URBAN AREA CLASSIFICATION
IN HIGH RESOLUTION SAR BASED ON TEXTURE FEATURES

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ABSTRACT:

Texture features in high resolution TerraSAR-X data were used for classification in this paper. In single band and single polarized SAR image, texture holds useful information for interpreting objects in urban area. In this paper, the gray level co-occurrence matrix (GLCM) was computed to extract texture images. We used contrast, energy, correlation and mean measures combination based on GLCM to characterize texture images. Window size is an important parameter for mapping textures. Larger windows lead to more stable texture features but tend to blur the edges, while smaller windows lead to erroneous boundary delineation and misclassify the boundary itself as an incorrect class. To get the appropriate window size, nine window sizes 3×3, 5×5, 7×7…19×19 were tested on the filtered SAR image. The transformed divergence (TD) distance was computed for comparing separability between two classes from vegetation, roads, buildings and water body. According to the TD distance, the windows with size smaller than 11×11 would lead to unstable seperability and not be enough to fully separate four classes. And when the windows were set from 11×11 to 19 × 19, the separability was stable and better. So, we adopted the 11×11 window size considering both separability of classes and boundary delineation. Then, SVM classification techniques were used. We had a conclusion that, with texture features as accessorial data, the accuracy has a great more improvement, which proves an effective method to classify high spatial resolution SAR image.

1. INTRODUCTION

Nowadays, due to all weather and all day imaging capability, SAR images have played more and more important roles for urban environment mapping. Owing to available of high resolution SAR data such as the TerraSAR-X, we can have more detailed analysis over urban area.

For single band and single polarization SAR images, it is very hard to well interpret different objects because of limited information available. But, abundant texture information in urban area is effective in interpretation of SAR image.

Many researches have shown that classification based on texture features can improve the accuracy (Ulaby.1986, Simard.2003, Dekker.2003, Hu de yong .2008). And, different methods have been proposed for the analysis of image texture, including those based on GLCM, Markov random fields (MRFs), fractal dimension, Gabor wavelets, etc.

A few comparisons between those texture feature extraction methods have been presented. Conners and Harlow (Conners and Harlow .1980) described the ability of four texture analysis algorithms to perform texture discrimination, which were the GLCM, run length difference, gray level difference density and power spectrum. Clausi (2001, 2004) compared the performance of GLCM, MRF, and Gabor features in classifying SAR sea ice imagery. Kandaswamy (2005) compared the GLCM and Gabor wavelets texture analysis methods. They all had a conclusion that the GLCM method produced a better result than others.

Therefore, in this paper, we adopt the GLCM method to extract

texture of single polarized TerraSAR-X data and classify with SVM classifier. The paper is organized as follows: dataset and methods are introduced in section 2. Section 3 deals with the processing and result of classification. Final conclusion is drawn in section 4.

2. DATASET AND METHOD

2.1 Study site and data

The study site is situated around the water cube at the north of the Beijing city. The cover types include buildings (BD), roads (RD), vegetation (VT) and water body (WB) in this region.

TerraSAR-X, German Earth Observation SAR Satellite, was launched on June 15, 2007.This satellite with a right-side looking X-band can provide high resolution SAR images. The data adopted in this article is provided with a single polarization HH and 3m resolution.

Figure1 is the TerraSAR-X image obtained for this paper. Bright tones mainly characterize BD class for corner reflection effects. Very dark tones mostly characterize WB class for low backscattering. RD and VT classes are mainly represented as gray tones.

2.2 GLCM and textures

The gray level co-occurrence matrix (GLCM) is the conditional joint probabilities of two pairs of gray occurring, given two parameters: inter-pixel distance (δ) and orientation (θ).Detail meaning was described in literature (Haralick. 1973). After

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Figure 1. Study site

GLCM computed, several features can be extracted from it. Among those, eight commonly used textures are used here:

Contrast：
$$con = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \qquad (1)$$

Dissimilarity：
$$dis = \sum_{i,j=0}^{N-1} P_{i,j}|i-j| \qquad (2)$$

Homogeneity：
$$hom = \sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \qquad (3)$$

Energy:
$$ene = \sum_{i,j=0}^{N-1} P_{i,j}^2 \qquad (4)$$

Entropy：
$$ent = \sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j}) \qquad (5)$$

Mean:
$$mean = \sum_{i,j=0}^{N-1} i \cdot P_{i,j} \qquad (6)$$

Variance:
$$var = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_i)^2 \qquad (7)$$

Correlation：
$$cor = \sum_{i,j=0}^{N-1} \frac{(i-u)(j-u)\cdot P_{i,j}}{\sigma^2} \qquad (8)$$

where $P_{i,j}$ =normalized GLCM values

u =mean value of original data

σ = standard deviation of original data

2.3 Separability

Statistical distance measures include divergence, transformed divergence (TD) (Richards.1999), Bhattacharyya distance and Jeffries Matusita (J-M) distance. TD distance and J-M distance are widely used in remote sensing application. Since TD distance is easy and efficient to calculate, we use TD distance in this paper. The TD distance between class c and d is given by:

$$TD_{cd} = 2(1 - \exp(\frac{-D_{cd}}{8})) \qquad (9)$$

$$D_{cd} = \frac{1}{2}tr(V_c - V_d)(V_C^{-1} - V_d^{-1}) + \frac{1}{2}tr((V_c^{-1} - V_d^{-1})(M_c - M_d)(M_c - M_d)_T) \qquad (10)$$

Where V_c, V_d = covariance matrix of classes c and d

M_C, M_D = mean value of classes c and d

tr = the trace function

The values range from 0 to 2.0 and indicate how well the selected classes are statistically separate. Values greater than 1.9 indicate that the two classes have good separability. Values less than 1.0 indicate that the two classes have bad separability.

2.4 Classifier

Lots of classifier can be used for image classification. Support Vector Machines (SVM) have been developed by Vapnik (1982) and played important role in classification problems due to many attractive features. It has generalization ability and excellent learning performance to solve limited sample learning, non linear and high dimension problems. Considering the not normal distribution of feature space and limited sample problems, SVM algorithm is selected in this paper.

3. PROCESSING AND RESULT

3.1 Pre-processing

For the coherent-imaging system, high resolution SAR images have inherent speckle noises, which have adverse influence on interpretation of urban objects.

The post-imaging filters are ordinary used to reduce noise in SAR image. Here, we adopt the locally statistical processing filters including the Enhanced Lee filter, the Enhanced Frost filter, and the Gamma MAP filter to suppress noise in the image.

In order to give a sufficient comparison, the following four quantitative evaluation indexes are performed: (1) normalized mean; (2) smooth index; (3) equivalent number of looks; (4) edge keep index.

According to the four indexes, the Enhanced Lee filter with 3×3 filter size is adopted because it not only smooths the speckle effectively, but also has a better performance in edge preservation.

3.2 Sample data

We select the regions of interest as samples of four classes. The Table1 is statistical values of min, max, mean and standard deviation (stdev) of the four classes.

From Table1, only values of WB and BD classes are in the range of [-23,-17] and [-4, 23] respectively. However, the values in the range of [-17,-4] consist of all four classes. Therefore, it is difficult to well interpret SAR images with backscatter values alone.

	min	max	mean	stdev
WB	-23.1732	-14.4650	-18.378	1.54787
BD	-11.4614	23.3282	8.4690	5.8508
VT	-13.2320	-4.8694	-9.1585	1.3656
RD	-17.7574	-5.7119	-12.9067	2.2254

Table 1．Statistic information of the four classes

3.3 GLCM

The GLCM texture analysis is related to parameters including gray level quantization, distance, and direction. Many researches experimented on the parameters to extract textures and had conclusions on the appropriate parameters (Barber and LeDrew.1991, Soh .et al.1999, Roneorp.et al.1998)

Gray level quantization: The gray level quantization plays not very important role in the SAR image, and it will cost too much time for the high gray level quantization. And the smaller the number of quantization levels, the more loss of the information. We adopt the gray level quantization level of 64 considering trade-off between computing time and information preserving.

Distance and orientation: According to Barber, δ =1 provides significantly better results then others. Better classification accuracy is obtained when the GLCM θ parameter is parallel to look direction of sensor. So, in this paper, we adopt δ =1. And, θ parameter is set as 0 degree because look direction of the used data is from west to east.

Gray level quantization of 64, θ =0°and δ =1 combination characterize GLCM from SAR image.

3.4 Texture

According to Mryka Hall-Beyer's web page http://www.fp.ucalgary.ca/mhallbey ，texture can be grouped into three groups that are contrast ,orderliness and statistics. Practically, one of contrast measures, one of orderliness measures, and two or three at most of descriptive statistics measures are chose for classification purposes.

The contrast group includes contrast, homogeneity and dissimilarity. From (1), (2) and (3) expressions, contrast is highly correlated to dissimilarity and inversely correlated to homogeneity. So, we select contrast measure, which is according with conclusion of Baraldi (1995).

The orderliness group includes energy and entropy. From a conceptual point of view, entropy is strongly, but inversely, correlated to energy (Baraldi .1995).Therefore, there is no need to use all of them in classification. Energy is preferred to entropy since its values belong to a normalized range. So, energy is adopted in this paper.

The statistics group consists of mean, variance and correlation. From a conceptual point of view, variance is highly correlated with contrast. Correlation is uncorrelated with energy, entropy and contrast. As to mean, it reflects black or blight degree of original SAR image which is important feature to discriminate different classes. So, in this group, we select mean and correlation for classification.

At last, contrast, energy, correlation and mean combination based on GLCM respectively from group of contrast, orderliness and statistics characterize texture images.
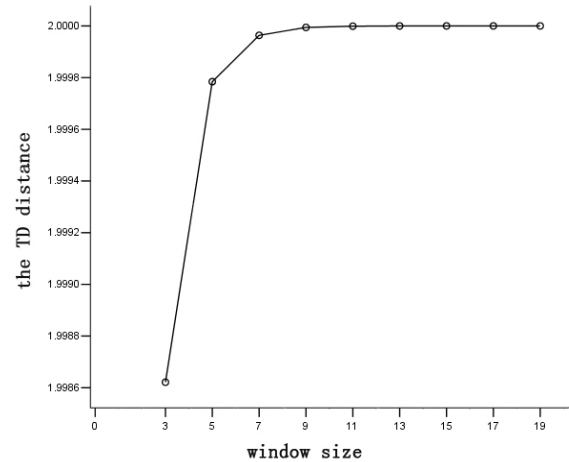
3.5 Window size

The choice of window size of texture characteristics has a great effect on accuracy of SAR image classification. Larger windows lead to more stable texture features but tend to blur the edges, while smaller windows lead to erroneous boundary delineation and misclassify the boundary itself as an incorrect class.

It is useful to scale all texture values to same range so that one measure will not dominate just because of greater dynamic range. So, we normalize these texture images to [0, 1] range. Nine window sizes from 3×3，5×5 and so on, up to 19×19 are tested. And the TD distances are computed for two cover classes for each window size.

The Figure 2 shows the TD distance obtained for two classes when the window sizes are variance from 3×3 to 19×19.
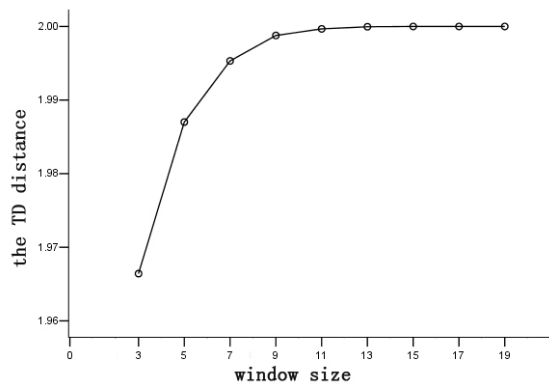
We can clearly see that the 3×3, 5×5, 7×7, 9×9 window sizes have noticeably unstable and low TD distance values than the others. From 11×11 window size to 19 × 19 window size, the TD distance is very stable and better. So, we adopt the 11×11 window size considering both separability of classes and boundary delineation.
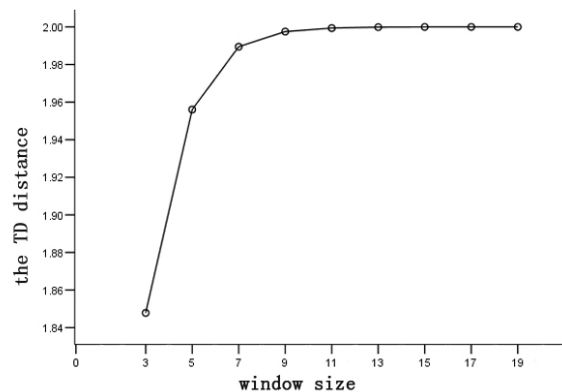

(a) BD—WB
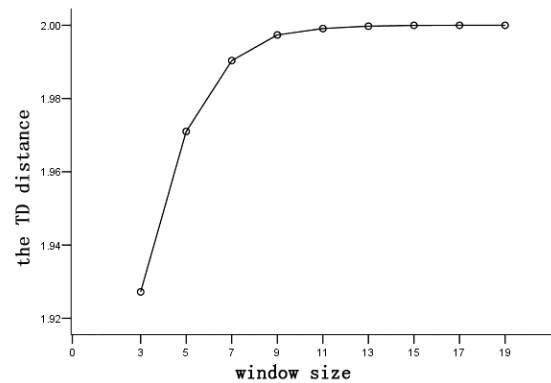
(b)BD—VT

(c) BD—RD

(d)WB—VT

Figure 2. Separability of two classes in various window sizes.

3.6 Classifications

We adopt the LIBSVM (Chang, C.-C. and C.-J. Lin.2001) to fulfil classify. It is critical of kernel function which can transform feature space to high dimension. Four basic kernels consist of linear, polynomial, RBF (Radial Basis Function) and sigmoid functions. Here, we use RBF kernel which works well in most cases.

The contrast, energy, correlation and mean textures based on GLCM along with original spectral data are classified with SVM classifier.

The Table2 is the accuracy assessment. The buildings have the high producer accuracy for their obvious different values then the others. But nearly 20% of buildings pixels are omitted as roads and vegetation. 100% of vegetation can be correctly classified as vegetation, in fact, nearly 40% are misclassified others as vegetation. The producer and user accuracies of the roads are all very low. As to the water body, no other classes are misclassified as water, but nearly 45% of water pixels are omitted as roads. The overall accuracy is 70.79%, and the Kappa coefficient is 0.6105.

We also do other two tests, one is classified with the single spectral value without texture images and the other one is classified according to Clausi's method (Clausi (2002) found that Contrast, Correlation and Entropy used together outperformed any one of them alone, and also outperformed using these and a number of others all together.).

The Table3 is the comparison between three methods. From the Table3, the accuracy of the last is only 45.32%. As to Clausi's method, the accuracy is increased by only 0.35%, which is nearly the same as using spectral data alone. When using our methods, the accuracy is increased to 70.79%.

Our classification result is not according with the conclusion of Clausi. It is different in choosing one from energy and entropy and whether or not adding mean texture between our method and Clausi's method.

The first point, we experiment on classifying with energy or entropy alone. The overall accuracy of former is higher then that of latter. That means it is more effective to use the energy than entropy to interpret our SAR image.

As to the second point, we classify the SAR image with and without mean texture as additional texture. The accuracy of the former (our method) is 70.79%. While, the accuracy of the latter is only 45.67%. It is easy to have a conclusion that former have high accuracy than the latter method.

The Figure 3 is classification maps with two methods in Table 2. Since the accuracy of the second and the last method is nearly the same, we did not give the classification map for the second method. Comparing two classification maps, it is easy to have a conclusion that the method in this paper obtains a better result.

|	BD	RD	VT	WB	Total	User
BD	445	0	0	0	445	100
RD	10	56	0	252	318	17.61
VT	83	148	362	0	593	61.05
WB	0	0	0	332	332	100
Total	538	204	362	584	1688	
Producer	82.81	27.45	100	56.85		
Overall Accuracy: 70.79% Kappa coefficient: 0.6105						

Table 2．Classification accuracy assessment

	Overall	Kappa
Our method	70.79%	0.6105
Clausi's method	45.67%	0.3089
Original data alone	45.32%	0.3055

Table 3．Comparison the accuracy between three methods

legend
vegetation
water body
roads
buildings
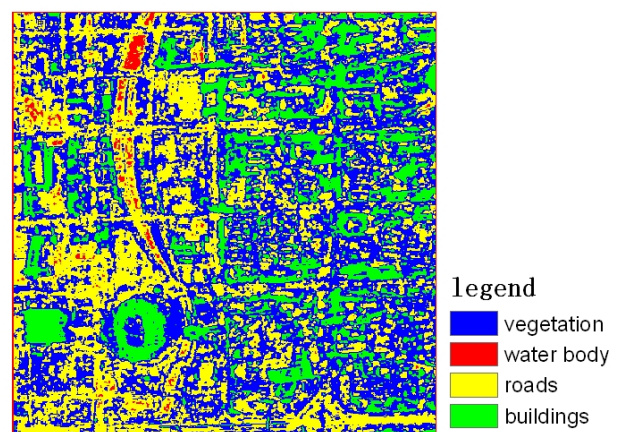
(a) Classification map using our method
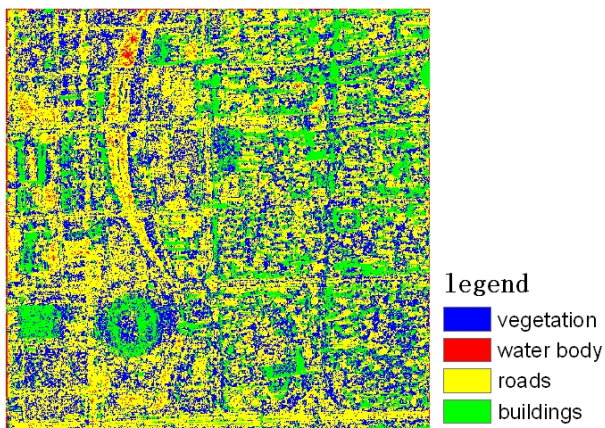
(b) Classification map using original data alone

Figure 3. Comparison classification maps

4. CONCLUSION

Our method in this paper is not according with Clausi's. It shows that, the conclusion Clausi gave is only fitted for classifying SAR sea ice.

According to above researches, radar-derived GLCM texture data with original data can improve classification accuracy. When using the method in this paper, the overall accuracy is greatly improved by about 25%. However, the user and producer accuracies of roads are very low. It is necessary to use automatic target recognition (ATR) rather than classification techniques to detect roads in SAR images.

Many factors have adverse influence on interpretation of SAR images like speckles. Though speckles were suppressed before texture extraction, as high occurrence of pepper and salt phenomena, the residual noise also has influences on the texture extraction. At the same time, the filtered noises maybe hold useful information and remove texture measures.

So, more researches should be contributed to a better accuracy of classification. Future works will include extracting more effective textures to well interpret different classes and improve the accuracy of classification in high spatial resolution SAR image.

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