New Methods of Active Fire Detection Using MODIS Data

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Abstract: Active fire detection using satellite thermal sensors usually involves thresholding the detected brightness temperature in several bands. The frequently used features for fire detection are the brightness temperature in the 4-micron wavelength band (T4) and the brightness temperature difference between the 4-micron and 11-micron bands (dT=T4-T11). The thresholds used are determined empirically without any theoretical considerations, and thus may not be optimal for a given fire detection task. In this paper, we discuss a new approach in active fire detection based on a stochastic model for target detection. This approach considers the probability density functions of the fire and background pixels and optimal thresholds are derived depending on the specific objectives of the detection tasks. For example, the optimal threshold can be found by minimizing a cost function which is a weighted sum of the omission and commission errors. Alternatively, the threshold can also be derived based on the maximum likelihood criterion. The implementation of the new methods and the results of comparison with the conventional algorithms will be described.

Keywords: Forest fire, MODIS, hot spots, stochastic model, target detection.

1. Introduction

Forest fire is a serious environmental concern in the Southeast Asia region, especially during the dry seasons. Episodes of transboundary haze pollution has occurred almost annually in the region. It is important to be able to have real time or near real time detection of active fires for early warning of impending haze and for aids in fire fighting and management. Satellite remote sensing provides a useful means of detecting regional fires. Active fires are usually detected using thermal sensors on-board remote sensing satellites by detecting the infrared radiation emitted from the fires. This procedure is commonly known as 'hot spot detection'. The conventional heritage algorithms for active fire detection with satellite imagery, such as those developed for AVHRR data, make use of two thermal infrared bands, usually near the 4 and 11 micron wavelength regions [1], [2], [3]. A given pixel is flagged as an active fire hotspot if the 4 μm brightness temperature (T_4) and the temperature difference in the 4 μm and 11 μm bands ($\Delta T = T_4 - T_{11}$) are greater than some predefined threshold values. Improvement can be obtained by using contextual algorithms to adaptively determine the threshold values [4], [5].

The Moderate Resolution Imaging Spectrometer (MODIS) on-board the TERRA and AQUA satellites have 36 spectral bands spanning from the visible to the thermal infrared regions. The thermal bands in the 3 to 4 μm (e.g. Bands 21, 22) and 10 to 13 μm (e.g. Band 31) wavelength regions are particularly useful for detection of active fires. The higher sensor saturation level and better geolocation accuracy of MODIS compared to NOAA-AVHRR enable more reliable detection of active fires [6], [7]. The standard fire hotspots detection algorithms developed for MODIS are also based on the conventional two-band thresholding method [5], [6], [7]. Both fixed and adaptive thresholds have been used for fire detection.

Due to the statistical nature of the fire and background temperature distribution, no matter how the thresholds are chosen, there are bound to be commission errors (i.e. false alarms) and omission errors (false negatives) in the detection outcomes [8], [9]. In the most fire detection algorithms, the thresholds are often arbitrarily defined, and hence may not be optimal for a given fire detection task. The optimal threshold values are expected to be site dependent. They are different in different regions and for different fire conditions (such as smoldering and flaming fires). Hence, a global set of threshold values may not work optimally for a specific site. In this paper, we propose new methods of fire detection based on the statistical distributions of fire and background temperatures.

2. Commission and Omission Errors in Active Fire Detection

Active fire detection is basically a dichotomic classification problem. The aim is to classify the pixels in the feature space into one of the fire or non-fire (background) classes. We will first illustrate the detection problem by assuming that the brightness temperature T of a single band (say, band 21 of MODIS) is used for fire detection. Suppose that the background temperature has a mean of 300 K while the effective brightness temperature of hot spot pixels has a mean of 330 K. Note that the effective brightness temperature of hot spot pixels is not the same as the brightness temperature of the actual fires since the fire may not completely cover the whole hot spot pixel. The temperature distributions of the background and hot spot pixels for this hypothetical case are shown in Fig. 1.

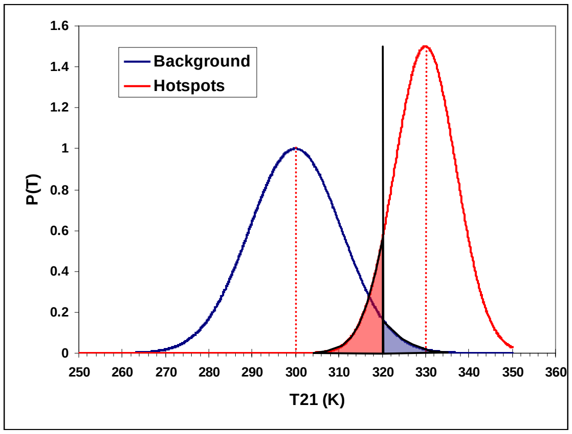

Fig. 1: An example of temperatue distributions of the background and hot spot pixels

Suppose that a threshold T_{th} is applied, i.e. a pixel is deemed a fire hot spot if its brightness temperature is greater than the threshold; otherwise it is considered a background pixel. Note that a fraction of the actual fire pixels are classified as non-fire pixels (represented by the red area in Fig. 1) and thus are not detected. Some background pixels are misclassified as fire pixels (represented by the blue area in Fig. 1) and constitute the false alarms. The undetection rate (omission error) can be reduced by lowering the threshold at the expense of increasing the false alarm rate (commission error). Conversely, increasing the threshold can reduce the false alarm rate but the undetection rate will increase. It can thus be seen that, there is no universal threshold that is optimal under all conditions. An optimal threshold needs to be defined for each task of fire detection, depending on the specific requirements of the task.

3. Stochastic Fire Detection Models

The problem of fire detection can be modeled by the statistical distributions of the fire and background temperatures. For simplicity, we will consider fire detection based on one parameter, say, the brightness temperature at one of the thermal bands. The models can be generalized to two or more feature parameters. Let $P(T \mid \text{fire})$ be the probability density function of the distribution of brightness temperature for fire pixels, and $P(T \mid \text{bkg})$ be the same for background non-fire pixels. Suppose that there are N pixels in the area of interest, out of which there are there are N_f actual fire pixels and N_b background pixels so that

$$N = N_f + N_b \tag{1}$$

The number of actual fire pixels that are wrongly classified as background, and thus not detected can be expressed as,

$$n_{bf} = N_f \int_0^{T_{th}} P(T \mid fire)\,\mathrm{d}T \tag{2}$$

and the number of background pixels wrongly classified as fire hot spots is

$$n_{fb} = (N - N_f) \int_{T_{th}}^{\infty} P(T \mid bkg)\, \mathrm{d}T \tag{3}$$

The number of correctly detected fire pixels is

$$n_{ff} = N_f - n_{bf} = N_f \left\{ 1 - \int_0^{T_{th}} P(T \mid fire)\, \mathrm{d}T \right\} \tag{4}$$

while the number of correct background pixels is

$$n_{bb} = N - N_f - n_{fb} = (N - N_f) \left\{ 1 - \int_{T_{th}}^{\infty} P(T \mid bkg)\, \mathrm{d}T \right\} \tag{5}$$

If the result of the detection task gives M_f hotspots and M_b background pixels, then we have,

$$M_f = n_{fb} + n_{ff}\,; \qquad M_b = n_{bf} + n_{bb} \tag{6}$$

$$N_f = n_{bf} + n_{ff}\,; \qquad N_b = n_{fb} + n_{bb} \tag{7}$$

Table 1 illustrates the relations between these quantities.

Table 1: Detection outcomes of a fire detection task

Detection outcomes	Actual		
	Background	Fire	Total
Background	n_{bb}	n_{bf}	M_b
Fire	n_{fb}	n_{ff}	M_f
Total	N_b	N_f	N

Thus, the numbers of error pixels, i.e. n_{fb} and n_{bf} are dependent on the threshold chosen and also on the probability density functions of the background and fire temperatures.

3.1 Minimum Error Detection

The omission error (un-detection rate) is defined as the fraction of actual fire pixels misclassified as background,

$$E_O = \frac{n_{bf}}{N_f} = \int_0^{T_{th}} P(T \mid fire)\, \mathrm{d}T \tag{8}$$

and the commission error (false alarm rate) is defined as the fraction of detected hot spots that are actually background pixels,

$$E_C = \frac{n_{fb}}{M_f} = \frac{n_{fb}}{n_{fb} + n_{ff}} = \frac{\int_{T_{th}}^{\infty} P(T \mid bkg)\, \mathrm{d}T}{\int_{T_{th}}^{\infty} P(T \mid bkg)\, \mathrm{d}T + \left(\frac{p_f}{1 - p_f} \right) \int_{T_{th}}^{\infty} P(T \mid fire)\, \mathrm{d}T} \tag{9}$$

It is seen that the commission and omission errors are functions of the threshold. In ref. [9], a minimum error method is proposed for determining an optimal threshold for active fire detection. In this method, a cost function is defined as a weighted sum of the commission and omission errors. The optimal threshold is the value that minimizes the cost function, i.e. a solution of the equation

$$\frac{\mathrm{d}}{\mathrm{d}T} \left[w_O E_O(T) + w_C E_C(T) \right] \Big|_{T = T_{th}} = 0 \tag{10}$$

3.2 Maximum Likelihood Detection

Given the observed temperature T, the probability that a given pixel is a fire pixel is given by the Bayes' theorem,

$$P(fire\,|\,T) = \frac{P(T\,|\,fire)P(fire)}{P(T)} \tag{11}$$

Similarly, the probability that a given pixel is a background pixel is,

$$P(bkg\,|\,T) = \frac{P(T\,|\,bkg)P(bkg)}{P(T)} = \frac{P(T\,|\,bkg)\,[1-P(fire)]}{P(T)} \tag{12}$$

In the maximum likelihood method of fire detection, a given pixel is classified as a fire pixel if

$$P(fire\,|\,T) > P(bkg\,|\,T) \tag{13}$$

i.e.

$$\frac{P(T\,|\,fire)}{P(T\,|\,bkg)} > \frac{1-p_f}{p_f} \tag{14}$$

where $p_f = P(fire)$ is the fire probability. Hence, the threshold is found by solving the equation,

$$\frac{P(T_{th}\,|\,fire)}{P(T_{th}\,|\,bkg)} = \frac{1-p_f}{p_f}$$

3.3 Constant False-Alarm Detection

It may be desirable to fix the false-alarm rate of the detection outcomes. In this case, the threshold is the solution of the equation,

$$\frac{\int_{T_{th}}^{\infty} P(T\,|\,fire)\,\mathrm{d}T}{\int_{T_{th}}^{\infty} P(T\,|\,bkg)\,\mathrm{d}T} = \left(\frac{1-R}{R}\right)\left(\frac{1-p_f}{p_f}\right) \tag{15}$$

where R is the constant false alarm rate desired.

3.4 Detection Based on testing of "Null-Hypothetis"

The problem of fire detection can be treated as a problem of statistical "null-hypothesis" testing. The null-hypothesis is that the pixel observed is not a fire pixel. Based on the observed temperature, a significance level is calculated and the hypothesis is accepted (i.e. the pixel is considered a background pixel) or rejected (i.e. the pixel is considered a fire pixel) accordingly. In this case, only the background probability density function is considered. Assuming the null-hypothesis, the probability that the observed temperature T of a background pixel is above a certain threshold T_{th} is

$$p = \int_{T_{th}}^{\infty} P(T\,|\,bck)\,\mathrm{d}T \tag{16}$$

If the observed pixel temperature is above this threshold, then the null-hypothesis is rejected with the given p-value. Hence, the threshold is determined by solving the equation (16) above, given the desirable p-value.

4. Concluding Remarks

In the above section, we have discussed the statistical foundation of active fires detection based on the probability density functions of the fire and background pixels. Thus, it is important that these functions be known a-priori. These functions $P(T\,|\,fire)$ and $P(T\,|\,bck)$ can be obtained from a reference MODIS data set validated with "ground-truth" data [9]. In ref. [9], high resolution SPOT data is used to validate the reference MODIS data set [10]. It is also desirable to parameterize the probability density functions in terms of a few parameters, such as the mean and standard deviation of the temperature distributions. Once a parameterized model of the probability density functions has been established, the functions can be adaptively determined by computing the statistical parameters from the pixels surrounding the suspected fire pixel concerned. This statistical approach enables the determination of optimal threshold value according to the specific requirements of the detection tasks.

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