SAR Image Classification Based on Its Texture Features

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1 Introduction

In the past twenty years, the texture analysis had been widely applied in computer vision and biology. In the applications of image division and object recognition, the contrast among image gray values is generally used to recognize objects. However, when those different objects have similar gray values, it is difficult to distinguish them from each other. Some auxiliary information is necessary for auto image classification under this condition. In daily life, human being uses eyes to analyze features of objects so as to recognize different objects. In the analysis process, the human eyes do employ the image texture features. It has been demonstrated that the texture analysis can improve accuracy of image classification.

The texture analysis methods are divided into two categories: one is structure analysis, which is used to extract texture elements and explore texture principle according to structure distribution; the other is the statistical analysis, which is used to analyze texture features of an image on the basis of statistical features. So far, most studies are conducted by using the statistical analysis. A famous example is the gray co-occurrence which has been applied to the texture analysis of multi-spectral images. Conner calculated the texture classes in different layers with the gray co-occurrence, and conducted experiments on air photos for classifications of residence districts, parking lots, highways, commercial districts, etc. with a classification accuracy rate of 83%.[3] Wolfs-
on also reached a good classification accuracy rate by using the gray co-occurrence on SPOT images.

In this paper, we have employed the gray co-occurrence to analyze and process the SAR image texture.

2 Gray co-occurrence

The gray co-occurrence is involved with calculations of the gray value configuration for any two pixels, that is, for a pair of pixels with an interval in any direction. The statistical principle of gray values is most suitable to the calculation of two ordered texture statistical features.

Suppose that in the $\theta$ direction there is a pair of pixels with an interval $d$, the probability of the gray value is $i, j$. Thus, the element is denoted as $p(i, j = d, \theta)$. If $\theta$ and $d$ are selected and the gray value of the image is 1, a pixel is defined as $p(i, j, i, j = 1, 2, \ldots, L)$, where $i, j$ is the gray values. Thus, the gray co-occurrence is a $L \times L$ matrix, whose gray value is $L$, and is a function of the interval $d$ and the direction $\theta$. Now, the gray co-occurrence matrix can be used to define the image texture features by the calculations of the following parameters:

1. **Energy**:
   \[ E = \sum_{i=1}^{n} \sum_{j=1}^{n} (P(i, j))^2 \]  
   (1)

2. **Inertia matrix**
   \[ I = \sum_{i=1}^{n} \sum_{j=1}^{n} (i - j)^2 P(i, j) \]  
   (2)

3. **Entropy**
   \[ H = \sum_{i=1}^{n} \sum_{j=1}^{n} \{P(i, j) \log P(i, j)\} \]  
   (3)

4. **Correlation**
   \[ C = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} (i - \mu_x)(j - \mu_y)P(i, j)}{\sigma_x \sigma_y} \]  
   (4)

where

\[ \mu_x = \sum_{i=1}^{n} \sum_{j=1}^{n} i P(i, j), \mu_y = \sum_{i=1}^{n} \sum_{j=1}^{n} j P(i, j), \]
\[ \sigma_x = \sum_{i=1}^{n} (i - \mu_x)^2 \sum_{j=1}^{n} P(i, j), \sigma_y = \sum_{j=1}^{n} (j - \mu_y)^2 \sum_{i=1}^{n} P(i, j). \]

Because the gray co-occurrence is a function of the interval $d$ and the direction $\theta$, these texture feature parameters are the functions of the interval $d$ and the direction $\theta$. Therefore, a critical issue is how to select the most suitable interval $d$ and direction $\theta$. In order to reach the best texture features, $d$ and $\theta$ should be different.

3 Experiment and result analysis

3.1 Methodology and procedure

The experimental data was an image of Canada GLOBE/SAR HV with an image size of 1 000 $\times$ 1 000. The gray value difference and contrast were little in the image, especially, because the front mountain slope and residence district had stronger scattering. Therefore, the original image was very difficult to classify. In our experiment, Eqs. (1)-(4) were used to calculate the texture features firstly for further auxiliary classification. The calculation procedure is shown in Fig. 1.

In the experiment, various windows, gray values, directions and distances were selected to compute the texture-features of the SAR image. It was found from these texture feature images that when the calculation direction was parallel to the flight direction and the distance was equal to 1, and then the moving window size had an effect on the texture sparcle size. Furthermore, for different spatial resolutions, different windows were needed to process the original images. However, when a window of 7 $\times$ 7 was used in the experimental zones, the calculation results were the best. When the calculation direction was parallel to the flight direction, the distance was equal to 1. And when the moving window size
was $7 \times 7$, the Inertia matrix feature and entropy feature images had better texture features. In addition, various distances ($d = 1$, $d = 2$, $d = 3$) and directions ($0^\circ$, $45^\circ$, $90^\circ$, $135^\circ$) were experimented in this paper. It was found that when the calculation direction was parallel to the flight direction, the calculation result was the best. However, the calculation of the image texture features was time-consuming. And the gray value $L$, in particular, had a direct effect on the calculation time. In our experiment, the gray value 16 was selected.

The texture feature images produced by the gray co-occurrence matrix showed different features. Particularly, the texture features of the residence districts were more obvious.

The classification experiments were conducted with ERDAS. The image data were images with three kinds of polarization VV, HV, HH of Globe SAR satellite which were acquired from Zhaoqing area in Guangdong province, China. Its spatial resolution was eight meters, and the image sizes were $1000 \times 1000$. Since the images of the three polarization modes were acquired the next day after the flight on the experimental zone, the registrations between the images were done with the two-ordered linear fit algorithms. When 16 control points were selected, the registration errors between VV and HV were $x = 0.2335$ pixel, $y = 0.3687$ pixel, $\sigma_{\text{median error}} = 0.4364$ pixel. But for HH and HV, the result was $x = 0.1186$ pixel, $y = 0.3653$ pixel, $\sigma_{\text{median error}} = 0.3841$ pixel.

### 3.2 Results and analysis

The training samples were selected by using a so-called seed point selection in EARDAS software. According to the characteristics of the images, the objects were divided into five categories: resident district (RD), rice field (RF), dry soil, mountainous area, and water body. The error matrix calculated from the training samples is shown in Table 1.

| Classification | RD      | DS      | MA      | RF      | WB      | Total |
|----------------|---------|---------|---------|---------|---------|-------|
| RD             | 132     | 119     | 130     | 65      | 22      | 468   |
| DS             | 93      | 109.5   | 157     | 3       | 0       | 134.8 |
| MA             | 116     | 126.5   | 115     | 9       | 108.7   |
| RF             | 203     | 16      | 303     | 895     | 25      | 144.2 |
| WB             | 19      | 0       | 0       | 11      | 997     | 102.4 |
| Total          | 563     | 144.2   | 124.5   | 108.9   | 105.3   | 537.2 |

The texture images calculated from Eqs. (1)-(4) were used for the auxiliary classification. The results are shown in Table 2.

| Classification | RD      | DS      | MA      | RF      | WB      | Total |
|----------------|---------|---------|---------|---------|---------|-------|
| RD             | 595     | 139     | 132     | 24      | 0       | 890   |
| DS             | 63      | 115.3   | 131     | 3       | 0       | 1350  |
| MA             | 35      | 118     | 946     | 61      | 0       | 1160  |
| RF             | 13      | 2       | 129     | 1013    | 2       | 1159  |
| WB             | 0       | 0       | 0       | 1073    | 1073    | 633   |
| Total          | 706     | 1412    | 1338    | 1101    | 1075    | 5632  |

From Table 1 and Table 2, it is found that the classification accuracy with the texture feature auxiliary is higher than that only with the training samples based on HH, HV, VV images.

In our experiment, the previous probability was set as 95%. About 200 points were se-
lected randomly from air photos or DEMs as reference points for the accuracy evaluation. The calculation results were shown in Tables 3-6, respectively.

1) Classification results based on HH, HV, VV images

The results of distribution of the reference points and classification were shown in Table 3 and Table 4, respectively.

| Classification | RD | DS | MA | RF | WB | Total |
|----------------|----|----|----|----|----|-------|
| RD             | 12 | 11 | 12 | 5  | 2  | 42    |
| DS             | 1  | 16 | 2  | 0  | 0  | 19    |
| MA             | 2  | 4  | 12 | 2  | 0  | 20    |
| RF             | 14 | 1  | 20 | 61 | 2  | 98    |
| WB             | 1  | 0  | 1  | 19 | 21 | 21    |
| Total          | 30 | 32 | 46 | 69 | 23 | 200   |

Table 4 Classification results from HH, HV, VV images

| Classification | Reference points | Classification points | Correct points | Correct percent |
|----------------|------------------|-----------------------|----------------|-----------------|
| RD             | 30               | 20                    | 12             | 60%             |
| DS             | 32               | 19                    | 16             | 84.2%           |
| MA             | 46               | 20                    | 12             | 60%             |
| RF             | 69               | 98                    | 61             | 62.2%           |
| WB             | 23               | 21                    | 19             | 90.5%           |

An average accuracy $K_1 = 71.2\%$, and a weighted average accuracy $K_2 = 68.1\%$.

2) Classification results aided by the texture feature images

An average accuracy $K_1 = 87.3\%$, and a weighted average accuracy $K_2 = 88.9\%$.

| Classification | RD | DS | MA | RF | WB | Total |
|----------------|----|----|----|----|----|-------|
| RD             | 20 | 5  | 4  | 1  | 0  | 30    |
| DS             | 1  | 24 | 3  | 0  | 0  | 28    |
| MA             | 1  | 6  | 46 | 3  | 0  | 56    |
| RF             | 1  | 0  | 7  | 55 | 1  | 64    |
| WB             | 0  | 0  | 0  | 22 | 22 | 22    |
| Total          | 23 | 35 | 60 | 59 | 23 | 200   |

Table 6 Classification results aided by the texture feature images

| Classification | Reference points | Classification points | Correct points | Correct percent |
|----------------|------------------|-----------------------|----------------|-----------------|
| RD             | 23               | 30                    | 20             | 66.7%           |
| DS             | 25               | 28                    | 24             | 85.7%           |
| MA             | 60               | 56                    | 55             | 98.2%           |
| RF             | 59               | 64                    | 55             | 85.7%           |
| WB             | 23               | 22                    | 22             | 100%            |

It is apparent that the classification results aided by the texture feature images are much better than those from HH, HV, VV images.

4 Conclusions

In this paper, we conducted a classification experiment on SAR images. It was found that when the texture features were employed in the process of image classification, the general classification accuracy reached 88.9%; without the texture feature auxiliary, the general classification accuracy was only 68.1%. Therefore, we can draw the following conclusions:

1) For dry soil and water body, both the two methods had good classification results.

2) For rice field, when the texture features were employed, its classification results were better with an accuracy of more than 85%.

3) When the texture features were employed, the classification accuracy of resident district could reach 66.7%; but without the texture feature auxiliary, the classification accuracy was only 60%.

4) The classification accuracy of mountainous areas could reach 98.2% when the texture features were employed; but without the texture feature auxiliary, its classification accuracy was only 60%. Therefore, the mountainous area classification aided by the texture features is the best.

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databases has been recognized as the valuable knowledge acquisition in the environment management, the resource utilization and the planning of industry and agriculture. On the basis of the general discussion of the spatial knowledge discovery and the spatial rule mining, this paper gives the principle of the comprehensive knowledge discovery, concept and mining algorithm, which has a wide application in comprehensive knowledge discovering and utilization. It is important to integrate mining both the spatial information and the attribute information. The theoretical analysis and the case study are given to attain this goal. Some points are summarized as below.

1) Data mining should consider both spatial relation and attribute character of spatial objects, which is called comprehensive knowledge discovery.

2) Spatial relation can be described from different views and only some key factors that have important influence on our study domain can be considered.

3) Spatial association relation and attribute character of spatial objects are researched in the case study and valuable patterns are obtained.

4) A comprehensive data-mining algorithm is introduced and used in this paper.

Although the comprehensive knowledge discovery proposed here focuses on the spatial association rule mining and attribute data, it can also be applied to other comprehensive knowledge discovery fields such as spatial classification, spatial clustering, etc., which will be included in future researches.

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