

An object-oriented classification method of high resolution imagery based on improved AdaTree

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Abstract. With the popularity of the application using high spatial resolution remote sensing image, more and more studies paid attention to object-oriented classification on image segmentation as well as automatic classification after image segmentation. This paper proposed a fast method of object-oriented automatic classification. First, edge-based or FNEA-based segmentation was used to identify image objects and the values of most suitable attributes of image objects for classification were calculated. Then a certain number of samples from the image objects were selected as training data for improved AdaTree algorithm to get classification rules. Finally, the image objects could be classified easily using these rules. In the AdaTree, we mainly modified the final hypothesis to get classification rules. In the experiment with WorldView2 image, the result of the method based on AdaTree showed obvious accuracy and efficient improvement compared with the method based on SVM with the kappa coefficient achieving 0.9242.

1. Introduction

Remote sensing image classification is a complex process and the method could be divided into two categories: cell-based and object-oriented one. Compared with the cell-based one, object-oriented classification method performs better in high spatial resolution remote sensing image classification. The major steps of object-oriented classification include image segmentation to identify image objects and classification of the identified image objects. ENVI EX using edge-based segmentation and eCognition using FNEA (fractal net evolution approach)-based segmentation are two pieces of frequently-used software dedicated to object-oriented classification. Besides, these two pieces of software provide the classifiers such as SVM and Nearest Neighbor algorithms. As a popular method in data mining, decision tree algorithm is widely used in the remote sensing image classification based on cells^[1-5], but not in object-oriented classification due to lack of support software.

This paper proposed a fast method of object-oriented automatic classification. It used the edge-based segmentation provided by ENVI EX or FNEA-based segmentation provided by eCognition to identify image objects and calculated the values of most suitable attributes of the image objects. Subsequently, AdaTree^[6] algorithm was used as classifier provided by self-developed software (GLC_Info) to classify the image objects. In the AdaTree algorithm, we mainly modified the final hypothesis to get classification rules. In the experiment with WorldView2 image, the classifier of AdaTree was compared with the SVM classifier based on the same image objects extracted by ENVI



EX and same samples. Furthermore, the integration of eCognition segmentation and AdaTree classifier was used in another classification, and kappa coefficient was used to evaluate the results.

2. Image Segmentation

Image segmentation is an important step of object-oriented classification. Using a certain criterion, it divides one remote sensing image into several regions with different attributes. Thousands of image segmentation methods were proposed since 1960s and these methods could be classified as two categories: edge-based and region-based one. Some assistant methods such as multiresolution segmentation and vector field were also used in image segmentation for improvement.

ENVI EX and eCognition are two pieces of frequently-used software devoted to image segmentation. ENVI EX uses an image segmentation method based on edge to identify image objects. It enables image segmentation quickly and accurately and could calculate the attributes of image objects such as spectrum shape and texture. eCognition uses an image segmentation method based on FNEA and multiresolution segmentation to identify image objects and the attributes of image objects calculated for classification provided by eCognition are more than that provided by ENVI EX. These two pieces of software with different methods of segmentation were all used in this paper.

3. AdaTree Algorithm

Decision tree algorithm is a popular algorithm in machine learning. Besides, boosting algorithm^[7] is usually used to improve the accuracy of decision tree algorithm such as C4.5^[8] and CART. Boosting decision trees learning algorithm is one of the most successful combination of decision tree and boosting algorithms such as AdaTree algorithm based on AdaBoost and C4.5 or CART algorithms. In this paper, AdaBoost.M1 algorithm was used as thruster and C4.5 was used as weak classifier. Subsequently, these two algorithms constituted the AdaTree algorithm.

3.1. Algorithm AdaBoost.M1

AdaBoost.M1 algorithm was one of the most frequently-used methods to improve the accuracy of decision trees, and its formal definition followed^[9].

Input: sequence of m examples $\langle(x_1, y_1), \dots, (x_m, y_m)\rangle$ with labels $y_i \in Y = \{1, \dots, k\}$

Weak learning algorithm **WeakLearn**

Integer T specifying number of iterations

Initialize $D_1(i) = 1/m$ for all i .

Do for $t = 1, 2, \dots, T$

1. Call **WeakLearn**, providing it with the distribution D_t .
2. Get back a hypothesis $h_t: X \rightarrow Y$.
3. Calculate the error of h_t : $\varepsilon_t = \sum_{i: h_t(x_i) \neq y_i} D_t(i)$. If $\varepsilon_t > 1/2$, then set $T = t - 1$ and abort loop.
4. Set $\beta_t = \varepsilon_t / (1 - \varepsilon_t)$.

$$5. \text{ Update distribution } D_{t+1}: D_{t+1}(i) = \frac{D_t(i)}{Z_t} \times \begin{cases} \beta_t & \text{if } h_t(x_i) = y_i \\ 1 & \text{otherwise} \end{cases} \quad (1)$$

Where Z_t is a normalization constant (chosen so that D_{t+1} will be a distribution).

$$\text{Output the final hypothesis: } h_{f_m}(x) = \arg \max_{y \in Y} \sum_{t: h_t(x) = y} \log \frac{1}{\beta_t}. \quad (2)$$

3.2. Algorithm C4.5

As used in the classification of remote sensing, the structure of C4.5 was transformed from multi-branches tree to binary tree. Because there is a little training data but a lot of image-objects needed to be classified in the classification of remote sensing image and the accuracy of binary tree is higher

than multi-branches tree although it costs more time^[10]. The formal definition of modified C4.5 in this paper followed.

Input:

Examples D with attributes and labels;

$Attribute_list$, the set of attributes;

$Attribute_selection_method$, the method of selecting attribute and its threshold, in this paper, it was choosing the attribute and its threshold with highest $GainRatio$.

Output: a decision tree

Process:

1. Create a node N ;
2. If all the members of D belonged to the same class C , set N leaf node and class C as its label. If the members of D did not belong to the same class but all attributes of them were the same or the height of decision tree achieved the height set by user, set N leaf node and majority class of D as its label.
3. Calculate middle values of $Attribute_list$ as preliminary thresholds.
4. Calculate the $GainRatio$ of $Attribute_list$ from splitting two parts on the every preliminary threshold and find the best attribute and its threshold with highest $GainRatio$.
5. Split D into two parts D_L and D_R .
6. Repeat above operation on D_L and D_R , until achieved leaf node.
7. Prune tree using EBP^[11] algorithm.

3.3. Combination of AdaBoost.M1 and C4.5

The normal AdaTree algorithm combined with AdaBoost and C4.5 or CART is not close, and the final hypothesis depended on the weights of decision trees but ignores the weight of every leaf node. In this paper, the final hypothesis was modified and converted into rules. Specifically one rule was from one leaf and the weight was given by its prediction accuracy and the weight of decision tree it belong to.

Set rule r covered n_{covers} members of examples and the correct number $n_{correct}$, the accuracy of rule

r was $accuracy(r) = \frac{n_{correct}}{n_{covers}}$ and the weight of rule r $prediction(r)$:

$$prediction(r) = accuracy(r) \times \log \frac{1}{\beta_t} \quad (3)$$

The final hypothesis of AdaTree was:

$$h_{fin}(x) = \arg \max_{y \in Y} \sum_{r: h_r(x)=y} prediction(r) \quad (4)$$

4. Experiment

Data: WorldView 2 image with 8 MUL bands and one PAN band of one region in Shanxi province of China. Soft: ENVI EX eCognition and GLC_Info which was developed to provide the AdaTree classifier. Interpretation signature: artificial area, crop, fallow land, water, forest, grass and bare land.

4.1. Main steps of experiment

First, image was inputted into ENVI EX or eCognition to identify image objects and calculated the values of most suitable attributes of image objects for classification. Second, a certain number of samples labeled with interpretation signature were select from these identified image objects as training data. Third, rules were generated by AdaTree classifier using the training data. Finally, the image objects were classified by the generated rules.

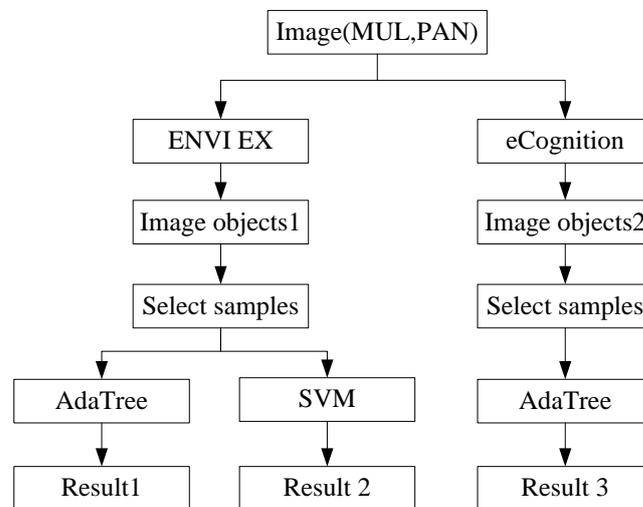


Figure 1. Processes of experiment.

As shown in figure 1, SVM algorithm was chosen as classifier to classify the image objects extracted by ENVI EX compared with AdaTree classifier. The integration of eCognition segmentation and AdaTree classifier was also used in another classification.

4.2. Results and analysis of experiment

Figure 2(RGB: 5, 4, 3) was the WorldView2 image in experiment and figure 3-5 were results. Among these results, figure 3 and figure 4 were based on the same image objects with 35 attributes (table 1) extracted by ENVI EX (Scale level 70, Merge Level 50) and same samples but different classifier: figure 3 was based on AdaTree (boost: 10, tree high 7) while figure 4 was based on SVM (Kernel: Radial Basis 0.02,100,0), figure 5 was based on the image objects with 43 attributes (table 2) extracted by eCognition (Scale 80) and AdaTree (boost: 10, tree high 7).



Figure 2. Original image.

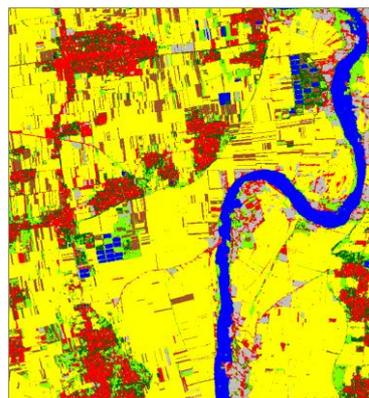


Figure 3. Result based on ENVI EX and AdaTree.

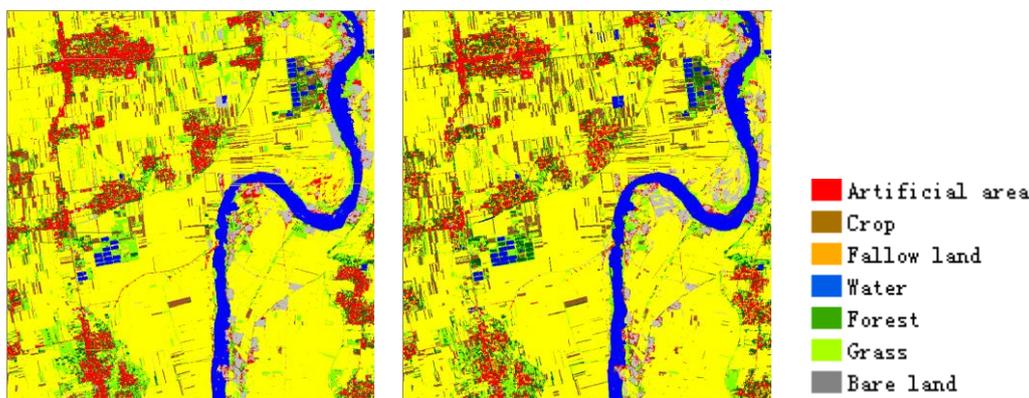


Figure 4. Result based on ENVI EX and SVM.

Figure 5. Result based on eCognition and AdaTree.

Table 1. Attributes of image objects selected in ENVI EX.

Attributes	
Spectrum	AVG Band 1-9, STD Band 1-9, BandRatio 5/8, HUE, Saturation, Intensity
Shape	Area, Length, Compact, Convexity, Solidity, Elongation, Rect Fit, Maindir, Majaxislen
Texture	TX_Mean, TX_Range, TX_Varianc, TX_Entropy

Table 2. Attributes of image objects selected in eCognition.

Attributes	
Customized	NDVI, NDWI
Layer Values	Mean(Brightness, Layer 1-9, Max diff), Standard deviation(Layer 1-9), Hue, Saturation, Intensity
Geometry	Extent(Area, Border length, Length, Length/Thickness, Length/Width, Number of pixels, Rel. Border to image Border, Thickness, Volume, Width), Shape(Asymmetry, Border index, Compactness, Density, Elliptic Fit, Main direction, Rectangular Fit, Roundness)

Table 3. Accuracy of classification.

Segment soft	ENVI EX		eCognition
	AdaTree	SVM	AdaTree
Kappa	0.9242	0.8979	0.9398

Because random function was used in AdaTree algorithm, the results using AdaTree were different if rules were created several times. One of 5 results of AdaTree was selected in this paper such as figure 5 and figure 7 and the kappa coefficient concern AdaTree in table 3 was the average of 5 results. Table 3 showed that, in the experiment, the accuracy of result using AdaTree was better than that using SVM based on the same image objects and samples, and the accuracy of result using eCognition was better than that using ENVI EX based on the same classifier. Furthermore, the accuracy was not the only criterion of remote sensing object-oriented classification but also the effect of segmentation in

application, thus, how to choose the most suitable segmentation and good classifier were the keys of remote sensing object-oriented classification. The classifier of AdaTree was a relatively good classifier whether with ENVI EX or eCognition in remote sensing object-oriented classification.

5. Conclusion

The Object-oriented classification is the main method of high spatial resolute remote sensing classification. Image segmentation and image objects classification are its main steps. This paper proposed a fast method of object-oriented automatic classification and it was an integration of image segmentation and the classifier of AdaTree. The experiment with WorldView2 image showed that the AdaTree classifier outperformed SVM classifier based on the same image objects and samples. Furthermore, the classifier of AdaTree performed well no matter using the image objects extracted by edge-based or FNEA-based segmentation.

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