AN OBJECT-BASED SEMANTIC CLASSIFICATION METHOD OF HIGH RESOLUTION SATELLITE IMAGERY USING ONTOLOGY

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ABSTRACT:

Geographic Object-Based Image Analysis (GEOBIA) techniques have become increasingly popular in recent years and are able to incorporate and develop ontology model within the classification process. They have been claimed to represent a paradigm shift in remote sensing interpretation. Nevertheless, it is lack of formal expression and objective modelling of the whole process of GEOBIA, and lack of the study of semantic classification method using ontology. A major reason is the complexity of the process of GEOBIA. The study has put forward an object-based semantic classification method of high resolution satellite imagery using ontology that aims to fully exploit the advantages of ontology to GEOBIA. A detailed workflow has been introduced that has three steps: ontology modelling, initial classification based on data-driven machine learning method, and semantic classification based on knowledge-driven expert rules method. The whole process of GEOBA is organized organically and expressed explicitly using ontology, and the semantic relations are expressed in the formal language that the computer could operate. Image objects are classified based on ontology model and using machine learning method and expert rules. From the result it is well understood that the method enhances the existing GEOBIA techniques with the help of the ontology, which expresses and organizes the whole process of GEOBIA, and establishes their relations, and provides semantic meaning for GEOBIA. In particular, we found that it provides an ontology model and method for further classifications and large scale applications, and the method using ontology is suitable for automatic classification.

1. INTRODUCTION

Geographic object-based image analysis (GEOBIA) is devoted to developing automated methods to partition remote sensing (RS) imagery into meaningful image objects, and assessing their characteristics through spatial, spectral, texture and temporal features, thus generating new geographic information in a GIS-ready format (Hay and Castilla,2008). There has been great progress compared to traditional pixel-based image analysis. GEOBIA has the advantages of having a high degree of information utilization, strong anti-interference, a high degree of data integration, extreme precision of classification, and less manual editing (Hay and Castilla,2006; Robertson and King,2011; Duro et al.,2012; Myint et al.,2011). Over the last decade, advances in GEOBIA research have led to numerous workshops, software packages, and peer-reviewed journal papers; five highly successful biennial international GEOBIA conferences; and a growing number of books and university theses (Addink et al.,2012; Blaschke,2010). It has recently been recognized as a new paradigm in remote sensing (Blaschke et al.,2014).

Ontology is originated in the western philosophy and then introduced into the GIS. The concept of domain knowledge is expressed in the form of machine-understandable and is utilised for semantic modelling, semantic interoperability, knowledge sharing and information retrieval service in the field of GIS (Li et al.,2014; Agarwal,2005). Recently, researchers begin to attach importance to the application of ontology in the field of remote sensing, especially in remote sensing image interpretation, which provides a new means for image classification.

Arvor D. et al. (2013) described how to utilise ontology expert knowledge to improve the automation of image processing and analysed the potential applications of GEOBIA, which can provide theoretical support for remote sensing data discovery, multi-source data integration, image interpretation, workflow management and knowledge sharing. Jesús et al. (2013) built a framework for ocean image classification based on ontology; the framework describes how low and high the level content of ocean satellite images can be modeled with ontology. In addition, decision tree classifiers and rule-based expert systems have been presented. Dejrriri et al. (2012) presented GEOBIA and data mining techniques for non-planned city residents based on ontology. Kohli D. et al.(2012) provided a comprehensive framework that includes all potentially relevant indicators that can be used for image-based slum identification. Forestier et al. (2013) built coastal zone ontology to extract coastal zone with background and semantic knowledge. Kyzirakos et al. (2014) provided wildfire monitoring services and combined satellite images and geospatial data with ontology. Belgiu et al. (2014)

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presented an ontology-based classification method for extracting types of buildings where airborne laser scanning data are employed and obtained effective recognition results. Belgiu et al. (2014) provided a formal expression tool to express object-based image analysis technology through ontology.

However, these studies focuses on some aspect that only expert knowledge or specific geographic entity, which is expressed formally using ontology. It is lack of formal expression and objective modelling of the whole process of GEOBIA, and lack of the study of ontology driven semantic classification method, and the whole process of GEOBIA expressed formally using ontology is rare. Therefore, the study puts forward an object-based semantic classification method of high resolution satellite imagery using ontology that aims to fully exploit the advantages of ontology to GEOBIA.

2. METHODOLOGY

The applied workflow of the object-based semantic classification is organized as follows: in the ontology model building step, the models of remote sensing image, object features, land cover class hierarchy and classifiers are built using the procedure described in Section 2.1 (Step 1, Figure 1), and the ontology frame file is built. Subsequently, the remote sensing image is classified using machine learning method and the initial classification result is imported into the ontology frame file (Step 2, Figure 1), which is described in Section 2.2. In the last step, the initial classification result is reclassified to get the final classification result based on the expert rules (Step3, Figure 1), which is described in Section 2.3.

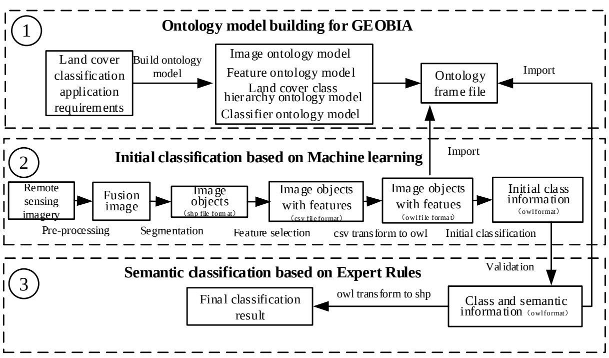

Figure 1. Overview of the methodology followed in this study.

2.1 Ontology Model for GEOBIA

Ontology helps in reducing the semantic gap that exists between the image object domain (Arvor et al., 2013). It is important to combine the whole process of GEOBIA into the knowledge formalization using ontology. The ontology model of remote sensing image, object features, land cover class hierarchy and classifiers are built with orientation toward land cover classification requirements. The information of remote sensing image, land cover class hierarchy, object features and machine learning classifiers is expressed in Ontology Web Language (OWL). The expert rules are expressed in Semantic Web Rule Language (SWRL). The FaCT++ reasoner is used to infer the relationship among all the individuals. The knowledge engineering method and the Protégé software developed by Stanford University are chosen to build the ontology model for GEOBIA. Thus the whole process of GEOBIA is expressed and modelled to form the semantic network model.

2.1.1 Ontology Model of the Remote Sensing Image: The ontology construction of the remote sensing image is as follows. 1) A list of important terms and concepts, such as satellite, sensor, image, spatial resolution and spectral resolution, are created. 2) The spectral resolution is defined through the top–down method. It is divided into visible and infrared. Visible is divided into blue, green and red, infrared is divided into near infrared, far infrared and thermal infrared. 3) The slot is defined. The slot includes associated_to, from_band, from_satellite, from_sensor, has_spatial_resolution and has_spectral_resolution. 4) The slot surface is defined. The range and scope of the slot are defined which is described in table 1.

Table 1. The range and scope of the slot

Slot	Range	Scope
associated_to	Region	Image
from_band	Image	—
from_satellite	Sensor	Satellite
from_sensor	—	Sensor
has_spatial_resolution	—	Spatial_resolution
has_spectral_resolution	—	Spectral_resolution

2.1.2 Ontology Model of the Image Object Features: It makes use of the feature concepts used in the eCognition software to develop a general upper level ontology (Definiens Imaging GmbH, 2011). The image object features are defined through the top–down method and are divided into six categories: LayerProperty, GeometryProperty, PositionProperty, TextureProperty, ClassProperty, and ThematicProperty. Each class continues to segmentation. For instance, the TextureProperty is divided into ToParentShapeTexture and Haralick. Haralick is divided into GLCMHom, GLCMContrast and GLCMEntropy. It is shown in figure 2.

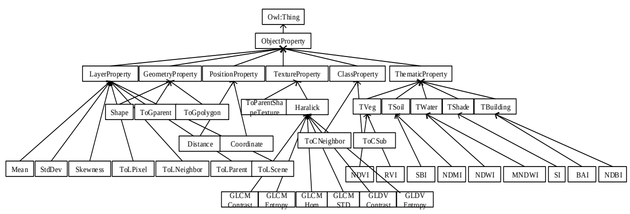

Figure 2. Object features hierarchy in ontology (Every subclass is shown with an “is.a” relationship).

2.1.3 Ontology Model of the Land Cover Class Hierarchy: It makes use the Land Cover Classification System (LCCS) (Di,2005)concepts to develop a general upper level ontology. It includes the various land cover classification scheme. The upper level classes defined in the ontology based on LCCS are shown in Figure 3. Detailed classes can be defined according to the actual situation.

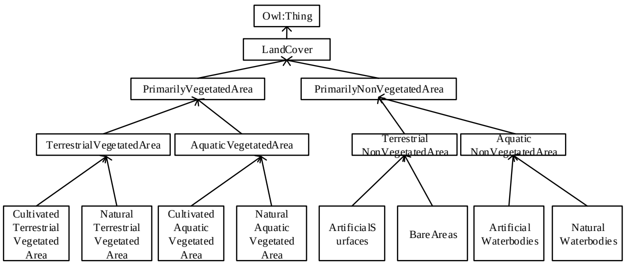

Figure 3. Land cover class hierarchy in ontology(Every subclass is shown with an "is.a" relationship).

2.1.4 Ontology Model of the Classifiers: Ontology is employed to express two typical algorithms, namely, decision tree and expert rules.

(1) Ontology model of the decision tree classifier
1) A list of important terms and concepts of the decision tree classifier is created, such as DecisionTree, Root, Node and Leaf. 2) The slot is defined. The slot includes GreaterThan, GreaterThanOrEqual, LessThan and LessThanOrEqual. 3) The individuals of the node of the decision tree are created according to the land cover class hierarchy. The ontology model of the decision tree classifier is shown in figure 4.

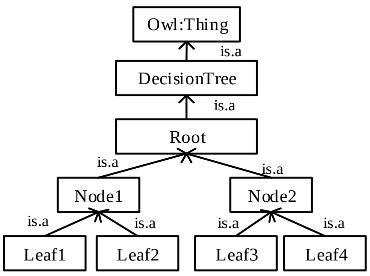

Figure 4. Ontology model of the decision tree classifier

(2) Ontology model of the expert rules
The process of modelling expert rules includes building mark rules and expert rules. Building mark rules is based on a semantic concept, and the process is from low-level features to semantic concepts. Expert rules is obtained based on mark rules and expert knowledge, the process is from advanced features to the identification of land cover. The ontology model of mare rules and expert rules are shown as follows:

(a)Ontology model of the mark rules
The objects are modelled from different semantic aspects according to the common sense knowledge, it is divided into strip and planar from the morphology; regular and irregular from the shape; smooth and rough from the texture; light and dark from the brightness; high, medium and low from the height; adjacent, disjoint and containing from the position relationship. The ontology model of the mark rules is shown in figure 5.

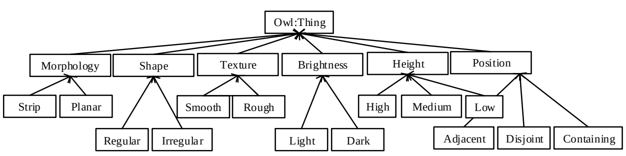

Figure 5. The mark rules in ontology (Every subclass is shown with an "is.a" relationship).

The mark rules are expressed in SWRL, and the semantic relationships between the object features and the classes are built. For example, the Brightness type is expressed in SWRL as follows:

- Mean (?x, ?y), greaterThanOrEqual(?y, 0.38) -> Light (?x);
- Mean (?x, ?y), lessThan (?y, 0.38) -> Dark (?x);

It means, Mean of an object greater than or equal 0.38 denotes Light, whereas that less than 0.38 denotes Dark.

(b)Ontology model of the expert rules
The expert rules for eight types of land cover are acquired from literature. In general, the expert rules are as follows:

- Fieldland = Regular + Planar+ Smooth+ Dark+ Low + Adjacent to Road ;
- Woodland = Irregular+ Planar + High + Rough + Dark + Adjacent to Fieldland;
- Orchardland = Regular + Smooth + Planar + Dark + Adjacent to Fieldland;
- Grassland= Irregular + Planar +Smooth +Dark+ Low + Adjacent to Building;
- Building = Regular + Planar + Rough+ High +Light + Adjacent to Road;
- Road= Regular + Strip+Smooth+ Light + Low;
- Bareland = Irregular +Planar +Rough + Lght + Low;
- Water =Irregular + Planar + Smooth + Dark + Low+Normal Differential Water Index(NDWI).

The expert rules are expressed in SWRL, and the semantic relationships between the mark rules and the classes are built. For example, the Fieldland is expressed in SWRL as follows:

- Regular (?x), Planar (?x),Smooth(?x),Darklight(?x),Low(?x) -> Field (?x);

It means, an image object with Regular, Planar, Smooth, Dark and Low features is a Fieldland. C(? X), X is an individual of C, P(? X? Y) represents attributes, and x and y are variables.

The other classifiers such as support vector machine (SVM), random forest could be expressed in SWRL. And the ontology model of the expert rules should be extended and supplemented to realize the semantic understanding of various category of land cover.

2.1.5 Semantic Network Model: The entire semantic network model is formed through the construction of the remote sensing image, land cover class hierarchy, image object features and the classifiers. It is shown in figure 6.

Figure 6. The semantic network model

The semantic network model is a type of directed network graph that expresses knowledge through the concept and its semantic relations. It has the following advantages. First, the concepts, features and relationships of geographical entities are expressed explicitly, it could reduce the semantic gap between low-level features and high-level semantics. Second, it can be traced back to the parent object, child objects and neighborhood objects through their relationships. Third, it is easy to express semantic relations by computer operable formal language (Tonjes et al., 1999).

2.2 Initial Classification based on Data-driven Machine Learning

The process includes pre-processing, segmentation, feature selection, sample collection and initial classification. The software PCI Geomatica developed by the Canadian PCI company is chosen to be the image pre-processing tool, it is good at geometric correction and image fusion. The software FeatureStation developed by the Chinese Academy of Surveying and Mapping is chosen to be the image segmentation and classification tool, it is good at segmentation and decision tree classification. The Protégé plugin developed by Jesús M. A. J is chosen to be the format transformation and semantic classification tool.

2.2.1 Preprocessing: The test site is in Ruili City, Yunnan Province in China. We utilised panchromatic (Pan) ZY-3 data with 2.1 m resolution and multispectral (MS) ZY-3 data with 5.8 m resolution (with four bands, including blue, green, red and near-infrared), which were acquired in April 2013. ZY-3 MS imagery is obtained and geometrically corrected to the Universal Transverse Mercator (UTM) projection and then re-sampled to 2.1 m to match the Pan image pixel size; it is then fused by using the Pansharp fusion method and the PCI Geomatica software. Figure 7 shows the resulting fused image based on MS bands 4 (near-infrared), 3 (red) and 2 (green). The part of the city selected for the study is characterised by classes identified as fieldland, woodland, grassland, orchardland, bareland, road, building and water.

Figure 7. The fusion image of ZY-3(false color)

2.2.2 Image Segmentation: The objective of image segmentation is to keep the heterogeneity within objects as small as possible, at the same time preserving the integrity of the object. The fusion image is segmented using the G-FNEA method which is based on graph theory and fractal net evolution approach (FNEA) within the FeatureStation software. The method could get high efficiency and maintain good feature boundaries (Yang et al. 2015).

There are three parameters in the G-FNEA method: T (scale parameter), w_{colour} (weight factor for color heterogeneity), and w_{compt} (weight factor for compactness heterogeneity). A high T value indicates fewer, larger objects than a low T value. The color heterogeneity w_{colour} describes the spectral information, which is used to indicate the degree of similarity between two adjacent objects. The higher the w_{colour} value, the greater influence color has on the segmentation process. The w_{compt} value reflects the degree of clustering of the pixels within a region: the lower the value, the more compact the pixels are within the region. It should be noted that the scale parameter is considered to be the most important factor for classification as it controls the relative size of the image objects and has a direct effect on the overall classification accuracy.

There are some methods on automatic determination of appropriate segmentation parameters, such as Estimation of Scale Parameters (ESP)(Drăguţ, L. et al.,2010), Optimised image segmentation (Gao Y. et al.,2011). In the study, the selection of image segmentation parameters is based on an iterative trial-and-error approach that is often utilized in object-based classification (Myint et al. 2011; Pu et al.2011). It can get good segmentation result with T=100, w_{colour}=0.8, and w_{compt}=0.3.

2.2.3 Feature Selection: The selection of appropriate object features can be based on experience and user knowledge, or can make use of feature-selection algorithms. The Random Forest classifier is capable of handling large numbers of features and a relatively small number of samples (Stumpf, A. et al.,2011). In this study, we make use of experience and user knowledge to guide the initial selection of object features, and thus keep to the following four rules: (1) the most important features of an object are the spectral characteristics, which are independent of test area and segmentation scale, (2) the ratio of bands is closely related to vegetation and non-vegetation, (3) the effect of the shape feature, which is used to reduce the image classification error rate, is small; therefore, it becomes effective when the segmentation scale reaches a certain level, (4) the auxiliary data is dependent on the scale; the smaller the scale, the more important the auxiliary data. Based on the above four rules, twenty-nine features (e.g., ratio, mean, NDWI, Normalized Difference Vegetation Index, homogeneity, and brightness) are selected and stored in Shpfile format, and then converted to OWL format.

2.2.4 Initial Classification: The C4.5 decision tree method is used for the construction of a decision rule, which includes generation stage and pruning stage (figure 8).

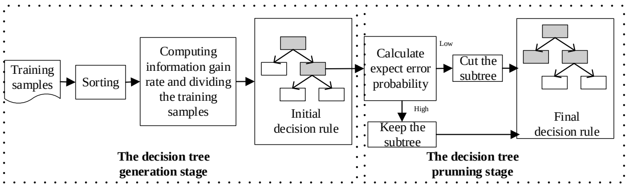

Figure 8. Decision rule based on C4.5 decision tree classifier

Stage 1：The generation of decision tree

1) The training samples are ordered in accordance with the "class, features of sample one, features of sample two, etc". The training and testing samples are selected by visual interpretation of imagery with their selection being controlled by the requirement for precision and representativeness, and by their statistical properties.

2) The training samples are divided. The information gain and information gain rate of all the features of training samples are calculated. The feature is taken as the test attribute, whose information gain rate is the biggest and its information gain is not lower than the mean of all the features, and the feature is taken as a node and leads to a branch. In this circulation way, all the training samples are divided.

3) The generation of decision tree. If all the training samples of the current node belongs to a class, the class is marked as a leaf node and marked for the specify feature; It runs on the same way, at last, it forms a decision tree until all the data of a subset are recorded in the main feature and their feature value are the same, or there is no feature to divide again.

Stage 2: The pruning of decision tree

The possible error probability of sub-node not leaf-node is calculated, the weights of all the nodes are assessed. The subtree is kept if the error rate causes by cutting off the node is high, otherwise, the subtree is cut off. At last, the decision tree with the least expected error rate is the final decision tree which is shown in figure 9. The decision tree is expressed in OWL is shown in figure 10.

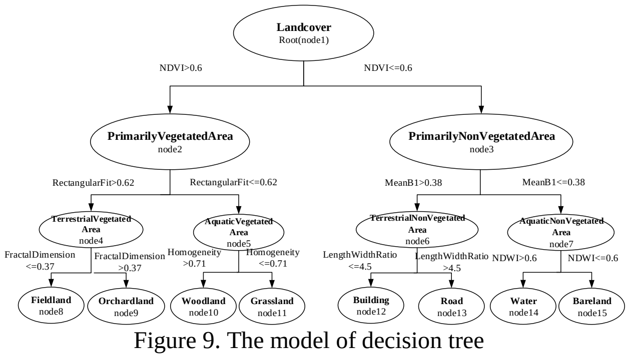

Figure 9. The model of decision tree

```
Individual:Node1
  Types:
        Root
  Facts:
        GreaterThan    Node2,
        LessThanOrEqual Node3,
        NDVI    0.60
Individual:Node2
  Types:
        Node
  Facts:
        GreaterThan    Node4,
        LessThanOrEqual Node5,
        RectangularFit  0.62
Individual:Node3
  Types:
        Node
  Facts:
        GreaterThan    Node6,
        LessThanOrEqual Node7,
        MeanB1    0.38
Individual:Node4
  Types:
        Node
  Facts:
        LessThanOrEqual Node8,
        GreaterThan    Node9,
        FractalDimension    0.37
Individual:Node5
  Types:
        Node
  Facts:
        GreaterThan    Node10,
        LessThanOrEqual Node11,
        Homogeneity    0.71
Individual:Node6
  Types:
        Node
  Facts:
        LessThanOrEqual Node12,
        GreaterThan    Node13,
        LengthWidthRatio    4.5
Individual:Node7
  Types:
        Node
  Facts:
        GreaterThan    Node14,
        LessThanOrEqual Node15,
        NDWI    0.6
Individual:Node8
  Types:
        Fieldland
Individual:Node9
  Types:
        Orchardland
Individual:Node10
  Types:
        Woodland
Individual:Node11
  Types:
        Grassland
Individual:Node12
  Types:
        Building
Individual:Node13
  Types:
        Road
Individual:Node14
  Types:
        Water
Individual:Node15
  Types:
        Bareland
```

Figure 10. The decision tree is expressed in OWL

The above decision rule is import into the ontology framework, all objects are classified using the decision rule, and the initial classification result is expressed in OWL file format.

2.3 Semantic Classification based on Knowledge-driven Expert Rules

On the basis of the initial classification, each object is reclassified by expert rules in SWRL to obtain the semantic information.

2.3.1 Expert Rules Building: The mark rules and expert rules of the eight classes of the test site are expressed in SWRL according to the ontology model of the above mark rules and expert rules.

1) Mark rules are shown as follows:

- RectFit (?x, ?y), greaterThanOrEqual(?y, 0.5) -> Regular (?x);
- RectFit (?x, ?y), lessThan(?y, 0.5) -> Irregular (?x);
- LengthWidthRatio(?x, ?y), greaterThanOrEqual(?y, 1) -> Strip(?x);
- LengthWidthRatio(?x, ?y), lessThan (?y, 1) -> Planar(?x);
- Homo (?x, ?y), greaterThanOrEqual(?y, 0.05) -> Smooth (?x);
- Homo (?x, ?y), lessThan (?y, 0.05) -> Rough(?x);
- Mean (?x, ?y), greaterThanOrEqual(?y, 0.38) -> Light (?x);
- Mean (?x, ?y), lessThan (?y, 0.38) -> Dark (?x);
- MeanDEM(?x, ?y), greaterThanOrEqual(?y, 0.6) -> High(?x);
- MeanDEM (?x, ?y), lessThan(?y, 0.2) -> Low(?x);
- MeanDEM (?x, ?y), greaterThanOrEqual(?y,0.2), lessThan(?y, 0.6) -> Middle(?x).

It means, RectFit of an object greater than 0.5 denotes Regular shape, whereas that less than 0.5 denotes Irregular shape.

2) Expert rules are shown by the following:

- Regular (?x), Planar (?x),Smooth(?x),Dark (?x),Low(?x) -> Fieldland (?x);
- Irregular (?x), Planar (?x),Rough(?x),Dark (?x),High(?x)-> Woodland (?x);

- Regular (?x), Planar (?x),Smooth(?x),Dark (?x),Middle(?x) -> Orchardland (?x);
- Irregular (?x), Planar (?x), Smooth (?x),Dark (?x),Middle(?x) -> Grassland (?x);
- Regular (?x), Planar (?x), Rough (?x), Light(?x), High(?x)-> Building(?x);
- Regular (?x), Strip (?x), Smooth (?x), Light(?x),Low(?x) -> Road(?x);
- Irregular (?x), Planar (?x), Rough (?x), Light (?x), Low (?x) -> Bareland(?x);
- Irregular (?x), Planar (?x), Smooth (?x), Dark (?x), Low (?x) -> Water(?x).

For example, an object with Regular, Planar, Smooth, Dark and Low features is a Fieldland. C(? X), X is an individual of C, P(? X? Y) represents attributes, and x and y are variables.

2.3.2 Sematic Classification: The initial classification result is reclassified to get the final classification result based on the expert rules. The exported OWL objects are a way to preserve the semantics of the features the image objects exhibits. The classified objects already exported in OWL format help in retrieving the object features of interest (Figure 11).

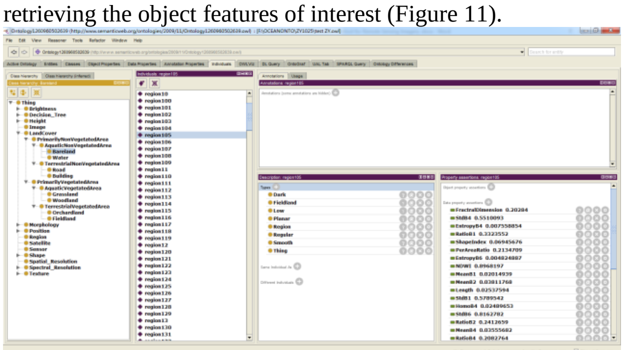

Figure 11. The sematic information of "region 105"

The classification information in OWL format is transformed to Shpfile format which is shown in figure 12.

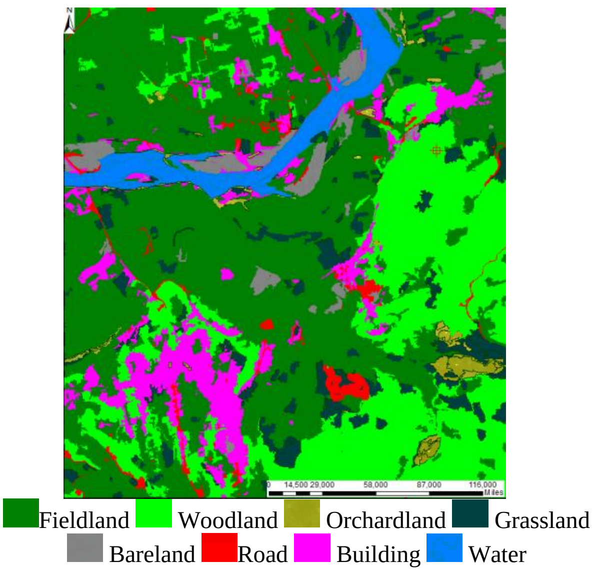

Figure 12. Land cover classification map of ZY-3 in the test site

3. ANALYSIS AND DISCUSSION

Accuracy assessment is necessary to validate the result. Error matrix based on samples is selected and used for performing accuracy assessment. The samples are selected depending on the visual interpretation performed over the image. Typical samples are collected from each land-cover type, with their selection being controlled by the requirement for precision and representativeness, and by their statistical properties. The requirement for precision ensures that the samples are accurately selected and that they actually come from the same types of land-cover, the requirement for representativeness ensures that the selected samples are typical of each land-cover type, and the statistical properties ensure that the samples selected are truly representative of the full distribution within each land-cover type. This procedure ensures that similar numbers of samples are used to represent each land-cover type, for both training and testing. Some samples from each land-cover type serve as the training samples used to derive the decision tree, while the others are used to test the classification accuracy. In the object-based image analysis, the sample refers to an object. The error matrix of the test is shown in table 2.

Table 2. The error matrix of the test

	Fieldland	Orchardland	Woodland	Grassland	Building	Road	Bareland	Water	Sum	Production accuracy (%)
Fieldland	52	2	0	4	0	1	0	0	59	88.14
Orchardland	5	57	2	1	0	0	0	0	65	87.69
Woodland	0	4	40	0	0	3	0	0	47	85.11
Grassland	3	1	3	35	0	3	1	0	46	76.09
Building	0	0	0	0	30	2	3	0	35	85.71
Road	0	0	0	0	3	27	2	0	32	84.38
Bareland	0	0	0	1	3	1	47	0	52	90.38
Water	0	0	0	0	4	0	0	30	34	88.24
Sum	60	64	45	41	40	37	53	30	370	
User accuracy (%)	86.67	89.06	88.89	85.37	75	72.97	88.68	100		

A graphical representation of the classification confusion matrix is shown in Figure 13.

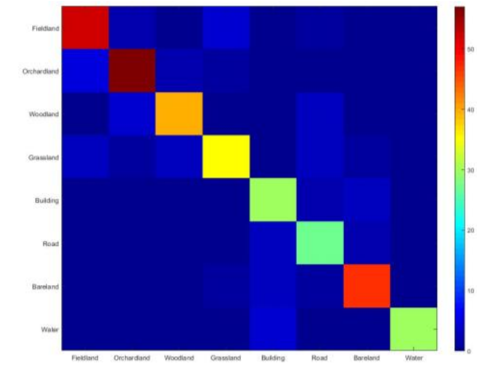

Figure13. Graphic representation of the classification confusion matrix. Rows represent reference class and columns classified data.

The user's and producer's classifications are shown in figure 14.

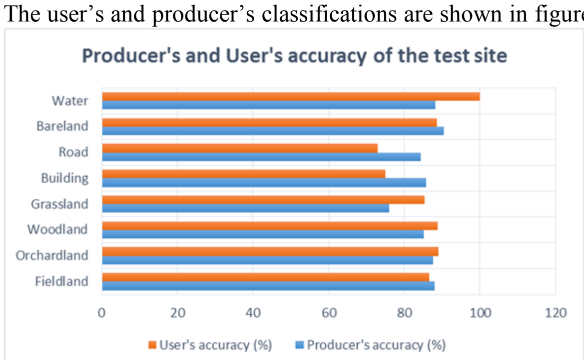

Figure 14. User's and producer's accuracies for land cover classification

The confusion matrix shows that the classification method can distinguish the eight types of land cover, the total accuracy is 85.95%. Road had a poor performance and presented several misclassification with and Building and Bareland classes. And Grassland had a poor performance and presented several misclassification with and Fieldland, Woodland and Road classes. Grassland class producer's accuracy is the lowest due to the confusion with classes Fieldland,Woodland and Road. Bareland presented the highest producer's accuracy due to their special spectral and shape comparing with others. The user's accuracy of Road is the lowest due to the misclassification with Building and Bareland classes. Given that the method employs expert rules to restrict, it reduces misclassification and leakage to a certain extent. However, obvious misclassification phenomena of Building and Road exists because the two types of spectral are close. The reason for low classification accuracy for Road is that the road in the study area is located in the Southern suburb of Ruili, which is narrow; thus, the method misinterpretes the spectrum of the Road as the Building spectrum. The shape is further utilised to restrict and high-level information is employed to distinguish.

The uncertainty of the method includes the determination of a segmentation scale, the importance of features, the choice of classifiers, and the determination of parameters. This study focuses on the implementation process of the method, and overall accuracy is used to evaluate the feasibility of the method. It should be pointed out that, various elements of GEOBA on the influence of this method is beyond the scope of the study.
From the result it is well understood that the ontology model helps in combining various elements of GEOBIA. It also helps in transferring information from one source to other. The ontology model of image object features uses the structure of eCognition as the upper level knowledge to be further extended. The ontological framework proposed in the study uses the concepts of Land Cover classification System (Di, 2005) knowledge as the upper level knowledge to be further extended. It only builds the decision tree ontology model and expert rule ontology model, they should be extended and supplemented to realize the semantic understanding of various category of land cover. The process of image interpretation in geographic domain is an expert process and many of the parameters need to be tuned depending on the problem domain (Arvor et al., 2013). Thus to improve the GEOBIA, the overall elements of GEOBIA should be modelled using ontology.

4. CONCLUSIONS AND OUTLOOK

The study has put forward an object-based semantic classification method of high resolution satellite imagery using ontology that aims to fully exploit the advantages of ontology to GEOBIA. A detailed workflow has been introduced that includes three steps: ontology modelling, initial classification based on decision tree machine learning method, and semantic classification based on expert rules. All kinds of elements for GEOBA were organized organically and expressed explicitly using ontology, and semantic relations were expressed in the OWL and SWRL formal language that the computer could operate. Image objects were classified based on ontology model and using decision tree and expert rules. It could supply objective model and new method for remote sensing image classification, and promote its automation development.

The ontology model of remote sensing imagery, image object feature, land cover class hierarchy and classifiers were built by use of OWL and SWRL, thus the entire semantic network model was built, which lays an ontology model for object classification. These knowledge for model are acquired either from literature (Belgiu,2014) or by using data mining techniques (Maillot, 2004; Belgiu, 2014). Ontology not only proves to be a source of knowledge the domain needs but also fills the semantic gap which exists in performing image classification (Blaschke et al., 2014). Image objects were classified by combining decision tree and experts rules, which not only provide the classification result of the geographical objects, but also master the semantic information of the geographical entities, and realize the reuse of the domain knowledge and the semantic network model. The test has proved the feasibility of the method. The authors are confident that the method has the potential to be applied to the land cover monitoring at regional and global scales.

In addition, the uncertainty of remote sensing information is an important and challenging research field in which many important theoretical and methodological issues need to be addressed. Due to the limitation of our research time and level, this research only discusses the classification that brings uncertainty. However, uncertainty remains in each stage of GEOBIA, an issue which is becoming a matter of concern for more and more researchers, especially for experts in GEOBIA.
Nevertheless, it is an emerging method that is still in the process of development and improvement. Further in-depth studies may be required to (a) improve and refine the ontology model, (b) build the ontology model for new classifiers such as deep learning, random forests and random fern, (c) investigate the factors influencing classification, such as the spatial scale, the segmentation method employed, and the choice of samples and object features, and (d) to investigate the automation and 'geo-intelligence' potential of the ontology-driven object-based semantic classification method.

The method is knowledge-driven and needs to be shared among the experts so as to enhance and share. Thus it is recommended that future researchers and experts utilize the existing ontology to form more domain specific ontology, and to enhance the automation of GEOBIA.

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