

# URBAN LAND COVER MAPPING USING OBJECT/PIXEL-BASED DATA FUSION AND IKONOS IMAGES

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## ABSTRACT:

The use of high resolution IKONOS imagery should make it possible to extract urban features like buildings and roads more easily than conventional satellite image data. This work examines the synergetic ability of using spectral information from multispectral data in combination with spatial information from panchromatic data in urban land cover mapping using IKONOS Imagery. In this work we tried to answer the question, how much data fusion influences the classification results at the pixel and object level? The work contains some main steps. First, the land cover classification based on the Object Oriented Classification (OOC) and Maximum Likelihood Classification (MLC) algorithms using multispectral IKONOS image has been carried out. Second, the panchromatic image was fused with multispectral data using wavelet data fusion and overly algorithms. Finally, land cover classification based on the wavelet fused images using MLC and OOC algorithms has been undertaken. The accuracy of the results was calculated and they show that the increase of spatial resolution in fused data has a positive influence on the results.

## 1. INTRODUCTION

Data fusion wants to get the highest potential of the fused data based on the spectral, spatial and temporal properties. The literature of data fusion covers high range of data, application and techniques. Many authors describe the data fusion in their viewpoints e.g. Data fusion in tend of photo-interpretation improvement as well as image classification. Also the domain of techniques covers high numbers which can be categorized in three main categories including pixel-based like IHS, PCS, Brovey's algorithm, wavelets, or local correlations, SVR (Munehchika et al. 1993), object-based data fusion (Chen et al., 2004) and decision-based data fusion (Margarita kokla et al. (2001). The different aspects of data fusion are discussed in more detail in F. J. Tapiador et al. (2002), Zhang (1999) and Pohl et al. (1998). The object oriented algorithm lets to use the original data in classification process while mostly the border objects bring from high resolution (because of high textual information) the spectral properties come from multispectral data. This combination of data can be addressed as object based data fusion and classification. Thus spectral property of image is principal of image classification and the image spatial property is the main factor for recognition the ground objects. City as a place for a human living, economy and social activities has an increasingly important in the past and future. The Land Use and Land Cover Changing (LUCC) mapping plays a vital role in urban mapping, monitoring and managing. Remote Sensing is an important technique to get information about urban features and dynamics. The launch of high resolution space-born satellites like IKONOS opened new opportunities for thematic information investigation in urban areas.

## 2. STUDY AREA AND SATELLITE IMAGERY

IKONOS data covering a part of the metropolitan area of Tehran, Iran are used in this study. The area is situated at 137° 25' 22" E and 36° 08' 44" N as shown in Figure 2. The site comprises diverse land covers types which have been aggregated to 4 major classes in this work: buildings, vacant, road, vegetation, and also an unrecognized class. Under this

The objective of the study is to try the fusion of IKONOS-Multispectral/Panchromatic imagery and assess the data fusion influences on classification processes. The general term of main categorization there are 9 sub classes as can be see in Figure 1.

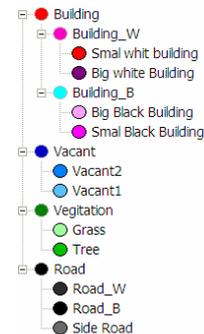


Figure 1. Object based land cover category

Panchromatic and multispectral images of IKONOS are obtained simultaneously on June 29th, 2004. The imagery have been delivered in standard imagery-PAN/MSI format with geometric and radiometric sensor corrections already applied. Due to clear weather conditions during data acquisition no atmospheric correction was applied. A panchromatic imagery with 1.00 m of spatial resolution shows diversity of textures, shapes and patterns of difference urban objects. The multispectral imagery with 4.00 m of spatial resolution and 4 spectral bands mostly represent the spectral properties of objects. (Table 1 and Figure 2)

Satellite	Sensor	Spectral Range	Bands	Scene Size	spatial Resolution
IKONOS	MS	455 - 853 nm	Blue, Green, Red, NIR	11 x 11Km	4 meter
	Pan	450 - 900 nm	Panchromatic	11 x 11Km	1 meter

Table 1. IKONOS-2 relative spectral and spatial properties



Figure 2. Overview of the study site and the visual effect of image fusion: (a) panchromatic image, (b) multispectral image, (c) fused image (IKONOS, June 29th, 2004, Tehran)

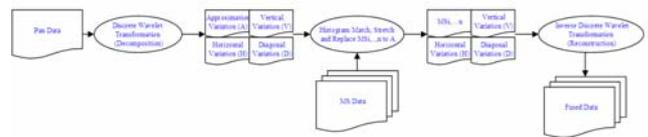
### 3. METHODOLOGY

With the rise of the new generation of hyper resolution satellites sensors new developments in image analysis was necessary. Due to the limitations of pixel-based classification algorithms there are so many things we could see in the images but couldn't classify. The software eCognition 3 as an object-based professional classifier software provides a powerful tool to simultaneously analyze data at different spectral, temporal and spatial resolutions. In this work we evaluated the usefulness of two general concepts of image fusion, namely pixel based and the object based fusion and assessed the influence these data fusion types on the results of image mapping in an urban area. The first step of image classification involved only the multispectral IKONOS image channels using Object Oriented Classification (OOC) and Maximum Likelihood Classification (MLC) algorithms. After that, the two classifications were done again, based on wavelet fused multispectral and panchromatic IKONOS images for MLC and overlaid multispectral and panchromatic data for OOC, respectively (Figure 5 and 7).

#### 3.1. Wavelet Data Fusion

A mathematical tool developed originally in the field of signal processing can also be applied to fuse image data following the concept of the multiresolution analysis. In this algorithm spatial information of the high resolution image can be collected in the

wavelet coefficient images and it could be directly injected into the multispectral image. This algorithm works at the pixel level in two main stages including decomposition and reconstruction. The basic theoretical aspect of the decomposition is, that an image can be separated into high-frequency and low-frequency components. More details can be found in Gauguet-Duport et al. (1996), Zhou et al. (1998), Ranchin and Wald (2000). In decomposition process image divided into four components as: Approximation coefficient (A), Vertical coefficient (V), Horizontal coefficient (H) and Diagonal coefficient (D) and in the reconstruction process the Approximation coefficients (A) component can be replaced with multispectral bands one by one and separately. (Figure 3) We used 2-Dimensional Discrete Wavelet Transform (2-D DWT) included in ERDAS 8.7 software and the results are shown in Figure 2.



Where: A: Approximation coefficients contains over all variation  
V: Vertical coefficients contains along the rows variations  
H: Horizontal coefficients contains along the columns variations  
D: Diagonal coefficients contains along the diagonals variations

Figure 3. Wavelet-based data fusion flowchart

The ability of this technique to protect the spectral properties of multispectral data is focused in this part of work. The comparison of the obtained results before and after the wavelet-based fused data using the MLC shows a good ability of this technique to protect the spectral and spatial properties of MS and Panchromatic data, respectively. (Table 2) but the spectral artifacts in the fused data are still one main problem of wavelet data fusion. These phenomena can somewhat be reduced using low pass filter over multispectral data before fusion process. Despite the reducing of the spectral artifacts the low pass filter reduces the sharpness of images (Figure 4). Thus, in this research unfiltered images have been used.



Figure 4. The wavelet-based fused data: (a) low-pass filtered fused data, (b) fused data without filtering

#### 3.2. Maximum Likelihood Classifier (MLC)

Despite the fact that pixel-based supervised classification algorithms are less sufficient at segregating between urban objects, especially in high resolution image classification domain, but they still supply somewhat reliable results for mapping the required urban land cover categories. Difficulties appear when the spectral signatures of heterogeneous urban objects are similar, e.g. built areas and roads. Another difficulty of a MLC is the salt-and-pepper effect in the classified image. In this study a supervised Maximum Likelihood Classifier (MLC), as a pixel-based technique, was chosen to assess the

influence of wavelet-based data fusion in image spectral properties. In order to reduce the number of salt-and-pepper pixels in classified data, the majority filter was applied over the MLC output map. The results are land cover images with predominantly homogenous objects (Figure 5).

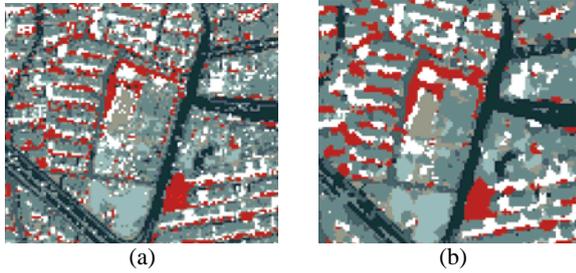


Figure 5. The MLC land cover results: (a) without the majority filter, (b) after the majority filtration

### 3.3. Segmentation

In a segmentation procedure, an image is segmented based upon several modifiable parameters of homogeneity or heterogeneity using color, shape, size, texture, pattern and context parameters (Baatz and Schäpe 2000). Due to the influence of segmentation on the classification outputs, trying until getting the best parameters by changing the respective weights of colour and shape is much recommended. It creates image segments based on four heterogeneity criteria: scale, color, smoothness and compactness. These criteria can be set in diverse ways to achieve different homogeneous objects in any wanting resolution. Scale is the most important parameter and affects the relative size of output polygons (Baatz and Schäpe, 2000). In this study, we applied different scales as well as different weights of colour and shape. In this process, the low number (10) for the scale parameter results the over-segmented (unnecessary dialed) and the high scale value (60) made the under-segmented (more general segments) the images. Thus, to get the optimum and meaningful object size, a medium scale value was set as 30. And also for the composition and homogeneity creation parameters we used the same number (0.5). Shape parameter also includes two components as compactness and smoothness that the same value (0.5) was set. (Figure 6)

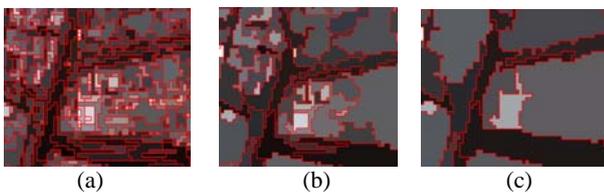


Figure 6. The segmented data: (a) over segmented, (b) optimum segmented, (c) under segmented data

### 3.4. Object Oriented Classification (OOC)

Because of the high feature complexity in urban areas, the information extraction is currently mostly done on the basis of visual interpretation. The new abilities of the eCognition software help us to do this process in a semi-automatic manner. The eCognition object oriented classification process is based on fuzzy logic, to allow the integration of a broad spectrum of different object features such as spectral values, shape or

texture for classification. Utilizing not only image object attributes, but also the relationship between networked image objects, results in sophisticated classification incorporating local context (Baatz et al., 2000). One sample object already contains many typical pixel samples and their variations the object-based training need fewer training samples in comparison to pixel-based training techniques. However, all class assignments in eCognition are determined by assigning distance values in the range (0, no assignment) to (1, full assignment). eCognition computes the distance as follows (eCognition 4, User Guide 2004) (Equation 1)

$$d = \sqrt{\sum_f \left( \frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right)^2} \quad (1)$$

- $d$  : Distance between sample object  $s$  and image object  $o$ .
- $v_f^{(s)}$  Feature value of sample object for feature  $f$ .
- $v_f^{(o)}$  Feature value of image object for feature  $f$ .
- $\sigma_f$  Standard deviation of the feature values for feature  $f$ .

Equation 1. The distance computation formula

The distance in the feature space between a sample object and the image object to be classified is standardized by the standard deviation of all feature values. Thus, features of varying range can be combined in the feature space for classification (Figure 8). Based on our knowledge from the study area, we tried to use a bottom-up hierarchical approach, first identifying the known classes as accurate as possible and in the following steps grouping of the classes to get meaningful classes (e.g. classification of grass and tree in the first step and combine them to the vegetation class). Figure 7 shows this hierarchical structure of land cover classification after combination of panchromatic and multispectral images.



Figure 7. Object based land cover classes after combination of Pan and multispectral images

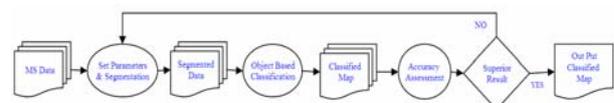


Figure 8. Object-based classification flowchart

### 3.5. Object Oriented Data Fusion (Combination)

Object-based fusion is not a separate process and it is included in the classification process. Figure 6 shows data fusion as a part of the classification process in this work. We obtained the segment borders from panchromatic and multispectral imagery simultaneously and in the next step classification was carried out. Due to the fact that in this process the multispectral and panchromatic data are only overlaid (combined) the whole spectral and spatial properties of the data will be preserved (Figure 9).

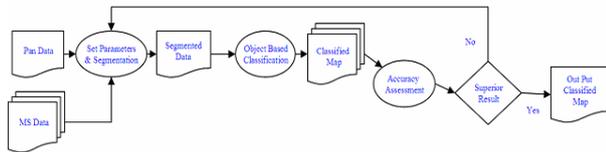


Figure 9. Object-based data combination and classification flowchart

After the land cover classification, we derived the land use map. The assumption of this approach is that the land use functions can be distinguished on the basis of object size and border length in land cover forms. The results show these two parameters cannot be merely sufficient to separate the objects with the same spectral properties while they have different functions. Thus, after trying to use these parameters we faced some problems. So the finalized land use map is not available at the time of writing and the study still is in progress.

#### 4. RESULTS

The work was based on the hypothesis that classical, pixel-based classification approaches like MLC are not suitable for high-resolution imagery analysis in urban land cover and land use classifications. The obtained results show a general increase in classification accuracy by the use of OOC compared to MLC and for fused data in comparison to original data sets (table 2).

	MLC Before Fusion	MLC After Fusion	OOC Before Combination	OOC After Combination
Over all Accuracy	68%	75%	75%	80%
Over all Kappa	0.625	0.701	0.705	0.760

Table 2. Land covers accuracy assessments for all classification presses

#### 5. CONCLUSIONS

In this work, wavelet data fusion and object oriented data combination as two of the main pixel and object based fusion approaches have been compared. The assessment of their abilities to fuse panchromatic and multispectral IKONOS imagery in image classification of urban areas was evaluated by means of land cover classification. The final results show the higher ability of object-based image classification in comparison to maximum likelihood classification. Land cover maps obtained using this object based algorithm is slightly better than those obtained by pixel based algorithms. Compared to traditional remote sensing image analysis software the object-based eCognition software can be more accurate using

shape, size, texture and hierarchical structure in image classification process.

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