A contextual algorithm for AVHRR fire detection

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Abstract. A contextual algorithm for fire detection with NOAA-AVHRR-LAC data was developed. Unlike 'traditional' fire detection algorithms (e.g., multi-channel thresholds), the decision to record a fire is made by comparing a fire pixel with the pixels in its immediate neighbourhood. The algorithm is self-adaptive and therefore very consistent over large areas as well as through seasons. The algorithm appears to operate successfully in most areas of the world. This Letter presents the contextual approach and describes the algorithm.

1. Introduction

Vegetation fires, in many countries around the world, are one aspect of the management of natural resources. They are mainly caused by the practices of people such as agriculture and poaching (e.g., Malinger and Tucker 1988), and under proper control, fires may be beneficial. Conversely, when used inappropriately they can devastate huge areas, degrade the environment and diminish natural resources availability. Regular information about fire events at local to national scales is a necessary prerequisite to understanding and documenting the extent of their occurrence, in space and time. In many places of the world (e.g., developing countries) however, such information is not directly available.

Under an ongoing programme of activities for improving direct access to environmental information where most needed, the Local Applications of Remote Sensing Techniques group (LARST) at the Natural Resources Institute (NRI) uses National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) data as a primary source of information for detecting vegetation fires. Local institutions in developing countries (e.g., Madagascar, Central African Republic, Nicaragua and Indonesia) are assisted in establishing routine fire detection and monitoring capabilities. They readily appreciate the usefulness of such remotely sensed information for environmental decision making in fire affected areas such as forests, parks and agricultural and grazing lands.

Within the framework of these activities and those of the Global Vegetation Fire Product project (Stuttard et al. 1995), we have developed and implemented a fire detection contextual algorithm capable of automatically detecting fires using NOAA-AVHRR Local Area Coverage (LAC) data.

2. Fire detection with AVHRR data

AVHRR data has long been used for fire detection activities (e.g., Levine 1991). Various algorithms have been used successfully to date: most commonly from single channel 3 threshold to multi-channel threshold algorithms (e.g., Justice and Dowty 1993). Nevertheless, for these algorithms to work efficiently and reliably, thresholds
must be defined for a given region and season of interest (e.g., Justice et al. 1993, Kennedy et al. 1994). This is because each region, and even each ecosystem will have its own specific fire regime, characterized by seasonal patterns of soil and vegetation conditions which will affect the response of AVHRR observations (e.g., Grégoire et al. 1993). Discussions on fire detection algorithms can be found for example in Robinson (1991), Kennedy (1992) and Langaas (1995). Defining thresholds can be time consuming and difficult especially when operational detection is required. Moreover, it can bring subjectivity and inconsistency to the results. It is important to note that these algorithms actually detect hot spots, that is one pixel showing a high temperature due to the presence of one or several sources of heat at the surface.

3. Contextual approach

3.1. Concept

The principles of this contextual approach were first found in a fire detection algorithm review by Justice and Dowty (1994). Further references to that approach were looked for without great success. Mainly Prins and Menzel (1992), Smith and Vaughan (1991), Lee and Tag (1990), and Flannigan and Vonder Haar (1986) implemented similar approaches in very specific cases. Since the concept was very promising, we adapted the idea and developed it further.

When interpreting an image visually, the human eye usually spots a fire because of the contrast resulting from the difference of heat between the fire itself and its surroundings. This is exactly the way the contextual algorithm works: a decision about whether a pixel is a fire is made by comparing the values of a possible fire with those of its immediate neighbours. If the contrast between the two is high enough, the pixel is identified as a fire. The main difference from 'traditional threshold algorithms' is that a decision is made on a relative basis rather than an absolute one.

This means that the algorithm is self-adaptive and automatically detects fire under different conditions. For example: in the cooler environment of a forest, fires tend to have a low response in AVHRR channel 3, whereas a fire in a warmer dry savannah will probably saturate the AVHRR signal. Using a traditional technique with the same thresholds for these two cases would lead to either (i) only the savannah fire being detected (high thresholds), or (ii) the forest fire being detected, as well as many pixels of the warmer area (low thresholds). However, the contextual algorithm detects fires correctly in both environments on the basis of the contrast between the fires and the background. Further to its self-adaptive and automatic advantages, the contextual detection offers a high degree of consistency over larger areas, as well as through time.

3.2. Algorithm

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

3.2.1. Potential fire detection

This first stage is intended to select roughly all those pixels that may be a fire. It uses thresholds similarly to traditional fire detection algorithms, using thresholds low enough to retain at least all those pixels that will be fires, and high enough to reject most pixels that will definitely not be fires. The following tests are employed:
Test 1: A pixel is selected as a potential fire (PF) if:

\[ T_3 > 311 \text{ K} \]

and

\[ T_3 - T_4 > 8 \text{ K} \]

where \( T_3 \) and \( T_4 \) (in deg K) are AVHRR brightness temperatures in channels 3 and 4 respectively. The choice of the thresholds used in these two tests was driven by our experience. The first threshold (1) may seem rather low. It was selected to reduce the likelihood that potential fires would be rejected in colder regions such as in a forested environment. The second threshold (2) was placed high enough to reject those pixels that would not be fire in any case (e.g., pixels with high brightness temperature in both channels 3 and 4) (e.g., Kaufman et al. 1990, Kennedy et al. 1994).

Even though the contextual algorithm does not require specific areas to be masked, its efficiency and performance will increase when clouds, desert and water are masked. Desert and water masks can be found in several databases, main water surfaces can also be detected using low NDVI values. Major clouds can be masked using simple combinations of channels 1, 2 and 5.

Test 2: Pixels with high reflectance. Since the band width of AVHRR channel 3 covers parts of both the solar and thermal ranges of the electromagnetic spectrum, it is important to reject those pixels whose value in channel 3 would saturate or would be too high due to high reflection rather than high temperature (e.g., from bright soils, clouds or Sun glints). This is assessed by looking at the reflectance in channel 2. PF is not a fire if

\[ \rho_2 \geq 20\% \]

where \( \rho_2 \) is the top-of-atmosphere bidirectional reflectance factor for AVHRR channel 2. When masks are applied, our experience showed that this test still eliminates remaining falsely detected fires, for example in areas of bright savannah or Sun glint on rivers.

3.2.2. Potential fire confirmation

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

Extraction of information on PF's neighbours. For each PF, statistical information is automatically calculated for a variable size context-window (from \( 3 \times 3 \) to \( 15 \times 15 \) pixels) around the PF, to operate until at least 25 per cent of the neighbouring pixels can be considered as fire-background, and at least 3 pixels are eligible to be used in the computation. When these conditions are not met, the PF is rejected and the pixel is marked as non-fire, otherwise, the following information is computed:

\[ T_{3b} = T_3 \text{ mean of the fire background} \]

\[ \sigma_{T_{3b}} = T_3 \text{ standard deviation of the fire background} \]

\[ T_{34b} = [T_3 - T_4] \text{ mean of the fire background} \]

\[ \sigma_{T_{34b}} = [T_3 - T_4] \text{ standard deviation of the fire background} \]
where \( T_3 \) and \( T_4 \) (in deg K) are AVHRR brightness temperatures in channels 3 and 4 respectively. Only those pixels that are relevant to a normal fire-background are eligible for statistical calculations, that is, they must not be a PF, and if known, neither 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 would 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: Context test.** Finally, 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

\[
T_{3PF} - [T_{3b} + 2\sigma_{T_{3b}}] > 3 \text{ K} \tag{4}
\]

and

\[
T_{34PF} > T_{34b} + 2\sigma_{T_{34b}} \tag{5}
\]

where subscript \( PF \) refers to potential fire temperatures.

4. **Results and discussion**

This algorithm has not yet been tested exhaustively, but its first applications under various conditions and ecosystems show great promise. Indeed, within the framework of the development of a Global Vegetation Fire Product (Stuttard et al. 1995), this contextual algorithm was evaluated against a visual interpretation of multi-date images as well as field data. These observations were carried out over a wide range of ecosystems including tropical forests, savannas, deserts and wetlands distributed worldwide (3625 observed fires). Details of this first validation procedure overtake the scope of this Letter, nevertheless, it is worth mentioning that the overall performance of this technique appears to be excellent: (i) the contextual algorithm automatically detected 90 per cent of the fires observed visually, (ii) only 15 per cent of the pixels detected by the algorithm as fires were misclassified. When compared to multi-channel threshold algorithm results, the contextual approach appears to be at least as good, without the trouble of setting specific thresholds for each different time and place.

Although these results are very encouraging, the algorithm is probably not perfect and will benefit from some improvements. So far, our experience has shown that the channel 2 test is essential to eliminate pixels that would be detected as fires otherwise. Nevertheless, this test is imperfect and implies absolute thresholds. Areas with a highly reflective atmosphere (e.g., thick haze, long atmospheric path at high satellite zenith angle) may present high values in channel 2, whereas fires can still be seen visually. Even though the use of this test may eliminate some real fires under these conditions, it allows the removal of many more falsely selected PFs. It is currently being investigated whether some way of extracting the reflected part of channel 3 (e.g., Holben and Shimabukuro 1993) would allow a more precise rejection of PFs in these cases.

The first results showed that there are still commission errors, where the contextual algorithm detects fires incorrectly. We believe that most of these errors are due to:

- \( \text{So} \)
- \( \text{Co} \)
- \( \text{Ti} \)
- \( \text{Th} \)
- \( \text{Ge} \)
- \( \text{Wh} \)

As for a threshold environment very much size dependent between forest, to warm savanna.

5. **Conclusion**

The algorithm was designed to be implemented from NOAA and is applied and tropical is taken definitely to fire detection.

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Steve B discussed this manuscript.

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Some clouds or cloud edges escaping the various tests.

- Cool backgrounds which are not distributed all around a hot area (detected as PFs) leading to erroneous classifications (we are currently testing the addition of a background distribution criterion).

- The background of the immediate neighbourhood being much cooler than the general background of the area (maybe due to sensor behaviour, as suggested by Setzer and Verstraete 1994), which also lead to erroneous identifications (we believe that a starting context-window greater than 3 × 3 would eliminate these errors).

As far as computation time is concerned, the contextual approach is slower than a threshold algorithm, since a decision about a pixel is made by also looking at the environment of that pixel. However, the actual time necessary to process an image very much depends on the type of image. For a 512 × 512 image, with a maximum size context-window of 15 × 15, using a PC 486, typical processing time will vary between 30 s for an image with few potential fires in a cool background such as forest, to 1 h for an image with a lot of potential fires on hot environment such as warm savannahs, and desert areas.

5. Conclusion

The performance of this fire detection contextual algorithm appears to be successful and very promising. Even though it is not the optimum solution yet, its implementation is already considered worthwhile for improved, automatic fire detection from NOAA-AVHRR-LAC data. The exact same algorithm with identical parameters is applicable to a range of different environments, such as dry hot savannah, desert, and tropical forest. The objectivity of the tests on which a decision about a fire pixel is taken, provides consistent results between locations and seasons. Moreover, it definitely reduces the amount of time, necessary with traditional algorithms, to apply fire detection operationally under different conditions.

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