A self-adaptive selective method of remote sensing image classification algorithms

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Abstract

Remote sensing image classification algorithms, which can obtain information of land use/cover quickly and inexpensively have been widely used in the field of GIS. The quality of classification results is not only affected by the quality of remote sensing data, but also affected by the character of classification algorithm. At present, despite a lot of algorithms have been proposed, but users usually meet difficulties in algorithm selection due to single classification algorithm cat not applicable to all classification cases. This study proposes a self-adaptive selective method for remote sensing image classification algorithms based on data complexity evaluation, through data complexity evaluation, our method can distinguish remote sensing data’s character even from same satellite sensor and give user recommendation of algorithm selection. Experiments indicate that the algorithms selected by this method can achieve higher classification accuracy, which provides the recommendation for the selection of appropriate classification models to users.

Keywords: Remote Sensing image, Classification, Algorithms Evaluate, Data Complexity

1 Introduction

Remote sensing image classification algorithms classify the entire images by using a few training samples, which can obtain information of land use/cover quickly and inexpensively and have been widely used in the field of GIS. At present, many different algorithms (including Naïve Bayes, ID3, CART, KNN, Neural Networks, SVM etc.) have been applied to remote sensing image classification [1]. The quality of classification results is not only affected by the quality of remote sensing data, but also affected by the classification algorithm [2]. Just as like No Free Lunch theorem represent: “If algorithm A outperforms algorithm B on some cost functions, then loosely speaking there must exist exactly as many other functions, where B outperforms A” [3], data set’s characteristics varying greatly and there are no single classification algorithm can applicable to all the cases [4], so select appropriate classification algorithm for remote sensing image classification is very important.

Many scholars have made research in classification algorithms selection field: Brodley proposed a knowledge based method to search an algorithm [5]; Gama proposed a linear regression method to predict algorithm’s accuracy [6], Brazdil further presented a meta-learning method to select candidate classification algorithms [7]. Song gave an automatic recommendation framework for classification model selection [4]. However, the studies above are based on data characteristic of feature structure, type, range features; remote sensing image data will have same data structure information, which obtained from same satellite sensor, and have similar data structure and statistical information, which from different satellite sensor, this will lead a difficulty to distinguish the date using the above methods. Therefore, it is necessary to introduce new evaluation method to describe remote sensing data’s character.

Data complexity is a method, which can characterize data measures on the training data instead of experimenting with train data [8]. A lot of data complexity measures, concerning statistical, geometrical and information theoretic descriptions have been proposed in past few years [9]. It can give a relation between classifier performance and training date character and we can further give recommendation for select appropriate classifiers by the help of data complexity evaluation [10-12]. Therefore, data complexity can be a more effective method to describe the characteristics of the data.

This study proposes a new method named Self-adaptive Selective Method of Remote Sensing Image Classification Algorithms based on Data Complexity Evaluation (SSMRSCADCE), which describes the characteristics of remote sensing images with data complexity, obtains the relationship between the characteristics of data and classification accuracy of algorithms through a large number of remote sensing datasets, and further proposes suggestions for the selection of classification algorithms on that basis. Experiments indicate that the algorithms selected by this method can achieve higher classification accuracy, which provides the knowledge for the selection of appropriate

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Section 4
Section 2 provides remote sensing data characterization method based on data complexity evaluation, section 3 provides the algorithm of proposed method, section 4 gives experiments result and section 5 draws conclusions.

2 Remote sensing data characterization based on data complexity

There are many formulas in data complexity evaluation field; it is difficult for a single formula to describe remote sensing data thoroughly. Therefore, we use a data complexity evaluation vector, which has three indexes to describe the character of a remote data set.

1) Index of Fisher’s discriminant ratio

Fisher’s discriminant ratio can describe how separated classes according to features:

\[ \begin{align*}
\alpha_i &= \sum_{k=1}^{\delta} n_k \times \delta(m_k, m_i) \\
\bar{i} &= \frac{\sum_{k=1}^{\delta} \sum_{j=1}^{\Delta} \delta(x_j, m_k)}{\sum_{k=1}^{\delta} \sum_{j=1}^{\Delta} \delta(x_j, m_i)},
\end{align*} \tag{1} \]

where \( n_i \) denotes the number of samples in class i, \( \delta \) is a metric, \( m_k \) is the overall mean, \( m_i \) is the mean of class i, and \( x_j \) represent the sample j belonging to class i [11].

2) Index of volume of overlap region

The volume of the overlap region for two classes can be calculated by the product of normalized lengths of overlapping ranges for all features [11]:

\[ \begin{align*}
\alpha_2 &= \prod_{k=1}^{n} \frac{\text{minmax}_k - \text{maxmin}_k}{\text{maxmax}_k - \text{minmin}_k},
\end{align*} \tag{2} \]

where \( k=1,2,3,\ldots,n \) and \( \text{minmax}_k = \text{min}[\text{max}(f_k, c_1), \text{max}(f_k, c_2)], \text{maxmin}_k = \text{max}[\text{min}(f_k, c_1), \text{min}(f_k, c_2)], \text{maxmax}_k = \text{max}[\text{max}(f_k, c_1), \text{max}(f_k, c_2)]; \text{minmin}_k = \text{min}[\text{min}(f_k, c_1), \text{min}(f_k, c_2)].
\]

3) Index of pooled Mahalanobis distance

Pooled Mahalanobis distance can describe the distance between classes i and j:

\[ \begin{align*}
D^i_{\text{pool}}(i, j) &= (\mu_i - \mu_j) \left( \frac{\sum_{k=1}^{n} + \sum_{j=1}^{\Delta}}{2} \right)^{-1} (\mu_i - \mu_j),
\end{align*} \tag{3} \]

where \( \mu_k \) is the mean vector of reflectance values, and \( \Sigma \) is the variance–covariance matrix. The index of pooled Mahalanobis distance can be describe as:

\[ \begin{align*}
i_3 &= \sum_{i=1}^{\delta} \sum_{j=1}^{\Delta} D^i_{\text{pool}}(i, j).
\end{align*} \tag{4} \]

Through formulas above, we can describe remote sensing data’s character by a vector from discriminant, overlap and classes distance level:

\[ \begin{align*}
dcV &= (i1, i2, i3).
\end{align*} \tag{5} \]

Data sets which have similar data complexity evaluation vector would have similar requirement in classification, the distance of two data complexity evaluation vector in a data set d can have represented by the following formula:

\[ \begin{align*}
dDCV(vi, vj, d) &= \sum_{k} \left| v_{ki} - v_{kj} \right| \left( \frac{dR}{d1} \right). \tag{6} \end{align*} \]

The following meta-information in a remote sensing image can distinguish between remote sensing images also plays an important role:

\[ \begin{align*}
m1 &= \text{number of bands}; \\
m2 &= \text{cellsize}; \\
m3 &= \text{Source Type}; \\
m4 &= \text{pixel Type}; \\
m5 &= \text{pixe Depth}.
\end{align*} \]

A meta-information vector can be represented as follows:

\[ \begin{align*}
\text{metaV} &= (m1, m2, m3, m4, m5); \tag{7} \end{align*} \]

the distance of two meta-information vector can have represented by the following formula:

\[ \begin{align*}
dMI(mi1, mi2) &= (\text{number of difference items})/5; \tag{8} \end{align*} \]

A remote sensing data character can be represented by meta-information vector and data complexity evaluation vector:

\[ \begin{align*}
RSC(data) &= \{ \text{miv; dcv} \} = (\text{meta-information vector; data complexity evaluation vector}); \tag{9} \end{align*} \]

the RSC can describe a remote sensing data set d and the differences between R1 and R2 can be calculate from following formulas:

\[ \begin{align*}
distance(R1, R2, d) &= \alpha_1 \times dMI(R1, R2) \\
&\quad + \alpha_2 \times dDCV(R1, R2, d). \tag{10} \end{align*} \]

The process of remote sensing data characterization can be represented as the following algorithm:

**Algorithm**: Remote Sensing Image Data Characterization (RSIDC)

**Input**: Remote Sensing image RS, training samples’ positions and catalogues SPC
Output: remote sensing data character RSC
1) dataSet=construct multi feature training data set from RS and SPC;
2) mateInfo= gather number of bands, cellsize, Source Type, pixel Type, pixel Depth information from RS;
3) metaV=construct vector by formula (7) from mateInfo;
4) dcV=construct vector by formula (5) from dataset;
5) RSC={ metaV ; dcV }
6) return RSC

End

From RSIDC Algorithm, we can characterize a remote Sensing Image Data and its training samples.

3 The self-adaptive selective method of remote sensing image classification algorithms

With the help of remote sensing data characterization from above section, we can realize the method of sensing image classification algorithms selection; the method can be described as follows:

Method: Self-adaptive selective method of remote sensing image classification algorithms (SSMRSICADCE)

Stage 1: Training Stage
Input: A large number of remote sensing image and their training samples
Output: Relationship data set RDS
RDS=Combine remote sensing image, data character, classification algorithm, classification accuracy together.

End

Stage 2:
Input: A remote sensing image RS and training samples TS
Output: recommend algorithms RAS
RAS= Self-adaptive recommend user to select classification algorithms with the help of RDS

End

Through SSMRSICADCE we can self-adaptive recommend user to select classification algorithms; it has two stages, as depicted in Fig 1, stage 1 aims at get the relationships from remote sensing image, data character, classification algorithm, classification accuracy. From Figure 1, the detail of Stage 1 can be represented as follows:

1) Construct a training database from Remote sensing images and training samples. In the database, each group of remote sensing image and corresponding samples can construct a train training sample set, and each set can obtain remote sensing data character through RSIDC algorithm;
2) Lots of classical classification algorithms were gathered and construct a Classification algorithms database.
3) Classification algorithms database provide algorithm and classification each training sample set and obtain their classification accuracy.
4) Each training sample set and each classification algorithms together with their data character and corresponding classification accuracy were combine into relationship, we can obtain the relation describe as follows:

<table>
<thead>
<tr>
<th>Images and training samples</th>
<th>Classification algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training sample sets</td>
<td></td>
</tr>
<tr>
<td>Data character</td>
<td></td>
</tr>
<tr>
<td>Classification Accuracy</td>
<td></td>
</tr>
</tbody>
</table>

Further save all the data mentioned above into Relationship data set RDS. Through stage 1, we can obtain a lot of relationships which can be regarded as knowledge to recommend classification algorithm selection. In stage 2 this knowledge are firstly used to select similar data character (see Figure 2).

Algorithm: Find similar data character (FSDC)
Input: Relationship data set RDS, A remote sensing image RS and training samples TS
Output: founded data characters FDC
1) T_RSC= get data character from RS and TS by algorithm RSIDC;
2) FDC= select RSC from RDS where RDS.DC. miv=T_RSC;
3) if FDC<>NULL Then return FDC; return data characters with exactly same data structure end if;
4) \( FDC\_distance \) = select all the DC from RDS, and calculate formula (10) with \( \alpha_1=0.5 \) and \( \alpha_2=0.5 \);
5) \( FDC \) = select the items from RDS with \( FDC\_distance < \) a threshold;
6) return \( FDC \); return data character with similar data structure.

End

Data characters: DC

<table>
<thead>
<tr>
<th>DC_ID: primary key</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIV: meta-information vector</td>
</tr>
<tr>
<td>DCV: meta-information vector</td>
</tr>
</tbody>
</table>

Classification algorithms: CA

<table>
<thead>
<tr>
<th>CA_ID: primary key</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name: algorithm’s name</td>
</tr>
</tbody>
</table>

Relationship: R

<table>
<thead>
<tr>
<th>R_ID: primary key</th>
</tr>
</thead>
<tbody>
<tr>
<td>DC_ID: corresponding data character</td>
</tr>
<tr>
<td>CA_ID: corresponding algorithm</td>
</tr>
<tr>
<td>ACCURACY: accuracy with specific data character and algorithm</td>
</tr>
</tbody>
</table>

FIGURE 2 The table structure of relationship

The algorithm FSDC we can find similar data characters, in the next step stage 2 need select most similar data character and select algorithms with may be archive higher classification accuracy (see Figure 3).

Algorithm: get recommend algorithms (GRA)

Input: founded data characters \( FDC \), relationship data set RDS, data character \( T\_RSC \), number threshold \( NT \);
Output: recommend algorithms \( RAS \)

1) \( DC\_distance = T\_RSC \) get all the distance from \( FDC \), calculate formula (10) with \( \alpha_1=0.5 \) and \( \alpha_2=0.5 \);
2) \( FDC \) = select top \( NT \) data characters from \( FDC \) with DC_distance ascend order;
3) Relations = select all the relationships RDS.R where \( RDS.R\_DC\_ID \) in \( FDC \);
4) \( OrderedGroup \) = Relations split into groups by \( RDS.R\_CA\_ID \) and each group’s corresponding accuracy grade = average(accuracy in this group) + (current group member number)/(\( FDC \) member), and all the group arrange in descending order by accuracy grade;
5) \( RAS \) = select classification algorithms from RDS.CA where RDS.CA.CA_ID in (OrderedGroup);
6) return \( RAS \).

End

The flowchart of classification algorithm recommendation and obtain a classification result can be seen as follows:

FIGURE 3 Classification algorithm recommendation and classification result

As can be seen from Figure 3:

1) remote sensing image and it’s training samples are characterized by RSIDC algorithm and then find similar characters from Relationship data set by FSDC algorithm, through GRA algorithm get Recommend algorithms with prediction accuracy descending order;
2) select corresponding algorithms and train it by raining samples to obtain a Classification model, this classification model can be used to classify the whole remote sensing image.

4 Result of experiments

Self-adaptive method of remote sensing image classification algorithms selection has two stages. In stage 1, the method need to construct relationship data set RDS; in this study RDS will be generated through the following data set. There are two different types of the remote sensing images in the data set list as follows:

TABLE 1 The details of data which to construct RDS

<table>
<thead>
<tr>
<th>Sensor type</th>
<th>Content</th>
<th>Number of sub-images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landset TM</td>
<td>forest, grass and water</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>building and farmland</td>
<td>20</td>
</tr>
<tr>
<td>SPOT5</td>
<td>wetland, grass and farmland</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td>building and road</td>
<td>15</td>
</tr>
</tbody>
</table>
Landset TM and SPOT5 are different remote sensing sensor which have different resolution, and images are further cut into sub-images with 200×200 pixel size from whole scene image, and each sub-image will be designated the training samples in manual interpretation way. Each group of sub-image and training samples are characterized by RSIDC Algorithm. The Classification algorithms database contains following 5 classical algorithms: Naïve Bayes, ID3 Tree, CART Tree, SVM and ANN. The entire classification algorithm classify all the sum-images (features maybe discretized for some algorithms) and obtain the corresponding classification accuracy, all the data collected and stored into database to construct RDS.

In order to verify the correctness of method proposed, this study has introduced a remote sensing images and cut into 10 sub-images as test data set, use 5 classification algorithm to classify and obtain the accuracy as Table 2:

<table>
<thead>
<tr>
<th>Data set</th>
<th>Classification Algorithms (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Naïve Bayes</td>
</tr>
<tr>
<td>1</td>
<td>70</td>
</tr>
<tr>
<td>2</td>
<td>83</td>
</tr>
<tr>
<td>3</td>
<td>82</td>
</tr>
<tr>
<td>4</td>
<td>75</td>
</tr>
<tr>
<td>5</td>
<td>90</td>
</tr>
<tr>
<td>6</td>
<td>99</td>
</tr>
<tr>
<td>7</td>
<td>85</td>
</tr>
<tr>
<td>8</td>
<td>78</td>
</tr>
<tr>
<td>9</td>
<td>60</td>
</tr>
<tr>
<td>10</td>
<td>89</td>
</tr>
</tbody>
</table>

The one marked with underlined in the table is the highest classification accuracy. Further, the elf-adaptive method of remote sensing image classification algorithms selection is utilized to select algorithm, which may have highest classification accuracy.

As can be seen from Table 3, there are 6 times in 10 selection process find the best algorithm, and 3 times select the 2nd algorithm, only 1 time select the 3rd algorithm. This proved that the proposed method has good algorithm selection ability.

<table>
<thead>
<tr>
<th>Table 3 Selected algorithm and its rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data set</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>1</td>
</tr>
<tr>
<td>2</td>
</tr>
<tr>
<td>3</td>
</tr>
<tr>
<td>4</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>6</td>
</tr>
<tr>
<td>7</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>9</td>
</tr>
<tr>
<td>10</td>
</tr>
</tbody>
</table>

5 Conclusions

To select appropriate classification algorithm for a remote sensing image classification is very important, but the similar data structure of remote sensing image data and statistical information hinders the traditional algorithm selection method, this research introduced data complexity evaluation into remote sensing image classification algorithm selection field, and proposed a self-adaptive selective method of remote sensing image classification algorithms (SSMRSICADCE). The method has two stages: in stage 1, users can input a large number of remote sensing image and their training samples, method can combine remote sensing image, data character, classification algorithm, classification accuracy together and save these information into Relationship data set RDS, the RDS is the knowledge of algorithm selection; in stage 2, A self-adaptive selective algorithm mechanism was proposed with the help of RDS. Experiments indicate that the algorithms selected by this method can achieve higher classification accuracy, which provides the recommendation for the selection of appropriate classification models to users.

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References

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<tr>
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<tbody>
<tr>
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</tbody>
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