Advances in Remote Sensing, 2013, 2, 242-246
http://dx.doi.org/10.4236/ars.2013.23026 Published Online September 2013 (http://www.scirp.org/journal/ars)

Application of Multi-Frequency SAR Images for Knowledge Acquisition

V. Battsengel[1], D. Amarsaikhan[2], A. Munkh-Erdene[2], Ch. Bolorchuluun[1], Ch. Narantsetseg[1]
[1]School of Geography and Geology, National University of Mongolia, Ulaanbaatar, Mongolia
[2]Institute of Informatics, Mongolian Academy of Sciences, Ulaanbaatar, Mongolia
Email: battsengel@num.edu.mn

Received May 8, 2013; revised June 8, 2013; accepted July 8, 2013

ABSTRACT

The aim of this research is to apply TerraSAR X-band, Envisat C-band and Palsar L-band synthetic aperture radar (SAR) images for a knowledge acquisition process. For the study, backscattering properties of different natural and man-made objects of urban environment are analyzed on the basis of statistics of signatures of the selected classes. After the knowledge acquisition, for the acquired knowledge representation, a rule-based approach is proposed. Overall, the research demonstrated that the multi-frequency radar images can be effectively used for the knowledge acquisition as well as for the analysis of different land cover types.

Keywords: Knowledge Acquisition; SAR; Microwave Wavelengths; Backscattering

1. Introduction

A knowledge-based system (KBS) is a part of artificial intelligence that emulates problem-solving processes of human experts in a specific domain. In many cases, a KBS consists of a user interface, knowledge base and inference engine. The knowledge base contains the rules and facts derived from human experts, while the inference engine performs the logical deduction reasoning and knowledge synthesis, and generates solutions to a given problem. The KBSs are especially useful when the solution of problems mainly relies on the empirical knowledge of human experts, when multiple solutions are in consideration [1]. These systems are not new in RS image analysis and in many cases which have been used for automatic image understanding and interpretation [2]. Different types of these systems have been and are being developed depending upon the solutions of the given problems and the structures of knowledge representation [3].

In general, the most commonly quoted problems for development of the KBSs are the unavailability of the good experts and knowledge engineers as well as the difficulties with the rule extraction process. In other words, it is a problem of knowledge acquisition [4]. As the main task of a KBS is to provide solutions to a problem in a specific domain, utilizing the knowledge and expertise embodied in it, the necessary knowledge should be mainly extracted from human experts through a knowledge acquisition process. Also, such knowledge may be taken from other sources such as literature in a given problem domain or other field and empirical data sets [5]. For the optical RS data sets, a set of knowledge can be acquired from the reflective and emissive properties of objects or classes of interest, whereas for the microwave images such knowledge could be acquired from the backscatter properties as well as natural and man-made features.

At microwave wavelengths, three types of scattering such as surface scattering, volume scattering, and double bounce scattering occur, and most radar image analyses are based on them. If the surface is homogeneous, then surface scattering will occur and it can be either specular or diffuse, or intermediate depending on the wavelength and surface roughness. If the surface is dielectrically inhomogeneous, then volume scattering where radar penetrates the surface and the return is due to scattering from the underlying materials, will occur. Double bounce scattering occurs, when the right angles are formed between natural and artificial objects. In addition, radar interpretations are environment or site specific and relative to the frequency as well as polarization, incidence angle, surface properties and the effects of water and soil moisture. The tonal variations on the radar images also depend on the changes of the boundary condition between specular and diffuse scattering [6,7].

The aim of this study is to analyze the backscattering characteristics of different urban land cover types used for a knowledge acquisition process and describe an appropriate technique for the acquired knowledge representation. For this purpose, different land cover classes have been selected from TerraSAR X-band, Envisat C-band and Palsar L-band radar images of urban area in Mongolia, and analyzed in relation to the surface and system parameters. For the final analysis, the grey level values of a group of contextually dependent pixels selected from different parts of the images have been used and compared on the basis of the mean values (M) and standard deviation (SD).

2. Test Site and Data Sources

As a test site, Ulaanbaatar, the capital city of Mongolia has been selected. The selected part of the city is characterized by such main classes as building area, ger area (Mongolian traditional dwelling), forest, grass, soil with high moisture, soil with low moisture, open area and water. The building area includes buildings of different sizes, while ger area includes mainly gers surrounded by fences. The forest class consists of different types of tall and short trees located along the Tuul River. The grass mainly includes grassland area, but there are some bush and short trees, too. The soil with high moisture is located along the area which previously was a river valley. The soil with low moisture is mainly distributed along the northern range of the Tuul River. The water class represents the Tuul River located in the southern part of Ulaanbaatar. **Figure 1** shows an Envisat image of the test site, and some examples of its land cover.

In the present study, the data consisted of TerraSAR X-band HH polarization image of March 2008 with a spatial resolution of 1m, Envisat C-band HH polarization image of March 2010 with a spatial resolution of 25 m, and Palsar L-band HH polarization image of May 2006 with a spatial resolution of 25 m. Also, as additional ground truth information a topographic map of 2000, scale 1:5000, multichannel SPOT XS image of 2009 as well as soil and vegetation maps of scale 1:100.000 were available.

3. Knowledge Acquisition

In general, knowledge acquisition is used for an initial intelligent guess of the spectral values of selected classes and it is important for selection of the reliable features as well as for definition of reliable spatial and spectral thresholds. In the present study, knowledge acquisition has been conducted based on the theory of backscattering mechanisms of each class available within the selected image frame.

Initially, from different parts of the SAR images, polygons representing the selected land cover types have been selected using local knowledge. Then, the polygons were transformed into primary signatures (ERDAS 1999) of the representative classes. As the images have high and very high spatial resolutions, the final signatures included different numbers of pixels. The signature selected sites from TerraSAR and Palsar images are shown in **Figures 2** and **3**, and the mean values and SDs for the chosen training samples selected from the multi-frequency SAR images are shown in **Table 1**.

As seen from **Table 1**, the building area has the highest mean values in X and C bands and the second highest mean value in L band. It is statistically separable from most classes, but in X band its backscatter values are highly scattered. Compared to the building area, a ger area might easily have some overlaps with other classes specifically in X band, unless accurate spectral threshold values are selected. In general, the backscatter from ur-

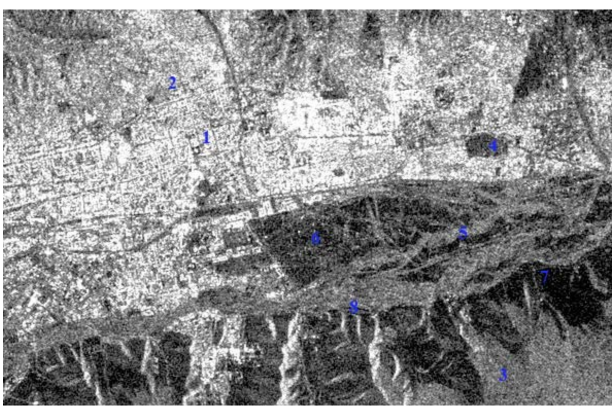

Figure 1. 2011 Envisat image of the selected part of Ulaanbaatar. 1—building area, 2—ger area, 3—forest, 4—grass, 5—soil with high moisture, 6—soil with low moisture, 7—open area and 8—water.

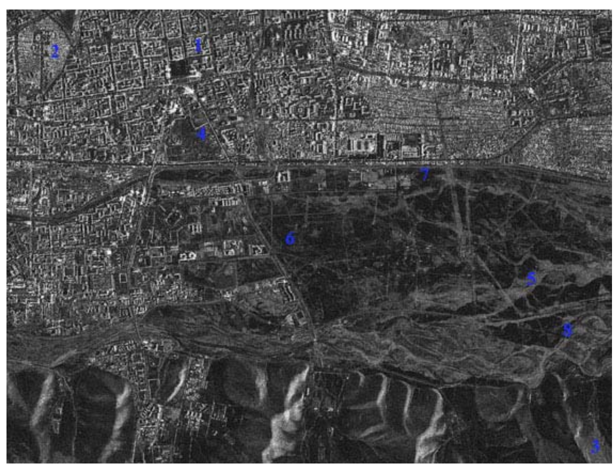

Figure 2. The signature selected sites in TerraSAR image of Ulaanbaatar. 1—building area, 2—ger area, 3—forest, 4—grass, 5—soil with high moisture, 6—soil with low moisture, 7—open area and 8-water.

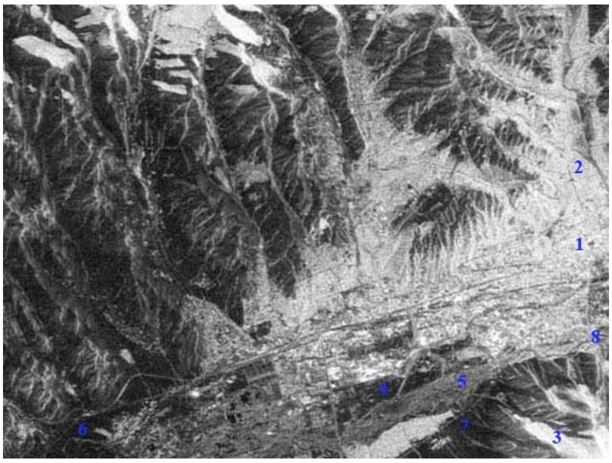

Figure 3. The signature selected sites in Palsar image of Ulaanbaatar. 1—building area, 2—ger area, 3—forest, 4—grass, 5—soil with high moisture, 6—soil with low moisture, 7—open area and 8-water.

Table 1. The mean backscatter values of the selected land cover classes and their variations in the TerraSAR and Quickbird bands.

No	Classes	TerraSAR		Envisat		Palsar	
		M	SD	M	SD	M	SD
1	Building area	175.2	71.3	231.6	33.2	201.6	41.2
2	Ger area	132.2	64.4	190.9	30.3	247.3	14.4
3	Forest	90.9	42.1	122.2	19.9	168.8	39.9
4	Grass	71.4	28.3	95.3	18.9	151.5	43.5
5	Soil with high moisture	147.3	50.2	134.3	23.3	115.4	38.1
6	Soil with low moisture	63.2	21.1	42.0	20.4	23.5	22.1
7	Open area	57.1	17.5	82.5	19.7	19.8	16.1
8	Water	89.1	29.1	29.2	13.1	37.8	23.5

ban areas should contain information about street alignment, building size, density, roofing material, its orientation as well as vegetation and soil, thus resulting in all kinds of scattering. Roads and buildings in urban areas can reflect a larger component of radiation, if they are aligned at right angles to the incident radiation. Here, the intersection of a road and a building tends to act as a corner reflector. The amount of backscatter is very sensitive to street alignment. The areas of streets and buildings aligned at right angles to the incident radiation will have a saturated very bright appearance and non-aligned areas will have a bright/dark appearance in the resulting image. Volume and surface scattering will also play an important role in the response from many of the urban features [3,7]. Using Rayleigh's criterion of surface roughness, for the TerraSAR X (3.1 cm) band data, the boundary between the diffuse and specular reflection can be determined as being between 0.38 cm and 1.45 cm, while for the Envisat C (5.6 cm) band data it could be in between 0.75 cm and 0.79 cm, depending on the incident angles. Many urban surfaces have variations that are just greater or less than these values.

To form the signatures of ger area and building classes, the polygons representing these classes were selected from more homogeneous parts of the images. However, the investigation of the individual pixels indicated that those objects aligned at right angles gave extremely high backscatter values and they reached their maximum in all X, C and L bands. In addition, as seen from **Table 1**, at X-band frequency ger area almost overlaps with soil with high moisture, but at C and L-band frequencies the two classes are completely separable. This is most probably due to the fact that soil moisture is more saturated at the upper 3 cm (penetrating capability of X-band) of the soil causing high backscatter return at X-band frequency, while at the depth of 6 cm - 23 cm (penetrating capability of C and L-bands) the soil surface condition is more homogeneous causing moderate backscatter return.

In case of forest, at X and C band frequencies, canopy scattering and attenuation will be caused primarily by leaves and needles, because the wavelength is too short to penetrate into the forest layer. However, at L-band frequency the wavelength will penetrate to the forest canopy and will cause volume scattering to be derived from multiple-path reflections among twigs, branches, trunks and ground. As seen from **Table 1**, the forest has moderate backscatter return and it has some statistical overlaps with the grass in L band. The grass will act as mixtures of small bush, grass and soil and the backscatter will depend on the volume of either of them [6]. Although plant geometry, density and water content are the main factors influencing the backscatter coming from the vegetation cover, ground truth information revealed that the contribution of vegetation is not very significant during this time of the year. Comparing the mean values of forest and grass, one can observe that they are more separable at short radar bands due to stronger volume scattering in the forest area at those frequencies.

There are two soil classes having different backscatter values. As seen, the soil with low moisture forms more compact signatures, whereas the soil with high moisture forms scattered clusters. The backscatter of soil depends on the surface roughness, texture, existing surface patterns, moisture content, as well as wavelength and incident angle. The presence of water strongly affects the microwave emissivity and reflectivity of a soil layer. At low moisture levels there is a low increase in the dielectric constant. Above a critical amount, the dielectric constant rises rapidly. This increase occurs when moisture begins to operate in a free space and the capacity of a soil to hold and retain moisture is directly related to the texture and structure of the soil [3,6]. As it can be seen from **Table 1**, soil with low moisture has lower values in comparison with all other classes. This indicates lower backscatter intensities caused by specular reflection due to lack of some surface features, low roughness properties and low dielectric constant of the dry soil. In contrast to the soil with low moisture, wet soil gives high backscatter return compared to the most of the classes because of the soil moisture content and increased dielectric constant.

In most cases, open area will behave as a specular reflector, but in short wavelengths and at some specific conditions where sufficient surface roughness is observed, it will have some components of diffuse scattering. As seen from **Table 1**, at SAR wavelengths the open area has very low average backscatter return compared to almost all other classes and it has a high statistical overlap with soil with low moisture in X and L bands. Specifically, in L-band, its backscatter values are lower than the water, which means that the selected site is totally dominated by a specular reflection and there is very little return signal toward the radar antenna.

Generally, in an urban environment, most of the available water resources will have specular reflection and should appear very dark on images for all incident angles except 0. To obtain some backscatter from a water surface, it must by some mechanism, be made rough. The principal mechanism for the roughening the water surface is the generation of waves and in reality the waves can be generated by strong wind. However, in the given case, there is contextual influence of grass, green vegetation and small bush (from both sides of the river) due to which there is increased backscatter return (especially in X-band).

4. The Proposed Knowledge Representation

In general, urban areas are very diverse and create complex systems that have very explicit characteristics. These make the urban system possible to distinguish from all other systems. For example, it is necessary to consider the physical aspects such as size, structural aspects such as composition, economic aspects such as cost, and environmental aspects such as relation with its environment as well as the aspects connected to its operation (*i.e.*, utilization by people, interaction with concerned users). In everyday life, an organization or a municipality manages an urban system and their work consists of arranging, planning and managing these urban systems [8]. Therefore, development of the urban knowledge base requires a complex approach that considers all urban aspects.

For development of a proper KBS used for the automatic interpretation of such multi-frequency SAR images, the above knowledge about backscattering properties of different natural and artificial objects of urban environment can be represented in a most efficient way, for example, using a rule-based approach. It is one of the most commonly used knowledge representation technique, in which different rules mainly containing the constraints on expert-defined variables, spatial objects, external programs and other spatial models are constructed and used for the hypothesis evaluation [9]. Thus, different parameters to be required might be formulated as a set of "IF THEN" rules and the actual image processing can be done on the basis of a forward chaining principle [10]. Moreover, the rule-based inference based on the forward chaining principle can be mapped into neural network architecture. For this purpose, at first, data attributes should be assigned to input nodes, final hypotheses should be assigned to output nodes and the hypotheses must be assigned to hidden units. Then, the initial domain rules determine how the attributes and hypotheses are linked and how the links are weighted.

5. Conclusion

The aim of this study was to conduct knowledge acquisition through the analysis of the backscattering properties of the urban land cover features in Mongolia using TerraSAR X-band, Envisat C-band and Palsar L-band SAR images. In case of equal calibration, it was possible to compare the backscattering properties of the separate radar bands. However, as the calibration of each SAR image was different, a comparison was made among the classes within the bands themselves. Within the framework of the study, an appropriate technique, which is a rule-based approach for the acquired knowledge representation was proposed. Overall, the study demonstrated that the multi-frequency radar images could be successfully used for the knowledge acquisition as well as for the investigation of different urban land surface features.

REFERENCES

[1] L. D. Xu, N. Liang and Q. Gao, "An Integrated Knowledge-Based System for Grasslands Ecosytems," *Knowledge-Based Systems*, Vol. 14, No. 5-6, 2001, pp. 271-280. doi:10.1016/S0950-7051(01)00106-X

[2] A. E. Daniels, "Incorporating Domain Knowledge and Spatial Relationships into Land Cover Classifications: A Rule-Based Approach," *International Journal of Remote Sensing*, Vol. 27, No. 14, 2006, pp. 2949-2975. doi:10.1080/01431160600567753

[3] D. Amarsaikhan, H. H. Blotevogel, J. L. van Genderen and M. Ganzorig, "Knowledge Acquisition on Urban Land Cover Features Using TerraSAR and Quickbird Images," *CD-ROM Proceedings of the Asian Conference on RS*, Beijing, 18-23 October 2009.

[4] W. P. Wagner, J. Otto and Q. B. Chung, "Knowledge acquisition for expert systems in accounting and financial problem domains," *Knowledge-Based Systems*, Vol. 15,

No. 8, 2002, pp. 439-447. doi:10.1016/S0950-7051(02)00026-6

[5] D. Amarsaikhan, M. Ganzorig and V. Battsengel, "Knowledge Acquisition in C-Band and L-Band Radar Frequencies," *CD-ROM Proceedings of the Asian Conference on RS*, Hanoi, 2006.

[6] D. Amarsaikhan and M. Ganzorig, "Interpretation and comparison of AirSAR quad-polarised radar images," *Proceedings of the* 20*th Asian Conference on RS*, 22-26 November 1999, Hong Kong, pp. 695-700.

[7] American Society of Photogrammetry, "Manual of Remote Sensing," 3rd Edition, 1999.

[8] A. Quintero and S. Pierre, "A Knowledge-Based Approach for Managing Urban Infrastructures," *Knowledge-Based Systems*, Vol. 15, No. 8, 2002, pp. 449-463. doi:10.1016/S0950-7051(02)00028-X

[9] D. Amarsaikhan, M. Ganzorig, P. Ache and H. H. Blotevogel, "The Integrated Use of Optical and InSAR Data for Urban Land Cover Mapping," *International Journal of Remote Sensing*, Vol. 28, No. 6, 2007, pp. 1161-1171. doi:10.1080/01431160600784267

[10] H. M. Onsi, "Designing a Rule-Based Classifier Using Syntactical Approach," *International Journal of Remote Sensing*, Vol. 24, No. 4, 2003, pp. 637-647. doi:10.1080/01431160010026041

