Evaluation of semivariogram features for object-based image classification

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(Received 8 April 2015; final version received 7 September 2015)

Inclusion of textures in image classification has been shown beneficial. This paper studies an efficient use of semivariogram features for object-based high-resolution image classification. First, an input image is divided into segments, for each of which a semivariogram is then calculated. Second, candidate features are extracted as a number of key locations of the semivariogram functions. Then we use an improved Relief algorithm and the principal component analysis to select independent and significant features. Then the selected prominent semivariogram features and the conventional spectral features are combined to constitute a feature vector for a support vector machine classifier. The effect of such selected semivariogram features is compared with those of the gray-level co-occurrence matrix (GLCM) features and window-based semivariogram texture features (STFs). Tests with aerial and satellite images show that such selected semivariogram features are of a more beneficial supplement to spectral features. The described method in this paper yields a higher classification accuracy than the combination of spectral and GLCM features or STFs.

Keywords: object based image analysis; image segmentation; image classification; texture feature; semivariogram

1. Introduction

Textural information has been shown useful for improving the object-based classification performance of high-resolution imagery (1). Texture analysis methods can be categorized into structural methods, model-based methods, transform-based methods and statistical methods (2). Structure methods consider texture as a repetition of well-defined texture elements, such as regularly spaced parallel lines (3–5). Though they can extract regular, periodic textures, remote sensing images often have a complex and varying background. Model-based methods use various models, such as Markov random filed (6), Gaussian-Markov random field (7), and fractal dimensions (8) to describe textures. Such methods are subject to high computational complexity and strict requirements on the selection of model and its parameters. Transform-based methods involve converting the image into a new form through filtering or Fourier transform or wavelet transform (9–12). These methods are able to extract texture information at multiple scales, but the information loss introduced in the transform or filtering will affect the subsequent classification quality. Probably the most popular group of texture analysis methods are the statistical ones. Haralick et al. are renowned for providing the gray-level co-occurrence matrices (GLCM) as a texture descriptor (3). The textural features are derived based on the statistics that summarize the relative frequency within a neighborhood. Local binary pattern histogram (13) is a simple, yet efficient operator to describe local image pattern and has achieved impressive results in face recognition, dynamic texture recognition and texture classification (14, 15). Statistical methods are able to analyze the spatial autocorrelation of an image, especially of the spatial variability structure (16).

Many researches have taken semivariograms to describe textural and spatial features of remote sensing images (17–21). Semivariograms enable spatial changes in a variable to be quantified (22) and are valuable for describing spatial patterns (23). The semivariogram-based texture description is achieved in either of the following two ways: One method models the semivariogram by fitting a mathematical function (for instance, exponential model, Gaussian model and spherical model) whose parameters such as sill and range are adopted as texture measures (18, 20, 23, 24). This method often suffers from the selection of a proper function since simple functions are not sufficiently distinguishable and complex ones may be subject to overfitting (19). Moreover, parametric models are always class specific (25). The other method utilizes semivariograms at various lags (17, 26). It is free of the problems caused by modeling and thus becomes more popular for describing spatial properties of remote sensing images (21, 26, 27). The classification accuracy is improved when the semivariogram is used in combination with spectral information (17). Semivariograms have been extensively used to quantify texture in remote sensing images based on moving windows (21, 26). Generally, semivariograms are calculated in terms of certain lags and certain window size (18).

New texture bands are created by assigning to each pixel
the semivariance calculated within a local window \( (21) \), and added as supplementary information to spectral classification \( (19) \). Since a window of pre-defined size may lead to inaccurate texture description for very high resolution images, Wu et al. \( (26) \) and Yue et al. \( (21) \) analyze the relationship between the window size and different land covers, while Chica-Olmo and Abarca-Hernandez \( (19) \) choose a window size that is valid for most of land cover classes. On the other hand, window-based semivariograms usually suffer from border effect and long computation time. To address these issues and unlike the aforementioned conventional approaches, Balaguer et al. recently derived plots based on the cartographic limits obtained from regular cadastral parcels \( (28) \). This is the basis of object-based semivariogram analysis approach, where the boundaries of objects are pre-defined and each object is represented by the semivariogram features extracted from its own image representation. However, the requirement on up-to-date vector data to provide prior knowledge of land cover classes is not practical. Yue et al. adopt image segmentation to derive objects and use object boundaries in addition to knowledge-based segmentation of semivariogram texture bands \( (21) \). A set of semivariogram texture features (STFs) is defined to describe texture in their experiments.

Although the semivariogram has been applied for image classification, few have focused on object-based classification and on high-resolution remotely sensed images \( (29–32) \). Therefore, the objective of this paper is to explore STFs and utilize them to object-based classification of high-resolution images. Instead of using auxiliary vector data \( (28) \), such as land cover maps, we derive semivariograms from segmented objects based on images. Each individual object is usually characterized by a uniform pattern of textures, so such calculated semivariogram should be more accurate and representative. It would allow us to consider the textural differences of objects of the same land cover. It should also be noted that only pixels within an object are taken into consideration in order to eliminate the border effect. Similar to the work of Ref. \( (28) \), the STFs are then extracted for each object. Moreover, we move on to evaluate the contribution of the calculated semivariogram features so that only significant features are selected for the subsequent image classification. For evaluation purpose, classical texture features of GLCM is included in the experiments to assess the contribution of semivariogram features. The method proposed by Yue et al. is also applied to compare the effects of window-based and object-based semivariograms \( (21) \). For the subsequent final supervised classification, we use a combination of texture and spectral features.

2. Methodology

2.1. Semivariogram calculation for objects

Semivariogram is first used in analysing spatial continuous data in geostatistics. It regards geographical characters as mathematical variables and describes the spatial dependence between them. For image analysis, semivariograms are suitable for characterizing regular patterns of image variation \( (16) \). Assuming that the spectral reflectance of pixels is a set of spatially randomly distributed continuous variables, the semivariogram is defined as one-half of the average of the squared difference between paired pixel values \( (25) \). Typically, it is computed as:

\[
\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [z(x_i) - z(x_i + h)]^2
\]

(1)

where \( \gamma(h) \) is the semivariance value at a certain lag distance \( h \), \( z(x_i) \) and \( z(x_i + h) \) represent digital values at location \( x_i \) and \( x_i + h \), respectively. \( N(h) \) is the number of paired pixels at lag distance \( h \). Specifically, \( h \) is a vector, which indicates the semivariance function is anisotropic, i.e. depending not only on distance but direction \( (23) \). In geology, the calculation of such anisotropic semivariogram is often required since typically there is much greater spatial correlation in a certain direction than others. But in analysis of high-resolution imagery, there is yet no proper method to deal with anisotropy and the computation of all possible directions is impossible. As an alternative, Balaguer et al. \( (28) \) calculate semivariograms in six directions, ranging from 0° to 180° with a step of 30° and then adopt the omnidirectional semivariogram by averaging them:

\[
\gamma(h_d) = \frac{1}{6} \sum_{i=0}^{5} \gamma^{30i}(h_d)
\]

(2)

where \( \gamma^{30i}(h_d) \) represents the semivariogram defined in Equation (1), 30° denotes the starting direction at a step of 30°, and \( h_d \) is the corresponding lag distance. When considering an object-based method, each object is characterized with one object-specific omnidirectional semivariogram. Only the pixels inside an object are considered for computation. As a result, the texture description is not affected by the border effect. Note that the above calculation is designed for a single-band image. For multispectral images, the most representative band can be selected for computation, or an average of the semivariances of all bands can be taken as the final semivariance.

It should be noted that object-based semivariogram is calculated differently from the window-based one. For a given lag distance, the latter computes the semivariance within a window and assigns it to the central pixel to form an extra band. Multiple bands are formed for different lag distances. As for object-based calculation, the boundary of each object is limited by the segmentation result rather than windows. Within the extent of an object, a sequence of semivariance values is calculated in terms of different lag distances. The collection of such semivariance values defines the curve or shape of the semivariogram of the object, from which features will be extracted to form a feature vector for image classification.
2.2. Semivariogram feature extraction

Semivariogram is a useful tool to present the spatial correlation against changing lags. As Figure 1(a) shows, a classical semivariogram curve increases monotonously and stabilizes asymptotically. The conventional modeled semivariogram \((33)\) is capable of providing informative description with parameters like nugget \(C_n\), sill \(s\) and range \(a\). However, these parameters can hardly reflect the typical cyclicity resulting from spatial periodicity of image (as shown in Figure 1(b)). To address this deficiency, Balaguer et al. \((28)\) use the first maximum \(\gamma(h_{\text{max},1})\), the first minimum \(\gamma(h_{\text{min},1})\), and the second maximum \(\gamma(h_{\text{max},2})\), which are more informative and representative for this purpose. The semivariogram-derived features are categorized into: (1) near the origin, (2) up to the first maximum, and (3) between first and second maxima according to the position of the lags used in their definition. As summarized in Table 1 (adopted from Ref. \((28)\)), the first group of features are defined to provide such information as the change ratio, slope, concavity and convexity level of the image at short distance. The combination of the other two groups of features is useful to distinguish between monotonic and cyclic semivariograms. For example, First Max Lag (FML) is usually considered as an approximation to the range of the image, and is influenced by the relationship between the average size of the texture structures or patterns. The distance between the first and the second local maximum (DMS), and the distance between the first local maximum and the first local minimum (DMM) reveal the regularity of cyclic curves.

Common objects are roughly identified as either homogeneous or heterogeneous in parallel to the two curve types. Figure 2 illustrates the samples of major land cover classes and their corresponding semivariogram curves. Homogeneous objects (Figure 2(a)–(c)) have internally stable structures without distinct texture variation. Their semivariograms are similar to Figure 1(a). The distance at which the curve starts to stabilize is approximately equal to the range and is thus equivalent to the influence area of various samples. Different kinds of homogeneous objects are distinguished by the value of range and the maximum semivariance. Heterogeneous objects (Figure 2(d)) usually contain abundant distinct texture information and show a more complicated spatial structure than homogeneous ones. When the interior texture appears in a regular pattern, the semivariogram presents a cyclical behavior like the one in Figure 1(b). The periodicity is embedded in the distance between the first local maxima and minima. These semivariogram-related features are quantified according to Ref. \((28)\). They extract a comprehensive set of features based on such properties as the first maximum, the first minimum, and the second maximum (Figure 1(b)) in terms of their locations. Using the set of points given above, 14 features (see Table 1) in total are extracted from the semivariogram curve, representing spatial variation of the objects at different distances respectively.

2.3. Feature selection

We argue that not all above-extracted features are significant and they may be, to certain extent, dependent to each other. This study uses an improved Relief algorithm \((34)\) and the principal component analysis (PCA) for feature selection. First, the improved Relief algorithm is conducted on the 14 semivariogram features to remove the less relevant features. Features with weight values greater than zero are kept. Then, PCA is used on the combination of the preselected semivariogram features and spectral features. The original high-dimensional feature set is transformed to a low-dimensional one whose components are less correlated. Finally, the most predominant components are selected as input for the subsequent classification. We use \(f\) for features, \(c\) for classes, \(i\) for samples to be traversed, and \(n\) for the size of all classes, \(m\) for the size of samples in a certain class, the implementation of the improved Relief algorithm is as follows:

1. Initialize the weight for each feature \(W_f^0\) to zero.
2. Find the nearest intra-class sample and the nearest inter-class samples (one sample from each dissimilar class) for every sample. Then, calculate the corresponding distances, namely \(\text{diff}_x(H(x_i))\) and \(\text{diff}_x(M(x_i))\), where \(x_i\) represents the sample of class \(x\). \(\text{diff}(\ )\) is the distance between samples, \(H(x)\) and \(M(x)\) are the nearest-neighbor sample points from the same class and the other classes, respectively. The standard Euclidean distance is used to calculate the distance here.

Update the weight for each feature \(f\) until convergence with the following formula:

\[
W_f^j = W_f^{j-1} + \left( \sum_{i \neq \text{class}(x)} \frac{\text{diff}_x(H(x_i), M(x_i))}{m_{\text{class}(x_i)}} - \frac{\text{diff}_x(H(x_i), M(x_i))}{m_{\text{class}(x_i)}} \right) \cdot \frac{1}{n} \sum_{i \neq \text{class}(x)} \text{diff}_x(H(x_i), M(x_i))
\]

(3)

where \(\frac{1}{m} \sum_{i \neq \text{class}(x)} \text{diff}_x(H(x_i), M(x_i))\) represents the mean distance between the traversed sample and the nearest samples each from one different class.

![Figure 1. Monotonous semivariogram (a), and cyclic semivariogram (b).](image-url)
Table 1. Summary of semivariogram features.

| Group | Feature | Formula |
|-------|---------|---------|
| Near the origin | Ratio between total variance and first semivariance | $RVF = \frac{\text{variance}}{\gamma_1}$ |
| | Ratio between the first and the second semivariance | $RSF = \frac{\gamma_2}{\gamma_1}$ |
| | First derivative near the origin | $FDO = \frac{(\gamma_2 - \gamma_1)}{h}$ |
| | Second derivative at third lag | $SDT = \frac{(\gamma_1 - 2\gamma_2 + \gamma_3)}{h^2}$ |
| | First maximum lag value | $FML=\frac{h_{max,1}}{\gamma_{max,1}} = \frac{1}{\max_1-1} \sum_{i=1}^{\max_1-1} \gamma_i$ |
| | Mean of the semivariogram values up to the first maximum | $MFM = \frac{1}{\max_1} \sum_{i=1}^{\max_1-1} (\gamma_i - \frac{\gamma_1 + \gamma_{max,1}}{2})^2$ |
| | Variance of the semivariogram values up to the first maximum | $VFM = \frac{1}{\max_1} \sum_{i=1}^{\max_1-1} (\gamma_i - \frac{\gamma_1 + \gamma_{max,1}}{2})^2$ |
| | Difference between MFM and the first semivariance | $DMF = \frac{\gamma_{max,1}}{\gamma_{max,1}} - \gamma_1$ |
| | Ratio between the first local maximum semivariance and MFM | $RMM = \frac{\gamma_{max,1}}{\gamma_{max,1}}$ |
| Up to the first maximum | Second-order difference between first lag and first maximum | $SDF = \gamma_{max,1} - \frac{2\gamma_{max,1}}{\max_1-1} + \gamma_1$ |
| | Area until the first maximum | $AFM = \frac{\gamma_{max,1}}{\max_1-1} - \frac{\gamma_{max,1} + \gamma_{max,2} - (\gamma_1(h_{max,1} - h_1))}{\max_1-1}$ |
| | Distance between the first and the second local maxima | $DMS = h_{max,2} - h_{max,1}$ |
| | Distance between the first local maximum and the first local minimum | $DMM = h_{min,1} - h_{max,1}$ |
| | Hole area | $HAA = \frac{h}{2(\gamma_{min,1} + 2(\sum_{i=1}^{\max_1-1} \gamma_i + \gamma_{min,1}))}$ |

Notes: Semivariogram features {$(h_1, \gamma_1), (h_2, \gamma_2), (h_3, \gamma_3), \ldots, (h_n, \gamma_n)$} are the points of the experimental semivariogram. The lags {$(h_2, h_3, \ldots, h_n)$} are equally spaced. Variance is the value of the total variance of the pixels belonging to the object. $h_{min,1}, h_{max,2}, h_{max,2}$ represent the locations of the first local maximum, the first local minimum, and the second local maximum, and $\gamma(h_{max,1}), \gamma(h_{min,1}), \gamma(h_{max,2})$ are the first local maximum, the first local minimum, and the second local maximum semivariance (adopted from Ref. (28)).

![Figure 2](image1.png)

Figure 2. Semivariograms computed from the red band for some land cover classes: cropland (a), grassland (b), residence (c), and orchard (d).

(3) Select the features weighted greater than the threshold $\delta$, i.e. $W^j > \delta$, as the optimal features. The standard Euclidean distance is used to calculate the distance between samples.

2.4. Classification

The use of semivariogram features in an object-based classification is conducted in a workflow shown in Figure 3. First, the input image is segmented by a multiscale approach. Second, the aforementioned semivariogram features are calculated for each segment (i.e. object). Such semivariogram features are subject to the improved Relief algorithm to determine the significant ones. Then, the normalized PCA is applied to the combination of the above preselected representative semivariogram features and the spectral features. Finally, such feature vectors for segmented objects are input to a support vector machine (SVM) classifier.
As the first step in object-based classification, image segmentation is crucial for the subsequent steps. An image segment should have a proper size to sufficiently represent its texture pattern. To this end, we apply the Minimum Span Tree-based multi-level image segmentation method \((35)\) after a down-sampling process for noise suppression. A multi-scale region-merging is included in the method, which analyzes the weighted edge graph of the image and utilizes statistical learning theory based on an optimal criterion to avoid over-segmentation.

When the semivariogram is calculated for each individual object, one important factor is the maximum lag distance. It should not be larger than the spatial extent of the object; on the other hand, exceedingly small distance fails to have a complete description of texture features. According to Ref. \((36)\), the selection of optimal maximum lag distance is class dependent due to the diversity in spatial variability pattern. In window-based semivariogram calculation, the maximum lag distance is usually no more than half of the window size. As a compromise, we try to find an appropriate optimal distance which works well for most land cover classes. With the knowledge of existing classes in a given scenario and the corresponding samples, the smallest distance with adequate distinguishability among classes is finally selected. In our study, a maximum lag distance of 20 pixels (at the input image resolution) turns out to be a satisfactory choice.

To achieve reliable classification, a compound feature vector composed of semivariogram and spectral statistics is constructed. Generally, the redundancy of original STFs together with the spectral feature may probably impede the efficiency of classification. The improved Relief algorithm attempts to eliminate redundant or highly correlated features based on a predetermined threshold, and the dimensionality is further reduced with the PCA. This reduced feature set is taken as the input for the SVM classifier.

3. Experiments and evaluation

3.1. Study areas and data

This study concerns two areas: the agricultural area in Huizhou (Site A) and rural-urban continuum in Yongning district, Yinchuan (Site B). Huizhou is located in the middle of Guangdong province in China. With mild climate and abundant rainfall, the major land covers of this area are forest and farms. The available data used in the experiment are digital aerial images containing three visible bands (red, green, and blue) at a spatial resolution of 0.2 m. To suppress the noise, the original image (about 4 km\(^2\)) is firstly down-sampled to a resolution of 0.8 m for segmentation. Figure 4(a) displays the experimental image in Huizhou (Site A) with its corresponding segmentation result, where object boundaries are congruent with most land cover classes. And Figure 4(b) shows seven samples of land cover classes in Site A. The other study area, Yongning district (Site B) is in Yinchuan city, Ningxia Province, China. Figure 5(a) shows its clipped multi-spectral GF-2 satellite image with an area of 36 km\(^2\), approximately. Four bands of visible-to-NIR spectral coverage are available at a resolution of 4 m. Compared to Site A, Site B has a much lower spatial resolution, and a satisfactory segmentation result can be achieved based on the original resolution image. So the down-scaling step is skipped. Five samples of land cover classes in Site B are presented in Figure 5(b).

3.2. Evaluation on feature selection

The calculation of semivariograms and extraction of related texture features are completed with FETEX2.0 \((37)\), which is a feature extraction tool for object-based image analysis. It is designed to work with land use/land cover databases to assist the classification of the existing objects. The calculation for semivariogram is normally for single-band image. For Site A, the available bands include red, green, and blue ones. Semivariograms are extracted from each band to compare the difference between them. As a result, their curves present similar trends and stay at the same level of semivariance. Since several types of vegetation are found in the study area, the red band is finally chosen for semivariogram calculation. For Site B, the near-infrared (NIR) band is chosen for semivariogram calculation since vegetation dominates the image.

For Site A, the semivariogram curves of the six main land cover classes are shown in Figure 6(a). The solid
curves are associated with the left vertical axis, while the dashed curves are associated with the right vertical axis. Only the semivariogram curve of orchard presents a cyclic trend, while the others remain monotonic. The cyclicity is related to a high level of human intervention, which contributes to the regularly arranged texture of orchard. The cropland and the grassland have similar semivariance curves especially at small lag distances, but the latter generally stays at a higher level. The curve of woodland is higher than the grassland and cropland and tends to reach its first maximum value in a short lag distance. The water has the lowest semivariance. The position of the first maximum is mainly related to the average diameter of the trees and the minimum distance between trees (38). As the typical man-made objects, residence has the highest value compared to other classes.

For Site B, the semivariogram curves of the four main land cover classes are shown in Figure 6(b). The solid curve is associated with the left vertical axis, while the three dashed curves are associated with the right vertical axis. Two extremes are noticed for water and residence, respectively. The former presents the smallest
average semivariance due to its low variation in radiation. The latter, as a composite class with a high-level human intervention, achieves the highest semivariance compared to other classes. Curves for other classes lie between them. As shown in Figure 6(b), the cropland has high and uniform vegetation cover. The bare field has virtually no vegetation except the junction between each field. The uniformly arranged bare field contributes the cyclicity in semivariogram, which is shown in Figure 6(b), while the abrupt change between individual fields leads to an averaged higher semivariance of bare field, compared to the cropland.

Fourteen (14) semivariogram features in Table 1 are used as candidates for feature selection. For Site A, as a result of the Relief algorithm, FML, DMM, and DMS are removed, and 11 semivariogram features including RVF, RSF, FDO, SDT, VFM, DMF, RMM, SDF, AFM, and HA are remained. Among these preselected features, HA is kept to describe and quantify the “hole effect” which informs the increase or decrease of the depression of maxima. DMM and DMS are highly related and seem to have similar information with HA according to their definition, so they are removed. As shown in Figure 6(a), most of the semivariograms are monotonic, which means that the FML feature cannot be extracted. This might be the reason that FML is removed firstly. For Site B, a total of 11 semivariogram features, including RVF, RSF, FDO, SDT, FML, MFM, VFM, DMF, RMM, SDF, AFM are kept, while DMS, DMM, and HA are removed. Among all the classes, DMS, DMM, and HA can only be extracted from the cyclic semivariogram. In other words, this group of features is merely useful for bare field. Among the features that are kept in both sites, the first group of features (including RVF, RSF, FDO, and SDT) describes the distinct difference between the monotic and non-monotic semivariograms at short distances. RVF indicates the relationship between the spatial variation at long and short distances, and FDO as well as SDT provide information about change ratio at the first four short distances. The parameter SDF, denoting the second-order difference between the first lag and the first maximum, is kept to complement the information provided by RVF. RMM implies influence of the total variability of the analyzed object. They both provide complementary information to RVF. VFM is directly related to the homogeneity of the values in the image, while AFM is also influenced by the variability of the object. MFM is complementary to VFM.

Figure 6. Semivariograms of selected classes in Site A and B.
Such texture features selected from the semivariogram curves are utilized together with conventional spectral features. Some most common spectral features are introduced for each object at each band, known as mean, standard deviation, maximum, and minimum. Then PCA is applied to the features, and the principal components with more than 90% information are finally selected. As a result, the features we used for Site A include a total of 3 (#band) times $[\text{MEAN}_i, \text{STD}_i, \text{MAX}_i, \text{MIN}_i]$ (features per band) and 11 (semivariogram) features. As for Site B, a total of 4 (#band) times $[\text{MEAN}_i, \text{STD}_i, \text{MAX}_i, \text{MIN}_i]$ (features per band)], NDVI and 11 (semivariogram) features are used for our classifier.

### 3.3. Classification assessment

We choose SVM as the classifier. As a group of theoretically superior machine learning algorithms, it has been frequently cited in pixel-based image classification and achieved empirical successes (39). They appear to be especially advantageous in the presence of heterogeneous classes for which only a few training samples are available. Here, the most widely used radial basis function kernel is taken for the classifier. Selection of training samples is one of the major factors determining to what degree the classification rules can be generalized to unseen samples. A group of samples are selected manually by visual interpretation and divided into two parts, one for classifier training and the other for classification assessment, as listed in Table 2.

Four tests are carried out to evaluate the semivariogram-assisted classification. One of them only utilizes spectral features for classification. The other two tests relate to the combination of spectral and textural features: spectral + GLCM features and spectral + semivariogram features. Since an object-based approach is used, only one GLCM is computed for each object to describe the co-occurrences of the pixels that are separated at one-pixel distance inside the polygon and the average value of six principal orientations (0°, 30°, 60°, 90°, 120°, and 150°) are considered. Six GLCM texture features (uniformity, entropy, contrast, inverse difference moment, covariance, and variance) are calculated. The last test utilizes the STFs defined by reference (21). The process of extracting STFs is as follows. First, the red band is utilized for window-based semivariance calculation, and several texture semivariogram bands corresponding to the discrete semivariance values are generated. Then the segmentation result is used as a thematic layer, which is considered in addition to the knowledge-based segmentation of texture semivariogram bands. The image object is formed using the inner border in calculating the texture feature values, thus STFs. STFs are divided into four different groups according to the feature calculation mode; the mean semivariance value of the pixel group at specific lags (denote as $\gamma_l(i = 1, 2, 3, \ldots, l_{\text{max}})$, where $l_{\text{max}}$ is the maximum lag distance), the mean value of $\gamma_l$ ($\gamma_{\text{mean}}$), the standard deviation of $\gamma_l$ ($\gamma_{\text{std}}$), and the semivariogram gradient in short and long lag distance ($S_{\text{gradient}}, L_{\text{gradient}}$, and $M_{\text{gradient}}$). The difference between these two semivariogram-based methods is as follows. Yue et al. (21) calculated the window-based semivariogram before image segmentation, while we firstly segment the image and then extract semivariograms from each object. For Site A, $\gamma_l(i = 16, 19, 20)$ are preselected to be combined with the spectral features for classification. For Site B, $\gamma_l(i = 5, 6, 7, 11, 13, 14, 17, 19)$ and $\gamma_{\text{std}}(i = 3, 14, 18, 19)$ are selected.

The difference between classification result and testing set is summarized in a confusion matrix, based on which several statistics are calculated to assess the classification quality. The accuracy assessment of Site A is given in Table 3. By introducing the GLCM the confusion is reduced between cropland and grassland, and the overall accuracy increases from 80.3 to 85.7%. What amazes us is that the user accuracy of orchards is improved significantly from 87.0 to 92.2%. The GLCM texture feature helps specifically to increase the producer accuracy for residences from 61.8 to 74.6% and for roads from 55.0 to 80.0%. In the case of woodlands the producer accuracy differs a little among feature combinations but the spectral + STFs and spectral + semivariogram both yield the highest user accuracy as large as 97.6%. The highest producer accuracy of water is achieved by spectral + GLCM method, increases from 57.1 to 71.4% compared to merely using spectral information. The overall accuracy of spectral + GLCM and spectral + STFs classification increases by 5.4 and 2.3%, respectively, compared with the spectral-only classification. When the STF texture feature is preferred, a better accuracy is expected for woodlands and residences. However, it is not helpful for reducing the confusion between grassland and cropland. Similarly, our method (spectral + semivariogram) achieves great improvement in all land cover classes compared to the spectral classification. Significant improvements of producer accuracy arise in orchard and residence which are quantized as 8.7 and 21.8%, respectively. Our method also possesses the highest overall accuracy as 88.7% among all feature

Table 2. Training objects and testing objects for the two study areas.

| Class      | Site A Training | Site A Testing | Site B Training | Site B Testing |
|------------|----------------|----------------|----------------|---------------|
| Woodland   | 127            | 127            | N/A            | N/A           |
| Grassland  | 68             | 68             | N/A            | N/A           |
| Orchard    | 116            | 114            | N/A            | N/A           |
| Cropland   | 120            | 122            | 54             | 54            |
| Road       | 42             | 40             | 27             | 27            |
| Residence  | 55             | 55             | 36             | 26            |
| Water      | 26             | 42             | 17             | 17            |
| Bare field | N/A            | N/A            | 44             | 44            |
| Total      | 554            | 568            | 178            | 168           |

Note: N/A indicates that the land cover class is not applicable in the corresponding study area.
combinations. The classified images are shown in Figure 7.

The accuracy assessment for Site B is given in Table 4. The classified images are shown in Figure 8. With assistance of NDVI (Normalized Difference Vegetation Index), the overall accuracy of spectral classification achieves 92.0%. By introducing the GLCM, the overall accuracy increases 1.4%. Notably, the improvement for residence and road is obvious from 82.6% and 66.7% to 93.5% and 70.4%, respectively. However, as for the other classes, little improvement is recognized. Spectral + Semivariogram and Spectral + STFs, by contrast, greatly improve the accuracy of residence class. The highest producer accuracy of road, as large as 81.5%, is achieved by spectral + STFs, while the highest producer accuracy of bare field of 100.0% is achieved with the help of semivariogram. In the study area, some water areas share similar spectral information with road, which leads to the confusion between them. As a result, the average classification accuracy of water and road are

| Class       | Spectral | Spectral + GLCM | Spectral + STFs | Spectral + Semivariogram |
|-------------|----------|-----------------|-----------------|--------------------------|
|             | PA (%)   | UA (%)          | PA (%)          | UA (%)                   | PA (%)   | UA (%) |
| Woodland    | 96.1     | 90.4            | 95.3            | 94.7                     | 97.6     | 91.2   |
| Orchard     | 87.0     | 79.4            | 92.2            | 93.0                     | 87.8     | 87.1   |
| Cropland    | 82.0     | 77.6            | 87.7            | 86.0                     | 90.2     | 70.7   |
| Grassland   | 70.6     | 65.5            | 73.5            | 71.0                     | 70.6     | 63.3   |
| Road        | 55.0     | 64.7            | 80.0            | 68.2                     | 50.0     | 60.0   |
| Residence   | 61.8     | 72.4            | 74.6            | 70.7                     | 67.3     | 65.0   |
| Water       | 57.1     | 84.6            | 71.4            | 76.9                     | 69.0     | 53.9   |
| OA (%)      | 80.3     | 85.7            | 82.6            | 88.7                     |

Note: PA, producer accuracy; UA, user accuracy; OA, overall accuracy.

Figure 7. Classification results of Site A using (a) spectral only, (b) spectral + GLCM, (c) Spectral + STFs, and (d) spectral + semivariogram.
relatively lower than other classes. Compared with spectral classification, the overall accuracy of spectral + GLCM and spectral + STFs increases by 1.4 and 2.7%, respectively. Spectral + semivariogram has the highest overall accuracy of 94.8% among all feature combinations. The overall accuracy of spectral + semivariogram and spectral + STFs is very close. It is noted that the spectral + STFs method has better performance in distinguishing roads, whereas the spectral + semivariogram method is affected, to certain degree, by the shape of the objects. When dealing with objects like narrow roads, the available lag distance is limited. As for spectral + STFs, the semivariogram is calculated before segmentation, which weakens the influence of shape.

In summary, the spectral + semivariogram can provide more reliable and better classification results. It is good at distinguishing different kinds of vegetation, such as woodland, cropland, and orchard, which are easily confused in spectral classification. Besides, semivariogram is suitable to describe the land covers with abundant textures, or complex structure, for example, the residence is well classified in both experiments. In other words, these features will be very supplementary to the extraction of land cover with high human intervention. Yet, the solution for extracting accurate semivariogram from object in objects of long and narrow shapes needs to be further studied.
4. Conclusions

This study demonstrates the feasibility and efficiency of semivariogram-derived features for object-based classification. With the assistance of semivariogram features, the original spectral classification results are considerably improved. The improvement mainly stems from the distinction between classes with similar spectrum but different textures. Compared with GLCM features, the semivariogram features are more appropriate for describing the textures of various land covers considered in this study. The STFs defined by Ref. (21) shows some effects in image classification. Their work only adopted a pseudo-object-based strategy since its object-wise feature description relied on the window-based semivariogram calculation. We extended this work by restricting the calculation within the boundary of each segment, which we claim as the true object-based semivariogram feature extraction. The new strategy completely avoids the involvement of pixels beyond segment borders and results in a much accurate and self-consistent texture description.

As a general situation, the semivariance-based features are much distinctive for heterogeneous objects, e.g. orchards, due to the cyclicity exhibited in their semivariograms. However, the application to homogeneous objects is more limited because of their monotonous semivariograms which are more difficult to distinguish. We conduct an empirical analysis on the 14 semivariogram features defined by Ref. (28) to reveal potential intrinsic rules for feature selection. With optimization methods, the most relevant features can be screened out in different land-cover specific experiments. In the case of monotonic semivariogram, the last group of features (DMM, DMS and HA) may not even be extracted. This limits their general applications. The first (RVF, RSF, FDO, and SDT) and second group (FML, MFM, VFM, DMF, RMM, SDF, and AFM) are crucial to distinguish between monotonic semivariograms. However, among the second group, some present similar information according to their definitions. They can be simplified or combined.

The first and most critical step in object-based analysis is the creation of image objects by image segmentation. Consequently, the success of classification is highly dependent on the image segmentation results. The semivariogram-based method is influenced by other factors, including image resolution, the size of the objects and the scale of segmentation. The scale of segmentation, which is related to image resolution, directly influences the size of objects. Moreover, the size of objects is connected to the available lag distance used in semivariogram calculation. How to deal with the semivariogram extraction for some duriously shaped objects remains a question. The relationship between the scale of segmentation and the maximum lag distance will be further explored.

Funding

This work was supported by the National Natural Science Foundation of China [grant number 41101410]; the Comprehensive Transportation Applications of High-resolution Remote Sensing program [grant number 07-Y30B10-9001-14/16]; the Key Laboratory of Surveying Mapping and Geoinformation in Geographical Condition Monitoring [grant number 2014NGCM]; and the Science and Technology Plan of Sichuan Bureau of Surveying, Mapping and Geoinformation, China [grant number J2014ZC02].

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