AN AUTOMATIC ALGORITHM TO DETECT VEGETATION FIRES GLOBALLY FROM NOAA-AVHRR DATA

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ABSTRACT

A contextual algorithm for fire detection using NOAA-AVHRR data was developed at the Natural Resources Institute (NRI). Unlike 'traditional' fire detection algorithms applied to NOAA data (e.g. multi-channel thresholds), the decision to record a fire is made by comparing a potential fire pixel with the pixels in its immediate neighbourhood. The procedure automatically extracts values in channels 3 and 4 of neighbourhood pixels, which are then compared to those of the potential fire pixel. The algorithm is self-adaptive and therefore is a very consistent method over large areas as well as through seasons, without the need to change the thresholds. The algorithm was successfully applied in several areas of the world. This paper describes the approach chosen, compares it with 'traditional' techniques, and analyses advantages and drawbacks in light of some examples.

INTRODUCTION

Within the framework of ongoing activities of Vegetation Fire Monitoring by NRI and the Global Vegetation Fire Products (GVFP) project (Stuttard *et al.*, 1995), the authors have developed and applied a fire detection contextual algorithm capable of automatically detecting fires, using NOAA-AVHRR-LAC data. An important development in the production of such GVFP is the establishment of algorithms that are capable of detecting fire events (from NOAA data) reliably, routinely and automatically for any part of the world. It is important that such algorithms be sensitive to seasonal effects, daylight conditions and ecosystem related phenomena. Indeed, each region will have its own characteristic burn regime, seasonal pattern of surface and climate conditions, that will affect background temperature and thus the response of NOAA-AVHRR channel 3.

After a review of existing fire detection techniques, this paper describes the contextual algorithm developed and gives the first results obtained within different ecosystems distributed around the world.

1. Fire detection with AVHRR data

Fire detection from NOAA data is achieved by a number of methods, all of which utilise the dominating effect of hot fires in the thermal infrared channel 3 (3.75 μm) signals at some stage. The methods can roughly be classified into four categories which are defined by the algorithm used: channel 3 Single Threshold algorithm, channel 3 Multiple Threshold algorithm, Multi-Channel Threshold algorithms and Contextual algorithms.

1.1 The simplest algorithm is to retain all pixels that are saturated (or near saturated) in channel 3. This approach relies only on channel 3 data and assumes that a single threshold value can be used to identify fire pixels (*e.g.* Malingreau and Tucker 1988, Setzer and Pereira 1991, Pereira 1993, Langaas 1994). In most cases, the saturation of the pixel in channel 3 would indicate unusually hot features and could be assumed to represent a fire. However, the single threshold method is susceptible to confusion with hot bare surfaces, warm dry savannahs and bright clouds, and may not be suitable for regional scale fire studies over time (Grégoire *et al.* 1993).

1.2 The channel 3 Multiple Threshold algorithm is rarely used, but appears to lie behind some of the developments in the implementation of contextual algorithms described below. Smith and Vaughan (1991) adopted an approach based on three tests of channel 3. The first test selects potential fire pixels using a single threshold in channel 3. Later, the potential fire pixel is tested with two algorithms that use contextual information. The standard deviation in channel 3 is calculated for surrounding pixels of a 5x5 window (centred on a candidate pixel). The surrounding pixels must not be identified as potential fire pixels. By assuming that fire pixels influence surrounding pixels, small standard deviations are assumed to be signal noise and are used to exclude some of the potential heat source pixels. The third test subtracts the candidate fire pixel value in channel 3 from the mean value of the 5x5 window. If the difference exceeds a certain value, the potential fire pixel is retained.

1.3 Multi-Channel Threshold algorithms have gained a great deal of support in recent years, as they have been shown to be regionally robust and simple to implement. A wide range of multi-channel threshold criteria exist, developed by, for example, Kaufman *et al.* (1989, 1990a,b), Langaas (1992, 1993), Belward *et al.* (1994), and Kennedy *et al.* (1994). All of these algorithms utilise combinations of two or more fixed thresholds for channels 3 and 4 (3.75 µm and 10.8 µ m, respectively) either singly or in combination. Some Multi-Channel Threshold algorithms also add a reflectance test in channel 2 (Kennedy *et al.,* 1994). As in the case of simple channel 3 thresholding, all the published multi-channel thresholds have been developed for specific regions and specific times. This approach is unfortunately insensitive to variations in normal land surface temperature conditions over time for a given area and over different ecosystems (Langaas 1994).

1.4 Spatial or Contextual algorithms are based on the spatial variability of thermal signals in a pixel neighbourhood. The brightness temperatures of potential fire pixels are checked against the brightness temperatures of cloud-free (assumed non-burning) neighbouring pixels. This takes into account the spatial thermal variability of the background, which is not easily dealt with in either single channel thresholding or pixel-by-pixel multi-channel thresholding (Langaas 1994). The principles of the contextual approach were first found in a fire detection algorithm review by Justice and Dowty (1993). Similar approaches have been shown to be successful for specific cases by Lee and Tag (1990) Smith and Vaughan (1991), and Flannigan and Vonder Haar (1986).

From all existing algorithms, the contextual technique was very attractive for an automatic and regionally sensitive Global Vegetation Fire Product, without the need to rely on highly variable, locally derived thresholds. Starting from the information collected in the literature, especially the NASA/GSFC approach described by Justice and Dowty (1993), the idea was adapted and developed further (Flasse and Ceccato, 1995). The following section presents the new algorithm.

2. Contextual algorithm

The contextual algorithm developed consists of two stages: the first selects candidate pixels that could potentially be fires (PFs) and the second confirms or rejects these PFs by comparing them with their immediate neighbours.

2.1 Potential Fire detection

This first stage is intended to roughly select all those pixels that may be a fire. It uses thresholds similar to traditional fire detection algorithms, applying thresholds low enough to retain at least all those pixels that could be fires, and high enough to reject most pixels that are definitively not fires. The following tests are employed:

Test 1: A pixel is selected as a Potential Fire (PF) if:

$$T^B(3) > 311\text{ K} \quad (1)$$

and

$$T^B(3) - T^B(4) > 8\text{ K} \quad (2)$$

where $T^B(x)$ = Brightness Temperature in channel x

$x = 3, 4$
K = Kelvin

The choice of the thresholds used in these two tests was driven by practical experience. The first threshold was selected low enough to reduce the likelihood that potential fires would be rejected in colder regions, such as a forested environment. The second threshold was placed high enough to reject those pixels that are not fires in any case (*e.g.* pixels with high brightness temperature in both channel 3 and 4) (*e.g.* Kennedy *et al.* 1994, Kaufman *et al.* 1990). Even though the contextual algorithm doesn't require specific areas to be masked, its efficiency and performance will increase when clouds, desert and water are not included. Desert and water masks can be found in several data bases and main water surfaces can be detected using low NDVI values. In addition, the authors also used simple combinations of channels 1, 2 and 5 to enable major clouds to be masked (Stuttard *et al* 1995).

Test 2: A PF pixel is NOT retained as a fire if:

$\rho 2 \geq 20\%$

where ρ2 is the top-of-atmosphere bi-directional reflectance factor for AVHRR channel 2 (0.9 μm).

Since the band width of AVHRR channel 3 (3.55 - 3.93 μm) covers parts of both the solar and thermal ranges of the electro-magnetic spectrum, it is important to reject those pixels whose value in channel 3 would be saturated due to high reflection rather than high temperature (*e.g.* from bright soils, clouds or sun glint). Even when masks are applied, this test still eliminates remaining falsely detected fires (*e.g.*, in areas of bright savannah or sun glint on rivers).

2.2 Potential Fire confirmation

The second stage confirms or rejects the potential fire (PF) selected in the first stage as being definitely a fire. For each PF, this decision is made in light of some knowledge of the potential fire and its neighbours. Indeed, if most of the latter appear to be sufficiently different from the PF, it is selected as fire.

The confirmation process begins by extracting information on a statistically significant neighbourhood population. For each PF, statistical information is automatically calculated for a varying sized context-window (from 3x3 to 15x15 pixels) around the PF, which is operated upon at least 3 pixels are eligible to be used in the comparison. If these conditions are not met, the PF is rejected and the pixel is marked as NON-fire. If the PF passes this test, the following information is computed:

$T^B(3)_b$ = mean of channel 3 brightness temperatures of the background

$\sigma T^B(3)_b$ = standard deviation of channel 3 brightness temperatures of the background

$T^B(3\text{-}4)_b$ = mean of the difference (channel 3 - channel 4, brightness temperatures) of the background

$\sigma T^B(3\text{-}4)_b$ = standard deviation of the difference (channel 3 - channel 4, brightness temperatures) for the background

Only those pixels that are relevant to a normal fire background are eligible for statistical calculations; that is, they must NOT be a PF, NOR water, NOR cloud. Indeed, the inclusion of the latter would bias the statistical information and therefore lead to erroneous conclusions. For example, a hot soil, selected as a PF and surrounded by water, could be confirmed as fire, since low values in channel 3 for water decrease the PF's background mean. Conversely, a small fire surrounded by other fires would not be confirmed as a fire, since the values of the other fires would erroneously increase the PF's background mean.

Test 3: A PF is classified and retained as a fire when it appears to be different enough from its background.

PF is confirmed as a fire when

$$T^B(3\text{-}4)_{PF} - [T^B(3\text{-}4)_b + 2\sigma T^B(3\text{-}4)_b] > 0 \text{ K} \qquad (3)$$

and

$$T^B(3)_{PF} - [T^B(3)_b + 2\sigma T^B(3)_b] > 3 \text{ K} \qquad (4)$$

where: PF subscript refers to potential fire temperatures.

The first equation refers to the NASA/GSFC approach and takes into account the difference between channels 3 and 4. Such a test is necessary in order to eliminate PFs whose difference between $T^B(3)$ and $T^B(4)$ is lower than the mean difference of the fire background. This test mostly eliminates pixels that produce a high value of radiance in both channel 3 and channel 4, such as hot bare soils.

The second equation verifies the brightness temperature in channel 3 against the mean brightness temperature of neighbouring pixels. Indeed, a fire is identifiable in its context if there is a significant difference between the brightness temperature of a candidate pixel in channel 3 and the brightness temperature of the background in channel 3. Thus, unlike the NASA/GSFC approach, the new algorithm also calculates the mean channel 3 brightness temperature and standard deviation of the background in order to compare it with the channel 3 brightness temperature of a given PF pixel. Nevertheless, the selection of an appropriate limiting value should be studied more. We decided to fix it at a level of 3 K. This value was chosen, based on our investigations on fire characteristics in the Ivory Coast and Central African Republic (Stuttard et al 1995). It was noticed that some pixels, in the range between 2 K and 4 K difference with the background, were confirmed fires and some were on the border line of confirmation (all PFs with a difference greater than 4 K were confirmed fires). We decided as a first approximation to retain as fires all PFs with a difference of 3 K or greater than the background. However, values included between 2 K and 4 K represent only a very small part of the total amount of real fires detected. More statistical validation and field information is required in order to refine the choice of this threshold value.

3 Results and Discussion

The initial results (Stuttard et al 1995) indicate that the contextual algorithm is an excellent fire detection algorithm for global application. Its detection of fires is comparable to conventional multi-channel threshold algorithms. Unlike the latter, however, it does not require to change continually threshold values, and it effectively rejects non-fire pixels in a hot environment.

In order to assess the quality of the global vegetation fire algorithm in detecting fires on a global scale, we performed a validation test. The validation procedure was performed comparing the outputs from the contextual algorithm with independent data sets containing the location of fire occurrences observed from the ground Due to the incompleteness of such existing data sets, a complementary validation procedure based on expert visual interpretation of AVHRR data was developed (Stuttard *et al.* 1995). The visual interpretation was performed by extracting fire information from nine test sites (Argentina, Australia, Brazil, Central African Republic, Chile, Ivory Coast, Namibia, Nicaragua, Zaire). These test sites of 512x512 pixels were extracted from the EROS Data Centre global data set. The regions were selected in order to be as representative as possible of different ecosystems, different geo-locations on the globe, and areas with fire detection problems (*e.g.* desert, sun glint, clouds, warm savannahs).

The extraction of fire information from these test sites was done visually by staff with substantial experience in visual detection of fires in AVHRR images. Fires were identified by comparing hot pixels in channel 3 to their background, noting smoke plumes in visible channels, using the inferential skill of the interpreters and tracking day-to-day changes (day-to-day changes are based on the principle that in certain regions, such as savannahs, fire rarely lasts more than one day and often moves quickly). On a pixel by pixel basis, experts classified each pixel as:

- **Definite Fire**. A pixel which is believed to be an active fire.
- **Possible Fire**. A pixel which looks like a fire, but which raises doubts in interpretation, due to its neighbourhood (*e.g.* sun glint, low contrast between possible fire and background, pixel adjacent to definite active fire).
- **Non-Fire**. A pixel which is believed not to be a fire.

The overall result of the comparison between fires detected with the new contextual algorithm and fires detected with visual interpretation is presented in the following table.

	Context algorith m		
Visual Data	Fire	Non-Fire	Total
Definite Fire	3265	350	3615
Non-Fire	598	2225607	2226205
Total	3863	2225957	2229820

Definite fires and non-fires:

- Of the number of pixels detected by visual interpretation as fire, 90% were detected by the algorithm as fire.
- Of the number of pixels detected by visual interpretation as non-fire, >99% were classified by the algorithm as non-fire.
- Of the number of pixels detected by the algorithm as fire, 85% were definite fires.

Possible fires:

- Of the total number of observed pixels, <1% were classified as possible fires (not included in the above computation).
- Of the total number of pixels detected as fire by the algorithm, 15% are possible fires.

The results obtained indicate that the overall performance of this technique is excellent. Nevertheless, there are still commission errors, where the contextual algorithm detects fires falsely. We believe that most of these errors are due to:

- Clouds or cloud edges which escaped the various tests. Techniques to mask clouds should be improved.
- Cool background that is not homogeneously distributed around a hot area (detected as PF). Edges of either hot areas or clouds have often been selected as fires because the background

provides enough influence in the statistic to accept the pixel as fire. We are currently testing the application of background distribution criterion around the PF.

- Background of immediate neighbourhood that is much cooler than the general background of the area. This may be due to sensor behaviour. This phenomenon leads to erroneous identifications, which could be eliminated by starting with a context-window greater than 3x3.

The validation procedure was however subject to limitations. The validation data set was extracted from the image data only and was therefore not truly independent. Moreover, visual interpretation of AVHRR data may be very difficult and implies possible human errors. In these conditions, the visual validation and the resulting extracted data must be considered at this stage as simply an indication of real fires in the field.

CONCLUSION

The use of the proposed fire detection contextual algorithm appears to be successful and very promising. Its fundamental principles, based on a comparison with the surrounding background, allow it to be used in diverse contexts such as dry, hot savannahs, deserts, and tropical forests without adjusting threshold values regionally and seasonally. The objectivity of the test, its automatic procedure and self-adaptive performance have demonstrated its usefulness in detecting fires with a high degree of accuracy. Even though it is not the optimum solution yet, its implementation is already operational for fire detection from NOAA-AVHRR-LAC data. Research to further develop the algorithm is ongoing and recent work in Indonesia and Madagascar has already provided indications of substantial improvement in fire detection activities.

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