Comparing Four Sub-pixel Algorithms in MODIS Snow Mapping

Hongen Zhang
College of Environmental Science and Engineering, Tongji University
1239 Siping Road, Shanghai, P.R.China, 200092

Jianfu Zhao
College of Environmental Science and Engineering, Tongji University
1239 Siping Road, Shanghai, P.R.China, 200092

Shi Jiancheng
Institute for Computational Earth System Sciences, UCSB,USA

Abstract –**Accurate monitoring of snow cover extent is an important research goal in the science of Earth systems. Now mixture modelling is important tool in the remote sensing community as researchers attempt to resolve sub-pixel, area information. In the paper, I tested four different sub-pixel analysis methods: Linear Mixture Model (LMM), Fuzzy c-means Clustering (FCM), Back-Propagation Neural Network (BPNN), and Support Vector Machine (SVM). Overall, the LMM and SVM method provided better estimates of the snow cover components than others, and the results of this study provide comprehensive information of the utility of sub-pixel analysis for the estimation of snow cover components and suggest that the comparatively accurate snow cover estimation is attainable from medium resolution satellite imagery.**

I. INTRODUCTION

Snow is an important component of the Earth's surface. Because of its importance from both a scientific and resource management standpoint, accurate monitoring of snow cover extent is an important research goal in the geoscience. The high spatial resolution and numerous MODIS spectral bands in the 0.4 to 2.5 μm wavelength region allow more accurate monitoring of snow cover extent on a global basis than is possible with other operational satellites.

Medium spatial resolution remotely sensed imagery is comparatively very cheap, but has a critical drawback "mixed" pixels. The problem leads to mis-classification of snow covered areas. Mixture modelling is becoming an increasingly important tool in the remote sensing community as researchers attempt to resolve the sub-pixel, mixture information, which arises from the overlapping land cover types within the pixel's instantaneous field of view.

In the paper, I tested four different sub-pixel analysis methods: Linear Mixture Model (LMM), Fuzzy c-means Clustering (FCM), Back-Propagation Neural Network (BPNN), and Support Vector Machine (SVM). These results are significant in that they demonstrate that medium resolution remotely sensed imagery such as Modis provide a cost effective image data source for snow monitoring.

II. THOERETICAL BACKGROUND

A. Linear Mixture Model

Linear spectral mixture model can be describe:

$$\mathbf{Ax}=\mathbf{b}. \qquad (1)$$

Where $\mathbf{A}\in R^{m\times n}, \mathbf{x}\in R^{n}, \mathbf{b}\in R^{m}, m>n$, **b** denote the $m\times 1$ image pixel and **A** is the $m\times n$ image matrix, each columns of **A** is an endmember spectrum for a specific endmember.

There exist many different linear spectral unmixing approaches, and most of them are derived from linear least squares approaches. Linear least squares estimation produces a concentration vector $\mathbf{x_{LS}}$ and a perturbation vector **r** subject to the following conditions:

$$\mathbf{Ax}_{LS}=\mathbf{b}+r \quad \text{s.t.} \|r\|^2 \text{ minimized}$$

$\|r\|^2$ denote the sum of squared components of the vector ***r***.

The solution to this problem when **A** is of full column rank is:

$$\mathbf{x}_{LS}=(\mathbf{A}^t\mathbf{A}^{-1})\mathbf{A}^t\mathbf{b} \qquad (2)$$

B. Fuzzy c-means Clustering

Fuzzy c-means clustering(FCM) is the best known and the most popular fuzzy clustering method. FCM measures the fuzzy membership value of data for each cluster based on the distance between the cluster center and the data in the feature space of remotely sensed imagery. The fuzzy membership value makes FCM more flexible and useful in practical applications, such as sub-pixel analysis[2].The performance of FCM has been shown to be better approach than the hard c-mean clustering method(Chi et al.1996).

The FCM is based on minimization of the following objective function to *U,* a fuzzy c-partition of the data set, and to *V*,a set of *K* prototype:

$$J_m(U,V)=\sum_{j=1}^{n}\sum_{i=1}^{c}(u_{ij})^m\left\|X_j-V_i\right\|^2, 1\le m<\infty \qquad (3)$$

Where m is any real number greater than 1, U_{ij} is the degree of member of X_j in the cluster i, X_j is the jth of d-dimensional measured data, V_i is the dimension of the cluster.

Fuzzy partition is carried out through an iterative of (3) with the update of membership uij and the cluster centers V_i by

$$u_{ij}=1/\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}} \qquad (4)$$

$$v_i=\frac{\sum_{k=1}^{n}(u_{ij})^m x_j}{\sum_{j=1}^{n}(u_{ij})^m},\ 1\le i\le c \qquad (5)$$

The criteria in this iteration will stop when $\max_{ij}\left[\left|u_{ik}-\hat{u}_{ik}\right|\right]<\varepsilon$,where ε is a termination criteria between 0 and 1.

C. Back-Propagation Neural Network

Since the mid 1980's ,artificial neural networks have been increasingly applied to diverse remote sensing analyses to overcome the limitations of traditional statistical methods and

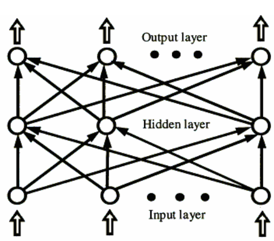

Figure 1. BP neural network

to fully utilize the potential of newly deployed satellite sensors. It has been applied on sub-pixel classification.[3]

Back-propagation is a supervised learning algorithm that applies to non-linear, multilayer, feed-forward structure of nodes (networks). The architecture of a BP network refers to the way it decodes information, that is the direction of information during recall. In a BP neural network the nodes are organized in input, hidden, and output layers, as Figure 1.

D. Support Vector Machine

The principle of the SVM-based solution for the learning process is very briefly described below[4]. Suppose that the training data:

$$D=\{(\mathbf{x}_1,y_1),\cdots,(\mathbf{x}_l,y_l)\},\quad \mathbf{x}\in R^n,\quad y\in\{-1,1\} (6)$$

can be separated by a hyperplane:

$$w^T x+b=0 \qquad (7).$$

The set of vectors is said to be optimally separated by the hyperplane if it is separated without error and the distance between the closest vector to the hyperplane is maximal.

A separating hyperplane in canonical form must satisfy the following constraints,

$$y_i[w^T x_i+b]\ge 1) \qquad (8)$$

Then the hyperplane that optimally separates the data is the one that minimises

$$\Phi(w)=\frac{1}{2}\|w\|^2 \qquad (9)$$

Classical Lagrangian duality enables the problem.The optimal separating hyperplane is given by

$$w^*=\sum_{i=1}^{l}\alpha_i y_i x_i \qquad (10)$$

$$b^*=-\frac{1}{2}w^{*T}(x_r+x_s)$$

where x_r and x_s are any support vector from each class satisfying,

$$\alpha_r,\ \alpha_s>0,\quad y_r=-1,\quad y_s=1 (11)$$

The hard classifier is then,

$$f(x)=\mathrm{sgn}(w^{*T}x+b^*) \quad (12)$$

A soft classifier is used here which linearly interpolates the margin,

$$f(x)=h(w^{*T}+b) \qquad (13)$$

where, $h(z)=\begin{cases}0 & : \quad z<-1\\ (z+1)/2 & : -1\le z\le 1\\ 1 & : \quad z>1\end{cases}$

III. DATA and METHODS

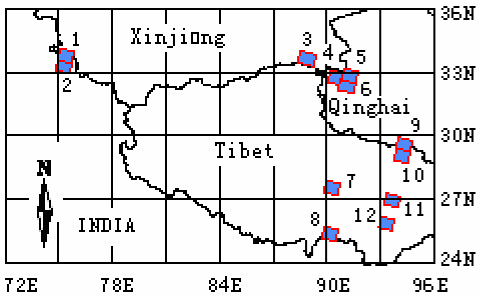

Figure 2. Location of Aster image

Aster provides high spatial resolution (15-90 m) multispectral images of the Earths surface. These data bridge the gap between field observations and data acquired by coarse spatial resolution instruments such as MODIS,and between local-process models and regional models.

Here we classify ASTER image in three visible and near-infrared channels with 15-m resolution as “ground truth” to validate our MODIS snow mapping algorithm.

The study area is situated in the Tibetan Plateau. The available data consist of 12 MODIS image and Aster image corresponding days and area for validation, as shown in figure 2.

Selecting endmembers is key in linear mixture model, here endmembers is determined by averaging the pixel value selected by scatter plot of band 4 and band 6 of MODIS data, image 5(fig.2) as an example is shown in figure 3.

In FCM, the fuzzy membership value is not linearly correlated with the class proportion. To utilize the fuzzy membershipvaue to estimate the actual composition of snow in a mixed pixel, simulated data is created through mixing the endmenbers spectral value. The simulated data and the image data is applied together in FCM, and the relation is found.

The simulated data is also took as training data to establish the networks in BP neural networks algorithm. The parameter in BP is set up by testing again and again.

The training data in SVM is selected manually from image, the data is split into two base class: snow and non-snow (soil, grass, shrubs, etc), image 5(fig.2) as an example is shown in figure 3.

IV. RESULT and CONCLUTION

The result of unmixing for snow is shown in table in TABLE Ⅰ. In FCM , only the pixels that the percent of snow cover area in it is greater than 15% are count,because previous work showed lower accuracy when the proportion is less than 15%.

The error of SVM is less than 4.4% as compared to the reference data from Aster image classification and the average of error is 1.9%, the least error just is 0.004%. The error of

TABLE Ⅰ UNMIXING RESULT of LMM，BPNN ,SVM and FCM

NO.	Aster Image	LMM		BPNN		SVM		LMM(>15%)	FCM(>15%)	FCM vs. LMA
	Area（Km2）	Area(Km^2）	Error(%)	Area(Km^2）	Error(%)	Area(Km^2）a	Error(%)	Area（Km2）	Area（Km2）	Error(%)
No.1	580.973	581.767	0.1366	558.693	-3.835	584.763	-3.8	516.516	519.326	0.5438
No.2	794.51	816.193	2.7291	813.484	2.3881	790.382	2.39	789.724	790.537	0.1029
No.3	607.591	627.412	3.2622	616.594	1.4817	629.622	1.48	604.658	604.80	0.0239
No.4	301.392	295.402	-1.987	303.79	0.7959	285.327	0.8	114.416	113.895	-0.455
No.5	592.745	597.395	0.7846	618.983	4.4266	612.598	4.43	583.440	580.972	-0.423
No.6	146.785	151.542	3.241	150.908	2.8087	142.346	2.81	123.875	123.904	0.0231
No.7	512.91	525.762	2.5055	533.928	4.0975	519.83	4.1	504.366	503.691	-0.134
No.8	346.45	343.891	-0.739	364.21	5.1258	343.92	5.13	359.915	356.754	-0.878
No.9	383.91	380.512	-0.884	370.313	-3.54	383.09	-3.5	326.733	326.88	0.0458
No.10	1015.1	993.112	-2.17	973.68	-4.085	1005.2	-4.1	960.585	959.232	-0.141
No.11	749.87	738.635	-1.498	731.981	-2.386	759.84	-2.4	724.375	723.487	-0.123
No.12	961.2	943.942	-1.796	960.829	-0.039	943.64	-0.04	961.2	941.605	-2.080

LMM is less than 3.26% compared to the reference data from Aster image classification and the average of error is 5.1%, the least error is 0.14%. The error of BPNN is less than 3.26% ompared to the reference data from Aster image classification and the average of error is 3.4%, the least error is 0.79%. The relative error between FCM and LMM is less than 2.08% ,and most of them is less than 0.5%. In summary, all of the four sub-pixel algorithms for MODIS snow mapping described previously provided considerable accuracy of snow cover area, and LMM and SVM method provided the best estimates of the snow cover components.

The linear mixture assumption of the endmembers spectra of LMM is upheld to a large extent as evidenced by the rather high accuracy of snow cover estimation. The results of this study provide comprehensive information of the utility of sub-pixel analysis for the estimation of snow cover components and suggest that the comparatively accurate snow cover estimation is attainable from medium resolution satellite imagery. These results are significant in that they demonstrate that medium resolution remotely sensed imagery such as Modis provide a cost effective image data source for snow monitoring.

REFERENCE

[1]Adams J. B., Sabol D. E.,Kapos V..Classification of multispectral images based on fractions of endmembers: application to land-cover in the Brazilian Amazon. Remote Sens. Environ.1995,52:137-154.

[2]Foody G M, Cox D P. Sub-pixel land cover composition using a linear mixture model and fuzzy membership functions. International Journal of Remote Sensing, 1994,15: 619-631

[3]Carpenter G., Gopal S., Macomber M. S., Woodcock C.. A neural network method for mixture estimation for vegetation mapping, Remote Sensing of Environment,70:138-152, 1999

[4]Steve R. Gunn .Support Vector Machines for Classification and Regression,,17-30,1998

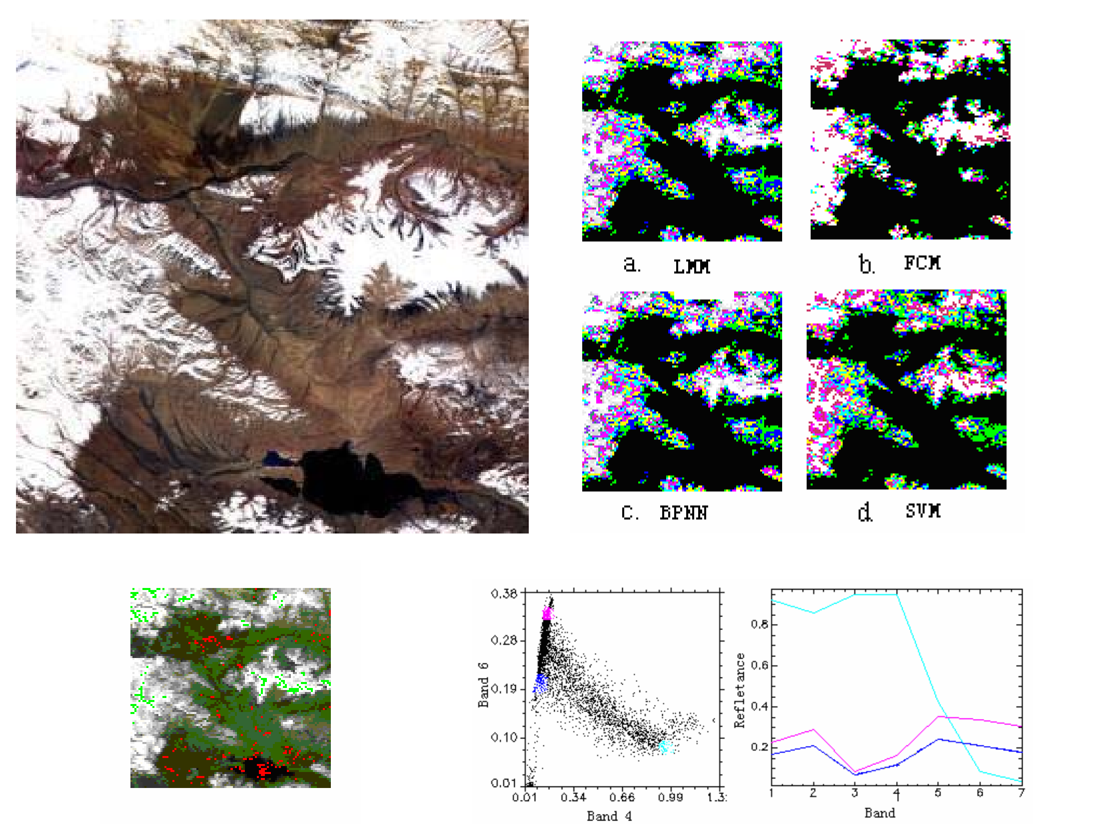

Figure 2. Aster image of No.5, the result of unmxing of it, the training pixel of SVM and the scatter of band 4 and band 6of it which help to select endmember manually from the image.