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Automated Extraction of Fire Line Parameters from Multispectral Infrared Images

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Abstract

Remotely sensed infrared images are often used to assess wildland fire conditions. Separately, fire propagation models are in use to forecast future conditions. In the Dynamic Data Driven Application System (DDDAS) concept, the fire propagation model will react to the image data, which should produce more accurate predictions of fire propagation. In this study we describe a series of image processing tools that can be used to extract fire propagation parameters from multispectral infrared images so that the parameters can be used to drive a fire propagation model built upon the DDDAS concept. The method is capable of automatically determining the fire perimeter, active fire line, and fire propagation direction. A multi-band image gradient calculation, the Normalized Difference Vegetation Index, and the Normalized Difference Burn Ratio along with several standard image processing techniques are used to identify and constrain the fire propagation parameters. These fire propagation parameters can potentially be used within the DDDAS modeling framework for model update and adjustment.

Keywords: fire propagation modeling, image gradient, fire detection, fire monitoring, infrared

1. Introduction

Wildland fires all over the world have effects that can range from the very destructive to beneficial. In either case it is desirable to monitor the progress of wildland fires so their affects can be assessed and controlled as needed. Two of the technological tools that are used to help monitor the progress of wildland fires are remote sensing and fire propagation modeling. The remote sensing tools range from global satellite sensors to airborne sensors. Satellite sensors such as Moderate Resolution Imaging Spectrometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) are used for remote monitoring of fire on a global scale and have even been useful for operations in wilderness areas despite their large ground spot size (Rauste *et al.*, 1997; Kaufman *et al.*, 1998; Li *et al.*, 2000). Finer resolution satellite sensors such as Bispectral Infrared Detection (BIRD) have also provided high quality data of active fires, but at the cost of repeat coverage (Wooster *et al.*, 2003). However, for most fire monitoring situations, finer resolution and geolocation and more frequent repeat coverage are desirable (Zajkowski *et al.*, 2003) and airborne remote sensing has been used to meet these requirements for many years in a variety of scenarios (Radke *et al.*, 2000; Ambrosia *et al.*, 2003; Zajkowski *et al.*, 2003; Li *et al.*, 2005). Fire propagation modeling tools have likewise been developed over a number of years using a variety of semi-empirical and physics-based approaches. The semi-empirical approaches are represented by the work of Rothermel (1972) and the large body of work based on his results (Andrews, 1986; Finney, 1994, 1998, 2002). The physics-based approach is represented by computational fluid dynamics models or finite element numerical models that calculate combustion reactions and rely on equations of heat and radiation balance (Albini, 1981, 1985, 1986; Asensio and Ferragut, 2002; Butler *et al.*, 2004). Data inputs to all these models include weather conditions, terrain, and fuel conditions that are provided prior to running the model. Adjustments to the model run require modifying the data inputs and rerunning the model. Further, the initial fire location is the only information on the fire itself used by these modeling approaches. Therefore, if the model output does not match the actual fire propagation the only recourse is to update the input data parameters and rerun the model.

Recently, work has begun on a fire propagation modeling framework based on the Dynamic Data-Driven Application System (DDDAS) concept (Darema, 2004). In the DDDAS concept, data for driving the model (either semi-empirical or physics-based) can arrive from remote systems and can be assimilated into the model to update and adjust it while it is running. Further, within the DDDAS concept the model should not only react to new data, the output should also be actively used to steer future data collections. In the DDDAS fire propagation modeling framework proposed by Mandel *et al.* (2005) images from airborne sensor will be one of the data sources and the model will adjust to the new information on the fire location

provided by the images. The ultimate goal is to provide a fire propagation forecast. In a procedure similar to that used in weather forecasting, the fire propagation forecast uses the uncertainty in the data and multiple instances of the model running simultaneously and faster than real-time. Within this modeling framework the airborne image data must be processed into a format that can be used for automated model update and adjustment.

Examples of image-derived parameters for model update and adjustment include the burned area and the fire propagation direction. The Normalized Difference Vegetation Index (NDVI) has been well used for burned area mapping (Cahoon *et al.*, 1992; Kasischke *et al.*, 1993; Kasischke and French, 1995; Li *et al.*, 1997) and the Normalized Difference Burn Ratio (NDBR) has likewise been used for burn severity and active fire mapping (Key and Benson, 2002). In this paper we use the NDVI and NDBR spectral indices combined with image analysis tools to calculate additional parameters from high resolution hyper-/multi-spectral images of active fires that can be used to provide the image-derived data for updating and adjusting the model dynamic behavior. The approach is a non-parametric way of determining the fire perimeter, the active fire line, and the fire propagation direction. The fire perimeter is defined as the outline of the area that was already burned when the image was captured and the active fire line as the portion of the fire perimeter that was actively burning at the time the image was acquired. The fire propagation direction is defined as the normal to the active fire line pointing toward the unburned fuel. These are all parameters that can be used for model update and adjustment. The block diagram of our technique is shown in Figure 1. For a given input image, the approach relies on three initial image processing procedures, which are calculations of the NDVI, NDBR, and the magnitude of the multi-band spatial gradient. By applying suitable thresholds along with image dilation to NDVI and NDBR, the contour of the active fire area and fire perimeter are separately extracted. The estimated active fire line is extracted by applying a Boolean **AND** to the NDVI and the multi-band gradient magnitude images. The extracted active fire line at this stage is in digital form with isolated pixels, outliers and gaps making it difficult to draw normals to the active fire line using an automated procedure. Hence, the active fire line image is dilated and fitted using B-splines to facilitate the drawing of normals. Fire spread modeling which is derived from Huygens' principle assumes the contour of a propagating fire front is elliptical (Burgan and Rothermel, 1984; Andrews, 1986; Richards, 1995; Finney, 1998). We use this assumption and also assume that portions of the active fire line with rapid varying curvature are regions of the fire line that are most rapidly propagating. This assumption is consistent with the rate of maximum spread by elliptical transformation (Richards, 1995). Thus, the parts of the active fire line with the highest multi-band spatial gradient value are found and labeled as dominant fire pixels. Normals to a second degree polynomial fit of the active fire line pixels near the dominant fire pixels are

calculated and the propagation direction is constrained using the NDVI or NDBR images. The ultimate use of this procedure will be to compare the fire perimeter, the active fire line, and the fire propagation direction with the same parameters derived from the fire propagation model and then update and adjust the model as needed within the DDDAS framework (Mandel *et al.*, 2005).

The remainder of this paper is organized as follows, Section 2 gives a brief overview of the essential image analysis tools and Section 3 describes the proposed technique. Experimental results and discussion are presented in Section 4 and conclusions are drawn in Section 5.

Figure 1. The block diagram of the method for extracting the image-derived parameters useful for model updating.

2. Overview of Image Analysis

In this section, we describe the suite of image processing tools that form the image processing methods described in Figure 1.

2.1. The Spectral Indices

The use of spectral indices like the NDVI to infer vegetation conditions and the NDBR to measure burn severity have been extensively documented in literature (see Section 1). These indices may be used to generate the active fire areas and burn scar. They are defined by the following equations

$$NDVI = \frac{R_{nir} - R_{red}}{R_{nir} + R_{red}} \quad (1)$$

$$NDBR = \frac{R_{nir} - R_{swir}}{R_{swir} + R_{nir}} \quad (2)$$

where R_{red} , R_{nir} , and R_{swir} are the reflected radiance in the red, near-infrared and short-wave spectral bands respectively. For some of the processing, we also used the modified NDBR index as given in equation 3.

$$NDBR_{Modified} = \frac{R_{swir} - R_{lwir}}{R_{swir} + R_{lwir}} \quad (3)$$

where R_{lwir} is the radiance in the long-wave infrared region. For unhealthy vegetation, the R_{red} value increases and the NDVI value drops and tends to be negative when the vegetation has been burned. Similarly, the NDBR is also negative for burned vegetation. These indices are used for classification of the active fire area and burn scar and are effective means of validating the direction of propagation of the fire fronts.

2.2. Multi-band Edge Detection

Edge detection routines exploit the contrast between fire pixels and background by highlighting regions of rapid intensity or radiance changes. These rapid changes across an image can be quantified by calculating the spatial gradient, where a large value change from one pixel to another results in a high gradient magnitude. Computation of edges in a single-band image is easily realizable with an edge kernel but the approach for a multi-band image deserves some attention. The gradient of a three-band color image field is described in Lee and Cok (1991) and Saber *et al.* (1997). In this paper, we show an extension of the algorithm to multi- and hyper-spectral imagery where more than three bands are involved. Consider a multi-band image defined by $\mathbf{I} = [I_1, I_2, \dots, I_n]^T$ where I_i represents the i^{th} band and n is the number of bands. The spatial gradient matrix, $\mathbf{D}$ at location (i, j) is given by

$$\mathbf{D}(i, j) = \begin{bmatrix} \frac{\partial I_1}{\partial u} & \frac{\partial I_1}{\partial v} \\ \vdots & \vdots \\ \frac{\partial I_n}{\partial u} & \frac{\partial I_n}{\partial v} \end{bmatrix} \quad (4)$$

where u and v are the spatial image coordinates. The gradient magnitude is computed by constructing the matrix,

$$\mathbf{D}^T \mathbf{D}(i, j) = \begin{bmatrix} p(i, j) & t(i, j) \\ t(i, j) & q(i, j) \end{bmatrix} \quad (5)$$

and the maximum eigenvalue, $\lambda(i, j)$ is defined by

$$\lambda(i, j) = \frac{1}{2} \left([p(i, j) + q(i, j)] + \sqrt{[p(i, j) + q(i, j)]^2 - 4[p(i, j)q(i, j) - t(i, j)^2]} \right) \quad (6)$$

where

$$p(i, j) = \sum_{k=1}^n \left(\frac{\partial I_k}{\partial u} \right)^2 \quad (7)$$

$$t(i, j) = \sum_{k=1}^n \left(\frac{\partial I_k}{\partial u} \right) \left(\frac{\partial I_k}{\partial v} \right) \quad (8)$$

$$q(i, j) = \sum_{k=1}^n \left(\frac{\partial I_k}{\partial v} \right)^2 \quad (9)$$

The magnitude of the multi-band image gradient, $\|\mathbf{D}(i, j)\|$ is therefore given by

$$\|\mathbf{D}(i, j)\| = \sqrt{\lambda(i, j)} \quad (10)$$

In our case, when the magnitude of the gradient is calculated for the multi-band image that includes the infrared bands, the resulting edge map effectively outlines the area of active burning based on the strong infrared emission from fire (see Figure 4b) . High values of the gradient also indicate dominant fire pixels (see Section 3.5).

2.3. Morphological Image Processing

Morphological image processing provides an effective means of filling in broken edges and reducing the effect of noise inherent in digital image processing routines such as edge detection. Two fundamental morphological operations are dilation and erosion. These operations are based on set theory which have been extensively reviewed in image processing texts like Gonzalez and Woods (2002); Seul *et al.* (2001); Parker (1997). Dilation adds pixels at region boundaries and consequently tends to cause the features to grow in size. However, it tends to suppress noise in the image. Image thinning may be used to remove the excessive features added by the dilation process without affecting the filled edges. The dilation of the edge map image is vital for removing noise and artifacts thereby allowing the extraction of the active fire line in an automated process.

2.4. B-spline Curves

B-spline curves have been extensively discussed in many computer graphics texts (Foley *et al.*, 1993; Schneider and Eberly, 2003). They are characterized by control points which are pixel coordinates in our case and are quite effective in noise suppression (Saber and Tekalp, 1997). B-splines are defined by

$$C(t) = \sum_{i=0}^n S_{i,j}(t)P_i \quad (11)$$

where j is the degree of the components of the polynomial $C(t)$. $P_i \in \mathcal{R}^2$ are control points and t_i are monotone sets of points also referred to as knots for $0 \leq i \leq n$ and $S_{i,j}(t)$ is a real valued polynomial $t \in [t_0, t_n]$, $1 \leq j \leq n$

$$S_{i,0}(t) = \begin{cases} 1 & , \quad t_i \leq t \leq t_{i+1} \\ 0 & , \quad \text{otherwise} \end{cases} \quad (12)$$

$$S_{i,j}(t) = \frac{(t - t_i)}{t_{i+j-1} - t_i} S_{i,j-1}(t) + \frac{(t_{i+j} - t)}{t_{i+j} - t_{i+1}} S_{i+1,j-1}(t) \quad (13)$$

The B-spline curves are used to approximate the active fire line segments. They capture the essence of the active fire line but not the high resolution details that would make it difficult to automatically draw a normal. We also use the smooth visualization provided by the B-spline in our figures, but more importantly, this parametrization of the active fire line gives us an option to the digital image for model update and adjustment within the DDDAS framework.

3. The Approach

3.1. Airborne Images

Input images used for our study are multi- and hyper-spectral images from the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), MODIS Airborne Simulator (MAS) and Wildfire Airborne Sensor Program (WASP). These sensors deliver images in different spectral bands. The AVIRIS sensor has 224 contiguous spectral bands and wavelengths ranging from 0.4 to 2.5 μm (Green *et al.*, 1998). MAS has 50 spectral bands with wavelengths spanning 0.55-14.2 μm (King *et al.*, 1996). These two sensors record information at 16-bit resolution. The WASP is a 12-bit system and was designed by the Laboratory for Imaging Algorithms and Systems (LIAS) group in the Center for Imaging Science at the Rochester Institute of Technology. It has a total of 3 infrared bands (short-, mid- and long-wave infrared) with wavelengths from 1.2 - 9.2 μm (McKeown *et al.*, 2005). The AVIRIS data set was from the 1999 San Bernardino Mountain fire in California (Figures 2 - 6). The image shows a portion of the fire that is backing into the wind. The MAS image also shows a

backing fire that occurred in the Santa Catalina Mountains in Pima County, in Arizona (Aspen fire, Figures 7 and 8). It was ignited on June 17, 2003 and burned for almost a month. The image used for our study was captured on June 24, 2003. Three WASP images obtained approximately at 10 minutes interval are from a prescribed burn in the Vinton Furnace Experimental Forest in SE Ohio on April 17, 2004 (Figure 9). This prescribed fire was in light and variable winds and the images show the progression of the fire as well as ongoing ignition of the fire.

3.2. Image Processing

The initial phase of our proposed approach involves the evaluation of the spectral indices NDVI and NDBR and the magnitude of the multi-band spatial image gradient to generate the edge map for the given multi- or hyper-spectral imagery (see Figures 2, 3, 4 and 7). With AVIRIS, the 155 spectral bands ranging from band 70 to band 224 were used for the multi-band image gradient. Shorter wavelengths were not used to avoid the influence of smoke. For the same reason, only bands 15 to 39 of MAS were used. For WASP, we used the modified NDBR equation but could not calculate an NDVI values based on the three infrared WASP bands. WASP includes an RGB camera allowing for the use of a modified NDVI that replaces the NIR band with the short-wave IR band in the NDVI equation. All three infrared bands of WASP were utilized for the gradient magnitude computation. Sobel operators were used to implement the partial derivatives given in equations 7 - 9. The choice of these operators was based on their combined ability to provide both the derivative and smoothing actions (Gonzalez and Woods, 2002). A threshold was applied to the resulting edge map using the technique discussed in Ononye *et al.* (2005). This sets the stage for the next phase which enables the active fire area and the fire perimeter to be extracted.

3.3. Extraction of Active Fire Area

Although both NDVI and NDBR tend to be negative for a given burned area, NDBR provides a better mapping tool for actively burning and burned areas (Key and Benson, 2002). Negative values of the NDBR image were used to define the active fire area. The outline of the active fire area was generated by applying zero-crossing to the NDBR image. Similarly, with NDVI a zero-crossing was also used to derive the fire perimeter. Zero-crossing may be defined as the act of locating the transition points in the image where the value changes from positive to negative or negative to positive. The derived NDVI image was dilated and then converted to a bilevel image to provide a constraint for extracting the direction of fire propagation. For WASP, the dilated NDBR image was used to provide the direction constraint.

3.4. Extraction of Active Fire Line Segments

The edge map derived from the multi-band gradient was transformed to a bilevel image with gray scale value of 255 denoting the active fire pixels and zero, for the non-active fire pixels. The fire perimeter image deduced from NDVI (or NDBR when processing WASP data) was also converted to the same form. Next, the Boolean **AND** operation was applied to the two images to extract the active fire line. Hence, a pixel was deemed to be a point on the active fire line if the gray scale values of that pixel in both the fire perimeter and edge map images were 255. By applying this operation to all pixels, the active fire line was extracted. The extracted active fire line at this stage is in digital form and also piecewise. To generate a fire line that would be used as input for the active fire propagation estimation, a class map of these piecewise active fire lines was created and then processed by B-spline curve fitting. Class regions with at least nine contiguous pixels were approximated using B-splines. The degree, j , of the polynomial that provided the best fit was 3.

3.5. Normal Estimation

The normals at dominant pixel points on the B-spline estimate of the active fire line were obtained by a numerical technique. Dominant pixels are defined as those with high gradient values. Driven by the fact that the shape of the propagating fire front is elliptical (as previously discussed in Section 1) and also given that an ellipse is a second order polynomial, a generalized quadratic curve shown in equation 14 was used to fit a selected number of points around the dominant fire points.

$$f = \sum_{i=0}^2 a_i x^i \quad (14)$$

A least squares maximum likelihood estimate was used to deduce the coefficients a_i . Once these coefficients were computed, the equation of a straight line

$$y = m(x - x_i) + y_i \quad (15)$$

(where the slope, $m = \frac{-1.0}{\nabla f}$) through each of the pre-determined dominant points was constructed. There is a tendency for high gradient magnitudes to cluster together rather than be distributed along the curve. To ensure a fairly good spread of the selected dominant fire points, the maximum gradient within a sliding 17×17 window was utilized to suppress the successive neighboring points from being selected as dominant. Once the dominant pixels were flagged, every other pixel on the active fire within the same local window was employed in the estimation of the local normal in the normal routine. This was to broaden the number of points used within the neighborhood of the dominant fire points without a drastic reduction in the computational speed.

3.6. Estimation of Direction of Propagation of Fire Front

The final phase of our technique is to specify the direction of fire propagation. A direction has to be assigned to the normal line found with equation 15 pointing in the direction of the unburned vegetation. With the extracted and processed active fire line, a straight line at each dominant fire pixel location was constructed and its direction was therefore assigned according to the constraint provided by the bilevel fire perimeter image.

4. Results and Discussion

The complete sequence of images showing the steps in our technique are presented for the AVIRIS image of the San Bernardino Mt. fire. The extraction of the active fire area from NDBR is shown in Figure 2. In this figure, a subset of band 107, the $1.3553\mu m$ band is depicted in (a) and the NDBR image is illustrated in (b). The appearance of the NDBR image indicates it could easily be classified by image processing techniques to extract relevant features. The active fire image found from negative values of NDBR as discussed previously is shown in (c) as the black region. The zero-crossing technique was used to outline the active fire area shown in (d) using the result in (b). This figure demonstrates the effectiveness of our approach as an image feature extractor.

The result of the fire perimeter extraction from the NDVI image is displayed in Figure 3. The NDVI image is displayed in (a). In (b), the fire perimeter extracted by the zero-crossing procedure using the NDVI image as the input is shown. A bilevel image that delineates the burned region from the unburned is shown in (c). In this image, the burned region is in black while the unburned is white. It therefore provides a useful mechanism for automating the calculation of the direction of fire propagation.

The active fire line extracted by applying the Boolean **AND** to the NDVI and the gradient images is shown in Figure 4. The fire perimeter (derived from the NDVI) is depicted in (a) and the multi-band image gradient magnitude which has been post-processed is shown in (b). In this image, the background was suppressed (set to black) to accentuate the fire area. The extracted active fire line is shown in (c). This fire line is noisy, with broken edges (raw form). The B-spline estimate of the active fire line is shown in (d).

In Figure 5, the constraints for validating the direction of fire propagation are shown. Location of dominant fire pixels deduced from high values for the multi-band image gradient magnitude are depicted as encircled

dots on the fire line, as shown in (a). The bilevel fire perimeter (derived from the NDVI image) is shown in (b). This image provides the validation for discerning the direction of the normal at each dominant position. Using the image pair in this figure, directions of propagating fire fronts were deduced and are shown in Figure 6. The result is in accord with the intuition that fire propagates from burned or active burning area to an unburned. In (b), the extracted active fire fronts are superimposed on the image (band 107).

The results using MAS imagery are shown in Figures 7 and 8. We show only a select set of images of the intermediate steps. A subset of band 40, a $5.272\mu m$ image is shown in Figure 7(a). In this figure, the multi-band gradient magnitude is displayed in (b) and the NDVI and NDBR images are shown in (c) and (d) respectively. The propagating fire front is displayed in Figure 8 superimposed on the input image.

For the three time sequential WASP images, we show the final result, thus, providing an opportunity to assess the success of the technique in automatically determining the fire propagation. The time sequence of the short-wave input images (10 -11 minutes apart) are displayed in Figure 9:(a)-(c). The figure demonstrates how the central unburned region in a textured pattern shown in (a) progressively shrank in size as illustrated in (b) and (c) as the fire began to spread. The image shown in Figure 9(b) was captured about 11 minutes after (a) and that in (c) was 10 minutes after (b). The lower left part of the fire in (b) and (c) were just ignited and hence the direction of propagation is not always correctly predicted because there is unburned vegetation on both sides of the narrow fire line. In (d) and (e), the extracted fire fronts are shown superimposed on the input data sets (a) and (b) respectively .

5. Conclusion

We have shown that we can successfully use a series of image processing tools to extract parameters related to fire propagation from multispectral infrared single images and image sequences. A multi-band image gradient process is effective in locating the active fire line in multispectral infrared images captured with three different sensors. The fire propagation parameters are needed for model update and adjustment within a Dynamic Data Driven Application System (DDDAS) framework for forecasting fire propagation. Visual analysis of the results for the three test images suggest that this automatic method for extracting fire line parameters will work quite well for fires that have well defined fire perimeters expanding from the ignition location. This image processing approach was able to extract the fire perimeter, active fire line, and fire propagation direction without the use of any ancillary data. It is not surprising that the propagation direction parameter has more errors when the fire is complex and newly ignited because of the difficulty in establishing

the propagation direction solely from the image.

An important aspect of further work will be establishing probabilities or error estimates to accompany the derived parameters. Low confidences can be assigned to new ignitions that are surrounded by unburned fuel and high confidences assigned when the NDVI and NDBR parameters allow for the unambiguous and automatic establishment of the fire propagation direction. These probabilities or errors are required within the DDDAS framework for model adjustment and updating. More analysis of image sequences for complex fires similar to those shown for the prescribed burn in Figure 9 will be useful for further establishing the accuracy of the method and assessing the potential for additional image processing tools for improving the fire parameter estimates. Finally, methods for comparing the image derived parameters with the fire propagation model require further study since the parameters we have derived, while useful for visualization, may not be optimal for matching to the model output during the automated model update and adjustment process.

Figure 2. *Extraction of active fire map from NDBR using AVIRIS: (a) Band 107-1.3553μm (b) NDBR image, (c) active fire area generated by negative NDBR values is shown in black and, (d) the contour active fire area extracted by zero-crossing technique.*

Figure 3. *Extraction of fire perimeter from NDVI: (a) NDVI image, (b) fire perimeter derived from the NDVI image in (a) by zero-crossing and (c) bilevel image derived from NDVI by dilation, with the burned area in black.*

Figure 4. *Extraction of the active fire line from gradient and fire perimeter images by a Boolean **AND** operation: (a) fire perimeter from NDVI, (b) magnitude of spatial multi-band gradient image, (c) the extracted active fire line in raw form and, (d) the processed active fire line fitted with a B-spline curve .*

Figure 5. Constraint for deducing the direction of propagation of the active fire front. (a) the encircled dots on the active fire line show the location of the dominant fire pixels where normals are to be constructed. (b) The bilevel fire perimeter image to be used to validate the direction of the fire propagation.

Figure 6. Extraction of active fire front. (a) The extracted active fire front of San Bernardino Mountain fire of 1999 - AVIRIS imagery. The arrows show directions of propagation of fire fronts. (b) The superposition of the extracted active fire front on the band 107 (the 1.3553μm) image.

(a)

(b)

(c)

(d)

Figure 7. *Computation of the multi-band image gradient magnitude and spectral indices with MAS imagery. (a) Band 40, a $5.272 \mu\text{m}$ image, (b) gradient magnitude (c) NDVI, and (d) NDBR.*

Figure 8. *The extraction of fire front with MAS imagery. The extracted fire front is superimposed on the band 40 (the $5.272\ \mu\text{m}$) image.*

Figure 9. Validation of our technique with a time sequence of WASP imagery captured over controlled burn (a two-level ignition) in Ohio, 2004. The unburned region in a textured pattern shows the progression of fire in the images. (a) SWIR image, (b) SWIR image sequence captured 11 minutes later, and (c) SWIR captured 10 minutes after (b). (d) and (e) are superposition of the extracted fire fronts on the input images (a) and (b) respectively. The directions that are either missed or incorrectly extracted tend to be in regions that were freshly ignited.

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References

- Albini, F. (1981). A Model for the Wind-blown Flame from a Line Fire. *Combustion and Flame*, **43**, 155–174.
- Albini, F. (1985). A Model for Fire Spread in Wildland Fuels by Radiation. *Combust. Sci. Technol.*, **42**, 229–258.
- Albini, F. (1986). Wildland Fire Spread by Radiation: A Model including Fuel Cooling by Natural Convection. *Combust. Sci. Technol.*, **45**, 101–113.
- Ambrosia, V., Wegener, S., Sullivan, D., Buechel, S., Dunagan, S., Brass, J., Stoneburner, J., and Schoenung, S. (2003). Demonstrating UAV-acquired real-time thermal data over fires. *Photogram. Eng. Remote Sens.*, (69), 391–402.
- Andrews, P. L. (January, 1986). BEHAVE: Fire Behavior Prediction and Fuel Modeling System – BURN Subsystem, Part 1. USDA Forest Service General Technical Report, NFES 0276.
- Asensio, M. and Ferragut, L. (2002). On a Wildland Fire Model with Radiation. *International Journal of Numerical Methods in Engineering*, **54**, 137–157.
- Burgan, R. E. and Rothermel, R. C. (June, 1984). BEHAVE: Fire Behavior Prediction and Fuel Modeling System . USDA Forest Service General Technical Report, INT -167.
- Butler, B., Finney, M., Andrews, P., and Albini, F. (2004). A Radiation-driven Model for Crown Fire Spread. *Canadian Journal of Forest Research*, **34**, 1588–1599.
- Cahoon, D. R., Stocks, B. J., Levine, J. S., Cofer, W. R., and Chung, C. C. (1992). Evaluations of a Technique for Satellite-derived Area Estimation of Forest Fires. *Journal of Geophysical Research*, **97**, 3805–3814.
- Darema, F. (2004). Dynamic Data Driven Applications Systems: A New Paradigm for Application Simulations and Measurements. Computational Science - ICCS 2004: . *4th International Conference, Krakw*,

- Poland, June 6-9, 2004, *Proceedings, Part III*, M. Bubak, G. Dick van Albada, P. M. A. Sloot, and J. J. Dongarra (eds.), *Lecture Notes in Computer Science series*, **3038**, 662–669.
- Finney, M. (1998). FARSITE: Fire Area Simulator - Model Development and Evaluation. *USDA Forest Service Research Paper RMRS-RP-4*.
- Finney, M. A. (1994). Modeling the Spread and Behavior of Prescribed Natural Fires. *12th Conference on Fire and Forest Meteorology*, pages 138–143.
- Finney, M. A. (2002). Fire Growth Using Minimum Travel Time Methods. *Canadian Journal of Forest Research*, **32**, 1420–1424.
- Foley, J., Dam, A., Feiner, S., and Hughes, J. (1993). *Computer Graphics: Principles and Practice*. Addison-Wesley.
- Gonzalez, R. and Woods, R. (2002). *Digital Image Processing*. Addison-Wesley, second edition edition.
- Green, R., Eastwood, M., Sarture, C., Chrien, T., Aronsson, M., Chippendale, B., Faust, J., Pavri, B.E. an Chovit, C., Solis, M., Olah, M., and Williams, O. (1998). Imaging Spectroscopy and the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). *Remote Sensing of Environment*, (65), 227–248.
- Kasischke, E. S. and French, N. H. E. (1995). Locating and Estimating the Areal Extent of Wildfires in Alaskan Boreal Forest Using Multiple-season AVIRIS NDVI Composite Data. *Remote Sensing of Environment*, **51**, 263–275.
- Kasischke, E. S., French, N. H. E., Harell, P., Christensen, N. L., Ustin, S. L., and Barry, D. (1993). Monitoring of Wildfires in Boreal Forests Using Large Area AVHRR NDVI Composite Image Data. *Remote Sensing of Environment*, **45**, 61–71.
- Kaufman, Y., Justice, C., Flynn, L., Kendall, J., Prins, E., Giglio, L., Ward, D., Menzel, W., and Setzer, A. (1998). Potential Global Fire Monitoring from EOS-MODIS. *Journal of Geophysical Research*, **103**(D24), 32,215–32,238.
- Key, C. and Benson, N. (2002). Measuring and Remote Sensing of Burn Severity. In *J.L. Coffelt and R.K. Livingston, USGS Wildland Fire Workshop, Los Alamos, NM October 31- Nov. 3, 2000. USGA Open-File Report 02-11.*, page 55.
- King, M., Menzel, W., Grant, P., Myers, J., Arnold, G., Platnick, S., Gumley, L., Tsay, S., Moeller, C., FitzGerald, M., and Brown, K.S. an Osterwisch, F. (1996). Airborne Scanning Spectrometer for Remote Sensing of Cloud, Aerosol, Water Vapor, and Surface Properties. *J. of Atmospheric and Oceanic Technology*, **13**(14), 777–794.

- Lee, H. and Cok, D. (1991). Detecting Boundaries in Vector Field. *IEEE Transactions on Signal Processing*, **39**, 1181–1194.
- Li, Y., Vodacek, A., Kremens, R., Ononye, A., and Tang, C. (2005). A Hybrid Contextual Approach to Wildland Fire Detection Using Multispectral Imagery. *IEEE Transactions on Geoscience and Remote Sensing*, **43**(9), 2115–2126.
- Li, Z., Cihlar, J., Moreau, L., Huang, F., and Lee, B. (1997). Monitoring of Fire Activities in the Boreal Ecosystem. *Journal of Geophys. Res.*, **102**, 29611–29624.
- Li, Z., Nadon, S., Cihlar, J., and Stocks, B. (2000). Satellite-Based Mapping of Canadian Boreal Forest Fires: Evaluation and Comparison of Algorithms. *International Journal of Remote Sensing*, **21**(16), 3071–3082.
- Mandel, J., Bennethum, L., Chen, M., Coen, J., Douglas, C., Franca, L., Johns, C., Kim, M., Knyazev, A., Kremens, R., Kulkarni, V., Qin, G., Vodacek, A., Wu, J., Zhao, W., and Zornes, A. (2005). Towards a Dynamic Data Driven Application System for Wildfire Simulation. in *Computational Science - ICCS 2005*, V.S. Sunderam, G.D. van Albada, P.M.A. Sloot, and J.J. Dongarra, (2), 632–639.
- McKeown, D., Cocburn, J., Faulring, J., Kremens, K., Morse, D., Rhody, H., and Richardson, M. (2005). Wildfire Airborne Sensor Program (WASP): A New Wildland Fire Detection and Mapping System. In: *Remote Sensing for Field Users. Proc. 10th Biennial USDA Forest Service Remote Sensing Applications Conference. Salt Lake City, UT*, pages CD-ROM, ISBN 1–57083–075–4, ASPRS.
- Ononye, A., Vodacek, A., Wang, Z., and Li, Y. (2005). Mapping of Active Fire Area by Image Gradient Techniques. In: *Remote Sensing for Field Users. Proc. 10th Biennial USDA Forest Service Remote Sensing Applications Conference. Salt Lake City, UT*, pages CD-ROM, ISBN 1–57083–075–4, ASPRS.
- Parker, J. (1997). *Algorithms for Image Processing and Computer Vision*. Wiley.
- Radke, L., Clark, T., Coen, J., Walther, C., Lockwood, R., Riggan, P., Brass, J., and Higgins, R. (2000). The WildFire Experiment (WiFE): Observations with Airborne Remote Sensors. *Can J. Remote Sens.*, (26), 406–417.
- Rauste, Y., Herland, E., Frelander, H., Soine, K., Kuoremaki, T., and Ruokari, A. (1997). Satellite-based Forest Fire Detection for Fire Control in Boreal Forests. *International Journal of Remote Sensing*, **18**, 2641–2656.
- Richards, G. (1995). A General Mathematical Framework for Modeling two-dimensional Wildland Fire Spread. *International Journal of Wildland Fire*, **5**(2), 63–72.

- Rothermel, R. C. (1972). A Mathematical Model for Predicting Fire Spread in Wildland Fuels. USDA Forest Service General Technical Report, INT-115 1573.
- Saber, E. and Tekalp, M. (1997). Region-Based Shape Matching for Matching for Automatic Image Annotation and Query-by-Example. *Journal of Visual Communication and Image Representation*, **8**(1), 3–20.
- Saber, E., Tekalp, M., and Bozdagi, G. (1997). Fusion of Color and Edge Information for Improved Segmentation and Edge Linking. *Image and Vision Computing*, **15**, 769–780.
- Schneider, P. J. and Eberly, D. H. (2003). *Geometric Tools for Computer Graphics*. Morgan Kaufmann.
- Seul, M., O’Gorman, L., and Sammon, M. (2001). *Practical Algorithms for Image Analysis*. Cambridge.
- Wooster, M., Zhukov, B., and Oertel, D. (2003). Fire Radiative Energy for Quantitative Study of Biomass Burning: Derivation from the BIRD Experimental Satellite and Comparison to MODIS Fire Products. *Remote Sens. Environ.*, (86), 83–107.
- Zajkowski, T., Queen, L., and VanBuren, D. (2003). Infrared Field Users’ Guide and Vendor Listings. *United States Dept. Ag. Forest Service-Engineering. RSAC-1309-RPT1*.