2010 3rd International Conference on Computer and Electrical Engineering (ICCEE 2010)
IPCSIT vol. 53 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V53.No.1.79

SAR Image Feature Extraction and Target Recognition Based on Contourlet and SVM

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Abstract. In this paper, we introduce a SAR images target recognition approach based on the contourlet transform and support vector machine (SVM), which takes technological advantages of both SVM and the contourlet transform for feature extraction.

Keywords: Contourlet; SVM; feature extraction

1. Introduction

SAR systems are important sensors due to their all weather, day/night, long standoff capability. Along with the development of radar technologies, as well as with increasing demands for target recognition (ATR) using SAR has become an active research area. The process of SAR image formation of a target or a scene is a sensitive function of the range of the system and scene parameters. Hence, the ATR algorithms need to be extremely robust to any variation in the imaging system and scene parameters. Some of the reports with excellent ATR performance reported have used a range of classification algorithm, starting from simple template matching and Gaussian-modeled Bayesian approach to those involving more involved algorithm such as the support vector machine approaches. The template-based method, however, is computationally inefficient. Here, high classification accuracy conditions the creation of large sets of filters for each class, which results in extensive computation both in the training and testing stages.

As a key step of ATR, the feature extraction plays an important part in performing the recognition task. Many efficient approached for target feature extraction have been developed, e.g, Princple Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis(LDA), Kernel PCA(KPCA), Kernel LDA(KLDA) and corresponding modified methods[1-7].. Contourlet, proposed by Minh N.Do and Martin Vetterli, is a real method for 2-D representation of image. Contourlet not only process the main features of wavelets in multi-resolution analysis, but also can specially decompose the subbands at each scale into different parts with flexible number. The Contourlet Transform (CT) was chosen as the basis for feature extraction methodology proposed. By analyzing each target in different scales it is possible to see characteristics that were not obvious in the original resolution [8-10].

The paper is organized as follows. In Section II, we present the principle of the contourlet transform. In Section III, we give a brief review of SVM. Section IV describes detail steps of our target recognition approach, including feature extraction and classification. Experimental results on the MSTAR data are presented and discussed in Section V. We conclude with our remarks on the proposed algorithm in Section VI.

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2. Contourlet Transform

The contourlet transform provides a multiresolution, local and directional image expansion. It mainly has two stages: multiscale Laplacian Pyramid decomposition and the directional filter bank. As shown in Figure 1, it has a double filter bank structure and the two stages are independent each other. The directional filter bank has a flexible number of directions and it only capture the high frequency of the input image because the low frequencies of the input image are removed before applying it.

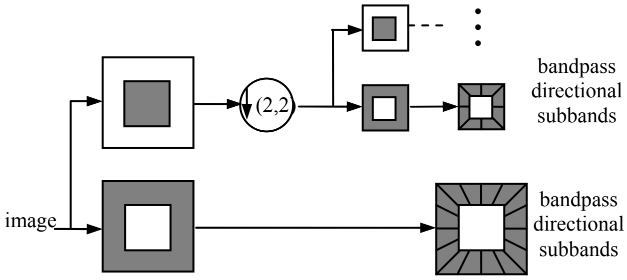


Figure 1. The block diagram of contourlet transform

The decomposition coefficients of contourlet are similar with wavelet coefficients in that most coefficients are almost zero and only few of them, near the edge of the objects in the image, have large magnitudes. Besides this feature, the characteristic of coefficients have strong dependences across decomposition levels. The different directions in each decomposition level can describe different features for same edge.

Contourlet is a geometry of transformation based on image. The multi-scale decomposition and the directional decomposition are two independent processes which will effectively to express the contours and texture-rich of image. They have "long strip" structure which aspect ratios have changed with the scale in the enlongated supported, it can effectively to track the characteristics of linear discontinuities and area discontinuities in the image. Compared with wavelet, contourlet has a rich basic function which can describe the smooth edges using less transform coefficients, and can take the point discontinuities which have the same direction together into a linear or area discontinuities.

3. SVM Classifier

Based on structural-risk minimization principles, SVM has achieved remarkable success in pattern-recognition problems. By non-linear mapping, it projects samples from low-dimension space to high-dimension space and implements the non-linear classifiable problem in the high-dimension.

SVM always finds a global minimum because it usually tries to minimize a bound on the structural risk, rather than the empirical risk. Empirical risk is defined as measured mean error rate on the training set as below

$$R_{emp}(\alpha) = \frac{1}{2l}\sum_{i=1}^{l}\left|y_i - f(x_i, \alpha)\right| \tag{1}$$

where l is number of observation, y_i is class label and x_i is sample vector. And structural risk is defined as a structure of divided entire class of function into nested subset and finding the subset of function which minimizes the bound on the actual risk. SVM achieves this goal by minimizing the following Lagrangian formulation:

$$L_p = \frac{1}{2}\|w\|^2 - \sum_{i=1}^{l}\alpha_i y_i (x_i w + b) + \sum_{i=1}^{l}\alpha_i \tag{2}$$

where α_i is positive Lagrange multiplier.

When dealing with nonlinear problem, we use the kernel trick to maximum-margin hyperplanes. In this paper, we use the Gaussian Radial basis function

$$k(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \quad (3)$$

Essentially, object recognition is a complex multi-classification problem. However, SVM is originally suited for two-class problem. When dealing with multi-classification problem, it is able to construct a multi-class classifier by combining several binary classifiers.

4. Proposed Recognition Method

In the proposed algorithm, we intend to find the best target representation while keeping the dimension of the feature vector reasonably low[11-12]. The feature of the lowpass and bandpass directional subbands are extracted respectively[14,15]. Energy, entropy of detail coefficients, energy of approximation, mean, variance, skewness are selected as different contourlet domain features. For an $N \times N$ subband $c(i, j)$, energy is calculated as:

$$E = \sqrt{\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} c^2(i, j)}{N^2}} \quad (4)$$

Entropy is defined as:

$$H = \sum_{k=1}^{M} p_k \log_2 p_k \quad (5)$$

where M is the number of random variable, α_i is the random variables with probabilities p_i. Mean and variance are defined as:

$$Mean = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j-1}^{N} c(i, j) \quad (6)$$

$$Var = \frac{1}{N^2}\sum_{i=1}^{N}\sum_{j-1}^{N} [c(i, j) - Mean]^2 \quad (7)$$

Shewness is a measure of the asymmetry of the data around the sample mean. The skewness of a distribution is defined as:

$$S = \frac{E(c - Mean)}{\sqrt{Var^3}} \quad (8)$$

where $E(t)$ represents the expected value of the quality c.

Then the features are merged and the SVM is used for target recognition in SAR images.

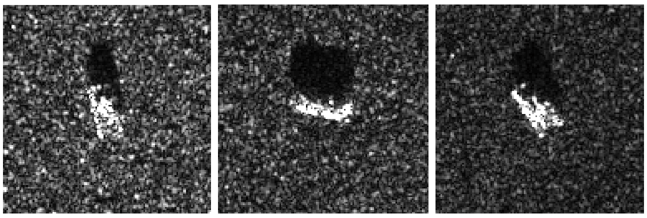
5. Experiments and Performance Evaluations

The SAR image dataset used for experimentation was collected under the Moving and Stationary target Acquisition and Recognition (MSTAR) program. It is composed of X band SAR images for 5 vehicle targets taken at two depression angles, 15 and 17 degrees, and different target orientation between 0 and 360 degrees. The resolution is 1ft by 1ft. Images of depression angle 17 degrees were used for 17 degrees were used for constructing the training set, whereas those of depression angle 15 degrees were used for testing. Unlike optical images, SAR images reflect the structure of target's point scatters, which does not have even reflect rate over different orientation angles. Thus SAR images of the same target taken at different orientation angles can show great differences, which make classification even more difficult[16-19].

Imagery distribution is detailed in Table I, whereas samples of these images are shown in Fig.2. The vehicles in MSTAR dataset contain the BMP2 (SN_9563, SN_9566, SN_C21) tracked Armored Personnel Carrier, the BTR70 (SN_C71) wheeled Armored Personnel Carrier and the T72 (SN_132, SN_182. SN_S7) Main Battle Tank. Different serial numbers in one-target class mean that vehicles are variants with small differences in configuration, articulation and damage under extended operating conditions, e.g., tanks with drum mounted or unmounted, carriers with antenna extended or shunk[13]. The proposed CT-SVM method can obtain 7% higher recognition rate than wavelet-based SVM. It was shown that the accuracy of the contourlet transform especially in remote sensing data acquisition systems.

Table I Summary of MSTAR Database

Type	Serial Number	Training Set Size	Testing Set Size
	SN_9563	233	195
BMP2	SN_9566	232	196
	SN_C21	233	196
BTR70	SN_C71	233	196
	SN_132	232	196
T72	SN_812	231	195
	SN_S7	228	191



(a) BMP2 (b) BTR70 (c) T72

Figure 2. Samples of SAR target

6. Conclusion

SVM motivated by the statistical learning theory is a probabilistic non-linear model. Since theoretically attractive features and profound empirical performance, SVM is gained popularity in many areas. This paper proposes a new approach for target recognition in SAR images based on exploiting the features of the contourlet transform combined with SVM classification. In particular, we have analyzed this technique both theoretically and experimentally. The efficiency of our method has been demonstrated on standard databases MSTAR. The experiments results show that the features are effective and robust to targets with the same configuration of configuration differences.

7. Acknowledgment

This work was supported in part by the China Postdoctoral Science Foundation (20090450953).

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