Three Dimensional Texture Computation of Gray Level Co-occurrence Tensor in Hyperspectral Image Cubes

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ABSTRACT: The traditional gray level co-occurrence matrix (GLCM) is in two-dimensional form. Because hyperspectral imagery in the feature space has the characteristic of volumetric data, it has a great potential for three-dimensional texture analysis. Previous studies have successfully extended traditional 2D GLCM to a 3D form (Gray Level Co-occurrence Matrix for Volumetric Data, GLCMVD) for extracting features in hyperspectral image cubes by considering pixel-pairs in 3D spatial relationship. However, the core of texture computation was still in a 2D texture matrix form. To truly explore volumetric texture characteristics, this study further extended traditional GLCM to a tensor form (Gray Level Co-occurrence Tensor, GLCT) that uses three voxels to extract subtle features from image cubes. For classification applications, the kernel size for texture computation has a significant impact to the results. This study developed an algorithm based on semi-variance and separability analysis to identity appropriate kernel sizes for three-dimensional computation. Experimental results demonstrate that GLCT performs better in classification than GLCMVD for the texture analysis of hyperspectral image cubes. In addition, the developed algorithm can obtain more reasonable kernel sizes for three-dimensional computation of hyperspectral remote sensing datasets.

1. INTRODUCTION AND BACKGROUND

The characteristics of remote sensing imagery exhibit a majority of irregular and complex patterns. Because texture analysis can achieve good results in extracting features from complex images by considering the relationship among adjacent pixels, it is an important method in remote sensing image analysis. Texture analysis of remote sensing imagery mainly uses statistics-based gray level co-occurrence matrix (GLCM) to extract features and improve the classification results.

The traditional GLCM is in two-dimensional form. Because hyperspectral imagery in the feature space has the characteristic of volumetric data, it has a great potential for three-dimensional texture analysis. A previous studied has extended traditional 2D GLCM to a 3D form (Gray Level Co-occurrence Matrix for Volumetric Data, GLCMVD) for extracting features in hyperspectral image cubes by considering pixel-pairs in 3D spatial relationship, and indicating that GLVMVD performed better in classification than GLCM for features extraction (Tsai et al., 2007). However, the core of texture computation was still in a 2D matrix form. To truly explore volumetric texture characteristics, this study further extended traditional texture matrix to a tensor form (Gray Level Co-occurrence Tensor, GLCT) that uses three voxels to extract subtle features from image cubes.

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For classification applications, the kernel size for texture computation has a significant impact to the results (Marceau et al., 1990). For GLCM and GLCMVD computation, kernel size can be determined effectively with semi-variance analysis (Tsai & Chou, 2006; Tsai et al., 2007). However, in a hyperspectral image cubes, one of the dimensions is in the spectral domain. Therefore, semi-variance analysis might yield improper kernel size in this dimension. To address this issue, this study developed an algorithm based on separability measures to identity appropriate kernel size in the spectral dimension for three-dimensional computation.

2. MATERIALS AND METHODS

The procedure of this study is shown in Fig.1. The kernel size and the GLCT computation are the focuses in this paper. Because the kernel size for texture computation has a significant impact to the results. This study developed an algorithm based on separability measures to identity appropriate kernel size in the spectral dimension. Combined with semi-variance based window size analysis in the spatial domain, it enables a more viable three-dimensional computation for the texture feature extraction of hyperspectral remote sensing datasets. In addition, to truly explore volumetric texture characteristics, this study further extended traditional GLCM to a tensor form (GLCT) that uses three voxels to extract subtle features from image cubes.

2.1 Test Data

Two hyperspectral image cubes (EO-1 Hyperion and Intelligent Spectral Imaging System) were used to test the developed algorithms. The properties of the datasets are displayed in Table.1. In order to reduce computation, the spectral resolution of ISIS was aggregated to become about 10 nm.

<table>
<thead>
<tr>
<th>Data source</th>
<th>Hyperion</th>
<th>ISIS (aggregated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td>Heng-Chun</td>
<td>Xi-Tou</td>
</tr>
<tr>
<td>Platform</td>
<td>Spaceborne (EO-1)</td>
<td>Airborne</td>
</tr>
<tr>
<td>Image size(pixels)</td>
<td>481×256</td>
<td>1200×400</td>
</tr>
<tr>
<td>Spatial resolution(m)</td>
<td>30</td>
<td>1.5</td>
</tr>
<tr>
<td>Spectral resolution (nm)</td>
<td>10</td>
<td>3.5–5 (10)</td>
</tr>
<tr>
<td>Spectral range(nm)</td>
<td>457.34–905.05</td>
<td>522.8–902.7</td>
</tr>
<tr>
<td>Bands</td>
<td>45</td>
<td>160 (40)</td>
</tr>
</tbody>
</table>
2.2 Semi-Variance Analysis

Semi-variance analysis is a useful method for describing the spatial variance and correlation of an image by pixel-pairs in a specified direction. It is defined as Eq (1), where \( N(h) \) is the number of pixel pairs in the dataset, \( Z(x) \) and \( Z(x+h) \) are gray values of pixel-pairs. A typical semi-variance curve in a specified direction is shown in Fig.2 (Zawadzki et al., 2005). When \( r(h) \) reaches maximum value (Sill), the range is a appropriate kernel size in spatial domain.

\[
r(h) = \frac{1}{2 N(h)} \sum \left[ Z(x) - Z(x+h) \right]^2
\]

(1)

![Fig.2 The typical curve of semi-variance in a specified direction](image)

2.3 Separability Analysis

Because one of the dimensions in a hyperspectral image cube is in the spectral domain, semi-variance analysis might not be suitable in determining the kernel size in this dimension. In this regard, Jeffries-Matusita (J-M) distance of separability analysis is adopted to identify appropriate kernel size in the spectral dimension. The J-M distance of a class-pair of normal distribution is defined as Eq (2), where \( \mu \) is the mean vector of a class-pair and \( \Sigma \) is the covariance matrix. Each class-pair can plot a chart of separability by different spectral intervals. The typical curve of J-M distance is shown in Fig.3, where J-M distance reaches a maximum, the spectral interval may suggest a suitable kernel size in spectral domain.

Based on previous studies, the classification result by traditional GLCM computation is not good enough for discriminating vegetation types. Furthermore, one of the dimensions in a hyperspectral image cube is spectral information. It may be helpful for discriminating plants type in three-dimensional texture computation. Vegetation has high reflection in the infrared. Therefore, in order to improve the discrimination of different vegetation types, separability measures of vegetation class-pairs are performed to determine the kernel size in spectral direction.

\[
J_{ij} = 2(1 - e^{-B})
\]

\[
B = \frac{1}{8} (\mu_i - \mu_j)^T \left\{ \frac{\sum_i + \sum_j}{2} \right\}^{-1} (\mu_i - \mu_j) + \frac{1}{2} \ln \left\{ \frac{\left( \sum_i^2 + \sum_j^2 \right)}{\sum_i \sum_j} \right\}
\]

(2)

![Fig.3 The typical curve of J-M distance by different spectral intervals](image)
2.4 GLCT Computation

To truly explore volumetric texture characteristics, this study further extended traditional GLCM to a tensor form (GLCT) that uses three voxels to extract subtle features from image cubes. The difference between GLCT and GLCMVD is displayed in Fig.4. The GLCT definition is shown in Eq (3), where \(x, y, z\) are denoted as the position in the moving box. \(M(i,j,k)\) reflects that within a moving box, how often the gray values of three pixels, \(W(x,y,z)\), \(W(x+dx_1,y+dy_1,z+dz_1)\) and \(W(x+dx_2,y+dy_2,z+dz_2)\), with the spatial relationship of \(d\), are equal to \(i, j,\) and \(k\), respectively.

Kayitakire et al. (2006) suggested Angular Second Moment (ASM), Contrast (CON), Entropy (ENT), and Homogeneity (HOM) statistical measures are suitable in remote sensing imagery. Therefore, this study also uses ASM, CON, ENT, and HOM indexes for texture analysis. The definitions of the indexes are shown in Eq (4), where \(i, j, k\) are denoted as the position in the tensor, and \(P_{ijk}\) is probability of GLCT.

\[
M(i,j,k) = \sum_{x=1}^{W_{xdx}} \sum_{y=1}^{W_{ydyy}} \sum_{z=1}^{W_{zdzz}} (\text{Condition}\{1:0\})
\]

\[
\text{Condition} = [W(x,y,z) = i \land W(x+dx_1,y+dy_1,z+dz_1) = j \land W(x+dx_2,y+dy_2,z+dz_2) = k]
\]

\[
\begin{align*}
\text{ASM} &= \sum_{i,j,k=0}^{N^4} P_{ijk}^2, \\
\text{CON} &= \sum_{i,j,k=0}^{N^4} P_{ijk}[(i-j)^2 + (j-k)^2 + (i-k)^2] \\
\text{ENT} &= \sum_{i,j,k=0}^{N^4} P_{ijk}(-\ln P_{ijk}), \\
\text{HOM} &= \sum_{i,j,k=0}^{N^4} \frac{P_{ijk}}{1+[(i-j)^2 + (j-k)^2 + (i-k)^2]}
\end{align*}
\]

Fig.4 The difference between GLCT and GLCMVD for extracting features

2.5 Classification

This study employs the Maximum Likelihood classified to classify predefined target categories in both test datasets. The overall accuracy (OA) and kappa results are examined to evaluate the classifications. There are seven target categories in Hyperion and ISIS case respectively. In the Hyperion case, the target categories includes building, water, land, grass, Taiwan Acacia, Negundo Chastetree, and White Popinac. For the ISIS case, they are building, road, land, grass, farmland, coniferous forest, and bamboo.

3. RESULTS AND DISCUSSIONS

3.1 Hyperion Case

According to training data and texture patterns, semi-variance analysis results of the Hyperion case are listed in Table.2. It appears that 5 is a suitable kernel size in spatial direction. J-M distance results from different class-pairs of vegetation are displayed in Table.3. It indicates that 7 is an applicable kernel size in spectral domain. In order to demonstrate that J-M distance combining semi-variance is a viable approach, kernel size of 5×5×5 and 5×5×7 are used in GLCT and GLCMVD computation to compare their results.
The OA and Kappa evaluations of GLCT and GLCMVD computation are shown in Fig.5 and Fig.6. It is clear that 5×5×7 produced a better result than 5×5×5 in GLCT or GLCMVD computation. GLCT also outperformed GLCMVD except for the HOM index. In other words, the analysis indicates that GLCT and J-M distance both resulted in better classification.

<table>
<thead>
<tr>
<th>Table.2 Semi-variance results of Hyperion</th>
</tr>
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<tbody>
<tr>
<td>Building</td>
</tr>
<tr>
<td>Pattern 1</td>
</tr>
<tr>
<td>Pattern 2</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th>Table.3 J-M distance results of Hyperion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Taiwan Acacia vs White Popinac</td>
</tr>
<tr>
<td>7</td>
</tr>
</tbody>
</table>

3.2 ISIS Case
Because the regions of grass, road, and land in the ISIS imagery were too small, there were not enough samples for semi-variance. Therefore, only four types of training data were used for ISIS semi-variance analysis. The results of semi-variance and J-M distance analysis are displayed in Table.4 and Table.5. From these tables, it seems that 5 is a suitable kernel size in spatial domain, and then 7 is an applicable kernel size in spectral domain. In this case, the kernel size of 5×5×5 and 5×5×7 were also used in GLCT and GLCMVD computation.

The OA and Kappa results of ISIS GLCT and GLCMVD computation are displayed in Fig.7 and Fig.8. It is obvious that 5×5×7 results are better than 5×5×5. However, the ASM and ENT GLCT results are not as good as the other two. The ASM and ENT are based on probability of GLCT and gray value of three voxels. However, a hyperspectral image cube consists of a spectral dimension. It may cause undesired effects in GLCT computation. If the dataset dimensions are all in spatial domain, such as magnetic resonance imaging (MRI) or communized tomography (CT), ASM and ENT of GLCT computation may perform equally better as the other two statistical texture indexes.

<table>
<thead>
<tr>
<th>Table.4 Semi-variance results of ISIS</th>
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<tbody>
<tr>
<td>Building</td>
</tr>
<tr>
<td>Pattern 1</td>
</tr>
<tr>
<td>Pattern 2</td>
</tr>
</tbody>
</table>
Table 5 J-M distance results of ISIS

<table>
<thead>
<tr>
<th></th>
<th>Grass vs Farmland</th>
<th>Grass vs Coniferous Forest</th>
<th>Grass vs Bamboo</th>
<th>Farmland vs Coniferous Forest</th>
<th>Farmland vs Bamboo</th>
<th>Coniferous Forest vs Bamboo</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>7</td>
<td>7</td>
<td>5</td>
<td>7</td>
<td>5</td>
<td>7</td>
</tr>
</tbody>
</table>

4. CONCLUSIONS

This study adapted separability measure and semi-variance analysis to determine appropriate kernel sizes for 3D texture computation of hyperspectral datasets. It also extended traditional GLCM to a tensor form (GLCT) that uses three voxels to extract subtle features from image cubes for truly 3D texture computation. Experimental results demonstrate that combing semi-variance analysis for spatial discrimination and separability measure in the spectral direction can determine more appropriate kernel sizes for 3D texture computation of hyperspectral datasets. In addition, calculating texture features in truly 3D by GLCT in general can result in better classification, indicating that it is capable of extracting subtle features from complicated hyperspectral datasets.

However, the computation of 3D texture analysis is intensive and time-consuming. Future work may be placed on improving the computation algorithm and procedures to increase the efficiency of 3D texture computation.

5. ACKNOWLEDGEMENT

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6. REFERENCES


