1-16-2007

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Recommended Citation

Y. Li, A. Vodacek, Y. Zhu An automatic statistical segmentation algorithm for extraction of fire and smoke region Remote Sensing of Environment, 108 (2007), pp. 171-178

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AN AUTOMATIC STATISTICAL SEGMENTATION ALGORITHM FOR EXTRACTION OF FIRE AND SMOKE REGIONS

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Abstract

Estimation of the extent and spread of wildland fires is an important application of high spatial resolution multispectral images. This work addresses a fuzzy segmentation algorithm to map fire extent, active fire front, hot burn scar, and smoke regions based on a statistical model. The fuzzy results are useful data sources for integrated fire behavior and propagation models built using Dynamic Data Driven Applications Systems (DDDAS) concepts that use data assimilation techniques which require error estimates or probabilities for the data parameters. The Hidden Markov Random Field (HMRF) model has been used widely in image segmentation, but it is assumed that each pixel has a particular class label belonging to a prescribed finite set. The mixed pixel problem can be addressed by modeling the fuzzy membership process as a continuous Multivariate Gaussian

Markov Random Field. Techniques for estimating the class membership and model parameters are discussed. Experimental results obtained by applying this technique to two Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) images show that the proposed methodology is robust with regard to noise and variation in fire characteristics as well as background. The segmentation results of our algorithm are compared with the results of a K-means algorithm, an Expectation Maximization (EM) algorithm (which is very similar to the Fuzzy C-Means Clustering algorithm with entropy regularization), and an MRF-MAP algorithm. Our fuzzy algorithm achieves more consistent segmentation results than the comparison algorithms for these test images with the added advantage of simultaneously providing a proportion or error map needed for the data assimilation problem.

1 Introduction

The effects of wildland fire are very important at local scales where impacts to human safety and property become critical. The continued development of models for forecasting wildland fire behavior and propagation, e.g., Clark *et al.* (1992), are now beginning to use Dynamic Data Driven Applications Systems (DDDAS) concepts (Douglas *et al.*, 2006) in which models react in real time to new data and where model output can be used to steer future measurements (Darema, 2004). These modeling systems can benefit from the use of high resolution wildland fire images from an airborne platform as a data

source for initiating and nudging model predictions. The details of the data assimilation techniques are beyond the scope of this paper, but an important aspect is that error estimates or probabilities are an important component of data assimilation.

Both airborne (Radke *et al.*, 2000; McKeown *et al.*, 2005; Greenfield *et al.*, 2003) and satellite (Prins and Menzel, 2004; Kennedy *et al.*, 1994; Kaufman *et al.*, 1998) remote sensing having the appropriate bands have been used to study wildland fire in the past several decades. Although visual analysis has remained important for operational use (Greenfield *et al.*, 2003), automated algorithms need to be developed for real time airborne applications, e.g. fire propagation modeling. Previous work on this topic includes mapping burn scars using temporal NDVI analysis and active fire information (Fraser *et al.*, 2000). In this paper, we present a technique for automatic segmentation of a multispectral image to map active fire front, hot burned scar, and smoke region. This method also produces fuzzy proportion maps, which are desirable input for automated data assimilation of remotely sensed images for adjusting or nudging fire propagation model output (Douglas *et al.*, 2006).

The problem of multispectral image segmentation is to partition an image into classes on the basis of pixel spectra. The Hidden Markov Random Field (HMRF) model has been used widely in image segmentation during the recent past (Geman and Geman, 1984; Besag, 1974; Cross and Jain, 1983; Pappas, 1992; Masson and Pieczynski, 1993; Bouman and Liu, 1991; Hazel, 2000). These methods usually use a Markov Random Field (MRF) to model the discrete la-

bel field containing the individual pixel classification. In a MRF model, the label field is locally dependent; that is the class label of a pixel statistically depends only on the label of its neighbors. The discrete label field is a Hidden Markov Random Field whose state sequence cannot be observed directly but can be estimated through the observed image. Given any particular label field, the observation on each pixel site is conditionally independent and has the same conditional density function dependent only on the label of the pixel site. The HMRF incorporates the spatial information in an image through contextual constraints of neighboring *labels* and spectral information by assuming the observations follow a known conditional probability distribution dependent on the class label.

The underlying assumption of using the discrete Markov Random Field to model the label field is that the observed measurement at each pixel is generated as an observation from a specified class with a known conditional probability distribution. The HMRF model of the discrete label field is limited in that it does not allow us to take into account mixed pixels, where different classes are simultaneously present. In remote sensing images, the limited spatial resolution of the imaging system inevitably leads to mixed pixels, especially at class boundaries. That is, individual pixels cover more than one ground cover type and leads to the spectral response at a pixel being a mixture of the underlying pure classes. This has lead to the development of a variety of approaches for fuzzy classification (Hazel, 2000; Nascimento *et al.*, 2003). In this paper, we devise an algorithm for the fire image problem by using a continuous Multivari-

ate Gaussian Markov Random Field (MGMRF) to model the fuzzy membership process for mixed pixels. The fuzzy membership of an observed pixel to a class expresses the proportion of the class's prototype (mean) reflected in the pixel. This way, the observation in a pixel may bear 60% of the prototype of class fire, and 40% of the prototype of class smoke, which simultaneously express the observation's membership to the respective classes.

We use upper case letters for random quantities/fields and lower case letters for their deterministic realizations. We assume that the observed image $\mathbf{Y}$ is a random field defined on a rectangular grid, S , of N points, and the vector-valued spectra of a pixel at location $s \in S$ is denoted by Y_s . Y_s takes values in R^d , where d is the band number of the multispectral image. $\mathbf{X} = (X_s)_{s \in S}$ denote the "hard" label field, which contains the crisp classification of each pixel in $\mathbf{Y}$. Sites in $\mathbf{X}$ will take values in the set $\{1, \dots, M\}$, where M is the number of underlying classes. There are M distinct vectors $\mu_l \in R^d, l = 1, \dots, M$, where μ_l represents the mean (prototype) of "pure type" from class l .

In a common statistical model for classification problems such as the HMRF model mentioned above, it is assumed that every random variable y_s is generated from a known conditional distribution dependent on the class label on pixel site s . Let us denote the membership process by Π . $\pi_{l,s}$ expresses the membership of the observation on pixel s in class $l (l = 1, \dots, M)$.

$$\mathbf{y}_s = \sum_{l=1}^M \pi_{l,s} \mu_l + n_s; \quad (1)$$

where μ_l is the mean of “pure type” observations from class l , n_s is Gaussian noise with mean 0 and variance κ . Then in the above model, $\pi_s = (\pi_{1,s}, \dots, \pi_{M,s})'$ is assumed to satisfy

$$\pi_{l,s} = 0 \text{ or } 1 \quad \text{for all } l; \quad \sum_{l=1}^M \pi_{l,s} = 1. \quad (2)$$

Thus, $\{\pi_s\}$ is a way of representing a random partition of Y into M underlying classes. Fuzzy clustering methods can modify the “hard” membership process $\{\pi_s\}$ into a “fuzzy” membership process by replacing the 0 or 1 restrictions in Equation 2 with

$$\pi_{l,s} \in [0, 1] \text{ for all } l; \quad \sum_{l=1}^M \pi_{l,s} = 1. \quad (3)$$

Then $\pi_s \in R^M$ expresses the proportion of pixel s which belongs to several classes simultaneously. Note that a “hard” classification of each pixel in the observed image can be achieved simply by choosing the dominant class l with the maximum membership $\pi_{l,s}$. Fuzzy clustering methods have been applied effectively in image processing, pattern recognition and fuzzy modeling. It has been shown to be advantageous over “hard” clustering in that a total commitment of a vector to a given class is not required in each iteration. The best known approach to fuzzy clustering is the Fuzzy C -Means (FCM) method (Bezdek, 1981), and generalized by other authors (Krishnapuram and Keller, 1993; Nascimento *et al.*, 2003). Although fuzzy clustering has been used widely, in practice it cannot deal well with high level noise because it neglects the spatial information by assuming the vector-valued image pixels to be statistically independent and

identically distributed.

To include the spatial correlation of vector-valued image pixels in fuzzy clustering, we use a *continuous* Multivariate Gaussian Markov Random Field (MGMRF) to model the fuzzy membership process $\{\pi_s\}$. This indicates that pixels close together tend to have similar membership of each class. The spectral information can be incorporated by adopting the Multivariate Gaussian model for “pure type” of each class l . In this application, we are trying to extract fire regions including the active fire front, hot burn scar, and smoke, all of which have relatively smooth image regions, especially compared to the background. In addition, we can consider the terrain textures to be noise, which is characterized by the covariance matrix and the random vector from “pure type” of class l can be modeled as a multivariate Gaussian distribution.

The complete technique devised here can be regarded as an extension of the Expectation Maximum (EM) algorithm with modifications based on MGMRF model of the membership process to include the spatial constraints and mixed pixels. Like the EM algorithm, our fuzzy segmentation algorithm is an iterative method. The fuzzy membership process and the parameters for each class are estimated and updated simultaneously and iteratively. Our algorithm estimates the parameters of each class at each stage of the iteration using the current estimates of the fuzzy membership process. The fuzzy membership process is then estimated according to the currently updated class parameters.

The organization of the paper is as follows. In the Section 2, we briefly review the MRF theory and describe the Multivariate Gaussian MRF model that

we used to model the fuzzy membership process. The algorithm is described in detail in Section 3. We describe the estimate of the membership process $\{\pi_s\}$ of each class and the updating of the class parameters in subsection 3.1 and 3.2, respectively. Section 4 compares the results of the application of different algorithms on a set of test images to illustrate the consistent results produced by our algorithm.

2 Statistical Model

In this paper, the multispectral images are classified from two imperfect (spectral and spatial) sources of information. The spectral data that is the “pure type” observation $\mathbf{v}_l$ from each class is assumed to obey a multivariate Gaussian distribution. That is

$$f(\mathbf{v}_l; \theta(l)) = \frac{1}{(2\pi)^{d/2} |\Sigma_l|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{v}_l - \mu_l)^T \Sigma_l^{-1} (\mathbf{v}_l - \mu_l) \right] \quad (4)$$

where μ_l and Σ_l are the mean and the covariance of class l , respectively. In the mixed pixel case, for every class l , $p(l) = \alpha_l$ is the mixing coefficient of class l . We assume that we have M classes mixed together with M mixing coefficients α_l , such that $\sum_{l=1}^M \alpha_l = 1$. We denote the parameter set by $\Theta = \{\alpha_l, \mu_l, \Sigma_l\}$.

The spatial constraint states that adjacent pixels tend to have similar membership of each class. MRF theory provides a convenient and consistent way to model this kind of context-dependent entity. The MRF model achieves the spatial constraints of the vector-valued image pixels and correlated features by

characterizing mutual influences among them using conditional MRF distributions. In an MRF, the sites in S are related to one another via a neighborhood system. The conditional distribution of a site in the field given all other sites in the field is identical to the conditional distribution of the site given only those sites in a finite symmetric neighborhood surrounding the site. The neighborhood of a pixel site $s \in S$ is a set of sites $N_s \subset S$ with the two properties that $\forall s, r \in S, s \in N_r \Leftrightarrow r \in N_s$, and s is not in N_s .

$$p(x_s|x_q, \text{ all } q \neq s) = p(x_s|x_q, q \in N_s) \quad (5)$$

We will use a Gaussian Markov Random Field (GMRF) to model the fuzzy membership process of the image $\mathbf{y}$. The fuzzy membership process is denoted by $\Pi = \{\pi_s|y, \Theta\}_{s \in S}$. The vector π_s represents the membership of pixel s in the M classes. The values of Π cannot be observed directly, but they can be estimated through the observed signal. Here, the observed signal is the fuzzy membership process calculated using Gaussian Mixture model and Equation 17 (see Section 3.2). We use z_l to denote the observed signal. For a given image y , z_l is computed directly from the image y and have specific values. Thus, estimating $\pi_{l,s}$ given y is equal to estimating $\pi_{l,s}$ given z_l .

The random field Π can be considered a multivariate GMRF (MGMRF). The membership π_s at each pixel site s can be treated as a vector-valued feature on the two-dimensional lattice S , which indicates the extent to which the mixed pixel belongs to several classes. Since the regions in this application have

unordered labels, the membership $\pi_{l,s}$ of class l , depends only on the neighboring pixel's membership in the same class. The MGMRF field can be simplified into M independent Gaussian Markov Random Fields $\{\Pi_l\}_{l \in \{0,1,\dots,M\}}$. The value of Π_l at location $s \in S$ is the membership of class l given $\mathbf{y}_{N_s}$. Thus, $\Pi_{l,s}$ takes continuous values between zero and one. The MRF property of the GMRF model states that $\pi_{l,s}$ only depends on its neighbors $\pi_{l,r}, r \in N_s$. Given the neighbors, $\Pi_{l,s}$ has conditional density (Besag, 1974, 1975)

$$p(\pi_{l,s}|\pi_{l,N_s}) \propto \exp\{-\frac{1}{2\lambda_s}(\pi_{l,s} - \sum_{r \neq s} \beta_{sr}\pi_{l,r})^2\}, \quad (6)$$

where $\beta_{sr} = 0$ unless s and r are neighbors, and $\beta_{sr}\lambda_r = \beta_{rs}\lambda_s$. λ and β are GMRF parameters which are assumed to be known. It follows from Equation 6 that

$$p(\pi_l) \propto \exp(-\frac{1}{2}\pi_l^T Q \pi_l) \quad (7)$$

where Q is an $n \times n$ positive definite symmetric matrix with diagonal entries $\frac{1}{\lambda_s}$ and off-diagonal (s, r) element $-\beta_{sr}$. This GMRF model prescribed here provides us a method of estimating the class membership on each pixel site s .

3 Segmentation Algorithm

In this section, we describe the automatic statistical segmentation algorithm for estimating the distribution of regions $\mathbf{x}$. The image is segmented by estimating the membership process $\mathbf{\Pi}$, given the observed image $\mathbf{Y}$ and distribu-

tion parameters Θ . In particular, we adopt the maximization of the posteriori marginal probability (MPM) method to obtain the “hard” segmentation (Marroquin *et al.*, 1987).

The criterion used for MPM is to minimize the expected value of the number of misclassified nodes in the rectangular lattice. The segmentation problem is formulated as an optimization problem, which can be viewed as the minimization of the conditional expected value of a cost function $R(x^*, x)$ given the observed image Y and parameters Θ , over all possible realizations of the label field $\mathbf{X}$. The cost function is given by

$$R(x^*, x) = \sum_{s=1}^N t(x_s^*, x_s) \quad (8)$$

where, $t(x_r, x_s)$ equals 0 when $x_s \neq x_r$, and 1 when $x_s = x_r$. x^* is the true value of the hard segmentation field $\mathbf{X}$. The cost function $R(x^*, x)$ is the number of pixel sites where the estimated hard segmentation $\mathbf{x}$ are different from the true value x^* , i.e., the number of misclassified pixel sites in S .

$$\begin{aligned} E[(R(x^*, x)|Y = y)] &= E\left[\sum_{s=1}^N t(x_s^*, x_s)|Y = y\right] \\ &= \sum_{s=1}^N E[t(x_s^*, x_s)|Y = y] \\ &= \sum_{s=1}^N (1 - \pi_{sx_s}|Y = y) \end{aligned} \quad (9)$$

To find the MPM estimate of x^* , it is necessary to find for each $s \in S$ the value of l which maximizes the membership $\pi_{l,s}$ at s given the observed image

y. While obtaining the “hard” segmentation result x , we can also get the fuzzy membership Π .

To estimate the fuzzy membership process, we assume the parameters Θ of these Gaussian clusters to be known *a priori*. On the other hand, the parameters Θ are calculated given the current estimated membership process. Thus, the estimate of the parameters Θ and the membership process (which uses Θ as *a priori* knowledge) must be carried out simultaneously. So the whole segmentation algorithm can be described as the following iterative procedure:

1. First obtain an initial estimate $\hat{\pi}$ of the true membership process π^* , and calculate the Maximize Likelihood Estimation (MLE) of the parameters Θ . The initial MLE estimation of the parameters Θ ignore the spatial constraint.
2. Carry out a single circle of iterated conditional modes (ICM) method (Besag, 1974) given the current Θ^{i-1} to estimate new fuzzy membership process $\{\pi_{l,s}^i | y, \Theta^{i-1}\}$ and then obtain a new x^i . This step is described in Section 3.1.
3. Estimate Θ^i using Equations 18 to 20 in Section 3.2, based on $\{\pi_{l,s}^i | y, \Theta^{i-1}\}$.
4. Return to 2, until the number of pixels in $\mathbf{x}$ that change during an iteration cycle is less than a threshold, or the iteration number is more than a prescribed number.

3.1 The Membership Process Estimation

Here we describe the iterated conditional modes (ICM) method based on the GMRF model to estimate the membership process, assuming that Θ is known.

We use $\pi_{l,s}^*$ to indicate the true but unknown value of $\pi_{l,s}$, and $\hat{\pi}_{l,s}$ to denote the

current estimate of $\pi_{l,s}$. We estimate $\hat{\pi}_{l,s}$ given the observed signal z_l and then assign $\hat{x}_s$ with $l = \max_l(\hat{\pi}_{l,s}|y_{N_s}, \Theta)$. In order to estimate the fuzzy membership process of each class, we model the membership process as a Gaussian MRF, which was described in Section 2. The observed signal z_l is the membership process calculated using the standard EM algorithm (Dempster *et al.*, 1977) which does not have spatial constraints using 17 (see Section 3.2). By using the Gaussian MRF model, we can suppose that the value of z_l at each pixel site s is generated independently by a normal distribution with mean $\pi_{l,s}^*$ and variance κ . By the maximum a posteriori (MAP) estimate criterion, the estimate $\hat{\pi}_l$ is chosen to have maximum probability, given the value of signal z_l . Thus, by Bayes' theorem, $\hat{\pi}_{l,s}$ maximizes

$$p(\pi_l|z_l) \propto p(z_l|\pi_l)p(\pi_l) \quad (10)$$

According to Equation 7, $\hat{\pi}_l$ is chosen to minimize:

$$\kappa^{-1}(z_l - \pi_l)^T(z_l - \pi_l) + z_l^T Q z_l. \quad (11)$$

We use $\hat{\pi}_l$ to denote a provisional estimate of the true π_l^* . The aim of ICM is merely to update the current estimate $\hat{\pi}_{l,s}$ at pixel site s , in the light of the observed signal $z_{l,s}$ and the current reconstruction $\{\hat{\pi}_{l,r}, \text{ all } r \neq s\}$ elsewhere. Specifically, the updating formula for ICM at pixel site s is a linear combination of the observed signal at pixel site s and the current estimates at the neighboring pixels (Besag, 1974):

$$\pi_{l,s}^i = (\lambda_s z_{l,s} + \kappa \sum_{r \neq s} \beta_{sr} \pi_{l,r}^{i-1}) / (\lambda_s + \kappa). \quad (12)$$

This can be simplified into the following equation:

$$\pi_{l,s}^i = (\alpha_s z_{l,s} + \sum_{r \in N_s} \gamma_{sr} \pi_{l,r}^{i-1}) \quad (13)$$

α and γ are parameters of the Gaussian Markov Random Field that effect the size, shape, and smoothness of the regions. Either the Gibbs sampler algorithm (Geman and Geman, 1984) or the simulated annealing algorithm (Kirkpatrick *et al.*, 1983) can be used to estimate the parameters. But these methods are computationally expensive so we use fixed values of $\alpha=1$ and $\gamma=1.5$ in this application. Besides the parameters, the size of neighborhood also has influence on the shape and size of the segmented regions. The larger the neighborhood, the larger and smoother the regions will be. Here, we are trying to segment the high resolution satellite or airborne images into regions of active fire front, hot burn scar, smoke, and background. We choose an 8-pixel neighborhood system. By doing so we are providing a generalization of the fire region rather than an exact mapping of isolated pixels. We feel this generalization is appropriate within the fire propagation application, for which the goal is to predict fire movement but not necessarily the complexity of the fire line itself.

3.2 Parameter Estimation

In order to perform the estimation of the membership process $\{\pi_{l,s}\}$ and the label field $\mathbf{x}$, we must estimate the class parameters Θ . As mentioned before, in this application, we model the “pure type” random variable generated from each class to obey multivariate Gaussian distribution. The parameter $\theta_l = \{\alpha_l, \mu_l, \Sigma_l\}$ is what needs to be resolved. We will use a modified version of the EM algorithm to estimate the values of Θ . The close relationship between the EM algorithm and fuzzy clustering methods has been established by Ichihashi *et al.* (2000). The EM algorithm can be considered as a probabilistic approach to fuzzy clustering confined to Gaussian distributions. The so called membership in fuzzy clustering is equivalent to the posteriori marginal probability in the EM algorithm. In the following, we describe the modified EM algorithm assuming that the values of the class memberships are known. In this paper, we use the term “membership” instead of “posteriori marginal probability”.

The EM algorithm estimates mixture-density parameters by assuming the existence of a set of unobserved or hidden data (Bilmes, 1997). In our formulation, the observed image $\mathbf{y}$ is the incomplete data set, and the label field $\mathbf{x}$ is the unobserved or hidden data. The EM algorithm maximizes the expected value of the complete-data log-likelihood $\log p_{Y,X}(y, x|\Theta)$ with respect to the class membership process π given the observed image $\mathbf{y}$ and the current parameter

estimates Θ^{i-1} to achieve new parameters Θ .

$$\begin{aligned} Q(\Theta, \Theta^{i-1}) &= E[\log p_{Y,X}(y, x|\Theta)|y, \Theta^{i-1}] \\ &= E[\log p_{Y|X}(y|x, \Theta)p_X(x|\Theta)|y, \Theta^{i-1}] \end{aligned} \quad (14)$$

where Θ^{i-1} are the current parameters, and Θ are the new parameters that we optimize to increase Q . As mentioned before, the vector-valued image pixels are conditionally independent given a particular class membership process. Then deriving from Equation 14 gives:

$$Q(\Theta, \Theta^{i-1}) = \sum_{s \in S} \left(\sum_{l=1}^M \log(\alpha_l p(y_s | x_s = l, \Theta^{i-1})) \pi_{l,s} | y, \Theta^{i-1} \right) \quad (15)$$

Then we can write Equation 15 as:

$$\begin{aligned} Q(\Theta, \Theta^{i-1}) &= \sum_{s \in S} \left(\sum_{l=1}^M \log(a_l) \pi_{l,s} | y, \Theta^{i-1} \right) \\ &+ \sum_{s \in S} \left(\sum_{l=1}^M \log(p(\mathbf{y}_s | x_s = l, \Theta^{i-1})) \pi_{l,s} | y, \Theta^{i-1} \right) \end{aligned} \quad (16)$$

In the Expectation step of the EM algorithm, the class membership process is estimated by the following equation:

$$\pi_{l,s} = \frac{a_l p(y_s | l, \theta_l)}{\sum_{k=1}^M a_k p(y_s | k, \theta_k)} \quad (17)$$

Equation 17 is achieved by assuming the vector-valued image pixels to be statistically independent identically distributed and neglecting the spatial information. The calculation of the class membership $\pi_{l,s}$ based on our MGMRF model

is different than Equation 17, which involves estimation of the class memberships in the neighborhood pixel sites. Instead we estimate the class membership $\pi_{l,s}$ using the ICM method as described in Section 3.1.

In the Maximization step of the modified EM algorithm, $Q(\Theta, \Theta^{i-1})$ must be maximized with respect to the last estimate Θ^{i-1} . By differentiating Equation 16 and setting it to zero, new values of Θ can be obtained. The estimate of the new parameters in terms of the old parameters are as follows:

$$a_l^{new} = \frac{1}{N} \sum_{s \in S} \pi_{l,s} \quad (18)$$

$$\mu_l^{new} = \frac{\sum_{s \in S} \mathbf{y}_s \pi_{l,s}}{\sum_{s \in S} \pi_{l,s}} \quad (19)$$

$$\Sigma_l^{new} = \frac{\sum_{s \in S} \pi_{l,s} (\mathbf{y}_s - \mu_l^{new})(\mathbf{y}_s - \mu_l^{new})^T}{\sum_{s \in S} \pi_{l,s}}. \quad (20)$$

Here, $\{\pi_{l,s}\}$ are the current estimates of class membership for the observed image using previously estimated parameters. The estimation of $\{\pi_{l,s}\}$ was described in Section 3.1.

4 Results and Discussion

4.1 Synthetic Fuzzy Images Segmentation

To assess the relative performance of the algorithm developed here and a set of published algorithms, a series of tests were conducted on a simple 200×200 synthetic image with three bands and 2 classes. Both pure pixels and mixed pixels are present in the synthetic image as illustrated in Figure 1(a). The mean intensities of the two classes in the 3 bands are:

$$\mu = \begin{pmatrix} 70 & 130 \\ 560 & 380 \\ 300 & 450 \end{pmatrix}$$

Figure 1(b) shows the same image with Gaussian noise added.

The standard EM algorithm, the MRF-MAP algorithm, and our algorithm were applied to the noisy simulated image. The results after 20 iterations are shown in Figures 2 to 4. High level noise is present in the result for the EM algorithm, because it does not consider any spatial constraints (Figure 2). On the contrary, both the MRF-MAP algorithm and our algorithm produce near perfect “hard” segmentation results, as illustrated in Figures 3 (a) and 4 (a). The corresponding error maps shown in Figure 3 (c) and Figure 4 (c) show misclassification only at boundaries. However, the MRF-MAP posterior marginal probability map (Figure 3 (b)) is little different from the “hard” segmentation while our algorithm (Figure 4 (b)) provides a very good membership propor-

tion map. Hence, for the wildfire detection problem, our algorithm achieves the desired result in that it can generate high quality fuzzy segmentation results for mixed pixels that can be used as probabilities within the context of data assimilation. (Douglas *et al.*, 2006).

4.2 Demonstration of the Segmentation Approach using AVIRIS Imagery

In this section we consider two AVIRIS images obtained over fires. AVIRIS measures reflected radiance of 20×20 meter pixels in 224 narrow spectral bands. The resulting image “cube” consists of 614 samples by 512 lines by 224 spectral bands. The spectral resolution of AVIRIS is 10 nm, and the range of spectral coverage is 380 to 2500 nm ($0.38 - 2.5\mu m$). Two AVIRIS images are used in this paper to test our algorithm. The first one is shown in Figure 5 (a). It is an image of Cuiaba, Brazil with a prescribed fire and was take on August 25, 1995. Figure 6 (a) is an image of San Bernardino Mountain, in California, USA. The image of this wildland fire was taken on September 01, 1999.

Feature selection is very important for classification implementations. It not only can reduce the cost of classification by reducing the number of features, but also can provide a better classification accuracy. Thus, different feature sets may be selected according to different purpose of the classification. In this application, our goal is to segment high resolution satellite or airborne image into four classes: active fire front, hot burn scar, smoke, and background. It is known that $1.8\mu m$ channel is very sensitive to flame energy and not very

sensitive to smoldering energy, while the $2.5\mu m$ channel is very sensitive to flame energy and also somewhat sensitive to smoldering energy. These two bands are important features for detection of active fire and hot burn scar, respectively. Because smoke scatters visible light and is almost transparent at near-IR (NIR) and shortwave IR (SWIR) wavelengths, we use SWIR band 217 (about $2.5\mu m$) minus visible band 12 (about $0.52\mu m$) as a feature to detect smoke. Our three features are then band 217 minus band 12, band 143 (about $1.8\mu m$) and band 217.

The detailed results of our algorithm working on the two images are discussed below. The results of our method are compared to those of the K-means algorithm, the EM algorithm and the MRF-MAP method (Zhang *et al.*, 2001). For performance comparison, we consider only simple visual evaluation of the four classes, since it is impossible to achieve ground truth for the segmentation task.

In the Brazil case presented in Figure 5 (a), the large fire in the left center of the image emitted heavy smoke. To the left of the large fire is a smaller fire with very thin smoke. Figure 5 (b) is the fire mask we obtained by setting a threshold manually on the $1501nm$ SWIR band. This fire mask emphasizes the actively burning region. The “hard” result of our algorithm is shown in Figure 5 (c), while the “hard” results of the MRF-MAP method, the K-means algorithm and the EM algorithm are displayed in Figure 5 (d), (e) and (f), respectively.

In this case, the MRF-MAP, K-means and EM algorithms can all separate the fire region from the background area, but their performances are very dif-

ferent. By examining the fire region shown in more detail, we can see that the MRF-MAP method and EM algorithm can segment the entire hot region from the background, but they do not separate the active fire front and the hot burn scar area. On the contrary, the K-means algorithm can separate the active fire front clearly, but it cannot separate hot burn scar from the background area. The result of the K-means algorithm also has a lot of salt and pepper noise in the segmentation result, which is undesired. In this case, our algorithm achieves a good and clean result. Comparing with the fire mask we obtained by using an SWIR band of the AVIRIS image (Figure 5 (b)), we find that the segmented fire front aligned well with the true fire front. The regions of the hot burn scar, smoke, and background achieved by our clustering algorithm also agree well with the visual inspection of the visible, NIR, and SWIR bands of the AVIRIS image.

In the image of San Bernardino Mountain presented in Figure 6 (a), a large fire was producing heavy smoke. The active fire map shown in Figure 6 (b) was obtained by manually setting a threshold on the $1501nm$ band. The results of our algorithm and the MRF-MAP, K-means, and EM algorithms are shown in Figure 6 (c), (d), (e), and (f), respectively. We observed that in this case, our algorithm also produces the desired result. The active fire front segmented by our algorithm is almost the same as the active fire map shown in Figure 6 (b). There are some small hot burn scar regions on the left side of the fire front. This result agrees well with our priori knowledge of the fire in this image: the fire was going against the wind and progressing slowly. The MRF-MAP

method produces a good result for the active fire and hot burn scar regions, but it overestimates the smoke region. Both the K-means algorithm and the EM algorithm have better results than in the case of the Brazil image, since the background of the San Bernardino image is more homogeneous.

In this paper, we devise a spectral-spatial segmentation algorithm that provides a fuzzy segmentation map for fire regions. Implementation of the algorithm is simple and it exhibits rapid convergence. Although we used the EM algorithm as part of our algorithm, different fuzzy clustering algorithms can be fitted into this framework. The results obtained by our algorithm using the two AVIRIS images show clean and neat regions of fire front, smoke, burn scar and background, which is typical of MRF-based clustering methods. These results demonstrate the relative effectiveness of our scheme. It is superior to histogram-based algorithms, because it utilizes not only the spectral information but also spatial information by incorporating an GMRF model of the class membership process. Our algorithm performs well with a high level of noise, even when the histograms of different regions overlap significantly because the methods incorporate spatial information. Our algorithm also compared well with the MRF-MAP method for these images. Most importantly, our method produces a fuzzy proportion map useful for data assimilation in advanced fire propagation models based on DDDAS concepts.

5 Acknowledgement

This material is based upon work supported by the National Science Foundation under Grant No. CNS-0324989 and by the National Aeronautics and Space Administration under Grant No. NAG5-10051.

References

- Besag, J. E. (1974). Spatial interaction and the statistical analysis of lattice systems. *Journal of Royal Statistic Society*, **B. 36**, 192–236.
- Besag, J. E. (1975). Statistical analysis of non-lattice data. *The Statistician*, **24**, 179–195.
- Bezdek, J. C. (1981). *Pattern Recognition with Fuzzy Objective Function Algorithms*. New York: Plenum Press.
- Bilmes, J. A. (1997). A Gentle tutorial of the EM algorithm and its application to parameter estimation for Gaussian Mixture and Hidden Markov Models. Technical report, University of Berkeley.
- Bouman, C. A. and Liu, B. (1991). Multiple resolution segmentation of textured images. *IEEE Trans. Patt. Anal. Machine Intell.*, **13**, 99–113.
- Clark, T. L., Coen, J. L., and Latham, D. (1992). Description of a coupled atmosphere-fire model. *Intl. J. Wildland Fire*, **13**, 2783–2799.
- Cross, J. R. and Jain, A. K. (1983). Markov random field texture models. *IEEE Trans. Pattern Anal. Machine Intell.*, **5(3)**, 25–39.

- Darema, F. (2004). Dynamic Data Driven Applications Systems: a new paradigm for application simulations and measurements. In M. Bubak, G. D. V. Albada, P. M. A. Sloot, and J. Dongarra, editors, *Computational Science - ICCS 2004: 4th International Conference, Kraków, Poland, June 6-9, 2004. Proceedings, Part III*, volume 3038, pages 662–669. Springer Berlin / Heidelberg.
- Dempster, A. P., Laird, N., and Rubin, D. (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal Statistical Society, Series B*, **39**, 1–38.
- Douglas, C., Beezley, J., Coen, J., Deng, L., Li, W., Mandel, A., Mandel, J., Qin, G., and Vodacek, A. (2006). Demonstrating the validity of a wildfire DDDAS. In V. N. Alexandrov, G. D. V. Albada, P. M. A. Sloot, and J. Dongarra, editors, *Computational Science - ICCS 2006: 6th International Conference, Reading, UK, May 28-31, 2006. Proceedings, Part III*, volume 3993, pages 522–529. Springer Berlin / Heidelberg.
- Fraser, R. H., Li, Z., and Cihlar, J. (2000). Hotspot and NDVI Differencing Synergy (HANDS): A New Technique for Burned Area Mapping over Boreal Forest. *Remote Sensing of Environment*, **74**, 362–375.
- Geman, S. and Geman, D. (1984). Stochastic relaxation, gibbs distribution, and the bayesian restoration of images. *IEEE Trans. Pattern Anal. Machine Intell*, **6(6)**, 721–741.
- Greenfield, P. H., Smith, W., and Chamberlain, D. C. (2003). Phoenix-the

- new forest service airborne infrared fire detection and mapping system. In *2nd Int. Wildland Fire Ecology and Fire Management Congress and the 5th Symposium on Fire and Forest Meteorology*, Orlando, Florida.
- Hazel, G. (2000). Multivariate Gaussian MRF for Multispectral Scene Segmentation and Anomaly Detection. *IEEE Trans. on Geoscience and Remote Sensing*, **38**, 1199–1211.
- Ichihashi, H., Honda, K., and Tani, N. (2000). Gaussian mixture PDF approximation and fuzzy c-means clustering with entropy regularization. In *Proc. of the 4th Asian Fuzzy System Symposium*, pages 212–221, Tsukuba, Japan.
- Kaufman, Y. J., Justice, C. O., Flynn, L. P., Kendall, J. D., Prins, E. M., Giglio, L., Ward, D. E., Menzel, W. P., and Setzer, A. W. (1998). Potential Global Fire Monitoring From EOS-MODIS. *Journal of Geophysical Research*, **103**, 32,215–32,238.
- Kennedy, P. J., Belward, A. S., and Gregoire, J. M. (1994). An improved approach to fire monitoring in West Africa using AVHRR data. *International Journal of Remote Sensing*, **15**, 2235–2255.
- Kirkpatrick, S., Gelatt, C., and Vecchi, M. (1983). Optimization by simulated annealing. *Science*, **220**, 671–680.
- Krishnapuram, R. and Keller, J. M. (1993). A possibilistic approach to clustering. *IEEE Trans on Fuzzy Systems*, **1**, 98–119.
- Marroquin, J., Mitter, S., and Poggio, T. (1987). Probabilistic solution of ill-

- posed problems in computational vision. *Journal of the American Statistical Association*, **82**, 76–89.
- Masson, P. and Pieczynski, W. (1993). Sem algorithm and unsupervised statistical segmentation of satellite images. *IEEE Trans. on Geoscience and Remote Sensing*, **31**, 618–633.
- McKeown, D., Cocburn, J., Faulring, J., Kremens, R., Morse, D., Rhody, H., and Richardson, M. (2005). Remote image and field data collection for a dynamic fire modeling system. In *Proc. 10th Biennial USDA Forest Service Remote Sensing Applications Conference*, Salt Lake City, UT. CD-ROM, ISBN 1-57083-075-4, ASPRS.
- Nascimento, S., Mirkin, B., and Moura-Pires, F. (2003). Modeling proportional membership in fuzzy clustering. *IEEE Trans on Fuzzy Systems*, **11**, 173–186.
- Pappas, T. N. (1992). An adaptive clustering algorithm for image segmentation. *IEEE Trans. Signal Processing*, **40**, 901–914.
- Prins, E. M. and Menzel, W. P. (2004). Geostationary satellite detection of biomass burning in south america. *Int. J. Remote Sensing*, **13**, 49 – 63.
- Radke, L. R., Clark, T. L., Coen, J. L., Walther, C., Lockwood, R. N., Riggins, P. J., Brass, J., and Higgins, R. (2000). The WildFire Experiment (WiFE): Observations with airborne remote sensors. *Canadian J. Remote Sensing*, **26**, 406–417.
- Zhang, Y., Brady, M., and Smith, S. (2001). Segmentation of Brain MR Im-

ages Through a Hidden Markov Random Field Model and the Expectation-
Maximization Algorithm. *IEEE Trans. on Medical Imaging*, **20**, 45–57.

Figure 1: Fuzzy membership ground truth. (a) Distribution of pure pixels and mixed pixels for the synthetic image. (b) Synthetic image with added Gaussian noise.

Figure 2: Result of the EM algorithm working on the synthetic image. (a) “Hard” segmentation result achieved by choosing the dominant class which has the maximum membership. (b) Fuzzy segmentation result of the EM algorithm. (c) Error for the “hard” segmentation result.

Figure 3: Result of the MRF-MAP algorithm working on the synthetic image. (a) “Hard” segmentation result achieved by choosing the dominant class which has the maximum posterior marginal probability. (b) Posterior marginal probability map of the MRF-MAP algorithm. (c) Error for the “hard” segmentation result.

Figure 4: Result of our algorithm working on the synthetic image. (a) “Hard” segmentation result achieved by choosing the dominant class which has the maximum membership. (b) Fuzzy segmentation result of our algorithm. (c) Error for the “hard” segmentation result.

Figure 5: Comparison of segmentation results on the Brazil image, $M=4$. (a) True color image of Cuiaba, Brazil, (b) Fire mask obtained by setting a threshold on the $1501nm$ band, (c) Segmentation result obtained using our algorithm, (d) Segmentation result obtained using the MRF-MAP method, (e) Segmentation result obtained using the K-means algorithm, (f) Segmentation result obtained using the EM algorithm. For the segmentation results, magenta is active fire, cyan is hot burned area, white is smoke, and black is the background.

Figure 6: Comparison of segmentation results, $M=4$. (a) True color image of San Bernardino Mtn, California, USA, (b) Fire mask obtained by setting a threshold on the $1501nm$ band, (c) Segmentation result obtained using our algorithm, (d) Segmentation result obtained using the MRF-MAP method, (e) Segmentation result obtained using the K-means algorithm, (f) Segmentation result obtained using the EM algorithm. For the segmentation results, magenta is active fire, cyan is hot burned area, white is smoke, and black is the background.