A SEMI-AUTOMATIC RULE SET BUILDING METHOD FOR URBAN LAND COVER CLASSIFICATION BASED ON MACHINE LEARNING AND HUMAN KNOWLEDGE

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ABSTRACT:

Classification rule set is important for Land Cover classification, which refers to features and decision rules. The selection of features and decision are based on an iterative trial-and-error approach that is often utilized in GEOBIA, however, it is time-consuming and has a poor versatility. This study has put forward a rule set building method for Land cover classification based on human knowledge and machine learning. The use of machine learning is to build rule sets effectively which will overcome the iterative trial-and-error approach. The use of human knowledge is to solve the shortcomings of existing machine learning method on insufficient usage of prior knowledge, and improve the versatility of rule sets. A two-step workflow has been introduced, firstly, an initial rule is built based on Random Forest and CART decision tree. Secondly, the initial rule is analyzed and validated based on human knowledge, where we use statistical confidence interval to determine its threshold. The test site is located in Potsdam City. We utilised the TOP, DSM and ground truth data. The results show that the method could determine rule set for Land Cover classification semi-automatically, and there are static features for different land cover classes.

1. INTRODUCTION

Classification rule set is an important method for remote sensing image classification (Forester, 2012). Rau presented a semiautomatic landslide recognition method using rule set, and validated that the rule set was suitable for various landslide (Rau, 2014). Ziaei presented a rule-based parameter aided with object-based classification approach for extraction of building and roads from WorldView-2 images (Ziaei, 2014). Yu explored the potential role of feature selection in global land-cover mapping (Yu, 2016). Chen measured the effectiveness of various features for thematic information extraction from very high resolution remote sensing imagery (Chen, 2015). However, these methods usually use semiautomatic detection, empirical description and fuzzy function classification. The whole process not only needs supervision, but also requires manual production. Against this background, the next section discusses a semi-automatic rule set building method based on machine learning and human knowledge. The use of machine learning is to build rule sets effectively which will overcome the iterative trial-and-error approach. The use of human knowledge is to solve the shortcomings of existing machine learning method on insufficient usage of prior knowledge, and improve the versatility of rule sets. Urban Land-cover classification test is carried out in order to validate the performance of the method.

2. METHOD

2.1 Rule Set based on Machine Learning

2.1.1 Feature Selection based on Random Forest: The Random Forest (RF) machine learning method is an ensemble classifier developed by Leo Breiman in 2001, based on multiple decision trees. It is a relatively new, non-parametric, data-driven classification method that can create a classification model automatically by learning and training using samples provided by the RS expert, without requiring any prior input (Breiman, 2001). It has the ability to analyze complex features and is robust for noisy and missing data; it is also able to estimate the importance of features and has a faster learning speed and greater accuracy than other similar algorithms that are currently popular (Breiman, 2001).

The RF classifier offers an internal feature evaluation step, through which it is able to estimate the importance of a particular feature, and to subsequently guide the construction of classification rules using significant features only, whereas a general classification method does not offer any form of feature evaluation. It is also able to use a smaller number of features and thus reduce computing time and memory requirements, with no detrimental effect on performance. The importance of the features is estimated by the RF algorithm, the difference between the current OOB (Out Of Bag) error and the previous OOB error is taken to represent the importance of the variable (Verikas, 2011). Variables with higher values are considered to be more important to the classification than those with lower values. Given a sample subset (s=1,2,…,S) the

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The computation of the importance value \( D_j \) of feature \( x_j \) is as follows:

(a) When \( s = 1 \), the OOB data \( L^{oob}_{oob} \) are classified by decision tree \( T_s \), and the classification number is recorded as \( N^{oob}_{oob} \).

(b) For variable \( x_j, j=1,2,...,N \). When \( x_j \) is changed, then \( L^{oob}_{oob} \) is also changed and recorded as \( L^{oob}_{oob} ; L^{oob}_{sj} \) is classified by decision tree \( T_s \) and the classification number is recorded as \( N^{oob}_{oob} \).

(c) For \( s=2,3,...,S \), repeat steps (a) and (b).

(d) The formula for the importance value \( (D_j) \) of feature \( x_j \) is then:

\[
D_j = 1/s \sum_{oob} (N^{oob}_{oob} - N^{oob}_{oob})
\]

### 2.2 Rule Set based on Human Knowledge

The description and decision rules of eight land-cover types are shown in Table 1.

<table>
<thead>
<tr>
<th>Description</th>
<th>Rule Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Field</td>
<td>Regular ∩ Planar ∩ Smooth ∩ Low ∩ Smooth ∩ Dark ∩ Low ∩ adjacentToRoading.</td>
</tr>
<tr>
<td>Orchard</td>
<td>Regular ∩ Planar ∩ Smooth ∩ Dark ∩ Medium ∩ adjacentToFiel d.</td>
</tr>
</tbody>
</table>

For example, mark rules are shown as follows:
- RectFit(?x, ?y), greaterThanOrEqual(?y, 0.5) -> Regular (?x);
- RectFit(?x, ?y), lessThanOrEqual(?y, 0.5) -> Regular (?x);
- Length WidthRatio(?x, ?y), greaterThanOrEqual(?y, 1) -> Strip(?x);
- Length WidthRatio(?x, ?y), lessThanOrEqual(?y, 1) -> Planar(?x);

This means RectFit of an object >0.5 denotes Regular shape, where ≤0.5 denotes Irregular shape. The thresholds are obtained by a statistical confidence interval approach.

### 2.3 Statistical Confidence Interval

In statistics, a confidence interval is a type of interval estimate of population parameter constructed by the sample statistic. Two-sided confidence limits from a confidence interval and one-sided limits are referred to as lower/upper confidence bounds (or limits). The affect factors include the size of samples and the confidence level. In the case of a fixed confidence level, the more the samples, the narrower the confidence interval. In the case of a fixed samples, the higher the confidence level, the wider the confidence interval. The confidence interval is defined as:

\[
[M-N^*STD, M+N^*STD]
\]

Where, \( M \) is the mean of the sample, \( STD \) is the standard deviation of the sample, \( N \) is used as the critical value.
3. EXPERIMENT AND ANALYSIS

3.1 Data

The data set is in the city of Potsdam. We used true orthophoto (TOP) data with four channels red, green, blue, infrared, and the DSM and ground truth (ISPRS, 2017). The TOP and DSM are used for classification, the ground truth is used for sample selection.

(a) True orthophoto (TOP) data

(b) DSM

(c) Ground truth data

Figure 2. Data set in Potsdam

3.2 Experiment

(1) Segmentation. Firstly, we use ArcGIS to make the ground truth data as a vector constraints. Then we use eCognition for multi-resolution segmentation. The trial-and-error method is adopted to find an approximate and reasonable scale parameter, where the scale is set to 100, the shape factor weight is 0.2 and compactness factor weight is 0.8.

(2) Feature Selection. Sixteen features (e.g., ratio, mean, Normalized Difference Water Index, Normalized Difference Vegetation Index, homogeneity, and brightness) are selected, and then are sorted using RF. The feature importance of Potsdam is shown in figure 3.

Figure 3. The feature importance of Potsdam

(3) Decision Rules Building. The initial decision rules are built using CART. Which is shown in figure 4 and table 2.

(4) Decision Rules validation. The initial rule is validated based on human knowledge and membership function, where we use statistical confidence interval to determine its threshold. For example, the confidence interval of building is shown in table 2.

Table 2. Decision rules

<table>
<thead>
<tr>
<th>Class</th>
<th>Decision rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woodland</td>
<td>NDVI&gt;0.09048 &amp; MeanDSM&gt;32.89235</td>
</tr>
<tr>
<td>Grassland</td>
<td>NDVI&gt;0.09048 &amp; MeanDSM&lt;=32.89235</td>
</tr>
<tr>
<td>Building</td>
<td>NDVI&lt;=0.09048 &amp; NDWI &lt;=0.269 &amp; MeanDSM&lt;=34.27115</td>
</tr>
<tr>
<td>Road</td>
<td>NDVI&lt;=0.09048 &amp; NDWI &lt;=0.269 &amp; MeanDSM&lt;=34.27115 &amp; RatioGreen&lt;=0.24408</td>
</tr>
<tr>
<td>Water</td>
<td>NDVI&lt;=0.09048 &amp; NDWI&gt;0.269 &amp; MeanDSM&lt;=34.27115 &amp; RatioGreen&lt;=0.24408</td>
</tr>
<tr>
<td>Bare land</td>
<td>NDVI&lt;=0.09048 &amp; NDWI&gt;0.269 &amp; MeanDSM&lt;=34.27115 &amp; RatioGreen&lt;=0.24408</td>
</tr>
</tbody>
</table>

(5) Classification. The image are classified using CART, and then are validated using human knowledge and membership function. The
The test site is located in Potsdam City. We utilized the TOP, use statistical confidence interval to determine its threshold. analyzed and validated based on human knowledge, where we introduced, firstly, an initial rule is built based on Random Forest and CART decision tree. Secondly, the initial rule is improved, and some obvious classification errors may be corrected already within the following validation step. This is based on the initial decision rules and the validation process, and some obvious classification errors may be corrected already within the following validation step.

Table 4. Overall accuracy.

<table>
<thead>
<tr>
<th></th>
<th>Grassland</th>
<th>Road</th>
<th>Woodland</th>
<th>Building</th>
<th>Water</th>
<th>Bare land</th>
<th>Overall</th>
<th>PA%</th>
</tr>
</thead>
<tbody>
<tr>
<td>grassland</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>31</td>
<td>96.77</td>
<td>10</td>
</tr>
<tr>
<td>road</td>
<td>0</td>
<td>28</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>96.55</td>
<td>30</td>
</tr>
<tr>
<td>woodland</td>
<td>0</td>
<td>0</td>
<td>29</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>building</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>30</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>water</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>5</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>bareland</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>80</td>
<td>0</td>
</tr>
<tr>
<td>overall</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>30</td>
<td>6</td>
<td>8</td>
<td>13</td>
<td>4</td>
</tr>
<tr>
<td>PA%</td>
<td>10</td>
<td>93.3</td>
<td>96.6</td>
<td>10</td>
<td>83.3</td>
<td>10</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>OA=97.01%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Kappa=0.96</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The overall accuracy is 97.01%, and the kappa coefficient is 0.96. Our method yields improvements as it depends on decision rule based on machine learning and human knowledge. Nevertheless, the method is still in the process of development and improvement. Further in-depth studies may be required to improve and refine rule set using human knowledge, investigate the factors influencing classification, such as the spatial scale, the segmentation method employed, and the choice of samples, and to investigate the automation of the method.

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4. CONCLUSION

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