SAR Image Target Recognition Based on Hu Invariant Moments and SVM*

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Abstract

Target recognition is a key step in the application of SAR images, but because of the existing of speckles in SAR images, targets can not be recognized well by using traditional methods. According to the advantages of invariant moments extraction and support vector machine (SVM) classification, an efficient method of SAR image target recognition is proposed. First, image preprocessing is performed by using wavelet transform. Second, seven Hu moments, which have the properties of rotation invariability, translation invariability and scaling invariability, are extracted as feature vectors and are normalized. Then a SVM classifier is designed and trained by using normalized feature vectors. Finally, the testing sets of SAR images are recognized by trained SVM. In the experiments of recognizing planes and tanks, better results have been obtained with this new method.

1. Introduction

Synthetic Aperture Radar (SAR) imagery has become an important source of information about the Earth’s surface and has been widely used in many fields, such as ecology, hydrology, geology, oceanography etc. However, SAR imagery usually exhibits a speckled appearance due to coherent imagery systems, so it is difficult to use traditional methods to recognize targets in SAR images. How to recognize targets rapidly and accurately is more and more important for us.

There are two key techniques to recognize targets in SAR images: the first one is feature extraction, and the second one is target classification. Feature extraction is a process that we extract targets information from the preprocessed SAR images and then use concise, efficient and accurate forms to describe them. Targets classification means that we design a classifier to train feature vectors, and then use the trained classifier to recognize and classify targets in SAR images.

We know that the same target in different images which are got in different times, positions and conditions is in different translation, scaling, rotation angle, but the invariant moment of an object is not affected by different translation, scaling, rotation angle of the target. Therefore, Hu invariant moments of a target are extracted as its features in this paper.

Support Vector Machine (SVM) is a new statistical learning method. Compared with other machine learning methods, the learning discipline of SVM is to minimize the structural risk instead of empirical risk the learning discipline of classical methods, and it gives SVM better generative performance.

This paper is organized as follows: in section 2, the method of feature extraction by using Hu invariant moments is reviewed. In section 3, the method of SVM is introduced briefly. According to the advantages of invariant moments extraction and SVM classification, a new SAR image target recognition method is proposed in section 4, and some results of tests on real data of SAR images are presented in this section.

2. Hu invariant moments

Seven Hu’s invariant moments are extracted from targets in SAR images as feature vectors in this paper.

The two order moment $m_{pq}$ of a two-dimensional digital image $f(x,y)$ is defined as

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y)$$

(1)

If the centroid of a target is on the same point as the origin of coordinates, namely $\bar{x} = 0$ and $\bar{y} = 0$, the moment $m_{pq}$ is called as the central moment $\mu_{pq}$:

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x,y)$$

(2)
Where $\mu_{pq}$ has the property of translation variability. Furthermore, $\eta_{pq}$ can be defined as

$$\eta_{pq} = \frac{\mu_{pq}}{(\mu_{20} + \mu_{02})^2}$$

(3)

in which $\gamma = (p + q + 2)/4$, $p + q = 2, 3, \ldots$, which has the property of scale invariability. Then, seven invariant moments, which are the nonlinear combination of $\eta_{pq}$, are given by Hu:

$$\phi_1 = \eta_{20} + \eta_{02}$$

(4)

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}$$

(5)

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

(6)

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

(7)

$$\phi_5 = (\eta_{30} - 3\eta_{12})[\eta_{30} + \eta_{12}(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03} + \eta_{21} + \eta_{03})$$

$$[3(\eta_{21} + \eta_{03})^2 - (\eta_{21} + \eta_{03})^2]$$

(8)

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$+ 4\eta_{11}([\eta_{30} + \eta_{12}]^2 - (\eta_{21} + \eta_{03})^2)$$

(9)

$$\phi_7 = (3\eta_{21} - \eta_{03})[\eta_{30} + \eta_{12}(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2]$$

$$- (\eta_{30} - 3\eta_{12})[\eta_{21} + \eta_{03}$$

$$[3(\eta_{21} + \eta_{03})^2 - (\eta_{21} + \eta_{03})^2]$$

(10)

The seven invariant moments have the properties of rotation invariability, translation invariability and scaling invariability.

### 3. Support vector machine theory

Support vector machine is a new machine learning technique developed since the middle of 1990s. Being different from traditional neural network, it is based on structure risk minimization principle, while the latter on empirical risk minimization principle. A large number of experiments have shown that, comparing with traditional neural network, support vector machine has not only simpler structure, but also better performances, especially better generalization ability. In addition, it is very fit for solving problems with small sample set and high dimension.

#### 3.1 The basic principle of SVM

The basic principle of the SVM is to find the optimal linear hyperplane such that the expected classification error for unseen test samples is minimized. On the basis of this principle, a linear SVM uses a systematic approach to find a linear function with the lowest VC dimension. For nonlinear separable data, the SVM can map the input to a high-dimensional feature space where a linear hyperplane can be found. Therefore a good generalization can be achieved by the SVM compared to conventional classifiers.

In the case of a linear separable two-class problem, with examples $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, the final optimal decision function can be obtained,

$$f(x) = \text{sgn}\{\sum_{i=1}^{n} a_i y_i (x \cdot x_i) + b\}$$

(11)

For a linear SVM, the kernel function is just a simple dot product in the input space. For a nonlinear SVM, the samples can be projected to a feature space of higher dimension via a nonlinear mapping function. Then the optimal decision function can be written as

$$f(x) = \text{sgn}\{\sum_{i=1}^{n} a_i y_i K(x, x_i) + b\}$$

(12)

where $K(x, x_i)$ is the kernel function. The kernel function in the SVM classifier plays the important role of implicitly mapping the input vector into a high-dimensional feature space. There is currently no technique available to learn the form of kernels. Common choices of kernel function are the linear kernels, polynomial kernels, and Gaussian RBF kernels in SVM research. They are defined as follows

1. Linear kernels
   $$K(x, x_i) = x \cdot x_i$$

(13)

2. Polynomial kernels
   $$K(x, x_i) = [(x \cdot x_i) + 1]^q$$

(14)

3. Gaussian RBF kernels
   $$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{\sigma^2}\right)$$

(15)

#### 3.2 Extend two-class SVM classifier to Multi-class classifier

Standard SVM is based on two-class classification problems. However, unclassifiable regions exist when they are extended to multi-class problems. Now there are two methods to solve this problem. One method is to construct a multi-class classifier directly, such as k-SVM which is proposed by Weston and Watkins. But this method has higher computational complexity. The other method is to construct a multi-class classifier by combining several 2-class classifiers. This method is widely adopted and easy to realize. Usually there are two strategies: one-against-one and one-against-all.

Here we adopt one-against-one method. For K-class event, the “one-against-one” method construct $M = \frac{K(K-1)}{2}$ classifiers, where each is
trained on data from the $i$th and the $j$th class, we solve the following binary classification problem:

$$
\min_{w^i, b^i, \alpha^i} \frac{1}{2} (w^i)^T w^i + C \sum_i \alpha_i \left( 1 - y^i - \xi_i^i \right)_+ + \xi_i^i,
$$

$b^i \geq 1 - \xi_i^i$, \quad if \quad $y_n = i$

$b^i \leq -1 + \xi_i^i$, \quad if \quad $y_n = j$

$\xi_i^i \geq 0$

(16)

where $k(x_n)$ is a kernel function, $(x_n, y_n)$ is a $i$th or $j$th training sample.

There are different methods for doing the future testing after all $M$ classifiers are constructed. After some tests, we decided to use the “Max Wins” strategy. In this strategy, each classifier casts one vote for its preferred class, and the final result is the class with the most votes. That is, if $x$ is decided is in the $i$th class, then the vote for the $i$th class is increased by one. Otherwise, the $j$th class is increased by one. Then we predict $x$ is in the class with the largest vote.

4. SAR image target recognition

By combining Hu invariant moments and SVM, a new method of SAR image target classification is proposed. We employ this new method to recognize planes and tanks of different types in SAR images. Some samples of planes and tanks are illustrated in fig. 1.

![SAR image samples to be recognized](image)

The basic steps of the new method are as follows:

(1) Image preprocessing: SAR images are denoised by traditional wavelet transform to improve their signal-noise-ratio, edge detection is performed with the Canny operator, then the images are segmented by threshold processing.

(2) seven Hu moments, which have the properties of rotation invariability, translation invariability and scaling invariability, are extracted as feature vectors and are normalized.

(3) Design a SVM classifier, then use normalized feature vectors to train this classifier. If it is a two-class classification problem, we design a two-class SVM classifier; if not, we adopt one-against-one strategy to construct a multi-class SVM classifier.

(4) Employ this trained SVM classifier to recognize targets in SAR images.

According to these steps, we recognize two-class targets and multi-class targets in SAR images respectively. Common choices of kernel function are the linear kernels, polynomial kernels, and Gaussian RBF kernels. After some tests, we choose Gaussian RBF kernels because they have better recognition effects.

The results are shown in Table 1.

<table>
<thead>
<tr>
<th>number of class</th>
<th>number of training samples</th>
<th>number of testing samples</th>
<th>kernel function</th>
<th>number of support vectors</th>
<th>Recognition accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>50</td>
<td>100</td>
<td>poly</td>
<td>16</td>
<td>97.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>rbf</td>
<td>9</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>90</td>
<td>180</td>
<td>poly</td>
<td>31</td>
<td>93.15</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>rbf</td>
<td>17</td>
<td>96.34</td>
</tr>
<tr>
<td>4</td>
<td>160</td>
<td>320</td>
<td>poly</td>
<td>113</td>
<td>88.43</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>rbf</td>
<td>59</td>
<td>92.21</td>
</tr>
</tbody>
</table>

As shown in table 1, both two-class targets and multi-class targets are well recognized by using the new method, the average of recognition accuracy is above 96%.

In reference [7], a method which combines texture features and neural network is used to recognize targets of planes and tanks in SAR images. In reference [8], a fuzzy clustering method is used to recognize targets in SAR images. Compare the results in this paper with reference [7] and [8], the result is shown in Table 2.

Obviously, the experimental results by using the new method are better than those by using other methods.
Table 2. Comparison of three methods

<table>
<thead>
<tr>
<th>recognition method</th>
<th>average recognition accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>the new method</td>
<td>96.18</td>
</tr>
<tr>
<td>neural network method</td>
<td>90.23</td>
</tr>
<tr>
<td>fuzzy clustering method</td>
<td>88.78</td>
</tr>
</tbody>
</table>

5. Conclusion

In this paper, seven Hu invariant moments are extracted as feature vectors, and a support vector machine is applied to recognize targets of planes and tanks in SAR images. The experimental results show that the new method has higher recognition accuracy than neural network method, and it is an efficient method for SAR image target recognition.

6. Acknowledgment

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7. References

[7] Xue Xiaorong. Research on SAR image processing[D]. Xi’an: Northwestern Polytechnical University, 2004