Feature Extraction and Multisource Image Classification

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Abstract: The aim of this study is to assess the integrated use of different features extracted from spaceborne interferometric synthetic aperture radar (InSAR) data and optical data for land cover classification. Special attention is given to the discriminatory characteristics of the features derived from the multisource data sets. For the evaluation of the features, the statistical maximum likelihood decision rule and neural network classification are used and the results are compared. The performance of each method was evaluated by measuring the overall accuracy. In all cases, the performance of the first method was better than the performance of the latter one. Overall, the research indicated that multisource data sets containing different information about backscattering and reflecting properties of the selected classes of objects can significantly improve the classification of land cover types.
Keywords: InSAR data, multisource data, features, classification.

1. Introduction

Multisource image classifications are of increasing interest in the present development of digital image processing. In the multisource classification, data from different sources such as optical and synthetic aperture radar (SAR) images as well as other thematic features are integrated to improve the classification accuracy. Remote sensing (RS) images taken in the optical range of the electro-magnetic spectrum (EMS) contain information on the reflective and emissive characteristics of the Earth surface features, while the SAR (intensity and coherence) images contain information on the surface roughness, texture, dielectric properties and change of the state of natural and man-made objects. Thematic features contain information about clear differentiation among different classes of objects. It is evident that a combined use of these data sets will have a number of advantages, because a specific object or class which is not seen on one image might be seen on the other images because of the complimentary information provided by different sources [1].

At present, there are a number of techniques for multisource image classification. In RS applications, the most widely used multisource classification techniques are statistical methods, neural networks and Dempster-Shafer theory of evidence [9]. A number of authors have assessed the potential of multisource images for discrimination of different land cover types using a method related to one of the above mentioned groups [2,5,6]. However, most authors integrated only optical and SAR intensity images for multisource classification. In recent years, InSAR images have been available for the users of RS products. Unlike, the traditional single band SAR data that are used for derivation of only intensity images, the InSAR data can be used for the derivation of coherence as well as multitemporal intensity images. These derived images or their enhanced features combined with other data sets can be used for different classifications to increase the performance of the applied decision rules.

The aim of this study is to assess the integrated use of different features extracted from spaceborne InSAR data and optical data for land cover discrimination. The initial multisource data set consisted of (interferometric) ERS-1/2 tandem pass SAR images and, visible and near infrared bands of ASTER data. In the feature extraction process, coherence image and other features have been derived from the InSAR data. For the classification, the statistical maximum likelihood decision rule (MLDR) and neural network (NN) method have been selected and the performance of each method was evaluated by measuring the overall accuracy.

2. Test Area and Data Sources

As a test site Ulaanbaatar, the capital city of Mongolia has been selected. The selected area is about 18kmx15km and is characterized by such classes as urban, forest, soil and water.

The data used consisted of ERS-1/2 tandem pass SAR single look complex (SLC) images acquired on 10 and 11 October 1997 with a spatial resolution of 25m, JERS-1 SAR intensity image of April 1997 with a spatial resolution of 18m and bands 1,2 and 3N of ASTER data of May 2001 with a spatial resolution of 15m. In addition, for ground truth checking a topographic map of 1984, scale 1:50,000 and a general urban planning map were available.

3. Feature Extraction

To extract different features from the ERS-1/2 tandem pass SAR SLC images, the below techniques have been applied.

1) Derivation of the InSAR Coherence and Amplitude Images

The InSAR coherence images are generated by using both the amplitude and phase information from a pair of SLC images. The coherence is a measure of the variance of the phase difference of the imaged surface in the time between the two SAR data acquisitions. The coherence values range between 0 and 1. If some land surface changes had occurred in a target area between the two image acquisition periods, then coherence is low and if no changes had occurred, then the coherence is high. In general, the coherence over a dense forest and shrub will be the lowest, while for the bare soil, the coherence will be the highest.

The coherence and other amplitude images have been derived as follows:

1. Initially, 200 ground control points (GCP) regularly distributed over the images were automatically defined using the satellite orbit parameters and the two SLC images were co-registered with 0.1pixel accuracy. Then, a course registration followed by a fine registration was performed.
2. Coherence has been calculated using 10x2 size window and the coherence image was generated.
3. From the complex images, amplitude images were generated.
4. The preliminary SLC images were converted from the slant range onto a flat ellipsoid surface.
5. The true size (5800x5800) SAR images were generated using image undersampling applying 3x3 size low pass filter.

2) Derivation of the Texture Features

To derive texture features occurrence and co-occurrence measures were applied to the coherence and average amplitude images of ERS-1/2 and JERS-1 intensity image. The occurrence measures use the number of occurrences of each grey level within the processing window for the texture calculations, while the co-occurrence measures use a grey-tone spatial dependence matrix to calculate texture values. By applying these measures, initially 30 features have been obtained, but after thorough checking of each individual feature only 7 features including the results of the mean and data range filters applied to all three images, and the result of variance filter applied to the JERS-1 image were selected. Detailed descriptions of the occurrence and co-occurrence measures as well as the texture filters are given in [3,4].

3) Principal Components (PC) and Ratio Images

To reduce the dimensionality of the dataset, the principal component analysis (PCA,[9]) has been performed to the extracted SAR features. For the PCA 10 features, including the ERS-1/2 coherence and average amplitude images, JERS-1 intensity image and 7 texture features have been used. The PCA has shown that the first 3PCs contained 99.6% (PC1=99.2%, PC2=0.25%, PC3=0.15%) of the total variance. Therefore, the first 3PCs have been selected for further analysis and the remaining PCs were rejected.

A ratio image has been created by taking the ratio of ERS-1 and ERS-2 amplitude images, multiplied by a compensation factor of 90.

4. Geometric Registration of the Multisensor Images

As the aim of this study was to demonstrate the separation of the chosen classes in the selected features, the images were not registered to map coordinates, instead, they were registered to the coordinates of the ASTER data. The GCPs have been selected on clearly delineated crossings of roads, streets and other clear sites comparing the locations of the selected points with other information such as topographic map and urban planning map. In total 24 more regularly distributed points were selected. For the transformation, a second order transformation and nearest neighbour resampling approach have been applied. The related root mean square (RMS) errors were 0.98pixel for the ERS products and 0.96pixel for the JERS-1 image, respectively.

5. Classification of the Features

Initially, from the multisource images, 2-3 regions of interest (ROI) representing the four selected classes such as urban, forest, soil and water have been selected using a polygon-based approach. Then, training samples were selected on the basis of these ROIs. The separability of the training signatures was firstly checked on the feature space images and then evaluated using transformed divergence (TD) [8]. Then the samples which demonstrated the greatest separability were chosen to form the final signatures. For the classification, the following feature combinations have been used:

1. Coh, (ERS1+ERS2)/2, ERS1/ ERS2,
2. (ERS1+ ERS2)/2, ERS1/ ERS2, JERS1,
3. Coh, (ERS1+ ERS2)/2, JERS1,
4. 10 features, including Coh, (ERS1+ERS2)/2, JERS-1 and 7 texture features,
5. First 3PCs,
6. ASTER (bands 1,2 and 3N),
7. Coh, (ERS1+ERS2)/2, JERS1, ASTER (bands 1,2 and 3N),
8. Speckle suppressed (Coh, (ERS1+ERS2)/2, JERS 1), ASTER (bands 1,2 and 3N).

For each of these feature combinations, MLDR and NN methods have been applied. For the MLDR, a statistical maximum likelihood classification assuming the equal class prior probabilities, while for the NN method, standard backpropagation using a logistic function for the activation and 2 hidden layers, have been used. Detailed descriptions of these methods are given in [7,8].

For the accuracy assessment of the final classification results, the overall performance has been used. As ground truth information, for each class several regions containing the purest pixels have been selected. In all cases, the performance of the MLDR was better than the performance of the NN method. The overall classification accuracies of the selected classes in the selected features are shown in table 1. As seen from table 1, the performance of the classifications using the ERS-1/2 amplitude and JERS-1 intensity combinations was the lowest, while the performances of the Coh, (ERS1+ERS2)/2, ERS1/ ERS2 and Coh, (ERS1+ ERS2)/2, JERS1 combinations were similar. The use of 10 features significantly improves the performance of the MLDR. This was most probably related with the fact that the texture filters improved spatial homogeneity of the primary features. As a result, decisions made for selection of the correct pixels in the decision boundaries of multidimensional feature space were improved. The performance of the classification using 3PCs was similar to the performance of the 10 features. Surely, it was due to the reason that these 3PCs contained 99.6% of the total data variance. As seen from table 1, the results of the classifications using ASTER data are higher than all SAR combinations. This means that the selected classes are statistically more separable in the optical range of the EMS than in the microwave range.

Table 1. The overall classification accuracy of the classified features.

Feature combinations	Overall accuracy of MLDR (%)	Overall accuracy of NN (%)
Coh, (ERS1+ERS2)/2, ERS1/ ERS2	60.14	53.12
(ERS1+ ERS2)/2, ERS1/ ERS2, JERS1	56.65	45.98
Coh, (ERS1+ ERS2)/2, JERS1	62.92	54.25
10 features	76.02	59.06
First 3PCs	74.67	57.19
ASTER	82.58	78.05
Coh, (ERS1+ERS2)/2, JERS1, ASTER	90.79	83.26
Speckle suppressed SAR, ASTER	94.02	85.93

As seen from table 1, the results of the multisource classifications using both MLDR and NN are higher than the results of any other combinations. This means that the multisource data sets containing different information about backscattering and reflecting properties of the selected classes of objects can significantly improve the classification of land cover types. Usually, before applying a classification decision rule, the speckle noise of the SAR images are reduced. The reduction of the speckle increases the spatial homogeneity of the classes which in turn improves the classification accuracy. In this study, to demonstrate the difference between the speckle suppressed and unsuppressed features, the combination of Coh, (ERS1+ERS2)/2, JERS1 features has been used. The speckle of the selected features have been suppressed by the use of a 5x5 size gammamap filter [4]. The speckle suppressed SAR features combined with ASTER data were classified using the same set of training samples. As it was seen from the result of the MLDR, some improvements were made in separation of the classes and confusion matrix indicated an overall accuracy of 94.02%.

6. Conclusions

The aim of this study was to extract reliable features from SAR data sets and perform multisource classification combining the extracted features with an optical image. For this end, ERS-1/2 tandem pass SAR data sets, JERS-1 SAR image and visible and near infrared bands of ASTER data were used.

For the classification of the individual features as well as the integrated data sets, the statistical MLDR and NN methods were used and the results were compared by measuring the overall accuracy. In all cases, the performance of the MLDR was better than the performance of the NN method.

Overall, the study indicated that multisource data sets that contain different information about backscattering and reflecting properties of the selected classes of objects can significantly improve the classification of land cover types. Furthermore, to increase the classification accuracy, these integrated data sets can be combined with other ancillary data or thematic features and used for the classification decision rules.

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