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Knowledge-based Classification of High Resolution Optical and Microwave Images

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Abstract: The aim of this study is to classify the optical and microwave features in terms of separation of urban land cover classes. As the classification methods, statistical maximum likelihood classification and knowledge-based method are used and the results are compared. Overall, the research indicated that multisource information can significantly improve the interpretation and classification of land cover types.

1. Introduction

For many years, for the extraction of thematic information from multispectral RS images, different supervised and unsupervised classification methods have been applied [10]. Unlike the single-source data, data sets from multiple sources have proved to offer better potential for discriminating between different land cover types. Many authors have assessed the potential of multisource images for the classification of different land cover classes [1,2,6]. In RS applications, the most widely used multisource classification techniques are statistical methods, Dempster–Shafer theory of evidence, neural networks, decision tree classifier, and knowledge-based methods [8,12].

The aim of this study is to apply a knowledge-based classification method for the extraction of land cover information from the integrated optical and microwave images in order to update urban geographical information system (GIS). The proposed knowledge-based method includes different rules based on the spectral and spatial thresholds. For the actual analysis, multisource satellite images with different spatial resolutions as well as some GIS data of Ulaanbaatar city have been used.

2. Test site and data sources

As a test site, Ulaanbaatar, the capital city of Mongolia has been selected. The study area chosen for the present study covers mainly the central and western parts and is characterized by such classes as built-up area, ger area, green area, soil and water. Figure 1 shows ASTER image of the test site, and some examples of its land cover.

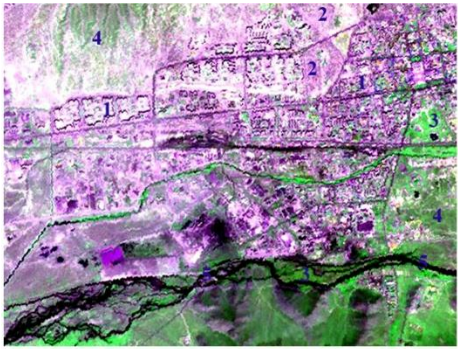

Figure 1. 2008 ASTER image of the selected part of Ulaanbaatar. 1-built-up area; 2-ger area; 3-green area; 4-soil; 5-water. The size of the displayed area is about 8.01kmx6.08km.

In the present study, for the enhancement of urban features, ASTER data of 23 September 2008, ERS-2 SAR data of 25 September 1997 and ALOS PALSAR data of 25 August 2006 have been used. Although ASTER has 14 multispectral bands acquired in visible, near infrared, middle infrared and thermal infrared ranges of electro-magnetic spectrum, in the current study, green (band 1), red (band 2) and near infrared (band 3) bands with a spatial resolution of 15m have been used. ERS-2 SAR is a European RS radar satellite which acquires VV polarized C-band data with a spatial resolution of 25m. ALOS PALSAR is a Japanese radar satellite carrying a cloud-piercing L-band radar which is designed to acquire fully polarimtric images.

3. Co-registration of multisource images and speckle suppression of the SAR images

At the beginning, the ALOS PALSAR image was rectified to the coordinates of the ASTER image using 12 ground control points (GCPs) defined from a topograpic map of the study area. The GCPs have been selected on clearly delineated crossings of roads, streets and city building corners. For the transformation, a second-order transformation and nearest-neighbour resampling approach were applied and the related root mean square error (RMSE) was 0.94 pixel. Then, the ERS-2 SAR image was rectified and its coordinates were transformed to the coordinates of the rectified ALOS PALSAR image. In order to rectify the ERS-2 SAR image, 14 more regularly distributed GCPs were selected from different parts of the image. For the actual transformation, a second-order transformation was used. As a resampling technique, the nearest-neighbour resampling approach was applied and the related RMSE was 0.98 pixel.

To reduce the speckle noise, four different speckle suppression techniques such as local region, lee-sigma, frost and gammamap filters [8] of 3x3 and 5x5 sizes were applied to the ALOS PALSAR image and compared in terms of delineation of urban features and texture information. After visual inspection of each image, it was found that the 3x3 gammamap filter created the best image in terms of delineation of different features as well as preserving content of texture information.

4. Urban land cover classification

4.1. Supervised classification

Initially, in order to define the sites for the training signature selection, from the multisensor images, two to four areas of interest (AOI) representing the selected five classes (built-up area, ger area, green area, soil and water) have been selected through thorough analysis using a polygon-based approach. The separability of the training signatures was firstly checked in feature space and then evaluated using transformed-divergence (TD) separability measure. After the investigation, the samples that demonstrated the greatest separability were chosen to form the final signatures. The final signatures included 2669 pixels for built-up area, 592 pixels for ger area, 241 pixels for green area, 1984 pixels for soil and 123 pixels for water.

In general, urban areas are complex and diverse in nature and many features have similar spectral characteristics and it is not easy to separate them by the use of ordinary feature combinations. For the successful extraction of the urban land cover classes, reliable features derived from different sources should be used. In many cases, texture features derived from the occurrence and co-occurrence measures are used as additional reliable sources [4]. However, in the present study, the main objective was to evaluate the original features. Therefore, for the classification the combined features of ASTER, PALSAR and ERS-2 SAR were used.

For the actual classification, a supervised statistical maximum likelihood classification (MLC) has been used assuming that the training samples have the Gaussian distribution [11]. The final classified image is shown in figure 2a. As seen from figure 2a, although the combined use of optical and microwave data sets produced a better result, it is still very difficult to obtain a reliable land cover map by the use of the standard technique, specifically on decision boundaries of the statistically overlapping classes.

For the accuracy assessment of the classification result, the overall performance has been used. As ground truth information, different AOIs containing 12578 purest pixels have been selected. AOIs were selected on a principle that more pixels to be selected for the evaluation of the larger classes such as built-up area and ger area than the smaller classes such as green area and water. The overall classification accuracy for the selected classes indicated 80.12%.

4.2. Knowledge-based classification

In years past, knowledge-based techniques have been widely used for the classification of different RS images. The knowledge in image classification can be represented in different forms depending on the type of knowledge and necessity of its usage. The most commonly used techniques for knowledge representation are a rule-based approach and neural network classification [1]. In the present study, for separation of the statistically overlapping classes, a rule-based algorithm has been constructed. A rule-based approach uses a hierarchy of rules, or a decision tree describing the conditions under which a set of low-level primary objects becomes abstracted into a set of the high-level object classes. The primary objects contain the user-defined variables and include geographical objects represented in different structures, external programmes, scalars and spatial models [8].

The constructed rule-based algorithm consists of 2 main hierarchies. In the upper hierarchy, on the basis of knowledge about reflecting and backscattering characteristics of the selected five classes, a set of rules which contains the initial image classification procedure based on a Mahalanobis distance rule and the constraints on spatial thresholds were constructed. The Mahalanobis distance decision rule can be written as follows:

$$MD_k=(x_i- m_k)^t V_k^{-1}(x_i- m_k)$$

Where:

x_i-vector representing the pixel
m_k-sample mean vector for class k
V_k-sample variance-covariance matrix of the given class.

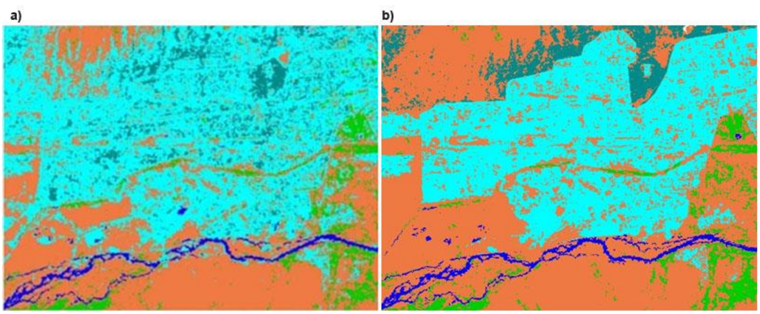

Figure 2. Classification result obtained by the supervised (a) and knowledge-based classifications (b) (cyan-built-up area; dark cyan-ger area; green-green area; sienna-soil; blue-water).

It is clear that a spectral classifier will be ineffective if applied to the statistically overlapping classes such as built-up area and ger area because they have very similar spectral characteristics in both optical and microwave ranges. For such spectrally mixed classes, classification accuracies can be improved if the spatial properties of the classes of objects could be incorporated into the classification criteria. The spatial thresholds can be determined on the basis of historical thematic spatial data sets or from local knowledge about the site. In this study, the spatial thresholds were defined based on local knowledge about the test area.

In the initial image classification, for separation of the statistically overlapping classes, only pixels falling outside of the spatial thresholds and the PC1, PC2 and PC4 of the PCA obtained using optical/SAR approach, were used. The pixels falling outside of the spatial thresholds were temporarily identified as unknown classes and further classified using the rules in which other spatial thresholds were used. As can be seen from the pre-classification analysis, there are different statistical overlaps among the classes, but significant overlaps exist among the classes: built-up area, ger area and soil. In the lower hierarchy of the rule-base, different rules for separation of these overlapping classes were constructed using spatial thresholds. The image classified by the constructed method is shown in Figure 2b.

For the accuracy assessment of the classification result, the overall performance has been used, taking the same number of sample points as in the previous classifications. The confusion matrix produced for the knowledge-based classification showed overall accuracy of 90.92%. As could be seen, the result of the classification using the rule-based method is much better than result of the standard method.

5. Update of a GIS layer

In general, a GIS can be considered as a spatial decision-making tool. For any decision-making, GIS systems use digital spatial information, for which various digitized data creation methods are used. The most commonly used method of data creation is the digitization, where hard copy maps or survey plans are transferred into digital formats through the use of special software programs and spatial-referencing capabilities. With the emergence of the modern ortho-rectified images acquired from both space and air platforms, heads-up digitizing is becoming the main approach through which positional data is extracted [5]. Compared to the traditional method of tracing, heads-up digitizing involves the tracing of spatial data directly on top of the acquired imagery. Thus, due to rapid development in science an technology, primary spatial data acquisition within a GIS is becoming more and more sophisticated.

The current GISs allow the users and decision-makers to view, understand, question, interpret, analyze and visualize data sets in many different ways. 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. Most of the information we have about our world contains a spatial reference, placing that information at some point on the Earth's surface. For example, when information about urban commercial buildings is collected, it is important to know where the buildings are located. This can be done by applying a spatial reference system that uses a special coordinate system. Comparing that information with other information, such as the location of the main infrastructure, one can evaluate the market values of the buildings. In this case, a GIS helps in revealing important new information that leads to better decision-making.

At present, GISs are being widely used for 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. Over the past few years, RS techniques and technologies, including system capabilities have been significantly improved. Meanwhile, the costs for the primary RS data sets have drastically decreased [3]. This means that it is possible to extract from RS images different thematic information in a cost-effective way and update different layers within a GIS.

In the present study, it is assumed that there is an operational urban GIS that stores historical thematic layers and there is a need to update a land cover layer. The current land cover layer was created using an existing topographic map of 1984 and for its digitizing ArcGIS system was used. The digitized map is shown in Figure3.

Figure 3. The digitized map, created from a topographic map of 1984 (cyan-built-up area; dark cyan-ger area; green-green area; sienna-soil; blue-water).

As the overall classification accuracy of the classified multisource images exceeds 90%, the result can be directly used to update the land cover layer of the operational GIS. For this end, a raster thematic map (i.e., classified image) extracted from the multisource RS data sets should be converted into a vector structure. After error cleaning and editing, the converted from raster to vector layer can be topologically structured and stored within the urban GIS. If one compares the land cover layers created from the topographic map and classified RS images, could see what changes had occurred.

6. Conclusions

The main purpose of the research was to evaluate the optical and SAR features in terms of separation of urban land cover classes. For the classification, statistical MLC and knowledge-based method were used and the results were compared. As could be seen from the classification results, the performance of the knowledge-based technique was much better than the performances of the standard method and output could be directly used to update urban GIS. Overall, the research indicated that multisource information can significantly improve the interpretation and classification of land cover classes and the knowledge-based method is a powerful tool in the production of a reliable land cover map.

7. References

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