Tensor Locality Preserving Projections Based Urban Building Areas Extraction from High-Resolution SAR Images

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***Abstract*—Currently, the majority of Manifold Learning algorithms applied for SAR image feature extraction are vector based; the For tensor based SAR images, a "convert to vector: process has to be taken before attribute extraction. During this process, curse of dimensionality would be occurred and information of space geometry structure could be lost. Those phenomenon are not conducive for target recognition of SAR images. In this paper, Radarsat-2 images were used as experimental data and the Tensor Locality Preserving Projections (TLPP) algorithm was applied for the attribute extraction of high-resolution SAR images, to improve the recognition accuracy and achieve fast extraction of urban building areas. A comparison was made for the recognition results of TLPP and Locality Preserving Projections (LPP). It is found that that TLPP algorithm has a strong adaptability of generalization, which indicates that TLPP can be effectively used for fast extraction of urban building areas from high-resolution SAR images, with high accuracy.**

***Index Terms*—synthetic aperture radar, manifold learning, feature extraction, tensor locality preserving projections**

I. INTRODUCTION

As an important part of urban land usage monitoring, extraction of urban building areas plays a significant role in urban planning management and military affairs. Especially in the process of New Urbanization of China, with the rapid increase of building areas, the realization of land supervision in a fast and effective way becomes a major technical issue. In recent years, with the fast development of high-resolution radar satellite, the acquisition of all-time all-weather data are convenient. In high-resolution SAR images, corner reflector is formed due to the multiple refraction between buildings and ground, which results in high brightness display in images; meanwhile, roads, plants and shadows darker tones alternating with bright spot of buildings, those regularly arranged light-and-shade generates distinguished texture features[1]-[2]. Researchers have taken advantage of texture information to extract urban building areas from high-resolution SAR images. In 2012, Xu *et al.* calculated eight kinds of GLCM texture features of SAR images [2], on the basis of Bhattacharyya Distance, Principal Component Analysis (PCA) was applied for selected texture features with good recognition to reduce correlations between different texture features, then building areas are extracted according to grey level. It is well known that PCA and Independent Component Analysis (ICA) algorithm are more suitable to handle data set with linear structures [3]. However, SAR images are affected by many complex factors such as target orientation, pitch angle of platform, polarization mode, wavelength and the electromagnetic environment around the target. Moreover, these factors are not independent of each other. Especially, with the improvement of the spatial resolution of SAR images, the target contains abundant information, which makes the inherent geometric structure of data are of highly complexity. Therefore, it is necessary to study new algorithms for the processing of this kind of data set. In recent years, Manifold Learning [4] has been developed rapidly in the area of pattern recognition. It is a new method of machine learning and provides new direction for dimensionality reduction of high-dimensional data set. Its goal is to find the low dimensional manifold structure which embeds in high dimensional space and then gives an effective low dimensional embedding coordinates. According to this concept, algorithms such as ISOMAP [5], Laplacian Eigenmaps (LE) [6] and Locality Preserving Projections (LPP) [7] were proposed.

Currently, Manifold Learning algorithms which were employed for feature extraction of SAR images are mostly vector based. However, SAR image is in tensor form. It is necessary to convert from tensor to vector form before feature extraction, this very process would results in the "dimensionality curse" and the loss of space geometry structure information. A series of algorithms were tired to combine tensor analysis technology with manifold learning theory, in order to solve those above mentioned problems, like Sparse Tensor Embedding (STE) [8], Local Tensor Subspace Alignment algorithm (LTESA) [9], Tensor

Manuscript received January 4, 2016; revised April 21, 2016.
This work was supported by the National Science Foundation of China under Grant No.61372189.

doi: 10.12720/jait.7.4.291-296

Discriminative Locality Alignment (TDLA) [10] and Sparse Tensor Alignment (STA) [11], etc. They have achieved good results in face recognition and hyperspectral remote sensing image classification. However, few tensor based manifold learning algorithms researches have been conducted for the feature extraction of high-resolution SAR images.

In this study, TLPP [12]-[13] algorithm was applied for the fast and accurate extraction of urban building areas in complex scenes from high-resolution SAR images. Firstly, wave filtration was conducted to reduce the impact of speckle noise on the extraction accuracy. Secondly, GLCM [14] texture features which are conducive to the identification of urban building areas were selected based on the principle of separability, and these selected texture features were calculated according to the optimal window size which was achieved by experiment. After that, samples were trained by TLPP algorithm, to obtain an optimal projection matrix which was operated with training sample and testing sample respectively in order to reduce dimension and achieve a new feature. Finally, the new feature was taken as the input of Otsu [15] method to extract urban building areas, and the final result of building areas was achieved by post processing. At the same time, TLPP algorithm was compared with LPP algorithm to verify the effectiveness of TLPP algorithm. The results showed that TLPP algorithm has a strong generalization ability. The new feature of test sample which was achieved by directly operating with the transformation matrix obtained based on the training sample showed better detection effect. And detection rates all exceeded 90%, with low false alarm rate. Therefore, TLPP algorithm is suitable for dimensionality reduction of high-resolution SAR images and the new feature has good detection capability as well.

II. Methodology

In this paper, extraction of urban building areas was studied as a pattern recognition problem. GLCM texture features with TLPP algorithm were proposed for extracting urban building areas from high-resolution SAR images. This method includes following technical approaches: wave filtration, feature screening, dimensionality reduction, target classification and post-processing.

Firstly, filtering of high-resolution SAR images was conducted by Lee algorithm. Secondly, GLCM texture features which are conducive to the identification of urban building areas were selected based on the principle of separability. Then the optimal window size was achieved by experiment, which was used to calculate those selected texture features. Thirdly, training sample was trained by TLPP algorithm, obtaining an optimal projection matrix which was operated with training sample and testing sample respectively to reducing dimension and achieve new features. Finally, the new feature were used as the input of Otsu method to extract building areas. Post-processing was also executed to achieve the final results.

A. Texture Features Based on Gray Level Co-occurrence Matrix (GLCM)

GLCM based texture attributes extraction is one of the most classical statistical analysis methods. The concept of GLCM was proposed by Haralick in 1973. Its basic idea is to firstly calculate gray co-occurrence matrix, and then texture features were acquired through statistical calculation of the gray level co-occurrence matrix. Haralick proposed fourteen kinds of texture features, where eight of them were commonly used, Energy, Contrast, Correlation, Mean, Variance, Dissimilarity, Inverse Difference Moment and Homogeneity.

B. Tensor Locality Preserving Projections

TLPP is a tensor manifold learning algorithm, which is put forward through introducing tensor analysis technique into LPP algorithm. Assuming $A=\{A_1,A_2,\cdots,A_n\}$ is a sample data set acquired from the tensor space $R^{I_1\times I_2\times\cdots I_N}$. And they embed in an unknown manifold $M\left(M\in R^K\right)$. TLPP algorithm is then used to find the best projection transformation matrix *K*, so that it can obtain the intrinsic geometrical properties of the data set while maintaining the local topological structure of *M*. The optimization objective function of TLPP algorithm is defined as:

$$\begin{aligned}&\arg\min Q\left(U_1,\cdots,U_K\right)\\&=\sum_{i,j}\left\|B_i-B_j\right\|^2W_{ij}\\&=\sum_{i,j}\left\|A_i\times_1U_1\cdots\times_nU_n-A_j\times_1U_1\cdots\times_nU_n\right\|^2W_{ij}\end{aligned}\qquad(1)$$

The constraint condition is defined in formula (2) in order to eliminate the arbitrary translation.

$$\sum_i\left\|A_i\times_1U_1\cdots\times_nU_n\right\|^2D_{ii}=1\qquad(2)$$

where, $B_i=A_i\times_1U_1\cdots\times_nU_n$ and $B_j=A_j\times_1U_1\cdots\times_nU_n$ are respectively the coordinates of the data points A_i and A_j in the low dimensional space. D is a diagonal matrix and is defined as $D_{ii}=\sum_j W_{ij}$. The purpose of using the weight *W* is to ensure that the adjacent sample points in the original space are mapped as close as possible. W_{ij} which is an element of the similarity matrix *W* is defined as:

$$W_{ij}=\begin{cases}\exp(-\dfrac{\left\|A_i-A_j\right\|^2}{t}), & \text{if} A_j\in N_p(A_i)\text{or}A_i\in N_p(A_j)\\0, & \text{others}\end{cases}\qquad(3)$$

In this formula, $A_j\in N_p(A_i)$ represents that A_j is in the nearest neighbor of A_i; t is a positive constant; and the values of p and t are both empirical values.

Since the optimization problem is a high order nonlinear programming problem in the high order nonlinear constraint, calculating every transformation matrix directly is not feasible. Therefore, we solved this problem by iterative method.

First of all, assuming that $U_1, U_2, \cdots, U_{f-1}, U_{f+1}, \cdots, U_K$ are known and U_f is unknown. And $U_i = I_{l_i} \left(i = 1, 2, \cdots, f-1, f+1, \cdots, K\right)$, then

$$B_i^f = A_i \times_1 U_1 \cdots \times_{(f-1)} U_{(f-1)} \times_{(f+1)} U_{(f+1)} \times_K U_K \tag{4}$$

According to the characteristics of tensor and matrix trace, the optimization problem which is shown in formula (1) is converted to:

$$\arg\min P_f\left(U_f\right) = tr\left\{U_f \left[\sum_{i,j}\left(B_i^{(f)} - B_j^{(f)}\right)\left(B_i^{(f)} - B_j^{(f)}\right)^T W_{ij}\right] U_f^T\right\} \tag{5}$$

And the constraint condition is converted to:

$$tr\left[U_f \left(\sum_i B_i^{(f)} \left(B_i^{(f)}\right)^T D_{ii}\right) U_f^T\right] = 1 \tag{6}$$

where, $B_i^{(f)}$ represents the f-mode flattening of B_i^f.

Thus, the unknown transformation matrix U_f can be obtained by solving the generalized eigenvalue equation shown in the formula (7). U_f is composed of feature vectors corresponding to the l_f smallest eigenvalue of this generalized eigenvalue equation. The transformation matrixes corresponding to other dimensions can be carried out in accordance with this method, until the projection transformation matrixes are all calculated.

$$\left[\sum_{i,j}\left(B_i^{(f)} - Y_j^{(f)}\right)\left(B_i^{(f)} - B_j^{(f)}\right)^T W_{ij}\right] U = \lambda \left[\sum_i B_i^{(f)}\left(B_i^{(f)}\right)^T D_{ii}\right] U \tag{7}$$

For a low dimensional embedding of a K dimension, the low dimensional embedding of data set, which is shown in formula (8), can be obtained by these K transformation matrixes.

$$B_i = A_i \times_1 U_1 \cdots \times_K U_K \tag{8}$$

C. Threshold Segmentation Based on Otsu Method

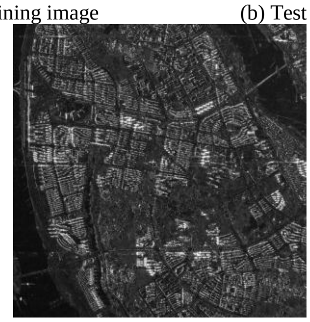
Otsu Method is a threshold segmentation algorithm proposed by Otsu in 1979. This method is of good segmentation effects, strong real-time performance and with fast operational speed. In this study, Otsu method is applied to execute binarization of the gray image formed by new features obtained from TLPP algorithm, for the identification of urban building areas. The approaches are shown as follow: (1) identify a threshold within the range of image gray level to maximum variance between two classes; (2) divide image into building areas and non-building areas according to this threshold, where the pixel with gray value bigger than the threshold is regarded as building areas.

III. Data

In this paper, we took Radarsat-2 images whose polarization mode is HH and spatial resolution is 1.5625m as the experimental data. And three sub images of 1000 × 1000 and 3000 ×3000 were selected (Fig. 1). The size of (c) is 3000×3000 except for (a) and (b). Where, (a) was taken as training image, (b) and (c) were taken as test images. And features of targets in (c) are more complex than (b). And the experimental images were filtered in order to reduce the effect of noise on the extraction accuracy of urban building areas.

(a) Training image

(b) Test image 1



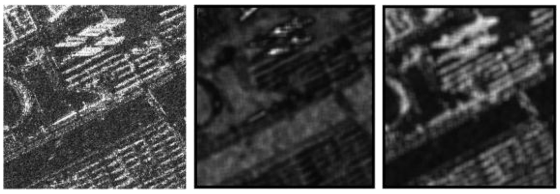
(c) Test image 2

Figure 1. Experimental images.

IV. Results

A. Selection of Texture Features

Since these eight texture features contain different information, it is necessary to screen texture features that are propitious to distinguish building areas and non-building areas. For this purpose, we conducted an experiment for feature selection. Images showed in Fig. 2 represent the original image and GLCM texture feature maps. And statistical characteristics of these texture features were shown in Table I. According to Table I, on the basis of Separability Principle, Contrast, Correlation, Mean, Variance and Dissimilarity were selected as the original high dimensionality feature set.



(a) (b) (c)

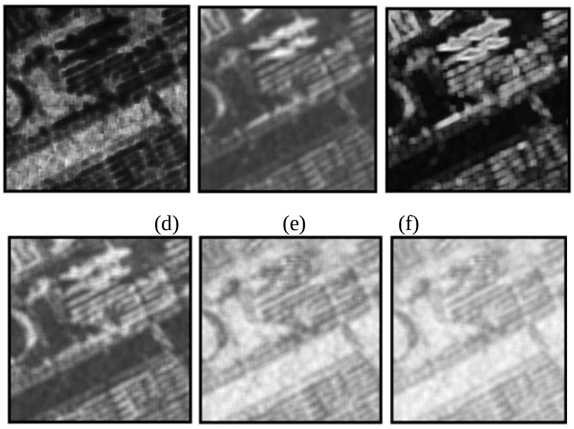


Figure 2. Original image and texture feature images. (a) Original image; (b) Energy; (c) Contrast; (d) Correlation; (e) Mean; (f) Variance; (g) Dissimilarity; (h) Inverse Difference Moment; (i) Homogeneity.

TABLE I. STATISTICAL CHARACTERISTICS OF TEXTURE FEATURES

Texture features	Statistical characteristics
Energy	It reflects the uniformity of the gray distribution of the image and the thickness of the texture. The value of Energy is larger in the homogeneous region. Compared with building areas, the values of plant and water are larger. However, the boundary of certain targets is not obvious so that cannot extract building areas effectively.
Contrast	It can effectively reflect the contrast of the image, extract the edge of the target and enhance the linear structure. Since building areas is composed of buildings, roads, plant and shadow, regional differences is large. So the value of building areas is higher than plant and water. Therefore, it can well identify building areas.
Correlation	The value is higher in homogeneous regions. In contrast to plant and water, the value of building areas is larger.
Mean	It is the average gray value within the window and reflects the uniformity of gray distribution.
Variance	It indicates deviation degree of each pixel within the window. And the value is larger in the region with larger gray change. The value of building areas is larger, compared with plant and water. So it is in favor of distinguishing building areas and non-building areas.
Dissimilarity	It is a statistical parameter that expresses the visual texture. It reflects the contrast of gray level in the window, and it is helpful to the extraction of urban building area.
Inverse Difference Moment	It reflects the uniformity of the image. Since the differences of building areas, plant and water are not significant, it is difficult to distinguish building areas and non-building areas.
Homogeneity	It is also difficult to identify urban building areas for the same reason as Inverse Difference Moment.

B. *Extraction of Texture Features*

Texture features were calculated pixel by pixel form in moving window. Gray level co-occurrence matrix is related to direction, step length, window size and image gray level. The influence of window size is the most pronounced one, its appropriate value needs to be confirmed according to the actual image. In this paper, it was determined by using programming calculation and result analysis. Since building areas, plant and water are main surface features in the city, multiple urban building areas (with varying building densities), plant and water are chosen as experimental images. Then we achieved the mean value of each texture feature. After that, we analyzed the trend of each texture feature curve to determine the optimal window size.

Taken Contrast as an example (Fig. 3): firstly, Contrast was calculated in different window sizes with interval of 4 between 3×3 and 43×43. And the value of Contrast is normalized. Then we analyzed the trend of the difference among building areas, plant and water with the window size to achieve the optimal window size.

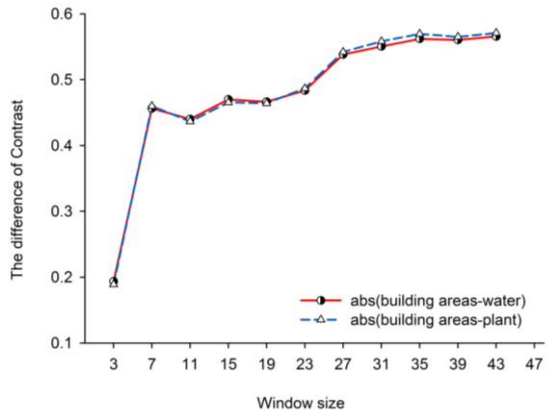


Figure 3. Variation trend of contrast with the window size.

As shown in Fig. 3, the differences in the value of Contrast among building areas, plant and water increase sharply between the window size of 3 and 7. The differences fluctuated between the window size of 7 and 35, but the overall trend is increasing. The differences increased slowly between the window size of 35 and 43.

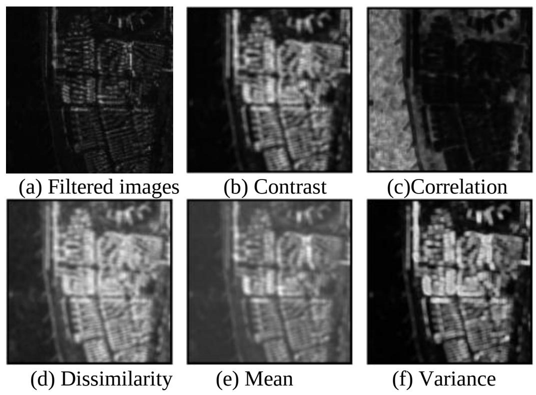
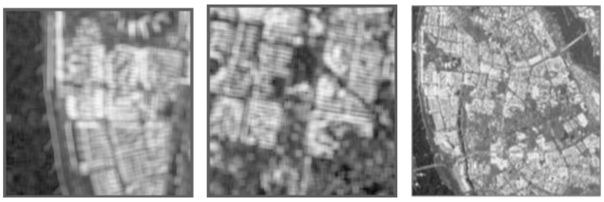


Figure 4. The filtered image and texture feature images.

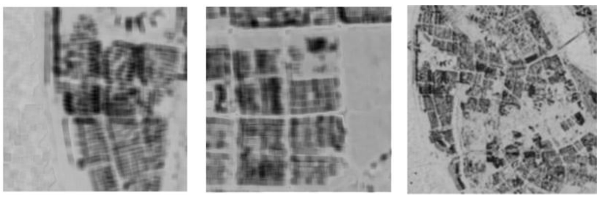
Since the purpose of this study is extracting urban building areas, it is not necessary to reflect the details inside urban building areas. Moreover, with the increasing of the window size, the edge of texture images became more and more blurring. Therefore, the window size of 35×35 is more appropriate. Images showed in Fig. 4 are respectively filtered image and texture feature images which were calculated in the window size of 35×35. As we can see from Fig. 4 that these texture feature images are more helpful to recognition of urban building areas than the initial image. However, there is correlation between these texture feature images, so it is necessary to reduce dimension.

C. Dimensionality Reduction of Texture Features

In this study, both experiments with TLPP algorithm and LPP algorithm are conducted to validate the effect of TLPP algorithm. An optimal projection transformation matrix is respectively obtained for both of these two algorithms. And then a new feature is achieved by operation between this matrix and the high-dimensional data set which is formed by five texture features. And the new feature is normalized to the range of 0 to 1 in order to facilitate the extraction of urban building areas (Fig. 5).



(a) TLPP algorithm



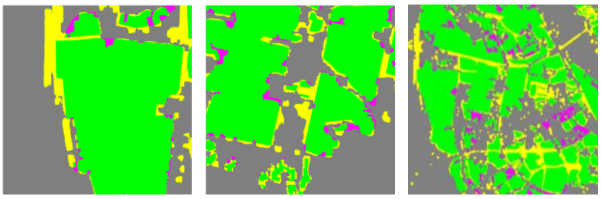
(b) LPP algorithm

Figure 5. New features extracted by TLPP algorithm and LPP algorithm.

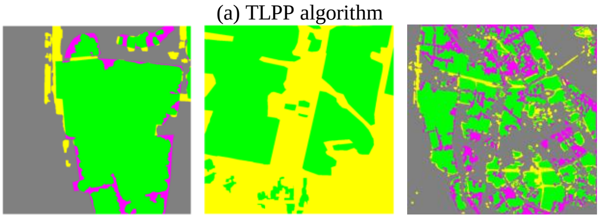
Urban building areas are in bright colors and non-building areas are close to black tone in the images formed by the new features based on TLPP algorithm. However, for the new features based on LPP algorithm, urban building areas are in dark colors and non-building areas are in gray tone. Therefore, compared with the LPP algorithm, the difference between different classes in the new features based on TLPP algorithm is higher, which is more conducive to the identification of urban building areas.

D. Extraction of Urban Building Areas and Accuracy Evaluation

The new features obtained were taken as the input of Otsu method to extract urban building areas. Then post-processing was made to achieve the final result of building areas which was shown in Fig. 6. Finally, Detection Rate (DR) [16], False Alarm Rate (FAR) and Missing Alarm Rate (MAR) were calculated to evaluate the accuracy of extraction of urban building areas (Table II).



(a) TLPP algorithm



(b) LPP algorithm

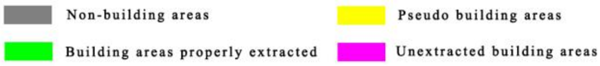


Figure 6. The extraction results of urban building areas.

TABLE II. VALUES OF ACCURACY EVALUATION INDEXES (UNITS:%).

Algorithm	Experimental images	Detection Rate	False Alarm Rate	Missing Alarm Rate
TLPP	Training image	97.31	15.90	2.69
TLPP	Test image 1	95.02	12.67	4.98
TLPP	Test image 2	90.26	22.84	9.74
LPP	Training image	90.03	8.98	9.97
LPP	Test image 1	100	47.56	0
LPP	Test image 2	70.91	15.39	29.09

As we can see from Fig. 6 and Table II that the new feature of the training image, achieved by TLPP algorithm, are in favor of extraction of urban building areas. Although False Alarm Rate is slightly high, Detection Rate also reached 90%. Therefore, TLPP algorithm can improve recognition accuracy by comprehensive utilization of texture features and the spatial geometry of the image. In the other hand, for test images, Detection Rate both reached 90%. Thus, TLPP algorithm has good generalization ability. The transformation matrix obtained by training sample can be directly applied to the dimensionality reduction of the new samples (test images), and the new features obtained have good discrimination.

Recognition is achieved to some extent (average detection rate reached 90%, with low false-alarm rate) from new features of the training image extracted by LPP algorithm. However, the new features of test image 1 failed to distinguish building areas and non-building areas. Moreover, Detection Rate of test image 2 is only 70.91%. it is concluded that an unfavorable performance of generalization is achieved by using LPP algorithm. This is mainly because the LPP algorithm is vector based, which makes it necessary to transform the tensor data set into vector form, during this process, spatial structure information of the original data set is destroyed. The loss of association information between different data points caused the redundancy information and higher order dependence of the original data being masked. We were unable to dig out the intrinsic geometry of the data set, the access to the compact pattern within data is blocked.

V. Conclusions

In this paper, we introduced Gray Level Co-occurrence Matrix based TLPP algorithm into feature extraction, to reduce the redundancy among these features. A new feature was obtained, which was employed for extraction of urban building areas. A comparison was made between TLPP algorithm and LPP algorithm as well. The experimental results showed that Detection Rates of the new features obtained by TLPP algorithm all reached 90%, with relatively lower False Alarm Rate. It is also found that in one of our experiments, the new feature obtained by LPP algorithm failed to identify urban building areas while TLPP achieved good recognition. In this study, TLPP algorithm successfully avoid the problem of "curse of dimensionality" caused by the vector formed data set, as well as making full use of tensor formed feature textures and the spatial geometry of the data set to improve the identification accuracy. Moreover, TLPP algorithm has strong generalization ability. According to the projection transformation matrix obtained from the training sample, we can obtain new features with good discrimination without training new sample, while achieving the goal of dimensionality reduction of new samples.

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