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Urban Impervious Surface Extraction from Remote Sensing Image Based on Nonlinear Spectral Mixture Model

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Abstract: Aiming at overcoming the limitations in extracting impervious surface by traditional methods, two non-linear spectral mixture models, Mixture Tuned Matched Filtering (MTMF) and Multi-Layer Perceptron(MLP) neural network, are used to decompose all pixels to the four fraction images representing the abundance of four endmembers. In these models, MTMF performs a "partial" unmixing by only finding the abundance of a single, user-defined endmember, by maximizing the response of the endmember of interest and minimizing the response of the composite unknown background. The MLP is a hierarchical structure of several perceptrons, and capable of learning a rich variety of nonlinear decision surfaces. The Maximum Noise Fraction(MNF) is used to transform the six bands of TM image into a new feature space and the first three components accounting for the majority (more than 90%) of total information content are used to endmember extraction. After that, the Pure Pixel Index(PPI) is used to select pure pixels. The *N*-dimensional visualizer is used for assisting selection of four endmembers: vegetation, high-albedo objects, low-albedo objects and soil. The fraction images are derived to represent the abundance of the above four endmember. Impervious surface is estimated by analyzing high-albedo and low-albedo fraction images. QuickBird multi-spectral image is used to evaluate the accuracy of impervious surface extraction by different methods. Experimental results indicate that the accuracy of artificial neural network is higher than others, which means non-linear spectral mixture models is also effective to impervious area extraction, even better than linear models.

Key words: Spectral mixture model; Impervious surface; Artificial neural network; Multi-layer perceptron

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0 Introduction

Impervious surface, defined as anthropogenic features which water can not infiltrate into, such as roads, rooftops, parking lots, and other man-made objects, has become a major indicator of the urbanization and environmental quality[1]. The approaches based on remote sensing data, including image classification and spectral mixture model, have been widely developed to extract impervious surface recently[2-3].

Due to the complexity of urban impervious surface materials and the heterogeneity of landscape, impervious surface is mixed by other land-cover types, it is very difficult to select sufficient training samples from medium resolution images, resulting in low accuracy in land cover/use classification. Mixed pixel is defined as a pixel that is composed of more than one ground objects (endmembers). Unmixing aims at decomposing mixed pixels to extract more information from sub-pixel scale, other than single pixel level. So it can help to solve those problems to a great extent.

Linear spectral mixture model (LSMM) is a physical theory based model in which a mixed spectrum is modeled as the combination of several

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pure spectra[4]. The problem with LSMM is the difficulty in endmember selection, which is directly caused by the within-class spectral variability. The other problem is the land cover types may be not be linearly combined within a mixed pixel. Therefore, there are also some nonlinear spectral mixture models, for example, mixture tuned matched filtering (MTMF), artificial neural network (ANN), etc.[5-6]. MTMF, a special type of spectral mixture analysis, is based on well-known signal processing methodology[7]. Due to its advantage over statistical methods and no assumption required about the probabilistic methods, ANN have been used to extract impervious surface, and the results indicated that the accuracy is better than LSMM[8-9].

In this study, impervious surface distribution is derived directly from Landsat TM image using linear and nonlinear spectral mixture model, including LSMM, MTMF and ANN.

1 Study area and datasets

1.1 Study area

Xuzhou City, the biggest city in northwestern part of Jiangsu Province, is chosen as the study area. It is located at 116°22′E～118°40′E, and 33°43′N～34°58′N, covering about 11 258 km^2. The region within highway around the city was selected to study. The selected region contains most land cover/use types: water, green vegetation, soil, high-and low-density residential and industry land, Central Business District (CBD) and so on.

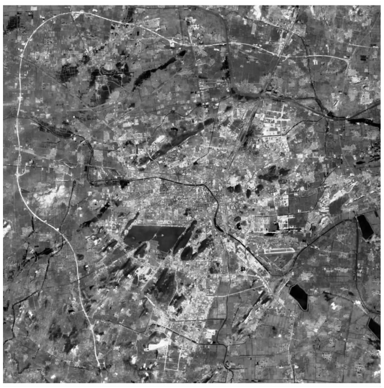

Fig. 1 The false color image of study area (2004, Landsat TM, Band 4(R), 3(G), 2(B))

1.2 Data and preprocessing

A Landsat TM image (path 121/row 36), acquired at Sep 17, 2004, is used to extract urban impervious surface information. The size of TM image is 900×900. The used bands of TM images are as follows: band1: Blue band; band 2: Green band; band 3: Red band; band 4: NIR band; band 5: MIR band; band 7: LIR band. In addition, 2.44 m QuickBird multispectral image acquired on Nov 11th, 2004, which covers the main regional of the study area, is selected to validate the impervious surface estimation results and evaluate the accuracy. Atmospheric correction is done by Quick Atmospheric Correction (QUAC) module in ENVI software.

2 Methods and experiments

2.1 Endmember selection

In order to obtain better spectral mixture results, the following conditions must be satisfied: 1) selected endmembers should be independent of each other, 2) the number of endmembers should be less than or equal to the spectral bands used, and 3) selected spectral bands should not be highly correlated[10]. In this study, detailed ground spectral information is not available. Thus, endmembers are chosen and derived from the Landsat TM image. Many researches unitize spectral scatter plots of image band after transforming the original image bands into a new feature space. The most popular one is principal component (PC). The principal component computes 90% of the variances of the first two/three components and reduces the bands′ correlation[11]. This transform method usually ignored some useful information because noise variance may be larger than signal variance in a band. Unlike PC transform, maximum noise fraction (MNF) consists of two separate principle component analysis (PCA) rotations, separating noise from signal and compressing spectral information in a few composite bands which account for the most of the variance in the original image[12].

Firstly, the maximum noise fraction (MNF) is used to transform the 6 bands of TM image into a new feature space and the first four components accounting for the majority (more than 90%) of total information content are used to endmember extraction. After that, we use pure pixel index (PPI) to select pure pixels. PPI is computed by repeatedly projecting N-dimensional scatter plots onto a random unit vector. The N-dimensional visualizer is used for assisting selection of four endmembers: vegetation, high-albedo objects, low-albedo objects and soil.

2.2 Linear spectral mixture model

LSMM assumes the reflectance of each material (or endmember) to be a linear combination in the pixel. The mathematical model can be expressed as

$$R_b = \sum_{i=1}^{n} f_i R_{i,b} + e_b \quad (1)$$

Under: $\sum_{i=1}^{n} f_i = 1$ and $f_i > 0$

where R_b is the reflectance of processed pixel at band b; f_i is the proportion of the i th endmember at band b; $R_{i,b}$ is the known reflectance of the i th endmember at band b; e_b is the error for band b.

2.3 Non-linear spectral mixture model

The MTMF and multi-layer perception (MLP) neural network are selected as non-linear spectral mixture model to decompose all pixels on the image to derive the fraction images representing the abundance of four endmembers: vegetation, high-albedo objects, low-albedo objects and soil.

The MTMF, a special type of spectral mixture analysis, is based on well-known signal processing methodologies. The MTMF performs a "partial" unmixing by only finding the abundance of a single, user-defined endmember, by maximizing the response of the endmember of interest and minimizing the response of the composite unknown background[8].

An ANN is a mathematical model or computational model that tries to simulate the structure and/or functional aspects of biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Many ANN models have been developed in recent years. The most popular one is the MLP network. There are an input layer, an output layer and many hidden layers in the MLP network. The architecture of MLP implies that each neuron of a layer is connected to all neurons of the next layer, but the neurons within a single layer are not interconnected. Specifically to remote sensing spectral analysis, the input layer represents the original image, and each node represents one band. The hidden layer processes the classification and deliveries the results to output layer. The output layer presents the results (Fig. 2).

In this study , a three - layer MLP neural network with a BP learning algorithm is applied . An input layer with six nodes corresponding to six TM image bands (expect thermal infrared band) and one output layer with four nodes corresponding to four endmembers are used. Specify to the TM image, the number of hidden layers' node is 4 and the learning rate should be between 0.1 and 0.2, while momentum factor should be between 0.5 and 0.6[9]. Through many experiments, the parameters used in this study are shown in Table 1.

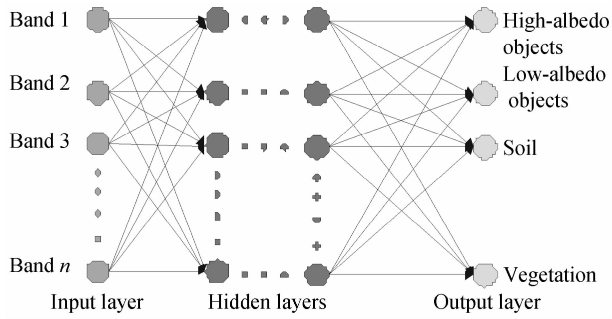

Fig. 2 The structure of MLP network

Table 1 Parameters of MLP

Parameter	Value
Hidden layers' node	4
Learning rate	0.2
Momentum factor	0.5

2.4 Impervious surface estimation

From the steps of 2.1 to 2.3, the high-albedo, low-albedo, vegetation and soil fraction images can be obtained. But the high-albedo and low-albedo objects can not be interpreted as impervious surface. Wu and Murray (2003) developed the method by adding high and low albedo fraction image to extract the impervious surface. The mathematical model can be expressed as

$$R_{imp} = f_{low} R_{low} + f_{high} R_{high} + e \quad (2)$$

Under: $f_{low} + f_{high} = 1$ and $f_{low}, f_{high} > 0$

where R_{imp} is the of impervious surface; f_{low} and f_{high} are the fraction of low albedo and high albedo; R_{low} and R_{high} are reflectance spectra of low and high albedo; and e is the error.

Before estimating impervious surface, Modified Normalized Difference Water Index (MNDWI) is used to remove the influence of water and shadow[14]. The equation can be expressed as

$$\mathrm{MNDWI} = \frac{\mathrm{Green} - \mathrm{MIR}}{\mathrm{Green} + \mathrm{MIR}} \quad (3)$$

where, Green is band two and MIR is band five of the original TM image. The impervious surface results are shown in Fig. 3.

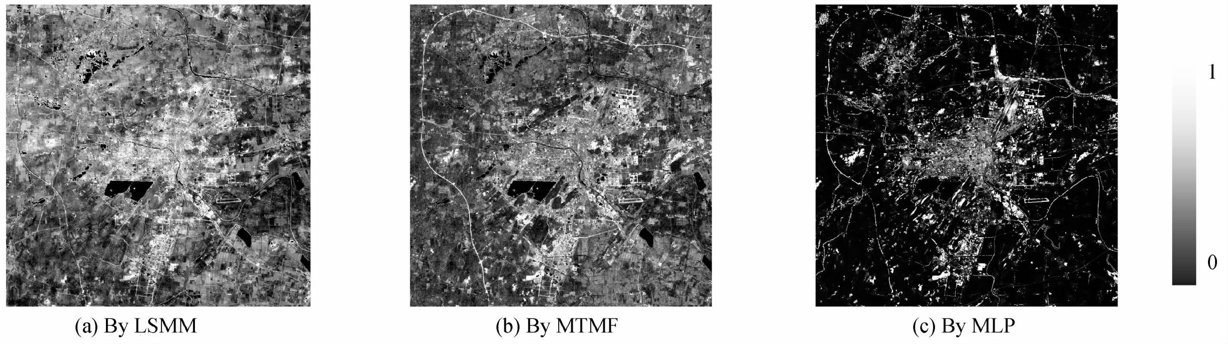

Fig. 3 Impervious surface fraction by LSMM, MTMF and MLP

3 Accuracy assessment

In order to evaluate the accuracy of linear and non-linear spectral mixture model for impervious surface extraction, QuickBird high resolution image by manual interpretation is viewed as the ground truth. QuickBird is used to rectify the TM image using 40 ~ 45 Ground Control Points (GCPs) with a Root Mean Square Error (RMSE) ranging from 0.2 to 0.5 pixels. And all images are all resampled to 2.5 m. The image 3×3 moving window is used to select testing samples from Landsat TM image, while it is corresponding to an image block of 36×36 on QuickBird image. RMSE and Systematic Error (SE), as demonstrated by Eq. s(4) and (5), are used to assess the accuracy.

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{N}(\hat{X}_i-X_i)^2}{N}} \tag{4}$$

$$\mathrm{SE}=\frac{\sum_{i=1}^{N}|\hat{X}_i-X_i|}{N} \tag{5}$$

where X_i is the fraction of impervious surface estimated from TM data, and $\hat{X}_i$ is the corresponding reference value on QuickBird image. Table 2 is a summary of the errors. The lower errors represent the higher accuracy.

Furthermore, linear regression is employed to relate the reference value with estimated value of impervious surface coverage. The reference value is the ground truth obtained from QucikBird high resolution image. Eq. s(6)~(8) are the regression equations between LSMM, MTNF, MLP and reference value. Fig. 4 demonstrates the impervious surface extraction results. The R^2 means the goodness of fit between real and estimated values. The higher value of R^2 can show the higher goodness of fit and higher accuracy. From the Eq. s(6)~(8), the R^2 of MLP is the highest.

Table 2 Accuracy of impervious surface extraction

	RMSE	SE
LSMM	0.1344	0.0348
MTMF	0.1296	0.0048
MLP	0.1249	0.0051

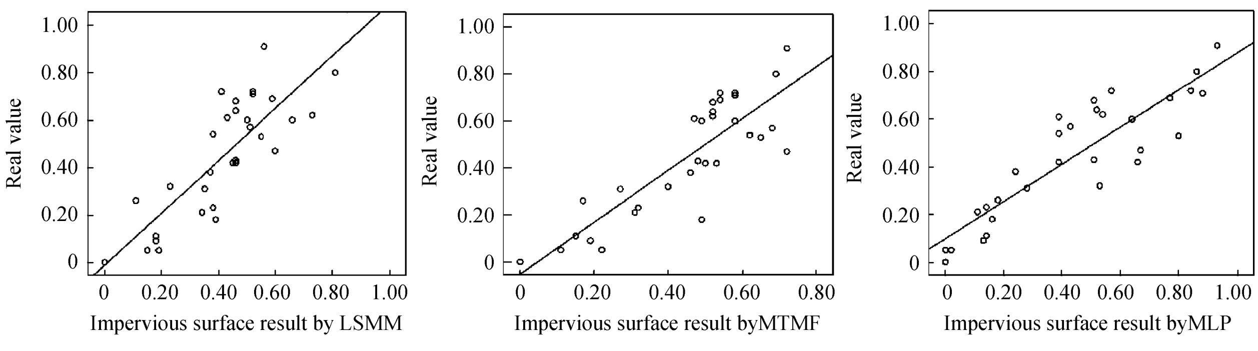

Fig. 4 Linear regression between reference and estimated value

$$\mathrm{Imp}_{\mathrm{real}}=1.105\mathrm{Imp}_{\mathrm{LSMM}}-0.013, R^2=0.669 \tag{6}$$

$$\mathrm{Imp}_{\mathrm{real}}=1.106\mathrm{Imp}_{\mathrm{MTMF}}-0.053, R^2=0.726 \tag{7}$$

$$\mathrm{Imp}_{\mathrm{real}}=0.782\mathrm{Imp}_{\mathrm{MLP}}+0.098, R^2=0.796 \tag{8}$$

Based on the errors and regression analysis, it is concluded that both linear and nonlinear spectral mixture models are suitable for impervious surface extraction, but the nonlinear models are superior to linear spectral mixture model and ANN model is a litter better than MTMF.

4 Disscusion and conculsion

LSMM, as a subpixel classifier, is gaining great advantage to solve the mixed-pixel problem. It can accurately extract the quantitative subpixel information using its strictly physically model. Impervious surface can be derived by the addition of high- and low- albedo fraction images, with both as the LSMM endmembers. Due to the linear assumption of LSMM, it can lead to the low statistical accuracy of impervious surface extraction. To avoid the limitations in LSMM, nonlinear spectral mixture models are used as a subpixel classifier to observe whether it can improve the accuracy of impervious surface extraction. The MTMF, a special type of spectral mixture analysis, is based on well-known signal processing methodologies. This method just considers the single, user-defined endmembers, not concerns with the linear combination of land cover types in a mixed pixel. ANN is used to simulate the structure and/or functional aspects of biological neural networks, not limited to linear assumption. The results indicate that the nonlinear spectral mixture model can improve the accuracy of impervious surface estimation. And the accuracy using ANN model is a bit higher than that of MTMF. From the chart map of extracting the impervious surface, we find that the selection of training samples is the most important step, which directly influenced the accuracy of the final result. Specify to other remote sensing images, the hidden layers and some parameters (learning rate, momentum. etc) of ANN are hard to set up properly. Although a lot of methods have been developed to determine these parameters, it is still impacted by many factors. Due to the limited spectral/spatial resolution of TM, it is hard to extract higher accuracy impervious surface. In the future, we'll experiment the performance of some high spatial multi-spectral image, like IKONOS, ALOS and hyspectral image, for example, Hyperion EO-1 image.

References

[1] WENG Qi-hao. Remote sensing of impervious surfaces[M]. Florida: CRC Press/Taylor and Francis, 2007: 454-457.

[2] LU Deng-sheng, WENG Qi-hao. Use of impervious surface in urban land-use classification [J]. *Remote Sening of Environment*, 2006, **102**(1-/2): 146-160.

[3] WU Chang-shan, MURRAY A T. Estimating impervious surface distribution by spectral mixture analysis[J]. *Remote Sensing of Environment*, 2003, **84**(4): 493-505.

[4] SMALL C. Estimation of urban vegetation abundance by spectral mixture analysis[J]. *International Journal of Remote Sensing*, 2001, **22**(7): 1305-1334.

[5] MARSAND J, CROWLEY J. Mapping mine wastes and analyzing areas affected by selenium-rich water runoff in southeast idaho using AVIRIS imagery and digital elevation data[J]. *Remote Sensing of Environment*, 2003, **84**(3): 422-436.

[6] CHANG D H, ISLAM S. Estimation of soil physical properties using remote sensing and artificial neural network [J]. *Remote Sensing of Environment*, 2000, **74**(3): 534-544.

[7] WILLIAMS A P, HUNT E R. Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering[J]. *Remote Sensing of Environment*, 2002, **82**(2/3): 446-456.

[8] WENG Qi-hao, HU Xue-fei. Medium spatial resolution satellite Imagery for estimating and mapping urban impervious surfaces using LSMA and ANN [J]. *IEEE Trans on Geoscience and Remote Sensing*, 2008, **46**(8): 2397-2406

[9] HU Xue-fei, WENG Qi-hao. Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks [J]. *Remote Sensing of Environment*, 2009, **113**(10): 2089-2102.

[10] WENG Qi-hao, LU Deng-sheng. A sub-pixel analysis of urbanization effect on land surface temperature and its interplay with imprevious surface and vegetation coverage in Indianapolis, United States [J]. *International Journal of Applied Earth Observation and Geoinformation*, 2008, **10**(1): 68-83.

[11] RICHARDS J A, JIA Xiu-ping. Remote sensing digital image analysis: an introduction [M]. 4th ed. Berlin: Springer, 2006: 137-154.

[12] SMALL C. High spatial resolution spectral mixture analysis of urban reflectance[J]. *Remote Sensing of Environment*, 2003, **88**(1-2): 170-186.

[13] XU H Q. A Study on information extraction of water body with the modified normalized difference water index [J]. *Journal of Remote Sensing*, 2005, **9**(5): 589-595.

基于非线性光谱混合模型的遥感影像提取城市不透水层

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摘　要:针对传统方法在提取城市不透水层中的许多局限性,采用两种非线性光谱混合分解模型,包括混合调谐匹配滤波和多层感知器神经网络,通过混合像元分解获取城市不透水层.混合调谐匹配滤波利用用户选择的端元,通过最大化端元响应并减少未知背景信息的影响,进行局部分解端元.多层感知器由多个感知器组成,能够很好的进行非线性学习.对 Landsat TM 遥感影像进行最大噪声分离,使其转换到另外一个特征空间.利用新生成数据集的前三个成分(占 90%以上信息量)进行纯净像元提取,并利用 N 维可视化分析器寻找出四个进行分解的端元:植被、高反射率地物、低反射率地物和土壤。不透水层则由高反射率和低反射率两个分量估算而成。对不同模型提取的结果,利用 QuickBird 多光谱图像评价其准确性.实验结果表明人工神经网络的精度最高,即非线性光谱混合模型同样可以有效地提取不透水层,精度甚至优于线性模型.

关键词:光谱混合模型;不透水层;人工神经网络;多层感知器