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Rule set of object-oriented classification using Landsat imagery in Donganh, Hanoi, Vietnam

Trinh Thi Hoai Thu[1)] · Pham Thi Lan[2)] · Tong Thi Huyen Ai[3)]

Abstract

Rule set is an important step which impacts significantly on accuracy of object-oriented classification result. Therefore, this paper proposes a rule set to extract land cover from Landsat Thematic Mapper (TM) imagery acquired in Donganh, Hanoi, Vietnam. The rules were generated to distinguish five classes, namely river, pond, residential areas, vegetation and paddy. These classes were classified not only based on spectral characteristics of features, but also indices of water, soil, vegetation, and urban. The study selected five indices, including largest difference index max.diff; length/width; hue, saturation and intensity (HSI); normalized difference vegetation index (NDVI) and ratio vegetation index (RVI) based on membership functions of objects. Overall accuracy of classification result is 0.84% as the rule set is used in classification process.

Keywords : Object-oriented classification, Rule set, Land cover, HSI.

1. Introduction

Classification of remote sensing data to extract information requires a high accuracy. Formerly, pixel-based classification methods, which are based on spectral characteristics of the features, remain some disadvantages such as low accuracy and "Salt and Pepper" appearance. In recent years, object-oriented approach has been a new method, which aims to improve the accuracy and deal with weak points of traditional pixel-based methods (Chena *et al*.2009; Dehvari and Heck 2009; Gaurav and Prasun 2010). The object-oriented classification method extracts land cover not only based on the spectral values of the pixels, but it also considers the shape, texture and contextual information (Chena *et al*.2009; Cu *et al*.2009). Object-oriented classification process begins by combining neighboring pixels into individual objects which is called image segmentation. Next, the objects are distinguished by fuzzy classification based on hierarchical rules. A set of knowledge-based classification rules for describing each class should be defined. Land cover mapping primarily employs the multispectral classification method; however, there are other methods that also utilize the application of the remote sensing index (As-syakur *et al*.2012). Donganh district is a peri-urban of Hanoi where land cover is still fragmentary by urbanization and industrialization. For this reason if classification is only based on spectral, the accuracy of the result will not be reliable, especially in residential areas extraction. Consequently, classes need describing by characteristics and appropriate indices.

Many researchers have made use of indicators to discriminate residential areas from other lands. A number of indicators have been used such as normalized difference vegetation index (NDVI), normalized difference built-up index (NDBI) and index-based build-up index (IBI) (Masek *et al* 2000; Zha *et al*.2003). Zha *et al* utilized

1) Hanoi University for Natural Resources and Environment (Email: trinhhoaithu.tnmt@gmail.com)
2) Hanoi University of Mining and Geology
3) International Centre for Advance Research on Global Change

Landsat TM band 5 (MIR) and band 4(NIR) to generate the NDBI for extracting residential areas of Najing City in China. Hanqiu Xu presented a new index–IBI to identify residential areas from multi-date Landsat images. The IBI was formed by three indices, soil adjusted vegetation (SAVI), modified normalized difference water index (MNDWI) and normalized difference built-up index (NDBI).

Vegetation has the highest reflectance in band 4 (NIR), but the reflectance of it in band 3 (R) is the lowest; those are used for creating two indices, ratio vegetation index (RVI) and NDVI. RVI index is quite sensitive to vegetation changes during the growing period, but it is not very sensitive when the vegetative cover is sparse. Meanwhile, NDVI is more sensitive to sparse vegetation densities than the RVI, but is less sensitive to high vegetation densities (Jackson and Huete 1991). Therefore, RVI and NDVI are used for distinguishing between paddy and vegetation. The aim of this study is to create the rule set for classification of five classes: river, pond, residential areas, paddy fields and vegetation using Landsat images in Donganh, Hanoi. The result of such a classification is a thematic map with label for each object of the classes with which it shows strongest membership. In this study, hue, saturation and intensity (HSI) are used as a new proposal for determining the residential areas based on comparing membership functions of objects.

2. Study area and material

Our study area was located in Donganh, where is a suburban district in the north of Hanoi with area of 182.3 km^2. The district is bordered by Soc Son to the north, Gia Lam to the east, Me Linh to the west and Tu Liem to the south. In 2009, the population of Donganh reached 336,633. Donganh is a transition zone from rural to urban, where the land cover has been dramatically changed during last ten years because of economic growth and urban sprawl.

The remote sensing data used in the study is a subset of a Landsat 5 TM image acquired on November 11^{th} 2009 with path #127 row #45(see table 1), this time was winter when paddy field had harvested and late green vegetation was growing. The TM image was geometrically registered to topography map 1:50000 in VN2000.

Fig. 1. Location of Donganh in Vietnam

Table 1. Information of landsat TM

Band	Wavelength range
1	0.45 - 0.52 μm
2	0.52 - 0.60 μm
3	0.63 - 0.69 μm
4	0.76 - 0.90 μm
5	1.55 - 1.75 μm
7	2.08- 2.35 μm

3. Methodology

The object-oriented classification is based on fuzzy logic. Segmentation represents the first step in any object-oriented image analysis. The accuracy of segmentation directly influences the performance of image classification (Benz *et al*. 2004). After that, the objects are assigned into land cover categories by setting different thresholds of rules. We collected 20 training samples (polygons covering less than 3 pixels within objects) for each class which was used in classification process. The workflow chart is shown in Fig. 2.

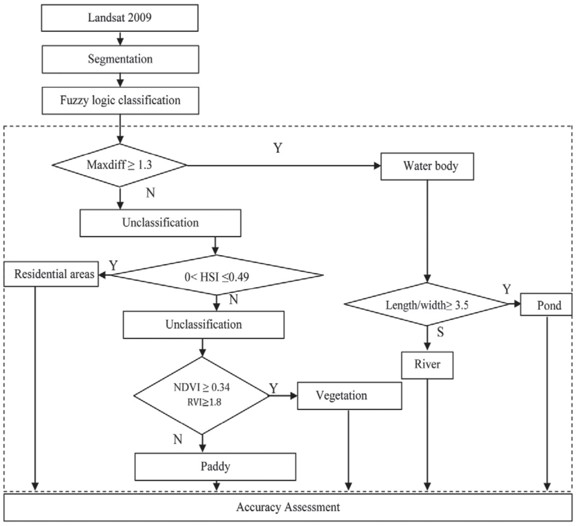


Fig. 2. The workflows chart of object-oriented classification procedure

3.1 Segmentation

Image segmentation is a consecutive combination process of neighboring pixels or image objects. Firstly, each pixel is considered as a separate object. Then adjacent objects on an existing image object level or the pixel level are merged into bigger ones. Multi-resolution segmentation is a basic procedure in the software eCognition for object-oriented image analysis; it creates image objects based on determination of scale parameter and homogeneity criteria. The scale parameter is an abstract term that determines the maximum allowed heterogeneity for the resulting image objects. For heterogeneous data, the resulting objects for a given scale parameter will be smaller than in more homogeneous data. The size of image objects can be varied by modifying the value in the scale parameter. Multi-resolution segmentation is a bottom-up region-merging technique starting with one-pixel objects. The merging process measures the change in spectral heterogeneity (h_{color}) and shape heterogeneity (h_{shape}) to check if these neighboring objects need to be merged or not, this grow iteratively changes until it reaches the user defined threshold (Benz *et al*. 2004). Definition of heterogeneity is expressed in the following Eq. 1 and Fig. 3 shows flowchart of multi-resolution segmentation.

$$f = w_{color} h_{color} + w_{shape} h_{shape} \quad (1)$$

$$w_{color} \in [0,1], w_{shape} \in [0,1] \text{ and } w_{color} + w_{shape} = 1$$

The parameters for the image segmentation in this article, including values of 7, 0.2, and 0.8 for scale parameter, shape, and compactness, respectively. They are suitable for classification of Landsat ETM in Donganh.

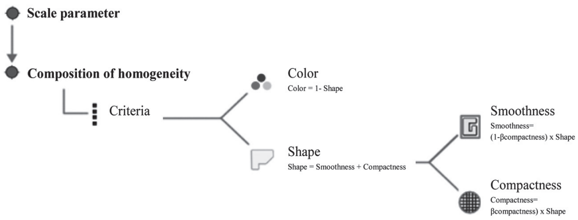


Fig. 3. Multi-resolution concept flow chart (Trimble Germany 2011)

3.2 Fuzzy logic classification

Fuzzy theory has been applied in various fields, such as image clustering, decision making and control. A fuzzy set is a set of ordered pair which is given by $A = \{x, \mu_A(x)\}: x \in X$, where X is a universal set and $\mu_A(x)$ is membership function the grade of the object x in A ($0 \le \mu_A(x) \le 1$). For detail $\mu_A(x)$=0 means that x does not belong to the A, $\mu_A(x)$=1 indicates that x fully belong to A, and 0 < $\mu_A(x)$ < 1 means that x belong to the degree μ_A. Fuzzy theory is applied for remote sensing with popular methods that are fuzzy C_mean clustering algorithm, fuzzy maximum likelihood classification and fuzzy rule-based classification. In this paper, a rule-based classifier is used. A typical fuzzy rule-based classification consists of three operations: fuzzification, inference and defuzzification. The first step, fuzzification is used to partition the feature space into fuzzy subspaces defined by membership function, and generate rules for each fuzzy subspace; the subspaces are determined by indices. The second step, inference requires the calculation of strength of each rule. The final step generates a nonfuzzy outcome. The core of this method is a list of so-called if – then statements rules.

Water body reflects mostly in visible wave from 0.4 to 0.7 μm, most strongly from 0.4 to 0.5 μm (band 1), nearly eliminated in band 4 and completely eliminated in band 5, 6, 7. In this research, Max.diff index is called largest difference index refers to the mean intensity values of different image layers of an image object (Trimble Germany 2011). It is used to indentify water bodies. The difference is calculated as follows:

$$\max.diff = \frac{\max_{i,j\in K_B}\left|\bar{c}_i(v)-\bar{c}_j(v)\right|}{\bar{c}(v)} \quad (2)$$

Where:

- i; j are image layers
- $\bar{C}(v)$ is the brightness of image object v
- $\bar{C}_i(v)$ is the mean intensity of image layer i of image object v
- $\bar{C}_j(v)$ is the mean intensity of image layer j of image object v
- K_B is the image layer of positive brightness weight $K_B = \{k \in K: w_k = 1\}$ with w_k is the image layer weight.
- Typically, the feature values are between 0 and 1.

Image objects with max.diff ≥ 1.3 are characterized as water body and then the length and width ratio are employed to distinguish between ponds and rivers.

Residential areas definition is complicated, especially peri-urban areas due to objects structure and the spectral values. We have correspondingly made a survey of some indices such as NDBI, IBI (Xu 2008) and HSI (color space) (Sazzad *et al.* 2013) to extract residential areas.

NDBI index is defined as following equation:

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \quad (3)$$

This index is based on built-up areas that have stronger reflection in the mid-wave infrared band (MIR) than that of the near-infrared bands (NIR). However, some previous studies show that residential area has been mixed with vegetation due to that similar reflection of dried vegetation in the MIR band is also higher than that in near-infrared band. In addition, residential area is a complex ecosystem composed of heterogeneous materials. Land use status of residential areas is grouped into the other three generalized categories, i.e., built-up land, vegetation, and open water. To solve this drawback Xu (2008) used the combination of three indices (SAVI, NDBI and MNDWI) to create a new index named IBI index which is determined by the following equation:

$$IBI = \frac{[NDBI - \frac{SAVI + MNDWI}{2}]}{[NDBI - \frac{SAVI + MNDWI}{2}]} \quad (4)$$

Where:

$$SAVI = \frac{NIR - R}{NIR + R + 0.5}$$

$$MNDWI = \frac{G - MIR}{G + MIR}$$

In RGB color model, there are three primary colors considered named Red, Green and Blue where RGB is defined as additive or subtractive model and hence different colors can be performed using the combination of these primary colors. In addition, HSI (hue, saturation, intensity) color spaces have been widely developing to distinguish and understand colors (Sazzad *et al.* 2013). For displaying, however, a false color composite image of band 4, band 5, band 7 on red, green, blue (RGB) respectively indicates that residential areas were determined clearly by visualization. Therefore, we used HSI (hue, saturation and intensity) color space index for extracting residential areas. Below equations describes the conversion from Red – Green – Blue (RGB) to HSI color space (Sazzad *et al.* 2013).

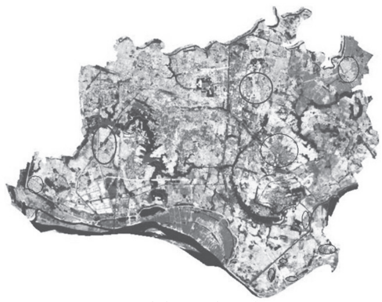
$$I = \frac{1}{3}(R + G + B) \quad (5)$$

$$S = 1 - \frac{3}{(R + G + B)}[\min(R, G, B)] \quad (6)$$

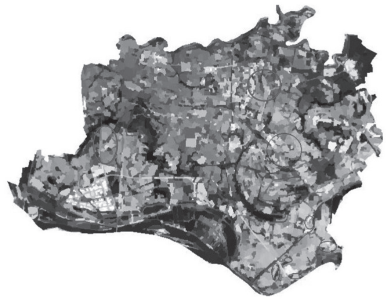
$$H = \cos^{-1}\left\{\frac{0.5[(R-G)+(R-B)}{\sqrt{(R-G)^2+(R-B)(G-B)}}\right\} \quad (7)$$

Where R, G and B are the display color bands

The NDBI, IBI index and HSI color space are used for residential classification as shown in Fig. 4 and table 2.

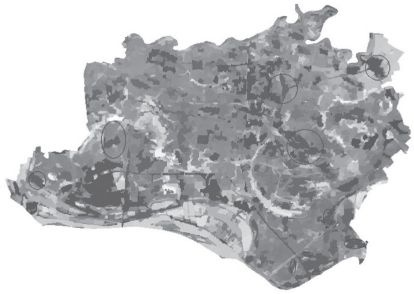


(a) "false color" image
Red = band 4, green = 5, blue= band 7



(b) NDBI image

(c) IBI image



(d) HSI image

Fig.4. Image indices

Table 2. Use of HSI is based on the comparison between membership functions of training data

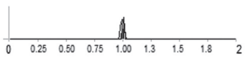
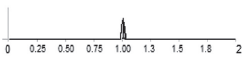
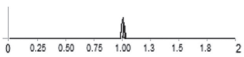
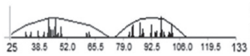
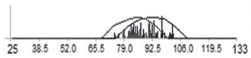
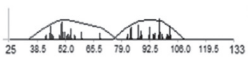
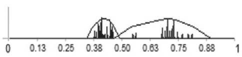
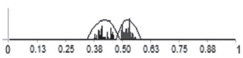
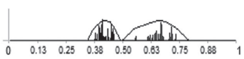
IBI	
Residential areas (black) – Water body (blue)	 IBI (NN) [0.996 - 1.004] StdDev.: 0.0001796390691 [0.9803922 - 1.004] StdDev.: 0.002855332476 Overlap : 0.10
Residential areas (black) – Paddy (blue)	 IBI (NN) [0.996 - 1.004] StdDev.: 0.0001796390691 [0.996 - 1.0117647] StdDev.: 0.0002573478468 Overlap : 0.93
Residential (black) – Vegetation (blue)	 IBI (NN) [0.996 - 1.004] StdDev.: 0.0001796390691 [0.996 - 1.0117647] StdDev.: 0.0005882509463 Overlap : 0.90
NDBI	
Residential areas (black)– Water body (blue)	 NDBI (NN) [81.3294118 - 102.5058824] StdDev.: 6.673 [31.7764706 - 62.6941176] StdDev.: 7.015 Overlap : 0.00
Residential areas (black) – Paddy (blue)	 NDBI (NN) [81.3294118 - 102.5058824] StdDev.: 6.673 [74.1294118 - 93.6117647] StdDev.: 5.1118736 Overlap : 0.21
Residential areas (black) – Vegetation (blue)	 NDBI (NN) [81.3294118 - 102.5058824] StdDev.: 6.673 [41.9411765 - 68.6235294] StdDev.: 5.9232663 Overlap : 0.00
HSI saturation (457)	
Residential areas(black) – Water body (blue)	 HSI Transformation Saturation(R=Layer 4,G=Layer 5,B=Layer 6) (NN) [0.3725490 - 0.4588235] StdDev.: 0.02496683214 [0.545 - 0.8117647] StdDev.: 0.06123659418 Overlap : 0.00
Residential areas (black) – Paddy (blue)	 HSI Transformation Saturation(R=Layer 4,G=Layer 5,B=Layer 6) (NN) [0.3725490 - 0.4588235] StdDev.: 0.02496683214 [0.4941176 - 0.5568627] StdDev.: 0.01645667278 Overlap : 0.00
Residential areas (black) – Vegetation (blue)	 HSI Transformation Saturation(R=Layer 4,G=Layer 5,B=Layer 6) (NN) [0.3725490 - 0.4588235] StdDev.: 0.02496683214 [0.553 - 0.7333333] StdDev.: 0.04197416688 Overlap : 0.00

Table 2 indicates information about comparing membership functions of three indices for extracting residential areas. IBI index spectral curve of residential areas and others are the same with overlapping rate from 0.10 to 0.93, and NDBI, the line graphs of built-up and water body are similar to built-up and vegetation ones with spectral range is distinguished. Meanwhile, line graphs of residential areas and paddy fields have been mixed between 81.329 and 93.612. The HSI(saturation) is based upon combination of R as band 4; B as band 5 and G as band 7, membership function of residential areas range from 0.372 to 0.458, whereas membership functions of water body and vegetation are greater than 0.491. Overall, the graphs show that HSI (saturation) is applied for extracting residential areas. The objects image with HSI index range from 0 to 0.49 is defined as residential areas.

The NDVI and RVI vegetation indices are formulated by red band (R) and near-infrared band (NIR) (Jackson, and Huete 1991). They are considered as useful indices for discriminating the differences between vegetation and non-vegetation. NDVI and RVI values are determined by the following formula:

$$NDVI = \frac{NIR - R}{NIR + R} \tag{8}$$

$$RVI = \frac{NIR}{R} \tag{9}$$

Image objects with NDVI $\geq$ 0.34 and RVI $\geq$ 1.8 are vegetation; the rest with other values is paddy.

4. Results and accuracy assessment

Accuracy assessment was performed for both segmentation and classification results. In the segmentation, a visual approach was carried out to compare the partitioned image with the topography map. The accuracy of classification result was defined by a confusion matrix, which was generated by using Congalton's method (Congalton and Green 2000). We selected 75 square plots on the GeoEye image (randomly distributed over the study area) as samples for assessment. The size of all samples covering the whole 34.8 ha area is about 1.9% of the study area. The confusion matrix (see table 3) shows that the overall accuracy of the image classification is 84.6%. This is a proper result for peri-urban areas; especially user's accuracy of residential areas is 80.80%. Therefore, the object-oriented classification with HSI index is good for residential areas determination.

Fig. 5. Classification result

Table 3. Confusion matrix of proposed method

	Paddy	Res.areas	Veg.	Pond	River	User's Accuracy
Paddy	859500	9800	123700	8700	0	0.858041
Res.areas	97400	595800	42300	1800	0	0.808084
Veg.	94800	92500	965200	12600	0	0.828427
Pond	24300	900	2700	401600	0	0.935041
River	0	0	0	25300	126900	0.833771
Producer's Accuracy	0.798792	0.8523605	0.851221	0.892444	1	0.846004 (Overall)

5. Conclusion

The advantage of object-oriented approach based on fuzzy logic classification is using individual features of each image band. This approach is used to distinguish land cover by hierarchical structures of objects. As a result, this method has gained high accuracy for all the classes.

The accuracy of classification result relies on the quality of segmentation and selection of indices. The better segmentation result will lead to a higher accuracy of classification process and vice versa.

In remotely sensed image classification, information classes often overlap with each other in feature space. The rule set of object-oriented classification on paddy, pond, vegetation, residential areas and river based on spectra and some indices. Comparing membership functions are suitable choices for detecting specific objects in the image. The results also show that HSI index is appropriate and efficient for residential areas classification with the overlapping value of other classes on membership functions to be 0.

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