THE STUDY ON LINEAR MIXED PARCEL UNMIXING FOR CLASSIFICATION

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ABSTRACT.:

Aiming at the disadvantage of hard per-parcel classification which can't solve the difficulty of mixed parcel resulting in the low accuracy, a new method of soft per-parcel classification is presented, that is linear mixed parcel unmixing. Based on the linear spectral theory for the parcel unmixing, the predicted fraction value is assigned to a parcel. The RMSE results show that the accuracy of this method is similar to the traditional linear spectral unmxing method, and is higher than that of hard per-parcel classification. There are two advantages about this method. Firstly, this method incorporating more than one pixel information ensures the result stability. Secondly, the problem of mixed parcel, which disturbs the hard per-parcel classification, can be solved. All of above improve the per-parcel classification accuracy.

1. INTRODUCTION

Land cover mapping has been among the most obvious applications of remote sensing (Gallego, 2004).Various methods have been developed to map sub-pixel land cover using remotely sensed imagery (Atkinson, 1998; Tatem et al., 2001), including per-pixel and per-parcel classification. Today the per-pixel classification is still used for the application widely, which mainly includes the hard classification (e.g., Maximum likelihood classification(Liu et al., 2002; Thomson et al., 1998), ISODATA classification (Pan et al., 2003; Salvador and San-minguel-ayanz, 2003), etc.) and the soft classification (e.g. linear spectral unmixing (Hu and Lee, 1993; Vikhamar et al., 2003; Zhu, 2005; Lu and Weng, 2006), neural network (Bastin, 1997; Foody, 2000), etc.), supervised fuzzy classification (Wang, 1990), etc.). The per-pixel method predicts the single pixel to the certain class or the proportional membership of each pixel to each class (Foody, 1996). The soft classification can provide a more realistic representation of land cover than hard classification (Lu and Weng, 2006; Foody, 2000), whereas both the hard classification and soft classification have their own advantages (Lo 2004). Lo (2004) synthesize the advantages of both methods for the land use/cover mapping in order to improve the accuracy of information extraction. The per-pixel classification can not utilize the texture, context and some expert information for the classification (David, 2003). Furthermore, this method is sensitive to the spectral variety caused by the effect of the sensor, topographty and relief, which results in the classification difficulty. In order to overcome such shortcoming, the per-parcel classification has been developed rapidly in recent years (Smith and Fuller, 2001; David, 2003, Dean and Smith, 2003). This method taking ‘parcel’ as the basic cell can utilize many kinds of information synthetically and thus can reduce the noise influence for classification at some degree. A lot of researches have been put forward to the per-parcel classification, which assigns land cover type to the parcels using some methods. The parcel is the collection of the homogeneous spectral pixels. However, even the high spatial resolution image, such

as IKONOS, there is not an optimum scale to segment the remotely sensed image for parcels. Usually, there are more than one land cover types within one parcel, which leads to a mixed spectral parcel. Thus, the traditional hard per-parcel classification which results in the classification error easily can not be avoided.

From the per-pixel classification to the per-parcel classification, the land use/cover information extraction methods have been developed. The mixed parcel is the serious problem which affects the accuracy of the hard per-parcel classification. In order to solve such problem, a mixed parcel unmixing method is presented, which takes the linear spectral unmixing model for the per-parcel unmixing. The predicted fraction value is assigned to the parcel. And the QUICKBIRD data is adopted as the ground truth data for the accuracy assessment to evaluate the feasibility of this method.

2.LINEAR MIXED PARCEL UNMIXING(LMPU)

Macroscopic combinations of homogeneous 'endmember' materials within GIFOV often produce a composite reflectance spectrum that can be described as a linear combination of the spectra of the endmembers (Singer and Mccord, 1979). If mixing between the endmember spectra is predominantly linear and the endmembers are known a priori, it may be possible to 'unmix' individual pixels by estimating the fraction of each endmember in the composite reflectance of a mixed pixel (Smith, 1990). The linear mixing model assumes that the net spectral reflectance profile of an area within the GIFOV of the sensor can be described as a linear combination of endmember spectra as:

$$f_1 E_1(\lambda) + f_2 E_2 + \ldots + f_n E_n(\lambda) = R(\lambda) \qquad (1)$$

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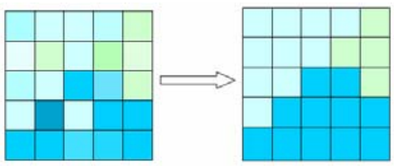
where $R(\lambda)$ is the observed reflectance profile, a continuous function of wavelength λ. The $E_i(\lambda)$ are the endmember spectra and the f_i are the corresponding fraction of the n endmembers contributing to the composite reflectance spectrum for the area within the IFOV. According to the linear mixed spectral unmixing model, the proportional membership of each pixel is predicted to each class.

Based on the theory of mixed pixel unmixing, a new approach, mixed per-parcel unmixing, is put forward that taking a parcel as the basic unit and unmixing the mixed parcel by linear spectral method instead of per-pixel as the basic unit. There are some key steps for this:

(1) Extract parcels

Using cluster or GIS method, the homogeneous spectral pixels of remotely sensed imagery can be merged into one parcel. And the spectral reflectance of the parcel is the mean spectral reflectance of all the pixels within the parcel (figure 1). In the Eq. (1), the $R(\lambda)$, $E_i(\lambda)$ and f_i represent the spectral reflectance of each parcel, the spectral reflectance of each kind of pure parcel and the fraction value of certain land cover type within a parcel, respectively.



Pixels images Parcels images

Figure. 1. Remote sensing image segment

(2) Choose the representative pure parcels

According to the linear spectral unmixing model, the representative pure parcels, which have the homogeneous and representative pixels within the parcel, are chosen for linear mixed parcel unmixing, in order to predict the fraction value within a parcel.

3. STUDY SITE AND SAMPLE DATA

A subset of Landsat5 TM scene (serial number: 123/32, 7 April 2006) covering the whole study site (116°53' 00.03" E ~116°45'58.43" E, 39°50'47.96" N ~39°56'10.99 N, 10km by 10km) was acquired in good quality and cloud-free. The image has a spatial resolution of 30m and six bands (the thermal band is excluded). The main land cover types in the study site were wheat, urban area, bare ground, river and grass, in which wheat occupied relative large proportion of the whole area of the study site. In order to validate the method in this study, the multi-spectral QUICKBIRD data (2 May 2006) with 2.4m consistent with the range of the study site is also acquired. The information of each land cover type is extracted from QUICKBIRD data with the help of ancillary data acquired from the field work on May 2006, and the accuracy validation is also undertaken. The result of classification from QUICKBIRD data was considered as the ground truth used for the accuracy assessment of the unmixing method.

4 . METHODOLOGY

The LMPU method includes several steps: data preprocessing, parcels extraction and the pure parcels selection, per-parcel linear spectral unmixing. The QUICKBIRD classification result as the ground truth is adopted for the accuracy assessment. The comparison is also done with the soft per-parcel unmixing, hard per-parcel classification and per-pixel unmixing respectively. The whole flow of LMPU was given in Fig 2.

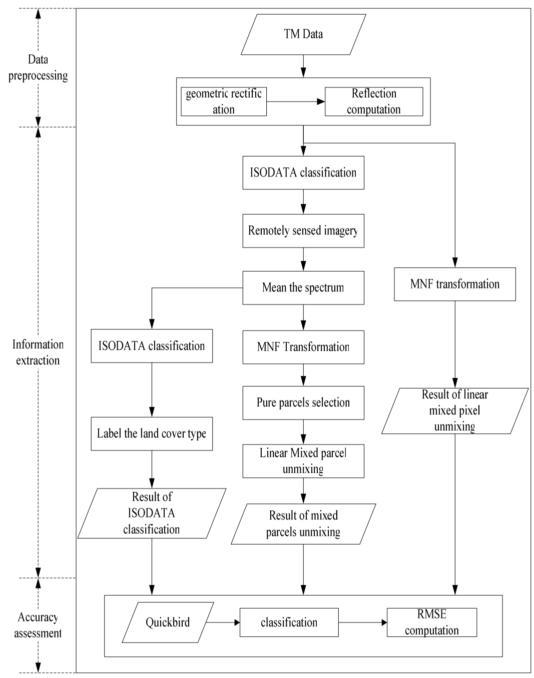


Figure 2. the flow chart of mixed parcel unmixing

4.1 Preprocessing

Data preprocessing mainly contains rigorous geometric rectification and reflectance calculation. First, the TM image and Quickbird data were co-registered. Specifically, the TM image was registered directly to the already registered Quickbird data using second order polynomial and bilinear interpolation. Then, a transformation from DN value to reflectance image was generated to TM image using the gain and bias parameters.

4.2 Parcels segmentation

The unsupervised classification can aggregate the similar spectral pixels into one land cover. Thus, spatially adjacent pixels belonging to the same land cover type are incorporated into one parcel. The producing work for parcels and land cover type determination was carried out by ERDAS IMAGINE 8.6. Firstly, the ISODATA classification divided the whole image into twenty land cover types, and then the CLUMP function was adopted to determine the parcels with the connected eight neighbor search parameter. The every band properties within a parcel are defined as the parcel information for classification (Volker, 2004; Bruzzone, 2000).

4.3 The pure parcels determined for LMPU

Just like the linear spectral unmixing method for endmember, LMPU also needs pure parcels to offer spectral information of each land cover type for mixed parcel unmixing. Since the spectral information within a parcel is homogeneous, the unmixing method is the same as that in the linear spectral unmixing model. In this study, the pure parcels are extracted according to the scatter diagram resulted from the MNF transformation and the visual interpretation. Because of the spectral similarity of grass and wheat, both of them were assumed to have the same pure parcels for the spectral extraction.

The average RMSE (EQ. 2) of LMPU was 0.00464, where $\hat{a}_{\mathrm{i}}$ is the predicted spectral reflectance value of a parcel, a_{i} is the actual spectral reflectance of a parcel. On the whole, the results of information extraction for all types of land cover were satisfactory. Due to the continuous distribution, the fraction value of wheat within a parcel was generally uniform. Other land cover types, such as water, information are extracted accurately. The seriously interblending spectra of buildings and bare induces a relative lower accuracy.

4.4 Accuracy assessment

Accuracy assessment was performed on the per-parcel spectral unmixing method and the traditional methods which include the parcel-based hard classification and the pixel-based linear spectral unmixing classification to indicate the relative advantages and disadvantages of each approach. The range of endmember for the per-pixel linear spectral unmixing is the same as that for the per-parcel unmixing, in so doing the consistency of the two methods can be ensured. The per-pixel linear spectral unmixing was carried out for all kinds of land cover types with the average RMSE (EQ. 2) of 0.006869 which is higher than that for the per-parcel unmixing. The hard per-parcel classification was also undertaken by the ISODATA unsupervised classification to extract the land use/cover information.

The QUICKBIRD classification result is taken as ground truth and resampled to 30m. The RMSE (EQ. 2) (David and Gregory, 2004) is introduced as an index for accuracy assessment.

$$\mathrm{RMSE}=\sqrt{\sum_{i=1}^{n}(\hat{a}_{\mathrm{i}}-a_{\mathrm{i}})^2 \Big/ n} \qquad (2)$$

where $\hat{a}_{\mathrm{i}}$ is the predicted value of a pixel, a_{i} is the ground truth value of a pixel, n is the number of pixels in the whole image. The results of RMSE for each method were given in Table 1.

Land cover type	Soft per-parcel classification	Soft per-pixel classification	Hard per-parcel classification
Wheat	0.23	0.24	0.32
Water	0.16	0.17	0.27
Urban	0.36	0.37	0.43
Bare	0.37	0.38	0.48
Average	0.28	0.29	0.37

Table 1 RMSEs for classification accuracy assessment

As table 1 has shown, the per-parcel hard classification gets the highest RMSE among all the three techniques, which means that it owns the lowest accuracy, primarily due to the lots of mixed pixels on the TM scale resulting in the mixed parcels produced with segmentation. The result of hard per-parcel classification assigns one land cover type for one parcel; thus, the mixed parcel problems can not be solved. For the per-parcel and per-pixel soft classification based on the linear spectral unmixing method, their RMSEs are relative lower than that of per-parcel hard classification and very close to each other, which shows that the presented method can be compared with the traditional soft classification with the high accuracy. What's more, the presented method has a little lower RMSE than that of the per-pixel spectral unmixing, which proves the feasibility of the new method more effectively. Besides, the pure parcel selection method was given in a simple way that only a few parcels are enough for satisfying the need for the per-parcel spectral unmixing. The pure parcel can be distinguished from the mixed parcel easily by the visual interpretation. The spectrum homogeneity within a parcel effectively resolves the problem of spectral disturbance which can easily result in the spectral unmixing error in the pixel-based classification.

5. CONCLUSION AND DISCUSSIONS

A new approach for land cover mapping is presented based on the per-parcel unit. According to the per-pixel linear spectral unmixing, the land cover information can be extracted. Three main conclusions have been drawn as follows:

Firstly, the per-parcel unmixing method is a little more accurate than the per-pixel unmixing method, and both the two methods have much higher accuracy than that of the per-parcel hard classification method, due to the mixed parcels assigned to a certain land cover type which is not accurate.

Secondly, the mixed parcel unmixing method combines more than one pixel and a lot of more useful information can be adopted for classification, which ensures the stability of the result. And the problem of multiple land cover types or mixed pixels within a parcel, which leads to the errors of the per-parcel hard classification, can be resolved.

Finally, for the parcel continuum, the pure parcels can be easily determined by the visual interpretation for the per-parcel unmixing method, which ensures the veracity of pure parcel selection at some degree and avoids the difficulty of the per-pixel endmember selection.

The method presented in this study is practicable, while there are some problems have not been resolved yet. (1) The linear spectral unmixing method is adopted for the mixed parcel unmixing, however, the spectral composition of the mixed parcel is non-linear in fact. The non-linear spectral unmixing method would be taken. (2) The rationality of segmentation scale influences the unmixing result directly. Therefore, there is an urgent need to find an effective method for parcel segmentation to ensure the homogeneity of parcels. (3) The per-parcel method can not solve the phenomenon of different object with same spectrum and the characteristic of the same object with different spectrums. All of the above problems will be paid more attention for the further study.

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