Fire Temperature Retrieval Using Constrained Spectral Unmixing and Emissivity Estimation

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ABSTRACT

Accurate retrieval of wildland fire temperature from remote imagery would be useful in improving prediction of fire propagation and estimates of fire effects such as burn severity and gas and particle production. The feasibility of estimating temperatures for subpixel fires by spectral unmixing has been established by previous work with the AVIRIS sensor. However, this unmixing approach can also produce optimizations for temperatures that may not be physically related to the fraction of flaming combustion in a pixel. Furthermore, previous techniques have treated fire as a blackbody and have modeled the mixed pixel transmitted radiance as two blackbody sources. This first order approximation can also affect the temperature retrieval. Knowledge of emissivity and use of a more complex radiance model should improve the accuracy of the temperature estimation. We therefore, propose a technique which improves the previous approach by using the potassium emission to pre-determine pixels that actually contain signal from flaming combustion and a modified mixed pixel radiance model. A non-linear, constrained multi-dimensional optimization procedure which estimates flame emissivity was applied to the model to estimate fire temperature and its areal extent. Results are shown for AVIRIS data sets acquired over Cuiaba, Brazil (1995) and the San Bernardino Mountains (1999).

Keywords: Fire temperature, areal extent of subpixel, emissivity estimation, mixed pixel radiance model.

1. INTRODUCTION

The effect of wildland fire can be catastrophic. It brings about the production of greenhouse gases, destruction of forests and above all, destruction of human livelihood and property. Accurate estimation of wildland fire temperature from remote imagery would be useful in improving prediction of fire propagation, measuring burn severity, ecosystem disturbance, intensity of fire incidents and other fire effects like aerosol and trace gas emissions. Previous work with hyperspectral and multispectral imagery have established the feasibility of estimating temperatures for subpixel fires by spectral unmixing. Using multispectral data, Dozier\(^1\) proposed a model for extracting temperatures and areal fractions from multiple pixels. Another related approach was also proposed by Prins\(^2\). Szymanski et al\(^3\) proposed a technique for extracting temperatures for materials that occupy less than a full pixel but their method was only applied to simulated scenes in which the atmospheric effects were disregarded. Some others like Oppenheimer\(^4\) and Green\(^5\) used hyperspectral AVIRIS data to extract volcanic hot spots and biomass fire temperatures respectively. They presented optimization techniques for extracting relatively high temperatures using an unmixing approach. However, this approach can produce optimizations for temperatures that are not physically related to the fraction of flaming combustion in a pixel. Our previous work\(^6\) on temperature extraction using the potassium emission signature and the mixed pixel transmitted radiance model proposed by Dozier\(^1\) and Green\(^5\) yielded high temperatures that were not typical of wildland fire.

In this paper, we propose a modified mixed pixel transmitted radiance model, which treats fire pixel pre-identified by the potassium band ratio algorithm as a spectral mixture or conglomeration of three regions. These, being the active fire, the burn scar (that has just been burned) and unburned regions. A non-linear, constrained...
spectral unmixing, multi-dimensional optimization procedure which also estimates effective emissivity for the constituents of the fire pixel, was applied to the model to estimate fire temperature and its areal extent. Results with AVIRIS imagery (Cuiaba, Brazil, fire of 1995 and San Bernardino Mountain, California, fire of 1999) show that the modal fire temperature was between 1000 and 1050 K, which is consistent with a typical forest fire. The extracted extreme temperatures were between 650 and 1200K.

2. THE POTASSIUM (K) EMISSION LINE PHENOMENON

With the discovery of potassium emission line in natural fire by Latham\textsuperscript{7}, we have exploited it for remote fire detection and temperature estimation. The use of this observation for remote fire detection was proposed by Vodacek et al.\textsuperscript{8} Burning biomass emits observable characteristic K line at wavelengths of 766.5 and 769.5 nm. In figure 1 (a), a 3ft×3ft controlled fire experiment conducted at the Missoula, Montana Fire Sciences Laboratory is shown. The fuel type was shredded excelsior produced from aspen trees. The spectral profile captured with Analytical Spectral Devices FieldSpec (ASD) radiometer with 2.7nm spectral resolution is shown in figure 1b. The K emission line is labeled on the spectrum. In figure 2, a similar observation is illustrated but this time with AVIRIS imagery. Figure 2a is a subset of a 2270.05nm (band 200) AVIRIS image, in which fire area is shown in white. The spectral profile of a typical fire pixel is shown in (b). The K emission line is also labeled. The use of these observations constitutes an essential part of our paper. The relative strength of the K signals in the direct field (full fire pixel, figure 1b) and remote (subpixel, figure 2b) measurements can be used to deduce the fire fraction in a mixed fire pixel.

![Figure 1](image1.png)

**Figure 1.** The Spectral profile of flame: (a) 3ft×3ft controlled fire (b) the average spectrum of the flame captured with ASD. The K emission line is labeled

![Figure 2](image2.png)

**Figure 2.** Spectral profile of fire image: (a) subset of band 200 AVIRIS Cuiaba 1995 fire image(b) the spectral profile showing K emission line. The AVIRIS sensor is saturated at wavelengths longer than about 1400 nm, except at the water vapor absorption bands.
3. PROCEDURE

We will now discuss our technique which consists of pre-identification of pixels containing flaming combustion by the K emission line algorithm followed by the temperature extraction. The block diagram of the procedure is shown in figure 3 below.

![Block Diagram of Fire Extraction Procedure](image)

**Figure 3. The Flow Chart for Fire Extraction by the Potassium Algorithm**

3.1. Potassium Emission Line Algorithm

The first phase of the two-phase process is the isolation of non-fire pixels from those that actually contain flame. This ensures that hot background and other highly reflective surfaces which sometimes pose as hot spots are eliminated from consideration. The K emission line algorithm discussed in detail by Vodacek et al provides the tool to realize this. The algorithm which is also referred to as K band ratio evaluates the ratio of the spectral band containing K signal to the adjacent one with longer wavelength. For AVIRIS imagery, these bands are adjacent and contiguous. The algorithm is summarized in the following steps:

1. Compute K band ratio image \( = \frac{\text{Band}_{K}}{\text{Band}_{adj}} \)
2. Compute the derived image global mean, \( \mu \) and variance, \( \sigma \)
3. Compute the pixel variance \( \sigma_p = \sqrt{(p(i, j) - \mu)^2} \) for pixel, \( p \) at \( (i, j) \) location
4. If \( \sigma_p > \kappa \sigma \) (where \( \kappa = 1, 2, 3, ... \)), classify pixel as fire pixel
5. Otherwise, classify as non-fire pixel and discard.

This algorithm is robust and not susceptible to false alarm. It eliminates factors that are common to the adjacent and contiguous bands such as variations in reflected solar illumination, upwelled radiance, specularity, smoke and atmospheric effects. The fire image detected by the algorithm would be used to flag the corresponding pixels for input to the multi-band optimization algorithm that follows.

It is important to mention that the location of the bands containing K signal depends on the spectral calibration of the sensor. For example, in 1995, the AVIRIS band numbers were 44 and 45 (Cuiaba) while in 1999, they were 45 and 46 (San Bernardino).

3.2. Mixed Pixel Radiance Model for Temperature Extraction

We hereby propose a typical fire pixel of an AVIRIS airborne imagery to be a conglomeration of three main regions; the active fire, the burn scar and the unburned regions as illustrated in figure 4 below. Each of these regions will contribute to the entire radiance reaching the sensor. To extract fire temperature from biomass burning, we therefore propose the following mixed pixel transmitted radiance model

$$L_T = f_1 \epsilon_1(\lambda) L_{B1}(T_1) + f_2 \epsilon_2(\lambda) L_{B2}(T_2) + f_3 \epsilon_3(\lambda) L_{B3}(T_3) + L_p + L_r$$

subject to the constraint $f_1 + f_2 + f_3 = 1$ and $\epsilon_i \leq 1$ for $i = 1, 2, 3$

where:

$f_i (i = 1, 2, 3)$ are areal extents of fire, burn scar and unburned regions respectively
$\epsilon_i (i = 1, 2, 3)$ are effective emissivities of fire, secondary and tertiary blackbody sources
$L_T$ is the total radiance measured by sensor
$L_{B1}(i = 1, 2, 3)$ are the Planck’s transmitted radiance model for active fire, burn scar and unburned regions respectively
$L_p$ is the upwelled radiance and
$L_r$ the reflected radiance

This is a modified version of the model previously used $^{1, 5, 6}$. MODTRAN 4 was used to model $L_p$ and $L_r$. The spectral terms in the above equation were modulated by atmospheric transmittance estimated by MODTRAN 4 radiative transfer code. A non-linear, constrained multi-dimensional optimization routine was

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**Figure 4. Illustration of a typical fire pixel as a spectral mixture of several parts: (a) active fire region (b) burn scar region and (c) unburned region**
used to provide a good spectral fit and invert the model to extract temperature. To avoid the effect of smoke and highly reflective surfaces, bands with wavelengths longer than 1000 nm were used in our routine. Pixels corresponding to the pre-determined fire pixels were flagged. Unlike Green’s approach, the flagged pixels were the only ones used in the optimization routine. This ensures that only fractions of pixels containing fire were optimized. The pre-identified pixels containing flame are shown in figure 5 (a). The spectra from six fire pixels are shown in 5(b). The spectra are highly saturated at wavelengths between 1400 and 2500 nm except at the water vapor bands. Some saturation are also observed at some other wavelengths for some pixels. The spectra are approximately flat and equal at saturation. Spectrum from the fire pixel with greatest radiance was used as a reference guide to automatically determine the on-set of saturation in our spectra. Powell’s multi-dimensional optimization algorithm was used for the spectral fit to estimate the fire model parameters. Like any other multi-dimensional routine, multiple convergence is possible. The choice of good initialization for the fire parameters is critical. The routine returns no parameters for pixels that violate the constraints. These pixels may be regarded as indeterminate because the routine could not determine a consistent set of parameters that would satisfy all the given constraints. A good choice will be one that gives a good spectral fit with little or no indeterminate returns. Based on the series of forest fire temperature we have directly measured, an initialization temperature of 1200 K was used. The table 1 below shows initialization for the model parameters. All the pre-determined fire pixels by the potassium algorithm were used in the fit but segments of the spectra in saturation were not used.

**Table 1.** The initialization for input fire parameters.

<table>
<thead>
<tr>
<th>Fire model parameters</th>
<th>Cuiaba</th>
<th>San Bernardino</th>
</tr>
</thead>
<tbody>
<tr>
<td>fire temperature</td>
<td>1200 K</td>
<td>1200 K</td>
</tr>
<tr>
<td>burn scar temperature</td>
<td>700 K</td>
<td>677 K</td>
</tr>
<tr>
<td>vegetation/soil temperature</td>
<td>350 K</td>
<td>350 K</td>
</tr>
<tr>
<td>areal extent of fire</td>
<td>0.052</td>
<td>0.03</td>
</tr>
<tr>
<td>areal extent of burn scar</td>
<td>0.60</td>
<td>0.30</td>
</tr>
<tr>
<td>effective emissivity of flame</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>effective emissivity of burn scar</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>effective emissivity of vegetation</td>
<td>0.80</td>
<td>0.80</td>
</tr>
</tbody>
</table>
4. RESULTS

Results with AVIRIS fire imagery of Cuiaba, Brazil (1995) and San Bernardino mountain (1999) are shown in figures 6 through 10 below. In figure 6, the AVIRIS image of band 200 (2270.05 nm) is shown in (a). The fire area is highlighted by solid red rectangle and the subset image showing the fire area, is shown in (b). The result of intensity stretching to accentuate the hot area is shown in (c). This highlighted hot area is mostly the burn scar which has the potentiality of being falsely classified as fire. The pixels that actually contain flaming combustion signal, that were pre-identified by K band ratio algorithm with pixel variance greater than $3\sigma$ ($\sigma$ being the global image variance) is shown in (d). The background, hot spots that do not actually contain flame have been eliminated. The spectral fit of the measured spectral radiance from one of the fire pixels with our model is shown in figure 7. This is a good fit within the limits of an error. Insufficient data were not available within the saturation region. The fit was also off at wavelengths lower than 1050 nm where the effect of upwelled radiance was quite significant. Results with San Bernardino mountain fire image are illustrated in figure 8 for band 150. In (a), the region containing fire is highlighted by the inscribed broken square. The result of fire detection by K band ratio for the given subset is shown in (b).

The temperature and areal extents for the two fire scenes are compared in figures 9 and 10. Figure 9 in particular, demonstrates that hotter fires correspond to higher fractional areal extents. For the Cuiaba fire, the extracted fire temperatures were between 650 and 1196 K with 0.0512 as the maximum areal fire extent. This translates to a fire area of 20.48 m$^2$ for a 400 m$^2$ pixel spatial size. For San Bernardino Mountain fire, the areal extent was between 0.02 and approximately 0.03 (8 to 12 m$^2$ spatial size). It had a low fire temperature of 815 K and the highest being 1200 K. The histogram for the temperature distribution for the two scenes are shown in figure 10. The results show that the dominant temperature was between 1000 and 1050 K for the two scenes. This is consistent with typical wildland fire temperature. Unlike previous results, there are no extracted temperatures in the 1600K range with corresponding to extremely small fire fractions. Our results show the intuitive result that larger fires are hotter (figure 9).

Figure 6. AVIRIS Imagery of Cuiaba fire of 1995: (a) Band 200 (2270.05 nm) image with the fire area in the rectangle, (b) sub set of image in (a) showing the fire area, (c) result of intensity stretching and (d) fire pixels determined by K band ratio.
Figure 7. The spectral fit of the measured radiance (AVIRIS) with our radiance model.

Figure 8. AVIRIS Imagery of San Bernardino Mountain fire of 1999: (a) Band 150 image (b) pixels containing flaming combustion - determined by potassium band ratio algorithm.
Figure 9. Temperature and Areal Extent Profiles for: (a) Cuiaba, 1995 and (b) San Bernardino Mountain, 1999.

Most temperatures are between 1000 K for San Bernardino and 1050 K for Cuiaba.

Figure 10. Histogram for fire temperature Distribution for: (a) Cuiaba, 1995 and (b) San Bernardino Mountain, 1999. Most temperatures are between 1000 K for San Bernardino and 1050 K for Cuiaba.
5. CONCLUSION

We have developed a more realistic technique for estimating the wildland fire temperature. Its utility is based on the application of potassium emission line signature to flag pixels that actually contain flame and also on the modified radiance model that employed non-linear multi-dimensional constrained optimization to provide a spectral fit. The optimization routine inverted the model to give temperature. Hotter fire area corresponds to higher fractional areal extents. The use of K algorithm ensured that only fire pixels containing flame signal were used for the optimization routine for temperature and areal extent. This did not only greatly reduce the computational load if the entire image were used but also reduced potential error if the hot background had been used as flame. The use of a more realistic mixed pixel radiance model that estimates effective emissivities has also resulted to more realistic wildfire temperatures estimation.

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REFERENCES