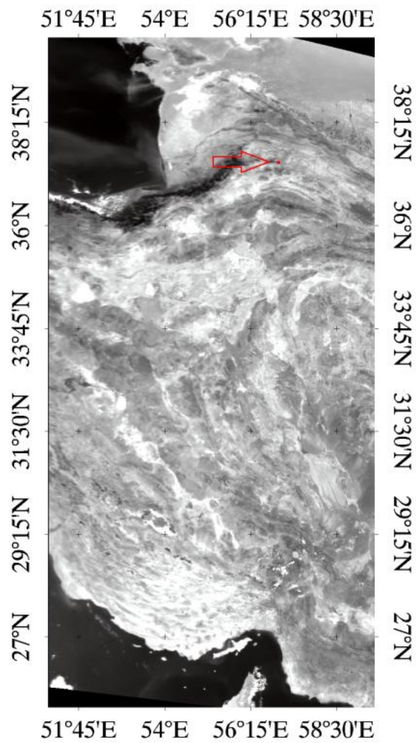

Figure 1. Detected fire in the first case study. As seen, fire event detected correctly and there are not any false alarms.

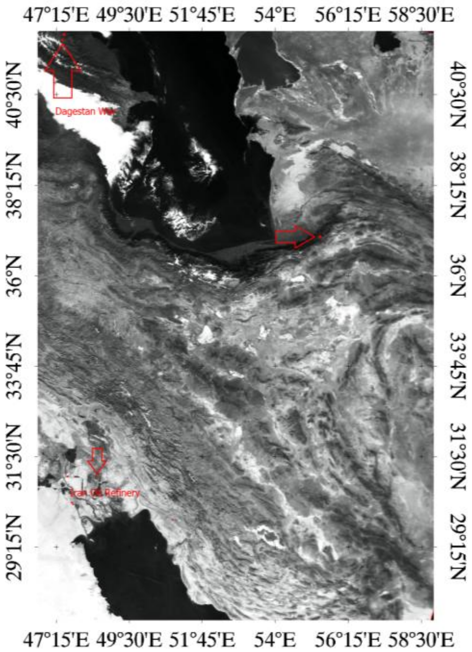

Figure2. Detected fire in the second case study.

6. CONCLUSION

An improved contextual active fire detection algorithm for the MODIS data has been described. It is combination of Giglio (2003) algorithm, known as version 4, and change detection between two thermal images. The algorithm was applied on two case studies and the results illustrated that joint Giglio and change detection method leads to detection of fire appropriately.

7. ACKNOWLEDGEMENT

The authors would like to thank Mr. Moeen Zohary for his assistance and helpful comments on programming.

8. REFERENCE

Boles, S. H., and Verbyla, D. L. (2000). Comparison of three AVHRR-based fire detection algorithms for interior Alaska. Remote Sensing of Environment, 72, 1−16.

Csiszar, I., Abdelgadir, A., Li, Z., Jin, J., Fraser, R., and Hao, W. M. (2003). Interannual changes of active fire detectability in North America from longterm records of the Advanced Very High Resolution Radiometer. Journal of Geophysical Research, 108(D2), 4075−4085.

Dozier, J. (1981). A method for satellite identification of surface temperature fields of subpixel resolution. Remote Sensing of Environment, 11, 221−229.

Flasse, S. P., and Ceccato, P. (1996). A contextual algorithm for AVHRR fire detection. International Journal of Remote Sensing, 17, 419−424.

Giglio, L., et al.,2003, An enhanced contextual fire detection algorithm for MODIS, Remote Sensing of Environment, 87, pp. 273-2

Giglio, L., Kendall, J. D., and Justice, C. O. (1999). Evaluation of global fire detection using simulated AVHRR infrared data. International Journal of Remote Sensing, 20, 1947−1985.

Justice, C. O., Giglio, L., Korontzi, S., Owens, J., Morisette, J. T., Roy, D., et al. (2002a). The MODIS fire products. Remote Sensing of Environment, 83, 244−262.

Justice, C. O., Kendall, J. D., Dowty, P. R., and Scholes, R. J. (1996). Satellite remote sensing of fires during the SAFARI campaign using NOAA advanced very high resolution radiometer data. Journal of Geophysical Research, 101, 23851−23863.

Kaufman, Y., Justice, C. O., Flynn, L. P., Kendall, J. D., Prins, E. M., Giglio, L.,et al. 1998. Potential global fire monitoring from EOS-MODIS. Journal of Geophysical Research, 103, 215−238.

Langaas, S. (1993). A parameterised bispectral model for savanna fire detection using AVHRR night images. International Journal of Remote Sensing, 14, 2245−2262.

Lasaponara, R., Cuomo, V., Macchiato, M. F., and Simoniello, T. (2003). A selfadaptive algorithm based on AVHRR multitemporal data analysis for small active fire detection. International Journal of Remote Sensing, 24, 1723−1749.

Li, Z., Kaufman, Y. J., Ichoku, C., Fraser, R., Trishchenko, A., Giglio, L., et al. (2001). A review of satellite fire detection algorithms: principles, limitations and recommendations. In F.Ahern, J. Goldammer, and C.O. Justice (Eds.), Global and regional fire monitoring from space: Planning a coordinated international effort (pp. 199−226).

Wang, W., et al., 2007, An improved algorithm for small and cool fire detection using MODIS data: A preliminary study in the southeastern United States, Remote Sensing of Environment, 108, pp. 163-170

Martin, W. H., and Boyce, S. G. (1993). Introduction: the southern setting. In William H. Martin, Stephen G. Boyce, and Arthur C. Echternacht (Eds.), Biodiversity of the Southeastern United States upland terrestrial communities
(pp. 1−46). New York: John Wiley.

Stanturf, J. A.,Wade, D. D.,Waldrop, T. A., Kennard, D. K.,andAchtemeier,G. L. (2002). Fire in Southern Forest Landscape, in Southern forest resource assessment. In David N.Wear and John G. Greis (Eds.), Gen. Tech. Rep. SRSW