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Information Extraction from High Resolution RS Image for Update of A GIS

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Abstract: The aim of this study is to extract land cover information from the high resolution satellite image and check the reliability to update thematic layers in a geographical information system (GIS). For the extraction of information from the selected remote sensing (RS) data set, a refined maximum likelihood classification (MLC) method that incorporates both spectral and spatial characteristics is constructed.

1. Introduction

Until the launch of very high resolution satellites such as Ikonos, Quickbird and WorldView, space images had been mainly used for a land cover mapping at regional or national scales, because the available high resolution satellite data sets (e.g., Landsat and SPOT) could fulfill the mapping conditions of up to a regional level. It is known that a scale of the thematic information to be extracted from digital RS data is dependent upon a spatial resolution of the acquired image (Wilson *et al.* 2011). To get an acceptable accuracy for a selected map scale using optical images, it is desirable to include sufficient number of pixels per centimeter. However, this number may change depending on the purposes of the study as well as the requirements of conducted projects (Amarsaikhan and Sato 2003). For example, for soil and vegetation mapping, there could be needed only 20 pixels per centimeter, while for urban area mapping, one might need at least 50 pixels per centimeter.

The traditional standard high resolution satellite data sets allow the mapping specialists to map the natural and man made features usually at a class level and it is very difficult to define the individual objects on such images (Amarsaikhan 2002). However, the current very high resolution satellite data sets allow the users of spatial information to map any feature at an object level (Boggs 2010). This means, by the use of the present satellite RS images, it is possible to produce all scale maps and update the layers of a GIS at all levels. The database level in a GIS cannot be directly related to the map scales, because different GIS users use different map scales for determination of the levels. However, as all spatial databases are based on map scales there could be a relationship between the levels and scales as mentioned above (Amarsaikhan 2002).

Over the years, for the extraction of thematic information from RS images at national, regional and local levels, different combinations of image processing techniques have been used. One of the most popular applications has been the production of land cover maps. The techniques used for generation of such maps are based on digital methods of classification which mainly assign the pixels to class labels based on their spectral and contextual properties. The widely used methods are parametric and non-parametric methods, neural networks as well as knowledge-based classifications (Gamba and Houshmand 2001, Linderman *et al.* 2004, Amarsaikhan *et al.* 2007, Gomez and Martin 2011, Laurin *et al.* 2013).

The aim of this study is to extract land cover information from the high resolution RS image and check the reliability to update urban GIS layer. For the identification of available urban land-cover types a refined MLC technique based on both spectral and spatial characteristics, has been constructed. The result of the constructed method was compared with result of a standard statistical MLC and it demonstrated higher accuracy.

2. Test site and data sources

As a test site, Baga toiruu area situated in central part of Ulaanbaatar, the capital city of Mongolia has been selected. The Baga toiruu is the city business district of Ulaanbaatar city where different government, educational, cultural and commercial organizations are located. Besides the Central Government, Parliament and headquarters of major political parties, the Baga toiruu contains many offices of different ministries, major government organizations, bank headquarters, state universities, diplomatic and international organizations as well as theatres and museums (Chinbat 2006). The location of the Baga toiruu area represented in a panchromatic Quickbird image of 2011 is shown in figure 1.

As the RS data source, multichannel Landsat ETM+ data set acquired in June 2011 has been used. The Landsat ETM+ data has seven multispectral bands (B1: 0.45–0.52μm, B2: 0.53–0.61μm, B3: 0.63–0.69μm, B4: 0.78–0.90μm, B5: 1.55–1.75μm, B6: 10.40–12.50μm and B7: 2.09–2.35μm) and one panchromatic band (0.52–0.90μm). In case of the multispectral data, a spatial resolution is 28.5m for the reflective bands, while it is 60m for the thermal band. Compared to the multispectral bands, a panchromatic image has a higher spatial resolution of 14m. In the current study, beside the panchromatic band, multispectral channels 2,3,4,5,7 have been used. In addition, a topographic map of 1984, scale 1:50,000 as well as GIS layer created on the basis of the topographic maps, were available.

Figure 1. The test area represented in a Quickbird image of 2011.

3. Radiometric correction and georeferencing of the RS images

At the beginning, all the available images were thoroughly analyzed in terms of radiometric quality and geometric distortion. The first band of the Landsat ETM+ data had high atmospheric noise and it was decided to exclude it from the further analysis. In order to extract geometrically accurate thematic information, thorough georeferencing should be applied to the original RS image. The panchromatic and multispectral bands of the Landsat ETM+ data were georeferenced to a Gauss-Kruger map projection using a topographic map of 1984, scale 1:50,000. The GCPs have been selected on well defined sites and in total 9 regularly distributed points were selected. For the transformation, a linear transformation and nearest neighbour resampling approach have been applied and the related RMS errors were 0.94 pixel and 0.98 pixel, accordingly. In both cases, an image was resampled to a pixel resolution of 14m.

4. Refined MLC method

Generally, it is very important to design a suitable image processing procedure in order to successfully classify any RS data into a number of class labels. The effective use of different features and the selection of a reliable classification technique can be a key implication for the improvement of classification accuracy (Lu and Weng, 2007). In this study, for the classification of urban land cover types, a refined MLC algorithm has been constructed. The MLC is the most widely used statistical classification technique, because a pixel classified by this method has the maximum probability of correct assignment (Erbek *et al.* 2004). The decision rule assuming Bayes' rule can be written as follows:

$$P(Ci|x) = P(x|Ci)*P(Ci)/P(x)$$

where $P(Ci|x)$-posterior probability, $P(x|Ci)$-conditional probability, $P(Ci)$-prior probability, $P(x)$-probability of finding a pixel from any class. The actual classification is performed according to $P(Ci|x) > P(Cj|x)$ for all j#i.

In the present study, for all classes equal prior probabilities have been assigned. Unlike the traditional MLC, the constructed classification algorithm uses spectral and spatial thresholds defined from the local knowledge. The local knowledge was defined on the basis of the spectral variations of the land surface features on the color images. It is clear that a spectral classifier will be ineffective if applied to the statistically overlapping urban classes, because they have very similar spectral characteristics. For such spectrally mixed classes, classification accuracies should be improved if both spectral and spatial properties of the classes of objects could be incorporated into the classification criteria. The spectral thresholds use the upper and lower limits of standard deviations (or values falling mainly within minimum and maximum) of training samples, while the spatial thresholds use a polygon boundary to separate the overlapping classes. When thresholds apply only the pixels falling within the threshold boundary are used for the classification. In that case, the likelihood of the pixels to be correctly classified will significantly increase, because the pixels belonging to the class that overlaps with the class to be classified using the threshold boundary are temporarily excluded from the decision making process. In such a way, the image can be classified several times using different threshold boundaries and the results can be merged (Amarsaikhan *et al.* 2006).

The selected site is characterized by such spectral classes as builtup area (mainly buildings), open area (mainly roads and pedestrian walking areas), central square and vegetation (trees and grass). The Landsat ETM+ data of the selected part of the capital city is shown in figure 2a. Generally, in the classification process, it is desirable to include only the features in which the signatures of the selected classes are highly separable from each other in a multidimensional feature space. To extract reliable features, a principal component analysis (PCA) has been performed to the multispectral data sets. The PCA is a statistical technique that transforms a multivariate data set of intercorrelated variables into a set of new uncorrelated linear combinations of the original variables, thus generating a new set of orthogonal axes. In digital image processing community, the most common understanding of the PCA is that it is also a data compression technique used to reduce the dimensionality of the multidimensional datasets (ERDAS 1999). The result of the PCA applied to the Landsat ETM+ image is shown in table 1.

Table 1. Principal component coefficients from panchromatic and five multispectral bands of the ETM.

	PC1	PC2	PC3	PC4	PC5	PC6
PAN	-0.42	-0.18	-0.41	0.79	0.05	0.01
ETM2	-0.39	0.36	-0.31	-0.24	-0.72	0.14
ETM3	-0.43	0.51	-0.20	-0.26	0.66	-0.04
ETM4	-0.39	-0.70	-0.18	-0.46	0.02	-0.32
ETM5	-0.43	-0.19	0.49	-0.03	0.06	0.72
ETM7	-0.38	0.18	0.64	0.19	-0.15	-0.58
Eigenvalue	3218.3	64.5	37.3	15.7	6.2	1.9
Variance (%)	96.24	1.92	1.11	0.46	0.18	0.09

As seen from table 1, in the PC1 that contains 96.24% of the overall variance, all bands have negative loadings. In the PC2 that contains 1.92% of the overall variance, red band has moderately high loading, but near infrared band has a high negative loading. In the PC3 that contains 1.11% of the overall variance, second middle infrared band has a high loading. Here, panchromatic and second middle infrared bands have moderately high negative and positive loadings, too. Moreover, as seen from the table 1, in the PC4 that contains only 0.46% of the overall variance, panchromatic band has a very high loading.

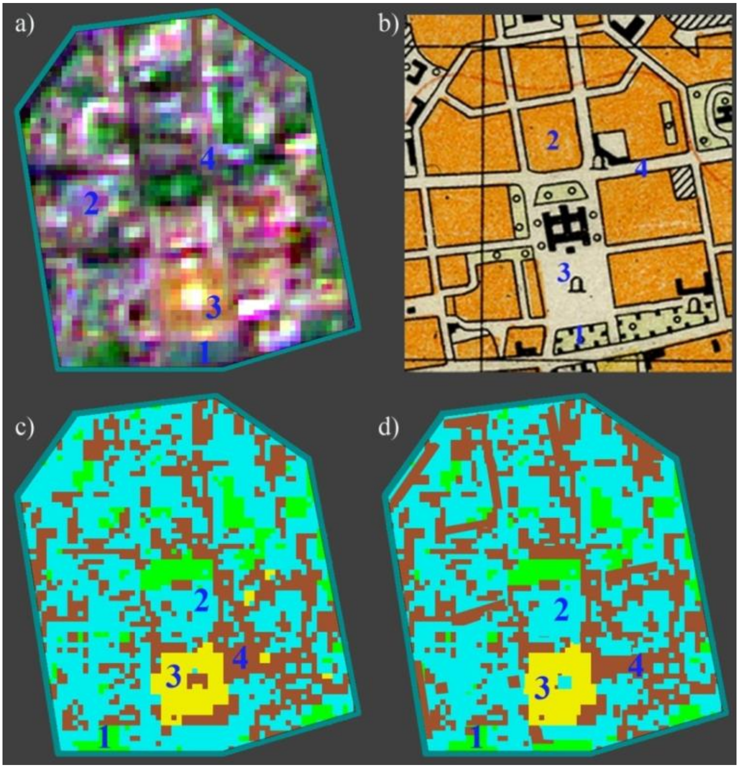

Figure 2. a) Landsat ETM+ image of the test area, b) A topographic map of the test area, c) The result of the MLC, d) The result of the refined method. (1-vegetation, 2-builtup area, 3-central square, 4-open area).

Meanwhile, all other bands have negative loadings or almost no influence on it. The inspection of the last two PCs indicated that they contained noise from the total data set. As could be seen, the first 3 PCs contain over 99% of the overall variance, and one could think that they might have been sufficient for the feature determination. However, visual inspection of the PC 4 indicated that it included useful information related to the image texture. Therefore, for the final features, PC1, PC2, PC3 and PC4 have been chosen.

To apply a classification decision rule, initially, the training signatures have to be selected. In the present study, to define the training signatures from the PCA image, several areas of interest (AOI)s representing the selected four classes have been chosen through accurate analysis based on local knowledge. The separabilities of the training signatures were firstly checked on the feature space images and then evaluated using Jeffries-Matusita (JM) distance. Then the samples which demonstrated the greatest separabilities were chosen to form the final signatures. The final signatures included about 50-177 pixels.

In general, it is very difficult to separate the classes if they have the same or very similar spectral characteristics. As we have urban environment, there are high mixtures among the classes except the green vegetation. When the classes overlap in a multidimensional feature space, the usage of thoroughly defined spectral and spatial thresholds can play an important role for separation of the overlapping classes. In the present study, as the spectral parameters, the values falling mainly within minimum and maximum of each class defined from the selected signatures have been selected. The pixels falling outside of these spectral parameters were temporarily identified as unknown classes and further classified using the constraints in which different spatial thresholds were defined. The spatial thresholds were determined using the polygon boundaries defined on the basis of a GIS layer (the layer was created from a topographic map of 1:50,000 shown in figure 2b).

For the accuracy assessment of the classification result, the overall performance has been used. This approach creates a confusion matrix in which the selected reference pixels are compared with the classes in the classified image and as a result, an accuracy report is generated indicating the percentages of the correspondence (ENVI 1999). As ground truth information, for each class several regions containing 418 purest pixels have been selected. The result of the MLC method is shown in figure 2d. The confusion matrix indicated an overall accuracy of 89.93%. To compare the performances of the developed algorithm and a standard method, the same set of features were classified using a standard statistical MLC. The image classified by the MLC method is shown in figure 2c. As could be seen from the figure 2c, the classified image has high mixtures of all classes. The confusion matrix indicated an overall accuracy of 78.09%.

5. Update of GIS Layer

Generally, a GIS can be considered as a spatial decision-making tool. For any decision-making, a GIS uses digital spatial information stored within its database. The power of GIS systems comes from the ability to relate different information in a spatial context and to reach a conclusion about this relationship. Therefore, current GISs are being widely used for urban planning and management. For an efficient decision-making, one needs accurate and updated spatial information. In urban context, spatial information can be collected from a number of sources such as city planning maps, topographic maps, digital cartography, thematic maps, global positioning system, aerial photography and space RS. Of these, only RS can provide real-time information that can be used for the real-time spatial analysis (Amarsaikhan and Saandar 2011).

In the present study, it is possible to assume that there is an operational urban GIS that stores historical thematic layers and there is a need to update land cover layers. As seen from the classification results shown in figure 2c-d, the result of the refined method looks better than that of the standard method, however, it contains large uncertainty in terms of delineation of individual objects. In general, urban areas comprise diverse environment containing a variety of different features and objects having very similar spectral characteristics and it is not easy to separate them even using sophisticated techniques. In the selected test area, the classes: built-up area, open area and central square have very similar spectral characteristics and there are different mixtures of specifically built-up area and open area classes on the final classified image. Therefore, this result cannot be considered as reliable and surely cannot be used for update of urban GIS layer.

6. Conclusions

The aim of this study was to extract information from the high resolution satellite image and check the reliability to update GIS layers. As a test site, central part of Ulaanbaatar, the capital city of Mongolia was chosen. For the information extraction from the selected RS data set, a refined MLC method based on both spectral and spatial thresholds was constructed. The result of the constructed technique was compared with result of a standard statistical MLC and it demonstrated higher accuracy. Overall, the study indicated that the information extracted from the high resolution satellite image contains large uncertainty in terms of delineation of individual objects and may not be used for update of a GIS layer specifically in urban context.

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