Comparison of Hyperspectral and Multispectral Sensor Data for Land Use Classification

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ABSTRACT

Remote sensing data is collected and analyzed to enhance understanding of the terrestrial surface. Since Landsat satellite was launched in 1972, many researches using multispectral data has been achieved. Recently, with the availability of airborne and satellite hyperspectral data, the study on hyperspectral data are being increased. It is known that as the number of spectral bands of high-spectral resolution data increases, the ability to detect more detailed cases should also increase, and the classification accuracy should increase as well.

In this paper, we classified the hyperspectral and multispectral data and tested the classification accuracy. The MASTER(MODIS/ASTER Airborne Simulator, 50channels, 0.4~13μm) and Landsat TM(7channels) imagery including Yeong-Gwang area were used and we adjusted the classification items in several cases and tested their classification accuracy through statistical comparison. As a result of this study, it is shown that hyperspectral data offer more information than multispectral data.

Keyword: *hyperspectral data, multispectral data, classification, statistical comparison*

1. INTRODUCTION

Geographers, ecologists and other scientists interested in the spatial distribution of phenomena for many decades have paid attention to the problem of describing the nature of the Earth's surface. Since the launch of Landsat satellite, people have used remotely sensed data efficiently to classify the world as a set of distinct and mutually exclusive regions. Multispectral images such as Landsat TM have used for various Earth-sciences application, mapping land use, geology, forest types, etc. Remotely sensed data collected by various imaging systems are becoming increasingly important. As Lillesand and Kiefer remark: 'The overall objective of image classification procedures is to automatically categorize all pixels in an image into land cover classes or themes.' This is to place each pixel into a single land cover class. More recently there has been the attitude that each pixel is allowed to have a 'class membership' probability rather than a single label representing one discrete and identifiable category of land cover. So the image classification is one of the most often used quantitative data analysis techniques to describe ground cover types or material classes independently of classifiers used.

Multispectral imaging in 4 spectral bands with the Landsat MSS was not adequate to discriminate among, much less identify, minerals on the earth's surface that were important in resource exploration and environmental assessment. The need for imaging spectrometry grew out of a recognition in the 1970's based on laboratory and field spectral measurements, primarily of rocks and soils. In 1981, the Shuttle Multispectral Infrared Radiometer (SMIRR) flew and showed that a direct identification of surface mineralogy could be made from orbit with contiguous, narrow-band spectral measurements. Researchers in the field of vegetation and water studies had not yet fully exploited the information that could be derived from multispectral sensors imaging in the visible near-infrared (VNIR) region until the early of 90's . In recent times information of the narrow spectral band is necessary for vegetation analysis, particularly for canopy studies

During the last 20 years the studies on the hyperspectral remote sensing have been carried out in the different ways and in the various application fields. The results have shown better classification of land cover, target detection and feature analysis. So we classified the hyperspectral and multispectral data and compared the accuracy from each classification, then intend to show the usefulness of hyperspectral data.

2. HYPERSPECTRAL DATA

The "hyper" in hyperspectral means "over" as in "to many" and refers to the large number of measured wavelength bands (refer to Figure 1). Hyperspectral images are spectrally overdetermined, which means that they provide ample spectral information to identify and distinguish spectrally unique materials. Hyperspectral image provides the potential for more accurate and detailed information extraction than possible with any other type of remotely sensed data (Dimitris Manolakis *et al*, 2001). This is because the narrow bandwidth of hyperspectral data provide information to resolve molecular absorption features and relate the measured radiance of each spectrum to a distinct absorption feature or detect and identify surface or atmospheric constituents. So it is possible to identify the chemical composition of the imaged target (rock, soils, or vegetation). Figure 2 explains how the hyperspectral data can contribute to a better earth surface-features discrimination.

Conventional remote sensing techniques such as ratios or differences or MLC(maximum likelihood classification) can be applied to make use of hyperspectral data. But to cope with the high spectral dimensionality typical for imaging spectrometer data the following techniques is used: binary encoding, waveform characterization, spectral feature fitting, spectral angle mapping, spectral unmixing, constrained energy minimization, classification and cross-correlogram spectral matching.

However, because these hyperspectral data have high spectral resolution it has the disadvantage of lower spatial resolution relatively and it includes useless or redundant data. Therefore sub-pixel classification technique and feature reduction researches have been carried out.

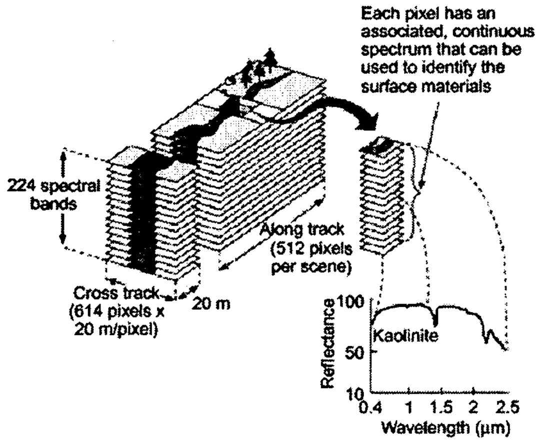


Figure 1. Concept of imaging spectrometry.

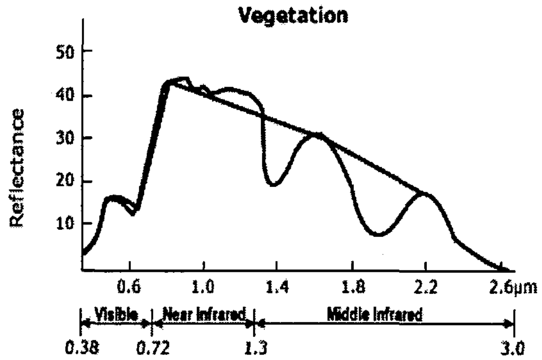


Figure 2. Comparison of spectral discrimination capabilities

ACTUAL TEST

Flow chart

In this paper, our aim is to compare the information of hyperspectral and multispectral sensor data for Land Use Classification using maximum likelihood classifier. MLC is generally known to produce efficient and accurate classification result (Te-Ming Tu et al, 1998). MASTER data which is georeferenced to geographic coordinates (ie, latitudes and longitudes), WGS84 datum was transformed to rectangular coordinates (Easting, Northing). In the coordinate transformation weighted distance resampling was used for constant grid intervals in x and y axis. TM image was registered to MASTER image. The procedure of this study is shown in figure 3.

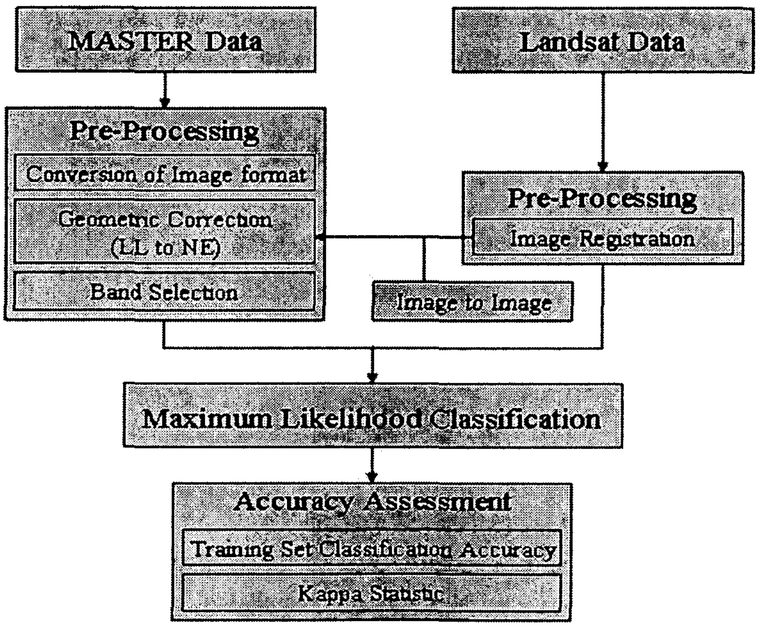
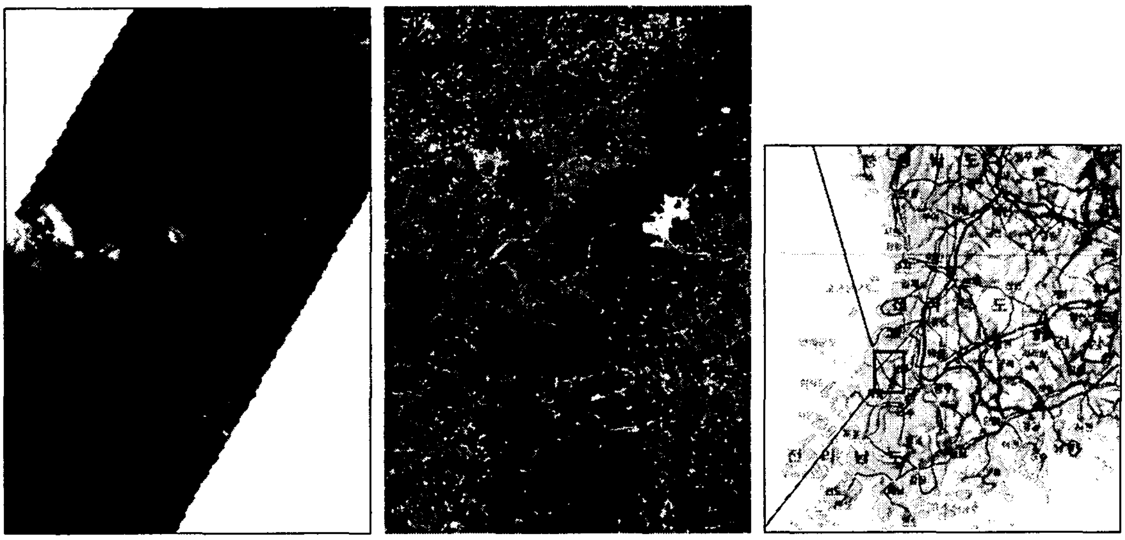


Figure 3. Flow chart

Test Area

Test area is around Hampyung-Gun, Changsung-Gun and Younggwang-Gun, Jeollanam-do. This area is composed of mountains, lakes, urban, agricultural area, and so on. Figure 4 shows remotely sensed images and topographic map for the test area.



(a) MASTER data (b) Landsat TM (c) topographic map

Figure 4. map and images in the test area

Specification of Multi- and Hyperspectral Sensor used

The MASTER instrument was developed by the NASA Ames Research Center in conjunction with the Jet Propulsion Laboratory. The MASTER supports a variety of scan speed allowing it to acquire contiguous image from a variety of altitudes with differing pixel sizes differently other instruments. Table 1 shows summary characteristics of the MASTER instrument and Landsat TM sensor.

Table 1. Specification of Master and TM

MASTER	
Wavelength range	0.4-13㎛
Number of channels	50
Number of pixels	716
IFOV	2.5 mrad
Platforms	DOE King Air Beachcraft B200, NASA ER-2, and NASA DC-8
Data Format	Hierarchical Data Format (HDF)
Digitization	16-bit
Product	Radiance at sensor (Level 1B)
Spatial Resolution	5-50m (20m, in this image)

Landsat TM	
Wavelength range	0.45-2.35㎛/10.4-12.5㎛
Number of channels	7
Swath	185km
Spatial Resolution	30m/60m
Repeat coverage interval	16 days
Quantization	8-bit
Product	Level 1R
Altitude	705km
Inclination	98.2-degree

CLASSIFICATION

In MASTER data, bands which have much noise is band 16~18, 26~29, and 30~41; total 19 bands. For an example, noisy band 17 is shown in the figure 5. So we classified MASTER data in three cases. In first case all bands was used and in second case only good-quality 15 bands was used. In third case 15 bands was used to apply MLC.

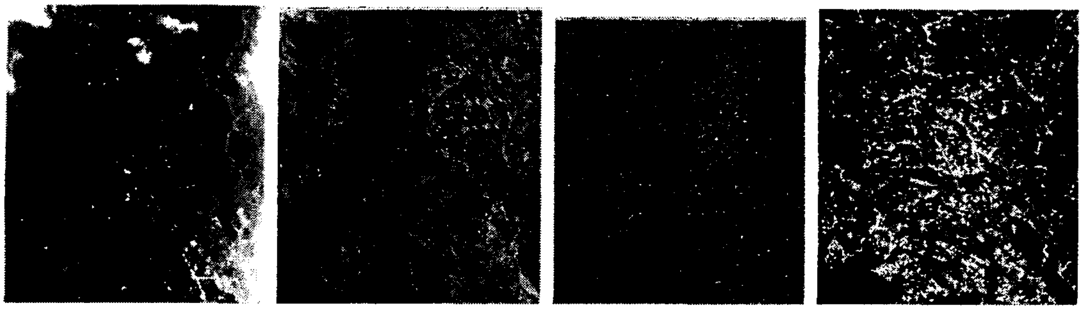


Figure 5. MASTER Image : Band 1, Band 9, Band 17, Band 49 (from left to right)

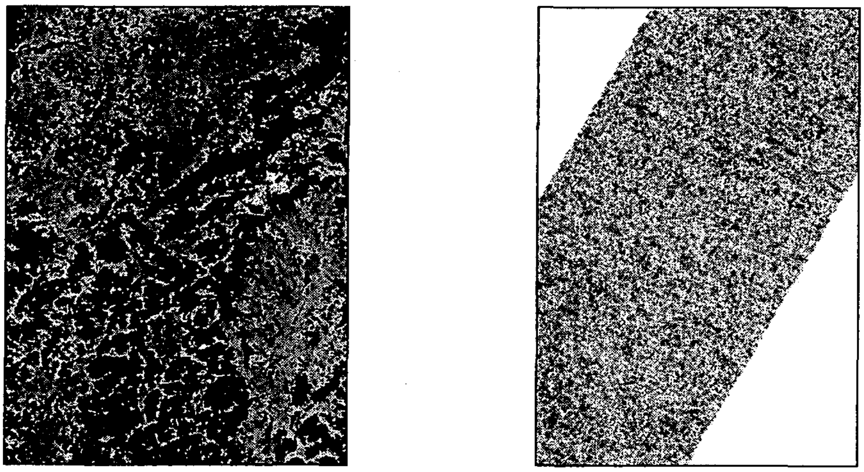


Figure 6. ISODATA classification result; TM (left), MASTER all (right),

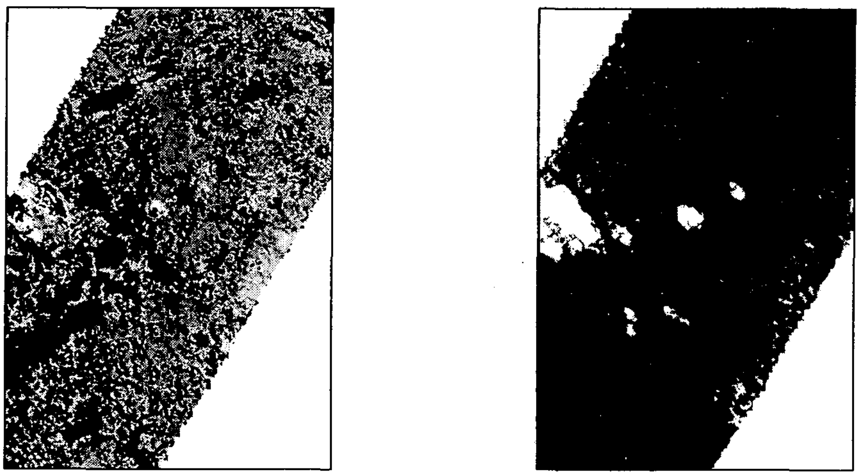


Figure 7. 15band used classification result; ISODATA (left), MLC(right)

Classification result using MASTER data is not good due to noisy band in the figure 6 and cloud is classified with white color in the figure 7. Hyperspectral data analysis technique was not applied in the different ways and classification accuracy assessment was not performed. We continue to test and will make a presentation of test result on symposium. Full paper will be uploaded on the web site (http://spins.snu.ac.kr)

DISCUSSION

In this study we cannot obtain good result. Because cloud and cloud shadow exist in the MASTER data and appropriate band selection was not performed. Another reason is that the bandwidth of MASTER data is about 50nm, which is much wider than 10nm hyperspectral bandwidth. We are scheduled to obtain reference data for training area and accuracy assessment, to remove the effect of cloud and cloud shadow, and to compare the classification result of TM and MASTER data.

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