AN UNSUPERVISED STATISTICAL SEGMENTATION ALGORITHM FOR FIRE AND SMOKE REGIONS EXTRACTION

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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 an unsupervised statistical segmentation algorithm to map fire extent, fire front location, just burned area and smoke region based on a statistical model. The results are useful information for a fire propagation model to predict fire behavior.**

The finite mixture (FM) model is a widely used model for image segmentation because of it is mathematically simple and tractable. However, it ignores the spatial constraint of images, and works only on well defined images with low level noise. This is an intrinsic limitation of histogram-based segmentation algorithm, such as K-means and EM algorithm. In this paper we propose model the hidden segmentation field as an Markov random field (MRF). The hidden segmentation field can not be observed directly but can be estimated through the observed vector-valued pixels of satellite/airborne multispectral images. The advantage of the MRF model is that it encodes spatial information by considering the mutual influence of neighboring sites. Based on the MRF property of the segmentation field, we propose model the posteriori marginal probability field on the image sites as a multivariate Gaussian Markov random field (MGMRF). And then implement a Maximize Marginal Probability method (MPM) to segment the images. Our algorithm is a generalization of the Expectation Maximization (EM) algorithm to incorporate spatial constraints in the image. The use of statistical method has the added advantage of providing a direct means of deriving a probability value that is required for new approaches to fire propagation modeling. Experimental results obtained by applying this technique to two AVIRIS real images show that the proposed methodology is robust with regard to noise and variation in fire as well as background. The segmentation results of our algorithm are compared with the results of K-means algorithm and EM algorithm. It is shown that the results of our algorithm are consistently better than those of classical histogram based methods.

I. INTRODUCTION

The affects 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 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 [7], [17]. Both airborne [1], [13], [16], [22] and satellite [14], [15], [21] remote sensing systems that have the appropriate bands have been used to study wildland fire in the past several decades. Although visual analysis has remained important for operational use [13], automated algorithms need to be developed for real time airborne applications such as fire propagation modeling. In this paper, we present a technique for unsupervised segmenting a multispectral image to map fire front, just burned area and smoke region.

The problem of multispectral image segmentation is that of estimating the "hidden" or "unobserved" realization of the label field X from the "observed" multispectral image y, which is a determined realization of observed field Y. The value of a given site in the label field indicates the class to which the corresponding pixel in the observed image belongs. Some clustering procedures such as K-means algorithm [11] and Expectation Maximization (EM) algorithm [9] neglect pixel-level spatial correction, by assuming the vector-valued image pixels are statistically independent and identically distributed. To incorporate both the spatial and spectral information, we use a 2-D Markov Random Field to model the hidden label field. The Markov Random Field (MRF) has been used widely in image segmentation during the recent past [2], [8], [12], due to its power to represent many image sources, and the local nature of the resulting estimation. There are two Bayesian methods to estimate the global optimum estimation of the label field X based on the MRF model: the MAP method and MPM method corresponding to different cost functions. The MAP method estimates the unobservable realization of label field X by x to maximize the *a posteriori* probability conditioned on $Y = y$. The MAP estimate minimizes the probability that any pixel in the image will be misclassified. The MPM method chooses the estimated realization of label field x such that for each pixel s, x_s maximize the *a posteriori* marginal probability, it minimizes the probability of classification error on each pixel site. It has been shown that the MPM estimation criterion is more appropriate for image segmentation than the MAP criterion [18]. This is because the MAP estimate assigns the same cost to every incorrect segmentation. MAP considers the segmentation as a whole, while regardless the incorrect classification at each individual pixel site, whereas the MPM estimation assigns a cost to an incorrect segmentation based on the number of incorrectly classified pixels and try to minimize it in the segmentation result.

Solutions of MAP can be approached by the simulated annealing (SA) [12], and MPM can be solved by using Gibbs sampler [19]. This type of classifiers have rarely been applied to multispectral data, primarily because they tend to be extremely computation expensive. However, the computation time can be greatly reduced by archiving local maximum through Besag's iterated conditional modes(ICM) [3]. It is reported that the typical ratios of compute time for ICM, Gibbs sampler and SA are 1:37:6000 [10]. We develop an algorithm opt for an analogue ICM to find an MPM estimation rather than using Gibbs sampler method. The segmentation field x and the parameters for each class are estimated and updated simultaneously. In order to use the ICM method to find MPM estimation of the "hidden" label field X, we model the posteriori marginal probability field as a multivariate Gaussian Markov field.

Our approach separates the pixels in the multispectral image into regions based on both their spectral and spatial information using MRF model. Since we are trying to extract fire regions including fire front, just burned area and smoke, which have relatively smooth surface and no texture, we assume we work on images of objects with smooth surface. In addition, we can consider the textured terrain types to be noise, which is characterized by the covariance matrix. Thus the image can be modeled as a mixture of Gaussian with spatial constraints. The technique proposed here can be regarded as a generalization of the EM algorithm with modifications to include the spatial constraints. The spatial constraint is introduced by modeling the label field as a Markov Random Field. The experimental results on real AVIRIS images indicates that the performance of our algorithm is clearly superior to the K-means clustering algorithm and the EM algorithm for retrieval of the fire front, just burned area and smoke region in multispectral images.

The organization of the paper is as follows. In the Section II, we briefly recall the Markov Random Field model for the label field of images we opt. The algorithm is described in detail in Section III. The feature set selected for the implication is described in Section IV. The Section V shows some results of the unsupervised segmentation algorithm on two real images. The paper's conclusions are summarized in Section VI.

II. Statistical Model

In this paper, we use upper case letters for random quantities/field and lower case letters for their deterministic realizations. We assume that the "observed" image Y is a random field defined on a rectangular grid, S, of N points, and the vector-value spectral 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. $X = (X_s)_{s \in S}$ denote the "hidden" label field, which contains the classification of each pixel in Y. Sites in X will take values in the set $\{1, ..., M\}$, where M is the number of classes. Given $x_s = l$, y_s follows a conditional probability distribution and is conditional independent.

$$p(y_s|l) = f(y_s; \theta(l)) \tag{1}$$

where, $\theta(l)$ is the set of parameters of class l. For all classes, the conditional probability density function family $f(\cdot; \theta_l)$ has the same known analytic form. The conditional probability density of Y given X can be assumed to exist and strictly positive. Using this framework, the image may be segmented by estimating the label field X given the observed image Y.

A. Finite Mixture of Gaussian Model

In the finite mixture of Gaussian model (MoG), for a given class $l \in \{1, ..., M\}$ and $s \in S$, the random variables y are independent samples from a multivariate Gaussian distribution, with the probability

$$\begin{aligned} & f(y_s; \theta(l)) \\ & = \frac{1}{(2\pi)^{d/2}|\Sigma_l|^{1/2}} exp\left[-\frac{1}{2}(\mathbf{y_s} - \mu_\mathbf{l})^\mathbf{T}\mathbf{\Sigma_l^{-1}}(\mathbf{y_s} - \mu_\mathbf{l})\right] \end{aligned} \tag{2}$$

where μ_l and Σ_l are the mean and the covariance of class l, respectively. For every class l, $p(X_s = l) = \alpha_l$ is mutually independent and called a mixing parameter. We denote the model parameter set by Θ, $\Theta = \{\alpha_l, \mu_l, \Sigma_l\}$. Then the joint probability of x and y can be calculated given the model parameters

$$\begin{aligned} p(x, y|\Theta) &= \prod_{s \in S} p(y_s, x_s|\Theta) \\ &= \prod_{s \in S} \{\alpha_{x_s} \cdot f(y_s; \theta_{x_s})\} \end{aligned} \tag{3}$$

Although this MoG model has been used widely, it is not considered to be a complete model in practice because it neglects the spatial information by assuming the vector-valued image pixels to be statistically independent and identically distributed. In order to model the spatial correlation of vector-valued image pixels, we adopt the Gauss Markov random field (GMRF) model in this paper. And the spectral information is incorporated by adopting the Multivariate Gaussian model for an image pixel y_s, given a specified classification x_s, while the spatial correlation is encoded by modeling the label field X as an MRF.

B. Markov Random Field Model

The aim of the segmentation algorithm is to classify the multispectral images from two imperfect (spectral and spatial) sources of information. The first is that associated with each pixel s, the vector-valued Y_s obey a known statistical distribution given its class(label). It is assumed that given any particular configuration $x \in X$, each vector-valued pixel follow a multivariate Gaussian distribution $y_s|x_s, \theta_{x_s} \sim N(\mu_{x_s}, \Sigma_{x_s})$, where θ_{x_s} are the involved parameters. In this paper, $N(\mu, \Sigma)$ denotes univariate/multivariate Gaussian distribution, with mean μ and variance/covariance Σ. The second states that adjacent pixels tend to from the same class (i.e. have the same label). It is desirable to construct a random field model to quantify the second source probabilistically. MRF theory provides a convenient and consistent way to model context-dependent entities such as image pixels and correlated features. This is achieved by characterizing mutual influences among such entities 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. In this application, we use an 8-point neighborhood.

$$p(x_s|x_q,\ all\ q \neq s) = p(x_s|x_q,\ q \in N_s) \qquad (4)$$

In this application, we model the label field $X = X_s, s \in S$ as an underlying MRF field. The label field X assumes values in a finite state space $\{1, 2, ..., M\}$, which is unobservable. According to the locally dependent property of MRF field, we assume

$$p(x_s|y) \cong p(x_s|y_{\lambda s}) \qquad (5)$$

where λs contains pixel s and its neighbors. For instance, in this paper we use a eight-pixel neighborhood, then λs is a 3×3 block centered on pixel site s. In addition, we propose using a Gaussian Markov Random Field (GMRF) to model the posteriori marginal probability field given y, which is denoted by $\Pi = (p(x_s|y_{\lambda s}, \Theta))_{s \in S}$. Π contains the posterior marginal probability $p(x_s|y_{\lambda s}, \Theta)$ for each pixel s in Y. It should be noticed that the random field Π is a multivariate GMRF (MGMRF). The posteriori marginal probabilities $\{p(x_s = l|y_{\lambda s}, \Theta)\}_{l \in \{0,1,...,M\}}$ at each pixel site s can be treated as a vector-valued feature on the two-dimensional lattice S. Since the label field X in this application has unordered labels, the conditional odds of x_s, in favor of class l, depend only on the same-labeled neighbors [6]. The MGMRF field can be simplified into M independent Gauss Markov Random Fields Π_l. The value of Π_l at location $s \in S$ is the marginal probability of $x_s = l$ given $y_{\lambda s}$. Thus, $\Pi_{l,s}$ takes continuous values in $[0, 1]$. The MRF property of the GMRF model states that the posteriori marginal probability $\pi_{l,s} = p(x_s = l|y_{\lambda s}, \Theta)$ is only depend on its neighbors $\pi_{l,r} = p(x_r = l|y_{Nr}, \Theta), r \in N_s$. And $\Pi_{l,s}$ has conditional densities [4], [5]

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

where $\beta_{sr} = 0$ unless s and r are neighbors, and $\beta_{sr}\lambda_r = \beta_{rs}\lambda_s$. λ and β are unknown parameters.

III. Segmentation Algorithm

In this section, we describe the unsupervised statistical segmentation algorithm for estimating the distribution of regions x. The image may be segmented by estimating the pixel classifications X, given the observed image Y and distribution parameters Θ. In particular, we adopt the maximization the posteriori marginal probability (MPM) estimation.

We described the MPM algorithm in the follow assuming that Θ is known. The criterion used for MPM is to minimize the expected value of the number of misclassified nodes in the rectangle 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 realization of the label field X. The cost function is given by

$$R(x^*, x) = \sum_{s=1}^{N} t(x_s^*, x_s) \qquad (7)$$

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

$$\begin{aligned} E[(R(x^*, x)|Y = y] &= E[\sum_{s=1}^{N} t(x_s^*, s_s)|Y = y] \\ &= \sum_{s=1}^{N} E[t(x_s^*, x_s)|y = y] \\ &= \sum_{s=1}^{N} p(x_s^* \neq x_s|Y = y) \\ &= \sum_{s=1}^{N} (1 - p(x_s^* = x_s|Y = y)) \end{aligned} \qquad (8)$$

To find the MPM estimate of x^*, it is necessary to find for each $s \in S$ the value of l which maximizes the posteriori marginal probability of x_s at s given y

$$p(x_s = l|y) = \sum_{X: x_s = l} p_{X|Y}(x|y, \theta) \qquad (9)$$

where, $l \in 1, 2, ..., M$. Note that $p(x_s|y)$ depends on all pixels to calculate almost all $p(x)$ and is computationally infeasible. A feasible local method estimate the realization of each x_s by maximize $p(x_s|y_{\lambda s})$. Even for local method, the computation demand is still enormous. For instance, if there are six classes and we want to use a neighborhood containing eight pixels, we have already a mixture of 6^9 distributions.

In this paper, we adopt iterated conditional modes (ICM) method to estimate $\hat{\pi}_{l,s} = \hat{p}(x_s = l|y_{\lambda s}, \Theta)$, and then assign $\hat{x}_s$ with l, $l = max_l(\hat{p}(x_s = l)|y_{\lambda s}, \Theta)$. We use $\hat{\pi}_l$ denotes a provisional estimation of the true π_l^*, ICM merely replaces sites in π_l with a value which maximizes the conditional density function, as shown in Equation 10, at each site s.

$$p(\pi_{l,s}|\pi_{l,r}, r \in N_s) \tag{10}$$

And then choose the label which has maximum conditional probability given the neighbors $\pi_{l,Ns}$. The random field Π_l has continuous intensities. It follows from Equation 6 that

$$\pi_{l,s}|\pi_{l,Ns} \sim N(\sum_r \gamma_{sr}\pi_{l,r}, \lambda_s). \tag{11}$$

Then the estimate $\hat{\pi}_l$ of the true value π_l^* is chosen to maximize the expectation of Π_l. Specifically, the updating formula at pixel s is a linear combination of $\pi_{l,s}$ and the current estimate at neighboring pixel sites [6]:

$$\hat{\pi}_{l,s} = (\alpha_l \pi_{l,s} + \sum_{r \in N_s} \gamma_{sr}\hat{\pi}_{l,r}) \tag{12}$$

α and γ_{rs} are parameters of the Gaussian Markov random field.The bigger the value of the parameter α_l, the more likely the pixel site x_s is belong to class l. Raising the value of γ has the effect of increasing regions' size and smoothing their boundaries. In addition, the value of different γ_{rs} determine the shape of the regions. Estimation of these parameters is difficult and computationally expensive. Besag [6] states that estimation of these parameter is unnecessary in applications. We use fixed values of α and γ in this application. Besides the parameters, the size of neighborhood also has influence on the shape and size of the segmented regions. The bigger the neighborhood is chosen, the larger and smoother the regions will be. In this application, we are trying to segment the satellite or airborne images into regions of fire front, just burned area, smoke, and background. These regions usually expand over a considerable large group of pixels, so there should not have small isolated regions in the segmented images. Especially for the background class, it may consists of different terrain types, i.e. road, river, forest, soil, and so on. In order to classify all these into the same class, i.e. background class, strong spatial constrain is needed to deal with this problem. We choose an eight-pixel neighborhood system. Experiments show that the value of γ does not obviously affect the segmentation results, we choose a value of 1.5 in this application. The value is seems to work well on discrete MRF field cases in former works [6] [20].

The algorithm for ICM may be stated explicitly as follows:

1. Calculate the posteriori marginal probability as an initial segmentation using the Equation 13. One should notice that Equation 13 is based on the assumption that y_s and x_s are both independent random variables. This initial segmentation does not consider any spatial information at all.

$$p(x_s = l|y_s) = \frac{a_l p(y_s|l, \theta_l)}{\sum_{k=1}^{M} a_k p(y_s|k, \theta_k)} \tag{13}$$

Here, all the parameters are assumed to be known.
2. Perform a weighted majority-vote solution acting on the initialization defined by Equation 12 at each pixel site $s \in S$.
3. Assign the pixel at site s to the class l, that is $x_s = l$. $l = max\{\hat{\pi}_{l,s}\}_{l\in\{1,...,M\}}$.
4. If no changes occur in x or reach a pre-defined iteration number then stop, otherwise repeat step 2.

In order to perform the ICM algorithm mentioned above, we must estimate the parameters Θ. We will use a modified version of the EM algorithm to estimate Θ, and segment the image (estimate the x) simultaneously. Like the EM algorithm, our algorithm is iterative. It alternates between estimating x and the parameters of all mixed Gaussian distribution Θ: given an initial label field x^i, and parameters Θ^i, update the parameters Θ^{i+1} and estimate the new label field x^{i+1}.

The EM algorithm has been widely used for the estimation of mixture-density parameters. EM algorithm solves this kind of problem by assuming the existence of a set of unobserved or hidden data. In our formulation, the observed image y is the incomplete data set, and the label field x is the unobserved or hidden data. The EM algorithm maximize the expected value of the complete-data log-likelihood $\log p_{Y,X}(y, x|\Theta)$ with respect to the label field x given the observed image y and the current parameter estimates Θ^{i-1} to achieve new parameters Θ.

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

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 conditional independent given a particular x. Then deriving from Equation 14 gives:

$$Q(\Theta, \Theta^{i-1}) = \sum_{l=1}^{M}\sum_{s\in S} \log(p_x(l)p(\mathbf{y}_s|x_s = l, \Theta^{i-1}))p(x_s = l|y, \Theta^{i-1}) \tag{15}$$

It should be noticed that Q function is calculated given x^{i-1}, so the probability of an element in x^{i-1} has the value of l, $p_x(l)$, is *a priori* knowledge of the relative likelihood of class l. We assume that we have M component densities mixed together with M mixing coefficients a_l, such that $\sum_{l=1}^{M} a_l = 1$. Then we can write Equation 15 as:

$$Q(\Theta, \Theta^{i-1}) = \sum_{l=1}^{M} \sum_{s \in S} \log(a_l) p(x_s = l | y, \Theta^{i-1})$$
$$+ \sum_{l=1}^{M} \sum_{s \in S} \log(p(\mathbf{y}_s | x_s = l, \Theta^{i-1})) p(x_s = l | y, \Theta^{i-1}) \tag{16}$$

By differentiating Equation 16 and set to zero, new values of Θ can be obtained. The estimation of the new parameters in terms of the old parameters are as follows:

$$a_l^{new} = \frac{1}{N} \sum_{s \in S} p(x_s = l | y, \Theta^{i-1}) \tag{17}$$

$$\mu_l^{new} = \frac{\sum_{s \in S} \mathbf{y}_s p(x_s = l | y, \Theta^{i-1})}{\sum_{s \in S} p(x_s = l | y, \Theta^{i-1})} \tag{18}$$

$$\Sigma_l^{new} = \frac{\sum_{s \in S} p(x_s = l | y, \Theta^{i-1}) (\mathbf{y}_s - \mu_l^{new})(\mathbf{y}_s - \mu_l^{new})^T}{\sum_{s \in S} p(x_s = l | y, \Theta^{i-1})}. \tag{19}$$

Here, $p(x_s = l | y, \Theta^{i-1})$ is calculated using the ICM method described above.

The estimation of the parameters Θ and the segmentation of the image (which uses Θ as *a prior* 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 $\hat{x}$ of the true segmentation x^*, and calculate the Maximize Likelihood Estimation (MLE) of the parameters Θ. The MLE estimation of the parameters Θ ignore the spatial constraints of field X.
2. Carry out single circle of ICM based on the current Θ^{i-1} to estimate new $p^i(x_s = l | y, \Theta^{i-1})$ and then obtain a new x^i.
3. Estimate Θ^i using Equations 17 to 19, based on x^i.
4. Return to 2, until the the number of pixels in x that change during an iteration cycle is less than a threshold, or the iteration number is more than a prescribe number.

IV. Feature Selection

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.

The test images we used are AVIRIS images. The AVIRIS measures reflected radiance of 20×20 meter pixels in 224 narrow spectral bands. The resulting image "cube" consisted 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 m). Different feature set should be selected according to different classification purpose. In this application, our goal is to segment the satellite or airborne image into regions of fire front, just burned area, smoke, and the 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. Smoke is salient in visible bands and almost transparent in near-IR (NIR) and SWIR bands. By inspecting the AVIRIS image, we choose three features empirically: 1. (band 217-band12); 2. band 217 (about $2.5\mu m$); 3. band 143 (about $1.8\mu m$).

V. Results

In this section we show the detailed results of our algorithm working on two AVIRIS images. Figure 1 (a) is an image of Cuiaba, Brazil with a prescribed fire, which was take on August 25, 1995. The big fire in the middle emitted heavy smoke coved a large area. To the left of the big fire is a smaller fire with very thin smoke. The result of our algorithm is shown in Figure 1 (b), while the result of K-means and the result of EM algorithm are displayed in Figure 1 (c) and (d), respectively. Four classes are assigned to all of the three algorithms, since the purpose of this application is to map fire front, just burn area, smoke and background.

Although, k-means and EM algorithm both can separate the fire region from the background area, their performances are very different. By examining the fire region shown in Figure 2, we can see that EM algorithm can segment the whole hot region from the background, but it can not give out detailed information about the fire front and the just burned area (which may be still smoldering). The EM algorithm combined the two regions into one class. On the contrary, k-means can separate the fire front clearly, but it can not separate just burn area from the background area. Besides that, there are a lot of pepper and salt regions in the segmentation result, which is undesired. In this case, our algorithm achieve a good and clean result. The fire front is indicated by blue color as shown in Figure 1 (b). By carefully inspection of the color bands, NIR band and SWIR band of the AVIRIS image, we find that the segmented fire front aligned well with the true fire front. The just burned and still hot area is denoted with red color. Since the just burned area in this case was still very hot when the image was taken, EM algorithm fails to separate the burn scar and the fire front. The smoke and background region are indicated using white and black, respectively. The segmentation result of our algorithm agrees well with the eye inspection of the visible, NIR and SWIR bands of the AVIRIS image.

Figure 3 (a) is an image of San Bernardino Mtn, in California, USA. The image was taken on September 01, 1999. A big fire was burning on left corner of the image, producing heavy smoke. The results of the three algorithms are shown in Figure 3 (b), (c), and (d), respectively. We observed that in this case, our algorithm also produce the best result. K-means and the EM algorithm have better results than the last image, since the background of this image is relatively homogeneous. The segmentation result of our algorithm is shown in Figure 3 (b). The smoke is indicated by green color. White regions behalf the just burned area. We can see small white regions on the left side of the fire front, which is shown using red color. This result agrees well with our priori knowledge of the fire in this image: the fire was going against the wind, and progressing slowly. It is noticed that both the K-means and the EM algorithm map the fire region and smoke region very similar to the result of our algorithm. But both of them failed to report the just burn area, which is very important information for a fire propagation model.

The results from the two AVIRIS images show that our algorithm can stand high level of noise by considerate spectral spatial information together. Even when the histogram of different regions overlap significantly, our algorithm can still achieve good segmentation result by incorporating spatial information.

VI. Conclusion

In this paper, we propose a clustering algorithm to map burn scar, fire extent, fire front location and smoke region based on a statistical model. Our algorithm is superior than histogram-based algorithms, since it utilizes not only the spectral information but also spatial information by incorporating an MRF model of the label field. Our algorithm can be viewed as a generalized EM algorithm by adding a stochastic component. This spectral-spatial based algorithm has several improvements, with respect to the EM algorithm. 1. It can cope images with high level noise by incorporating spatial information. 2. It can get rid of isolated small regions. 3. The solution is essentially independent of the initialization.

We applied our algorithm on two true AVIRIS images, the segmentation results show clean and neat regions of fire front, smoke, burn scar and background. The results are useful information for a fire propagation model for initiating and nudging model predictions.

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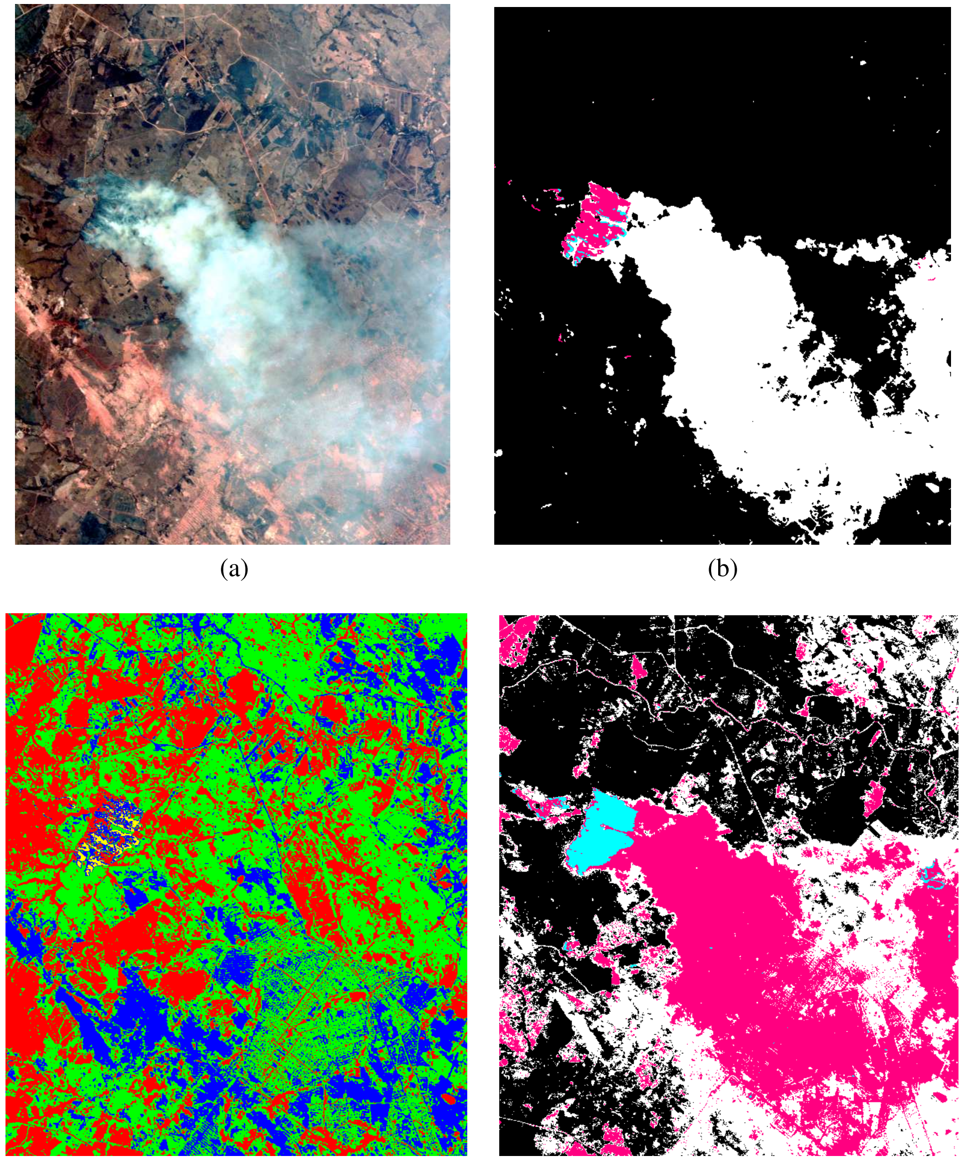
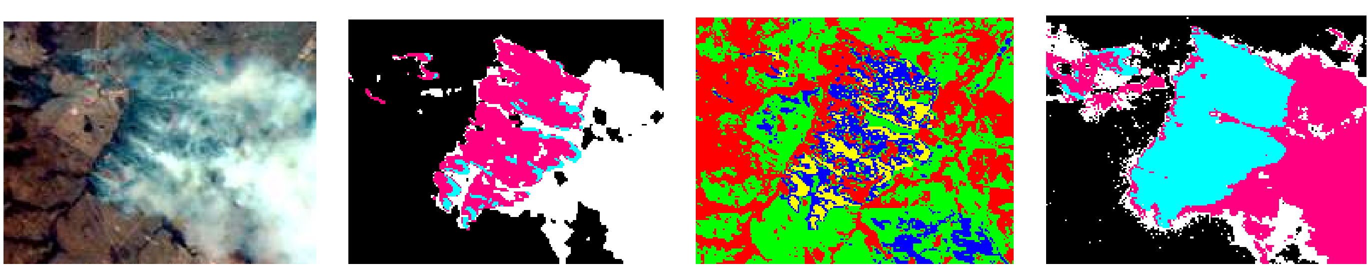


(a) (b) (c) (d)

Fig. 1. Comparison of segmentation results of our algorithm and two histogram-based algorithms: K-means algorithm and EM algorithm, M=4. (a) Original AVIRIS image of Brazil on a prescribed fire, (b)Segmentation result of our algorithm working on the image in (a), (c)Segmentation result of K-means algorithm on the image in (a), (d)Segmentation result of EM algorithm on the image in (a).



(a) (b) (c) (d)

Fig. 2. Comparison of segmentation results of our algorithm and two histogram-based algorithms: K-means algorithm and EM algorithm, M=4. (a) original image, (b) the result of our algorithm, (c) the result of K-means, (d) the result of EM algorithm.

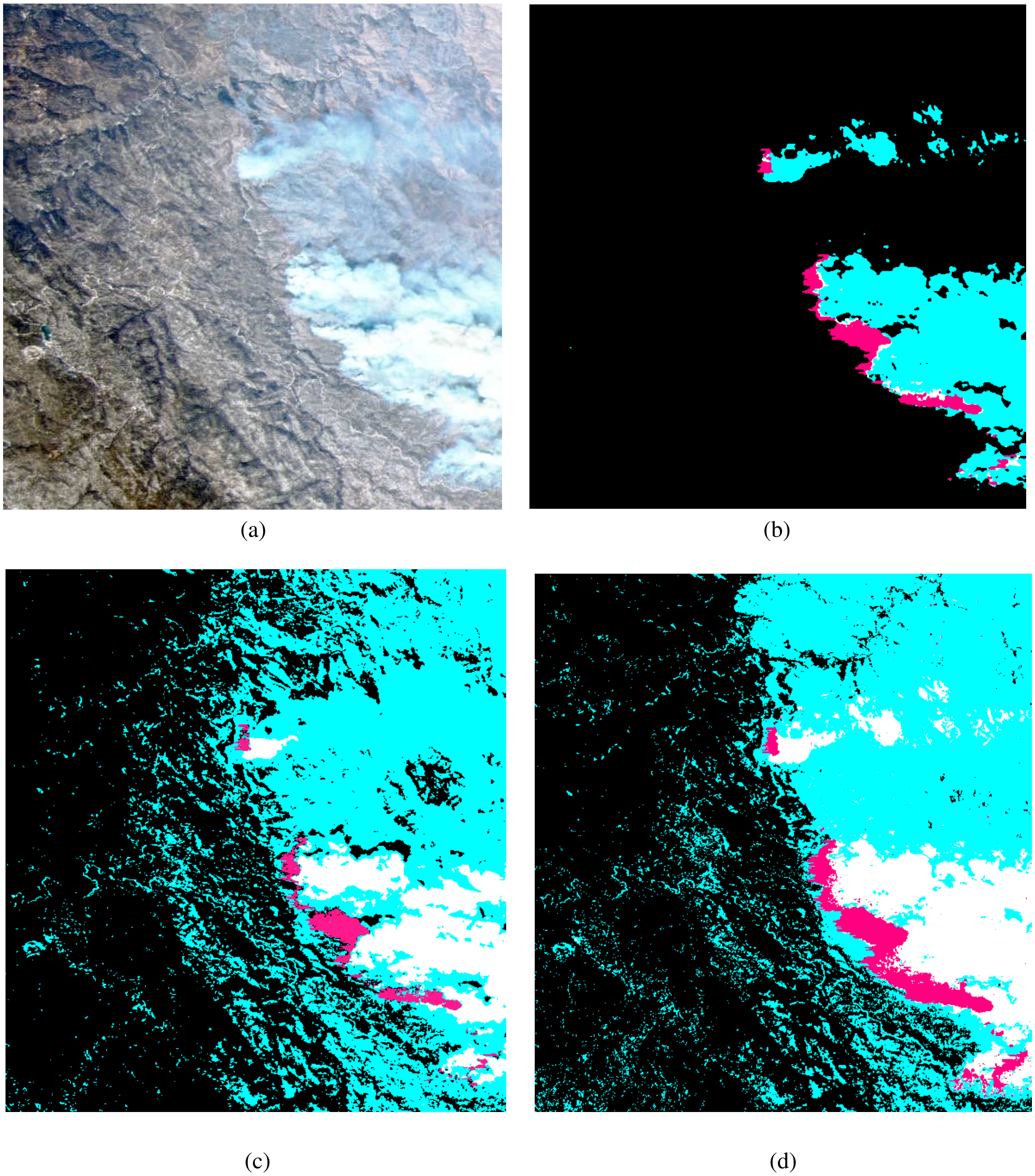


Fig. 3. Comparison of segmentation results of our algorithm and two histogram-based algorithms: K-means algorithm and EM algorithm, M=4.(a)Original AVIRIS image of California, USA, (b)Segmentation result of our algorithm in (a), (c)Segmentation result of K-means algorithm on the image in (a), (d)Segmentation result of EM algorithm on the image in (a).

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Biography

Ying Li received the B.S., and M.E. degree from the University of Science and Technology of China, HeFei, P. R. China, in 1997, and 2000, respectively. From 2000 to now, she is a Ph.D student of Center for Imaging Science in Rochester Institute of Technology. She is now working on wildland fire detection and mapping using satellite/airborne images.