Abstract—With the development of earth observation technology, a series of high spatial resolution remote sensing satellites has been successfully launched. The earth observation data, especially high spatial resolution remote sensing image, is becoming more accessible. Therefore, the ability and efficiency of high spatial resolution remote sensing image classification has become a prominent problem for its further applications. This paper presents an object-based image classification framework based on decision fusion for high spatial resolution remote sensing image. This framework mainly included three steps. Firstly, high spatial resolution remote sensing image was segmented by multi-resolution segmentation method. Secondly, the multi-source features of segmented regions were extracted and classified by Support Vector Machine classifier, respectively. Finally, the multi-source classification results were integrated by decision fusion and reclassification strategy. Quick-bird satellite data was performed to classify the land surface using the proposed classification framework; and the classification results using different feature spaces were compared. The results show that the classification method based on decision fusion takes fully advantage of multi-source region features and finally obtain higher classification precision.

Index Terms—high spatial resolution remote sensing image, image segmentation, image classification, decision fusion

I. INTRODUCTION

With the development of remote sensing technology, high spatial resolution remote sensing data had been more easily acquired and widely applied. High spatial resolution remote sensing data contains more spatial texture and details [1]. They have been widely used for urban change detection, forest dynamic monitoring, land cover classification, ecological environment monitor and so on. Remote sensing image classification is the foundation of these applications. Therefore, the classification of high spatial resolution satellite remote sensing image is becoming a hotspot.

Comparing to low and medium spatial resolution remote sensing images, more details were contained in high spatial resolution images. However, the improvement of spatial resolution increases the internal spectral variability of each land cover class and decreases the spectral variability between different classes [2]. In decades, many classification methods have been proposed to improve classification precision of high spatial resolution remote sensing images. These methods can be divided into different groups based on different standards. According to the size of basic processing unit, classification methods can be divided into pixel-based and object-oriented. The early traditional classification methods were pixel-based methods. The pixel was considered as the minimum basic processing unit. The shape, texture and contexture characteristics around the central pixel were not fully considered. And the application of traditional pixel-based classification methods in high spatial resolution remote sensing images have been proven to have some drawbacks, such as low classification accuracy, the derivation of very limited spatial information, and salt and pepper effects [3]. With the development of image analysis technologies, the object-based analysis method was introduced into the classification of high spatial resolution remote sensing images. High spatial resolution remote sensing images were firstly segmented and the objects replace the pixels as the minimum processing unit. Object-based image analysis technology is very effective for high spatial resolution remote sensing image classification. More and more object features were mined and used for classification. Chen et al. proposed a modified object-oriented classification method for high spatial resolution remote sensing images [3]. Multi-source features of image objects were computed and the fuzzy-logic classifier was used to divide the feature space. Zhang and Zhu presented a knowledge-rule-based classification method for high spatial resolution remote sensing images [4]. The spectral features, texture features, and shape features were integrated to establish classification ruler. From the above, the multi-source features were simply combined together and straightly classified. The characteristics of multi-source features were not considered separately.

In view of the characteristics and problems of high spatial resolution remote sensing image classification, an
object-based image classification framework based on the
decision fusion has been proposed. The regional spectral,
texture and vegetation index features were extracted
through the corresponding extraction methods, and
classified by Support Vector Machine classifier,
respectively. The multi-feature classification results were
fused by decision fusion mechanism. In the presented
classification framework, the multi-scale characteristics
of the image and multi-source region features were
integrated by decision fusion and reclassification
mechanism and finally got high classification precision.

II. METHOD

This section introduced the framework of decision
fusion classification for high spatial resolution remote
sensing images. The image segmentation, the multi-
source feature extraction, classification and decision
fusion mechanism were detailed. The flowchart of the
proposed method is shown in Fig. 1.

A. Image Segmentation

High spatial resolution remote sensing images contain
more spatial information of ground objects and show
great diversity of them. Image segmentation is an
essential step for object-based analysis of high spatial
resolution remote sensing images [5]. Image
segmentation is a process of dividing an image into
meaningful homogenous regions.

Many segmentation approaches have been proposed
for segmentation of high spatial resolution remote sensing
images. There are some representative segmentation
methods, such as the clustering method, the mean shift,
the wavelet transform method, the active contours
method, the watershed transform method and so on. The
segmentation methods can be divided into different
categories based on different classification standards. The
segmentation methods can be classified into single-scale
and multi-scale classes according to whether or not to use
the multi-scale image information.

The multi-scale segmentation technique is one of the
most important techniques for image segmentation. The

region-based multi-resolution segmentation method
available in eCognition software was used. The
segmentation process was controlled by the scale, shape
and compactness parameters specified by users. The most
suitable parameters were determined by experimenting
and users’ subjective assessment.

B. Multi-source Feature Extraction

After image segmentation, the regional spectral,
texture and vegetation index features were extracted
using the corresponding calculation methods. The
regional spectral vector was calculated by the mean
spectral vector of pixels contained in each region.

Texture is an important feature in identifying interest
regions in image. In 1973, Haralick introduced the grey-
level co-occurrence matrix and texture features for rock
image classification [6]. The grey-level co-occurrence
matrix is one of the effective techniques for image texture
analysis. The texture features based on co-occurrence
matrix were widely used for different images analysis
tasks.

The co-occurrence matrix was controlled by the move
window size, move step length and direction parameters
specified by users. Texture features were calculated based
on the grey-level co-occurrence matrix. Eight statistical
indicators of texture information, namely mean, variance,
homogeneity, contrast, dissimilarity, entropy, second
moment and correlation, were selected for composing the
object texture feature space.

The vegetation indexes were defined by referring to
the calculation formula of normalized difference
vegetation index (NDVI). The NDVI computation
formula is as follows:

$$\text{NDVI} = \frac{\text{Band}_1 - \text{Band}_2}{\text{Band}_1 + \text{Band}_2}$$  (1)

where Band 1 stands for the near-infrared band of high
spatial resolution remote sensing image, and Band 2
represent the red band of high spatial resolution remote
sensing image.

For high spatial resolution remote sensing image,
generally, it has four spectral bands, and then six imitated
vegetation indexes can be obtained from every two bands.

C. Multi-source Features Classification

With the development of artificial intelligence and
machine learning, a lot of new machine learning
algorithms were brought into the classification of high
spatial resolution remote images. Each algorithm had its
unique advantages and weaknesses.

Support vector machine (SVM) is a supervised
nonparametric statistical learning technique. A
hyperplane or set of hyperplanes were constructed in a
high-dimensional space by SVM, which can be used for
classification, regression, or other tasks. Intuitively, a
good separation is achieved by the hyperplane that has
the largest distance to the nearest training data point of
any class. The larger the distance means the lower the
generalization error of the classifier. SVM is very good at
solving nonlinear, high dimensional and limited training
samples, and widely applied to classification of remote sensing images [7]. There are many kinds of kernel functions used for space transform. The Gaussian radial basis function (RBF) kernel was employed for all experiments. In order to integrate the characteristics of different features, the spectral, texture and vegetation indexes were classified separately.

D. Multi Classification Results Decision Fusion

Decision fusion is the process of fusing information from individual sources [8]. The spectral, texture and vegetation index features were classified separately. The multi classification results were fused by decision fusion mechanism. The decision fusion scheme can be considered to be two-stage processes, including soft majority voting and reclassification.

Firstly, the classification results provided by the different features were aggregated by majority voting. The final decision was assigned with the majority class. The soft majority voting can reject regions if either the majority or all of the classification labels for the region do not agree on one class.

After soft majority voting, the unclassified regions will be reclassified based on spectral and context information. The minimum distance classification method was used to classify the unclassified regions to the closest class. The Euclidian distance between the mean of a class and an unclassified region in the n dimensional spectral feature space is given as [9]:

\[
D_{ED} = \left( \sum_{i=1}^{n} (x_i - C_i)^2 \right)^{1/2}
\]  

(2)

where n is the dimensionality of feature space, \(x_i\) is the mean spectral value of \(i_{th}\) feature of the unclassified region, and \(C_i\) is the mean spectral value of the \(i_{th}\) feature of one class. The unclassified region is then assigned to the class where \(D_{ED}\) is minimal. All unclassified regions are classified to the most similar class.

III. EXPERIMENTS AND DISCUSSION

To evaluate the performance of the proposed decision fusion classification approach, one subset of Quick-bird satellite remote sensing image is employed to classify the land surface. The Quick-bird dataset includes one panchromatic band with resolution of 0.6 m and four multispectral bands with resolution of 2.4 m. The size of multispectral image is 256 × 256, while the size of the panchromatic image is 1024 × 1024.

The SVM classifier with Gaussian radial basis function (RBF) kernel was applied for all experiments. The optimal parameters C (parameter that controls the amount of penalty during the SVM optimization) and \(\gamma\) (parameter that describes the spread of the RBF kernel) were chosen by fivefold cross validation [10]. Table I reports the optimal parameters of all SVM classification experiments.

To assess classification accuracy of different methods, the confusion matrixes are constructed. The reference classification image is generated through a precise manual interpretation on fusion images. The producer, user and overall classification accuracies are calculated from the confusion matrix.

<table>
<thead>
<tr>
<th>Features</th>
<th>Optimal Parameters</th>
<th>C</th>
<th>(\gamma)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral</td>
<td></td>
<td>32768</td>
<td>0.125</td>
</tr>
<tr>
<td>Vegetation Indexes</td>
<td></td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>Texture</td>
<td></td>
<td>2048</td>
<td>0.5</td>
</tr>
<tr>
<td>All three features</td>
<td></td>
<td>32768</td>
<td>0.001953125</td>
</tr>
</tbody>
</table>

Figure 2. Classification results using different feature space. (a) is the classification result based on spectral space, (b) is classification result using vegetation index features, (c) shows the classification result of texture features.

Figure 3. Classification results by different method. (a) is the classification result based on combined all feature space, (b) shows the classification result through decision fusion.

Figure 4. Accuracy comparison of different classification methods.

By comparing the accuracies of the various classification results, the proposed decision fusion method obtained the best classification result than other methods. Fig. 4 shows the comparison of different classification methods.
Table II, III and IV showed that different feature space produced different classification accuracies. The accuracy using vegetation indexes was higher than that of spectral and texture. As shown in Table V, the classification accuracy by combining multiple features together was higher than that of single feature. From Fig. 4, it can be found that the proposed decision fusion method obtained highest overall accuracy; the overall accuracy was 79.86%, increased by about 2.5% than the best single feature space classification. It can be concluded that the presented decision fusion classification framework can make full use of multi-source region features and improve the final classification precision.

IV. CONCLUSION

An object-based image classification framework based on decision fusion has been presented. Quick-bird satellite data was performed to classify the land surface...
using the proposed classification framework; and the classification results using different feature spaces were compared. Experimental results show that the classification accuracy using all features is higher than that of single feature, and the classification accuracy using decision fusion strategy is higher than that of simply combining the multiple features. It is concluded that the proposed decision fusion method can be effectively improve the classification accuracy of high spatial resolution remote sensing images.

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