Remote Sensing Image Retrieval Based on Attribute Profiles

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Abstract—In recent years, many approaches based on mathematical morphology have been applied in remote sensing image processing. In the paper, we proposed to use attribute profiles (APs) for textural extraction to the problem of content-based image retrieval (CBIR). In particular, four different attributes of APs with multi-scale were applied to spatial information description. Then, the obtained textural images were processed by Gabor filters to generate the amplitude and energy coefficients. Finally, the extracted features along with histogram and color-moments were used for retrieval. The performance of textural descriptors were evaluated based on the UC Merced Land Use–Land Cover data set. The experimental results show that the proposed method performs better than the popular Gabor texture.

Keywords- mathematical morphology, content-based remote sensing image retrieval, attribute profiles, texture features.

I. INTRODUCTION

During the last three decades, huge quantities of remote sensing (RS) data have been acquired, and how to efficient store, organize and retrieve the data has become urgent and challenging.

Compared with keyword-based image retrieval, content-based image retrieval (CBIR) needs no keywords from manual annotation. It mainly makes use of low-level image features including color, texture, shape and so on. In these methods, image processing algorithms are used to extract feature vectors that represent image properties. It is possible to retrieve images similar to one chosen by the user (query-by-example) [1][2]. Similar to general image, content-based RS image retrieval is the process of retrieving and getting interesting images from RS image library through the visual features and quantitative indices which are generated from image contents [3]. In particular, texture has been widely applied as it can describe coarseness, directionality characteristics of images. Several texture descriptors have been employed, such as Gabor filters [4], grayscale co-occurrence matrices [5], global morphological texture [6].

In this paper, a new image retrieval method based on attribute profiles (APs) [7] is proposed. In the method, APs are first used to extract texture features. Then, texture images are filtered by Gabor transform to calculate the amplitude and energy coefficients. The obtained vectors concatenated with histogram and color-moments to form the image features. Finally, image retrieval experiments on the UC Merced Land Use–Land Cover data set are carried out for performance evaluation of the proposed method.

II. APs-BASED IMAGE RETRIEVAL

Like morphological profiles (MPs) [8], APs are also based on mathematical morphology, but they can model other geometrical characteristics rather than the size of the objects.

The AP is an extension of the MP. Given a grayscale image $f$, an AP is defined according to a certain criterion $T$ as follows [9]:

$$\text{AP}(f) = \{\phi^T(f), \phi^T_{e+1}(f), \ldots, \phi^T_n(f), \gamma^T(f), \ldots, \gamma^T_{e+1}(f), \gamma^T_n(f)\}$$

(1)

where $\phi^T$ and $\gamma^T$ are morphological attribute thickening and thinning operators, respectively. The two operators are implemented based on the evaluation where the criterion $T$ compares the value of an attribute $\text{attr}$ measured on the component $C$ against a given reference value $\lambda$. If the attribute meets $\text{attr}(C) > \lambda$, then the region keeps unchanged; otherwise, it is set to the gray level of a darker or brighter surrounding region (the operation can be performed through thinning or thickening). When multiple thresholds $\{\lambda_1, \lambda_2, ..., \lambda_n\}$ are available, an AP is obtained.

When different attributes are applied to the AP, the distinct geometrical characteristics of the image are shown. Figure 1 is examples of APs with four attributes including area, length of the diagonal of the bounding box, moment of
inertia and standard deviation. The corresponding threshold values are set to 100, 10, 0.2 and 20, respectively. In the figure, each column presents an AP built by a different attribute, and the center image is original image $f$.

After APs are built, the resulting images are to be filtered by Gabor transforms with 4 scales and 5 orientations which generate the coefficients of amplitude and energy. Besides, common color features including color histogram, color moments and color auto correlogram, and wavelet moments are also calculated. All the features are concatenated into a long vector as an image feature.

Figure 2 presents the flowchart of image retrieval. For image library available, feature extraction is first applied to the images in it to obtain the image features. Given a query image, similar feature extraction step is done. Then, the feature of query image is compared with those of library images based on some similarity metric. Finally, the query results are obtained according to the metric values.

III. EXPERIMENTS

In the experiments, we use a subset of the UC Merced LULC data set [10]. The used data set consists of 100 256*256 color images in 10 classes, with 10 images per class. The classes include agricultural, airplane, baseball diamond, beach, buildings, forest, golf course, river, intersection and tennis court. Figure 3 shows examples of each class.
To evaluate the performances of different attributes of APs, the proposed method uses four attributes (area, length of the diagonal of the bounding box, moment of inertia and standard deviation) to build the APs. The corresponding values of thresholds are empirically set as follows:

1) area of the region:
   \[ \lambda_a = [100, 500, 1000, 5000] \]
2) length of the diagonal of the bounding box:
   \[ \lambda_d = [10, 25, 50, 100] \]
3) moment of inertia:
   \[ \lambda_l = [0.2, 0.3, 0.4, 0.5] \]
4) standard deviation of the grey-level values of the pixels in the regions:
   \[ \lambda_s = [20, 30, 40, 50] \]

For performance comparison, the popular Gabor descriptor with 4 scales and 5 orientations is also analyzed, and the mean and standard deviation are used as features. Two popular distance metrics, \( L_1 \) and \( L_2 \) [11], are employed to measure the similarities between query image and library images. The metrics are defined as:

\[
L_1(x, y) = \|x - y\|_1 = \sum_{j=1}^{d} |x_j - y_j| \quad (2)
\]

\[
L_2(x, y) = \|x - y\|_2 = \left( \sum_{j=1}^{d} (x_j - y_j)^2 \right)^{1/2} \quad (3)
\]

where features \( x, y \in \mathbb{R}^d \).

In addition, to incorporate the prior knowledge, support vector machine (SVM) [12] is used to improve the match performance. The image library is randomly divided into two groups: training and test subsets. SVM is first trained by the training samples in the image library. Then, the class labels of test images including the query one are predicted by SVM. Finally, the similarity values are calculated among test images with the same labels as the query one, and these images are ranked according to the distance metrics. If the number of images assigned with the same labels as the query one is smaller, other images with higher similarity values in the test samples are added into the query results.

For remote sensing images retrieval, there are two common quantitative indices for performance evaluation. One is recall, the other is precision [13]. Precision is the fraction of retrieved images that are relevant to the query; recall is the fraction of the images that are relevant to the query that are successfully retrieved. They are computed as follows:

\[
\text{recall} = \frac{\# \{ \text{Relevant} \cap \text{Retrieved} \}}{\# \{ \text{Relevant} \}} \quad (4)
\]

\[
\text{precision} = \frac{\# \{ \text{Relevant} \cap \text{Retrieved} \}}{\# \{ \text{Retrieved} \}} \quad (5)
\]

In the experiments, we mainly use precision as the evaluation criteria. SVM is implemented by LibSVM [14]. RBF kernel is used, and the related parameters are determined by the ten-fold cross validation. Before AP texture extraction, all the RGB images are converted into gray level ones through Gray=0.299×R +0.587×G+0.114×B.

Table I lists the retrieval precision when different texture descriptors are applied. 20%, 30%, 40% and 50% of images are randomly selected as training samples, and the rest ones are for test. From the table, we can see that: 1) APs with attribute of area and diagonal generally perform better than the rest methods, and APs with attribute of standard deviation show poor performance. 2) Among three performance indices, SVM outperforms the others except when 20% training samples available. The possible reason is the performance of supervised SVM is largely affected by the amount of prior information. In the two distance metrics, \( L_2 \) is better than \( L_1 \).
TABLE I. RESULTS OF RETRIEVAL

<table>
<thead>
<tr>
<th>Number of training samples</th>
<th>L1</th>
<th>L2</th>
<th>SVM</th>
<th>L1</th>
<th>L2</th>
<th>SVM</th>
<th>L1</th>
<th>L2</th>
<th>SVM</th>
<th>L1</th>
<th>L2</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>0.475</td>
<td>0.5013</td>
<td>0.4297</td>
<td>0.4959</td>
<td>0.5286</td>
<td>0.5633</td>
<td>0.5139</td>
<td>0.5278</td>
<td>0.5972</td>
<td>0.5240</td>
<td>0.5240</td>
<td>0.6080</td>
</tr>
<tr>
<td>30%</td>
<td>0.4844</td>
<td>0.5125</td>
<td>0.4656</td>
<td>0.4939</td>
<td>0.5388</td>
<td>0.6102</td>
<td>0.5028</td>
<td>0.5222</td>
<td>0.6139</td>
<td>0.5040</td>
<td>0.5280</td>
<td>0.5720</td>
</tr>
<tr>
<td>40%</td>
<td>0.4734</td>
<td>0.5109</td>
<td>0.4516</td>
<td>0.4796</td>
<td>0.5184</td>
<td>0.5551</td>
<td>0.4972</td>
<td>0.5139</td>
<td>0.6250</td>
<td>0.5000</td>
<td>0.5240</td>
<td>0.6200</td>
</tr>
<tr>
<td>50%</td>
<td>0.4437</td>
<td>0.4766</td>
<td>0.4266</td>
<td>0.4510</td>
<td>0.5000</td>
<td>0.5816</td>
<td>0.4667</td>
<td>0.4944</td>
<td>0.5722</td>
<td>0.4880</td>
<td>0.5000</td>
<td>0.5960</td>
</tr>
</tbody>
</table>

IV. CONCLUSION

In the paper, we propose a new image retrieval method based on APs. In the method, AP texture is first extracted. Then, the texture images are processed by Gabor transform to produce the amplitude and energy coefficients. Finally, the obtained vectors concatenated with histogram and color-moments to form the image features. In the image retrieval experiments on the UC Merced Land Use–Land Cover data set, we compare the performances of APs with four attributes and Gabor descriptor. The retrieval results show the effectiveness of the proposed method.

REFERENCES