

An Improved AP-Wishart Classifier for Polarimetric SAR Images by Incorporating a Textural Feature

Chen Jun^{1*}, Du Peijun², Tan Kun¹

¹ Jiangsu Key Laboratory of Resources and Environmental Information Engineering, China University of Mining and Technology, Xuzhou City, Jiangsu Province, 221116, China

² Jiangsu Provincial Key Laboratory of Geographic Information Science and Technology, Nanjing University, Nanjing city, Jiangsu Province, 210093, China
Corresponding author, e-mail: studyias@163.com

Abstract

An improved classifier is presented by imposing a textural feature to solve the problems of vague initial clustering results, low classification accuracy and unchangeable class number in the iterative classifier, based on H/α decomposition and the complex Wishart distribution for fully polarimetric SAR (Synthetic Aperture Radar) images. First, wavelet transformation is used to extract texture from polarimetric SAR images. Second, an AP (Affinity Propagation) algorithm is applied to create the initial clustering result. This result is then applied to the iterative classifier based on the complex Wishart distribution to obtain the final result. Two PALSAR (Phased Array type L-band Synthetic Aperture Radar) images from ALOS (Advanced Land Observing Satellite) are used for the experiments carried out on experimental plots in Binhai Prefecture, Yancheng City, Jiangsu Province. The results show that the improved classifier has some merits, including clear initial clustering results, flexible class number and high classification accuracy. The improved classifier has better overall performance than the original, and can be effectively applied to the classification of polarimetric SAR images.

Kata kunci: POLSAR, H/α -wishart classifier, AP cluster, texture, wavelet transform

1. Introduction

There are two main types of machine learning algorithm in classification of PolSAR (Polarimetric Synthetic Aperture Radar) images, namely supervised and unsupervised learning. The former requires a certain number of training samples; the latter does not need training samples. Classification accuracy of supervised learning depends substantially on the quality of training samples. However, a PolSAR image is different to an optical image. It belongs to active microwave remote sensing and is greatly affected by the interference of different waves. It therefore has shortcomings such as serious speckle noise, low contrast between objects and background, edge blurring and other uncertain factors. Although some measures can be taken to eliminate such noise, image quality is significantly degraded at the same time. So, after being contrasted with the optical image, the PolSAR image is harder to interpret. There may be some difficulty in using a supervised learning algorithm directly on a PolSAR image.

The polarimetric features of a PolSAR image are expressed by a coherent scattering matrix, which has a complex Wishart probability density distribution. Therefore, a classifier developed under these circumstances may achieve higher classification accuracy. Lee [1]-[4] proposed an unsupervised classifier after combining H/α decomposition [5]-[7] with a complex Wishart distribution, called an H/α -Wishart classifier.

The H/α -Wishart classifier is widely used in remote sensing. Laurent et al. [8] utilized it for classification of a multi-frequency PolSAR image. Many improvements have been made to the H/α -Wishart classifier: Kimura et al. [9] and Cao et al. [10] added span to form the H/α -span-Wishart classifier. Wu et al. [11] used four component decomposition to divide a pixel into a four base scatter-type and a compound scatter-type, and they classified the image using the Wishart classifier. Yang et al. [12] imposed an optimal correlation coefficient and span to the classifier to automatically extract road and soil. Zhang et al. [13] combined H/α decomposition and the Markov Random Field for classifying the image. Yang et al. [14] combined H/α decomposition with a polarimetric whitening filter to the imagery classification. Yang et al. [15] proposed a weighted unsupervised Wishart classifier. Zhao et al.

[16] used a likelihood-ratio test to calculate the distance between each pixel and every class center; and Lang et al. [17] added H , A and Freeman decomposition to the classification.

All of these improvements have been based solely on polarimetric information. But at the same time there are plenty of other features, such as texture, in PolSAR image. How to combine these features with polarimetric information for classification of PolSAR image is still a hotly debated topic. Liu et al. [18] united texture with SVM into the classification and achieved high performance; however, texture is still less commonly used in improvement of the $H/Alpha$ -Wishart classifier. Therefore, in this article a new unsupervised classification scheme is proposed, by imposing texture to improve the accuracy of the $H/Alpha$ -Wishart classifier.

2. $H/Alpha$ -Wishart Classifier

Cloude & Pottier [6] developed $H/Alpha$ decomposition to extract polarimetric characters from scattering information. They defined *Entropy* (H) as the dominant scattering mechanism in each pixel. Its function is as follows [6]:

$$H = \sum_{i=1}^3 -P_i \log_3 P_i \quad (1)$$

Here P_i is computed as follows:

$$P_i = \frac{\lambda_i}{\sum_{j=1}^3 \lambda_j} \quad (2)$$

and define:

$$\bar{\alpha} = P_1 \alpha_1 + P_2 \alpha_2 + P_3 \alpha_3 \quad (3)$$

α (*Alpha*) here stands for the scattering angle; it expresses the mean scattering degree of the object. *Anisotropy* [19,20] (A) is defined as follows:

$$A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \quad (4)$$

Anisotropy denotes a different scattering mechanism other than the mean scattering one. So *Entropy* (H), α (*Alpha*) and *Anisotropy* (A) can be used to replace scattering characters of ground objects.

On the basis of $H/Alpha$ decomposition, Cloude and Pottier [6] proposed an $H/Alpha$ classification scheme. They defined an $H/Alpha$ plane to divide ground objects into eight different types. The plane is shown in Figure 1:

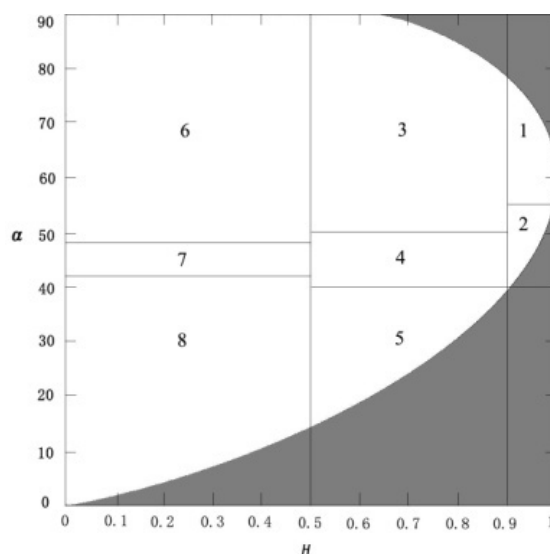


Figure 1. *H/Alpha* plane

In Figure 1, 'Zone 1' stands for high entropy even scattering, 'Zone 2' stands for high entropy multiple scattering, 'Zone 3' stands for medium entropy multiple scattering, 'Zone 4' stands for medium entropy vegetation scattering, 'Zone 5' stands for medium entropy surface scattering, 'Zone 6' stands for low entropy multiple scattering, 'Zone 7' stands for low entropy dipole scattering, and 'Zone 8' stands for low entropy surface scatter [6]. If a proper threshold, namely *Anisotropy (A)*, is chosen, ground objects can be divided into sixteen further types.

With the classification result of the *H/Alpha* initial classifier, cluster centers can be gathered by averaging the features within each class. After this, these cluster centers can be imported to the Wishart iterative classifier to obtain the final classification result.

The *H/Alpha*-Wishart unsupervised classifier can fulfill the classification automatically. It is used in some areas of PolSAR image classification, but it has the following disadvantages:

The class number is unchangeable. If the *H/Alpha* is used, 8 classes can be obtained, or, if the *H/A/Alpha* is used, 16 classes can be attained. However, in reality, the class number can change at any time.

The *H/Alpha* classification is based on the *H/Alpha* plane, but real ground objects are not strictly reflected in the *H/Alpha* plane, particularly when *H* is too high ($H > 0.7$) to use the *H/Alpha* plane.

The classification accuracy of the *H/Alpha*-Wishart classifier is directly affected by the result of the *H/Alpha* initial classifier, so it is necessary to improve the classification accuracy of the *H/Alpha* classifier.

3. Improved AP-Wishart Classifier

Considering the *H/Alpha*-Wishart classifier's disadvantages, an improved AP-Wishart classifier is proposed—one which combines the AP algorithm with the Wishart iterative classification to achieve the final result. The flowchart of the AP-Wishart classifier is shown in Figure 2.

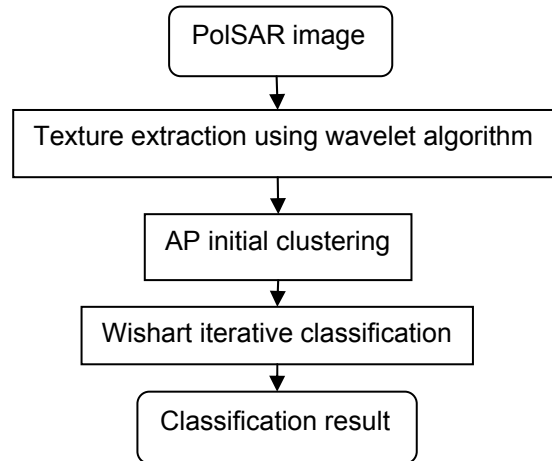


Figure 2. Flowchart of improved AP-Wishart classifier

The process of the improved classification scheme is as follows:

A wavelet extraction algorithm is used to extract texture from the PolSAR image. The wavelet as a kind of information extraction method is widely used in signal processing and image analysis [21],[22]. After Daubechies' wavelet basis function is chosen, a pyramid algorithm from Mallat is used to extract texture from a polarimetric span image. Vertical, horizontal and diagonal information are extracted as the texture character of the PolSAR image.

The texture information above is used to fulfill the AP initial cluster. The AP algorithm was proposed by Frey and Dueck in 2007 [23],[24]. It is one of the best clustering algorithms at present. Most of the current clustering algorithms are based on initial cluster centers, which are commonly related to classification accuracy. However, the AP algorithm is different. It considers each piece of data as a potential cluster center, which is called the 'exemplar'. Consequently, the result of the AP algorithm is not affected by initial cluster centers. The AP algorithm calculates similarity between different data points by a defined distance measure, and then changes data values into $N \times N$ (N is the size of the data) similarity matrix S . By iterative updating of, *Responsibility* (R) and *Availability* (A), an exact exemplar can be found and considered as the final cluster center. The process of the AP algorithm is as follows:

Algorithm initialization: Calculating the similarity matrix using a Euclidean distance measure, $S(i,j)$, $0 < i < N$, $0 < j < N$, the formula is as follows:

$$d = \sqrt{(T_{i1} - T_{j1})^2 + (T_{i2} - T_{j2})^2 + (T_{i3} - T_{j3})^2 + \dots + (T_{in} - T_{jn})^2} \quad (5)$$

T_i stands for 'texture of sample i '; T_j stands for 'texture of sample j ', n represents the dimensions of texture.

Iterative update of R and A , $R(i,k)$ shows that data point k is suitable for the candidate exemplar of point i — it reflects the accumulated evidence about how well-suited point k is to serve as the exemplar for point i [23]. The formula is :

$$R(i,k) = S(i,k) - \max \{A(i,j) + S(i,j)\} \quad (6)$$

subject to $j \in \{1,2,\dots,N, \text{ but } j \neq k\}$.

$A(i,k)$ stands for the degree that point i will select point k as its candidate exemplar, and reflects the accumulated evidence on how appropriate it would be for point i to choose point k as its exemplar A [23],[24]. The formula is:

$$A(i,k) = \min \left\{ 0, R(k,k) + \sum_j \{ \max(0, R(j,k)) \} \right\} \quad (7)$$

subject to $j \in \{1, 2, \dots, N, \text{ but } j \neq i \text{ and } j \neq k\}$.

Maximize $R(i,k)+A(i,k)$, if $k=i$ then consider i as an exemplar, else consider k as the exemplar of point i . In this way the cluster centers can be obtained.

Using the cluster centers shown above and Euclidean distance, every data point can be clustered to its own centers.

Above is the principle and process of the AP clustering algorithm. The AP algorithm can be used on the texture feature extracted from the wavelet extraction algorithm to find each cluster center.

Wishart iterative classification: Using cluster centers created by the AP algorithm, a Wishart iterative classification based on the Wishart distance can be used to obtain the final classification result. The formula is as follows:

$$\text{dist}([T]||[\sum_i]) = \ln ||[\sum_i]|| + \text{Tr}([\sum_i]^{-1}[T]) \quad (8)$$

$[\sum_i]$ stands for the average polarimetric coherency matrix of the cluster center i , $[T]$ stands for the polarimetric coherency matrix of an unknown sample.

According to the maximum-likelihood criterion, when the following condition is met:

$$\text{dist}([T]||[\sum_i]) > \text{dist}([T]||[\sum_j]) \quad (9)$$

The unknown sample is considered to belong to cluster center j . An iterative process can be used in this way until all unknown samples have their cluster centers.

4. Experiment and analysis

4.1. Research area and data

Two scenes of the PALSAR image from ALOS were used as data source for this research. The image time was April 9, 2009. Research areas are located on the Binhai wetland in Yancheng city. These are two blocks of square area with the size of 800*800 pixels. There are five types of land cover in each of these research areas: 'field', 'building', 'road', 'water' and 'suaeda', which are disorderly and unsystematically located on the research areas. They are thus suitable for comparing the diversity between the original *H/Alpha*-Wishart and the improved AP-Wishart algorithm. Images of span and pauli decomposition (polarimetric calibration) with a false color composite are shown in Figure 3.

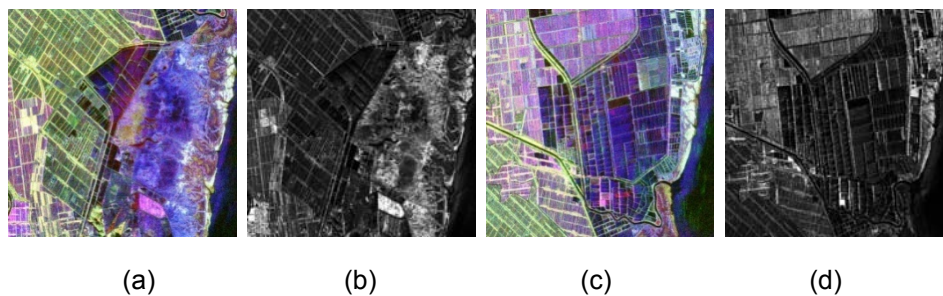


Figure 3. Pauli decomposition and span image of two experimental plots ((a) and (b) are the Pauli decomposition and span image of Research Area 1; (c) and (d) are the Pauli decomposition and span image of Research Area 2)

4.2. Texture extraction with wavelet decomposition

T_{11}, T_{22}, T_{33} , which are the main diagonal elements of the polarimetric coherency matrix are shown in Figure 4: The span image is extracted from T_{11}, T_{22}, T_{33} , and wavelet decomposition is conducted on this image.

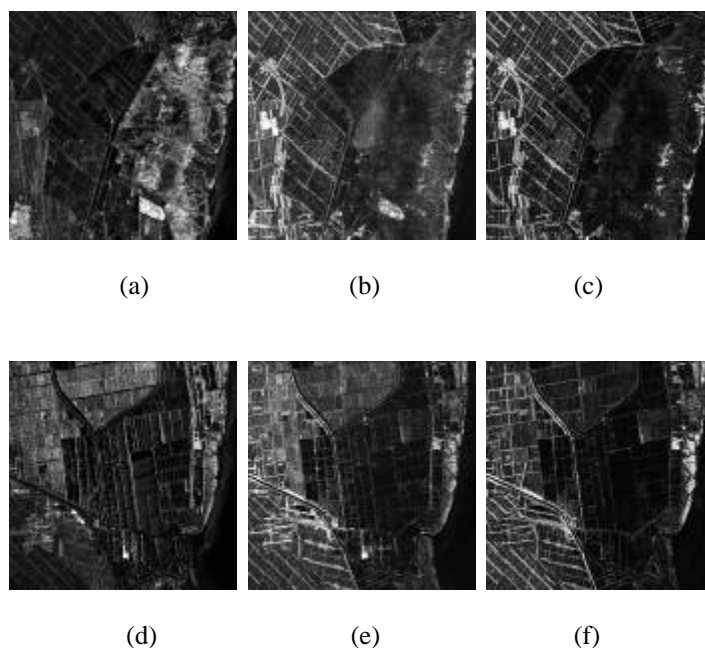


Figure 4. Main diagonal elements of polarimetric coherence matrix of two experimental plots ((a)-(c) are T11, T22, T33 images on experimental one; (d)-(f) are T11, T22, T33 images on experimental two)

Span image is extracted from T11, T22, T33, and wavelet decomposition is conducted with it.

4.3. The AP-Wishart classification

AP clustering was performed using texture extracted by the wavelet extraction algorithm, the class number was set manually. After the AP clustering, cluster centers were acquired. Next, a refined Lee [25] filter was conducted to eliminate speckle noise with a window size of 7. Following this, Wishart iterative clustering was implemented to obtain the final result. For a comparison of different algorithms, SVM was used on texture and polarimetric information to fulfill the supervised classification. For convenience, when evaluating classification accuracy, similar classes of unsupervised classification were merged and the following classification result images were obtained:

4.4. Classification result and analysis

From Figure 5 it can be observed that the *H/Alpha*-Wishart cannot distinguish 'field' from 'water' in (b) and (c), and this raises important questions about the misclassification of 'field' into 'water'. By contrast, the AP-Wishart is able to avoid this situation and perform better on the classification of 'field' and 'water'. From Figure 5 (f) and (g) raise further issues about the *H/Alpha*-Wishart classifier, such as the fact that it can extract less 'road' and 'building' than the AP-Wishart.

After a field study on these two experimental plots, some practical measured data were acquired and considered as sample data, to perform an accuracy assessment. The result is shown in Table 1.

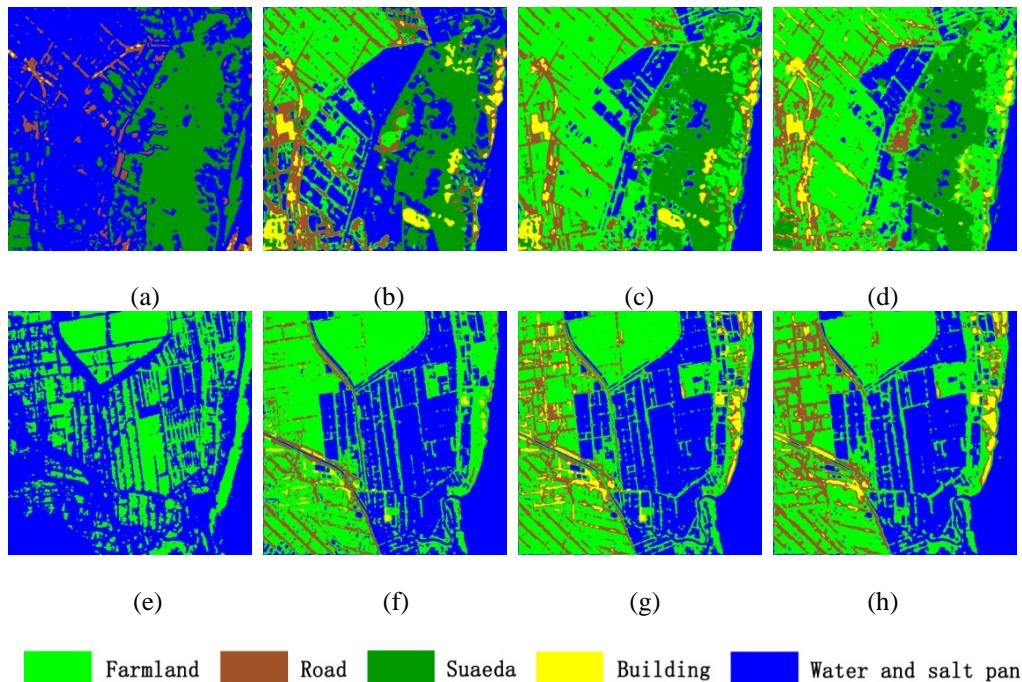


Figure 5. Comparison of *H/Alpha* classifier, *H/Alpha*-Wishart classifier, SVM classified and improved AP-Wishart classifier result in two experimental plots (a, b, c, d are respectively result of *H/Alpha*, *H/Alpha*-Wishart, SVM, AP-Wishart classifier in experimental plot one; e, f, g, h are corresponding result in experimental plot two)

Table 1. Comparison results from different classifier on two experimental plots

Classifier	Experimental plots	Total accuracy (%)	Kappa coefficient
<i>H/Alpha</i> -Wishart	one	73.73	0.52
	two	79.87	0.68
AP-Wishart	one	85.95	0.77
	two	90.38	0.85
SVM	one	86.56	0.78
	two	88.53	0.82

Compared with the *H/Alpha*-Wishart classifier, the AP-Wishart classifier can be considered to greatly enhance classification accuracy from Table 1. Its accuracy even exceeds that of the popular supervised SVM classifier. The AP-Wishart is an unsupervised classification scheme; it is more convenient and efficient than the SVM.

5. Conclusion

In this paper a brand new AP-Wishart classification scheme was proposed. By synthesizing polarimetric and textual information, which was extracted by the wavelet decomposition algorithm, a high performance AP clustering algorithm was combined with the classic Wishart iterative clustering algorithm to form a powerful unsupervised AP-Wishart clustering algorithm. Experiments were conducted on two research areas and the results demonstrated that the AP-Wishart achieved a higher classification accuracy and Kappa coefficient than the *H/Alpha*-Wishart and the supervised SVM. Therefore, it can be concluded that:

Texture extracted by a wavelet decomposition algorithm can assist polarimetric information to improve classification performance;

An AP algorithm on texture information can obtain better initial cluster result than the *H/Alpha* classification scheme.

The AP-Wishart classification scheme is more suitable for unsupervised classification of PolSAR image than the H/α -Wishart.

Acknowledgements

This research is supported by the National Natural Science Foundation of China under Grant No.41171323, a project funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions under Grant No. SZBF2011-6-B35, and the China Geological Survey Project under Grant No. 1212011120229.

References

- [1] Lee JS, Grunes MR, Kwok R. Classification of Multi-look Polarimetric SAR Imagery Based on Complex Wishart Distribution. *International Journal of Remote Sensing*. 1994; 1(15): 2299-2311.
- [2] Lee JS, Grunes MR, Ainsworth TL. Unsupervised Classification Using Polarimetric Decomposition and the Complex Wishart Classifier. *IEEE Transactions on Geoscience and Remote Sensing*. 1999; 37(5): 2249-2258.
- [3] Lee JS, Grunes MR, Pottier E, et al. Unsupervised Terrain Classification Preserving Polarimetric Scattering Characteristics. *IEEE Transactions on Geoscience and Remote Sensing*. 2004; 42(4): 722-731.
- [4] Pottier E, Lee JS. *Application of the H/A/alpha Polarimetric Decomposition Theorem for Unsupervised Classification of Fully Polarimetric SAR Data Based on the Wishart Distribution*. Proceeding of Committee on Earth Observing Satellites SAR Workshop. Toulouse. 1999.
- [5] Cloude SR, Pottier E. A Review of Target Decomposition Theorems in Radar Polarimetry. *IEEE Transactions on Geoscience and Remote Sensing*. 1996; 34(2): 498-518.
- [6] Cloude SR, Pottier E. An Entropy Based Classification Scheme for Land Applications of Polarimetric SAR. *IEEE Transactions on Geoscience and Remote Sensing*. 1997; 35(1): 68-78.
- [7] Pottier E. *The H/A/alpha Polarimetric Decomposition Approach Applied to PolSAR Data Processing*. In Proceedings PIERS Workshop Advances in Radar Methods. Baveno. 1998; (7):120-122.
- [8] Laurent FF, Pottier E, Lee JS. Unsupervised Classification of Multifrequency and Fully Polarimetric SAR Images Based on the H/A/Alpha-Wishart Classifier. *IEEE Transactions on Geoscience and Remote Sensing*. 2001; 39(11): 2332-2342.
- [9] Kimura K, Yamaguchi Y, Yamada H. *PISAR Image Analysis Using Polarimetric Scattering Parameters and Total Power*. 2003 International Geoscience And Remote Sensing Symposium. Toulouse. 2003; 1: 425-427.
- [10] Cao F, Hong W, Wu Y. *An Improved Cloude-Pottier Decomposition Using H SPAN and Complex Wishart Classifier for Polarimetric SAR Classification*. Radar, 2006. CIE '06. International Conference on Topic(s): Aerospace, Communication, Networking & Broadcasting, Engineered Materials, Dielectrics & Plasmas, Fields, Waves & Electro- magnetics. 2006: 1-4.
- [11] Wu ZC, Ouyang QD, Sun XA, et al. Improved Iterative Wishart Classification Algorithm Based on Polarimetric Scattering Characteristics Preservation. *Science of Surveying and Mapping*. 2011; 11(36):161-163.
- [12] Yang J, Shi L, Li P X. Wishart-H/Alpha Classification Based on SPAN and Best Polarimetric Coherency. *Geomatics and Information Science of Wuhan University*. 2012; 1(37): 22-25.
- [13] Zhang B, Yang R, Xie X, et al. Polarimetric SAR Image Classification Based on Polarimetric Target Decomposition and WMRF. *Geomatics and Information Science of Wuhan University*. 2011; 3(36): 297-300.
- [14] Yang J, Lang FK, Li DR. A Polarimetric SAR Image Classification Utilizing Cloude-Pottier Decomposition and Polarimetric Whitening Filter. *Geomatics and Information Science of Wuhan University*. 2011; 1(36): 104-107.
- [15] Yang L, Liu W, Wang ZG. Weighted-based Unsupervised Wishart Classification of Fully Polarimetric SAR Image. *Journal of Electronics and Information Technology*. 2008; 12(30): 2827-2830.
- [16] Zhao LL, YANG J, Li PX. Statistical Classification of Weak Backscattering Scatterers of PolSAR Image. *Journal of Remote Sensing*. 2013; 17(2): 307-318.
- [17] Lang FK, Yang J, Zhao LL. Research on Classification of SAR Image Based on Freeman Scatter Entropy and Anisotropy. *Acta Geodaetica et Cartographica Sinica*. 2012; 41(4): 556-562.
- [18] Liu M, Zhang H, Wang C. *Applying the Log-Cumulants of Texture Parameter to Fully Polarimetric SAR Classification Using Support Vector Machines Classifier*. 2011 IEEE CIE International Conference on Radar. 2011; 11:728-731.
- [19] Pottier E. *Unsupervised Classification Scheme and Topo-graphy Derivation of PolSAR Data Based on the H/Alpha/A Polarimetric Decomposition Theorem*. Proceedings of the 4th International Workshop on Radar Polarimetry. 1998; 7: 535-548.

-
- [20] Pottier E, Lee JS. *Application of the H/A/ α Polarimetric Decomposition Theorem for Unsupervised Classification of Fully Polarimetric SAR Data Based on the Wishart Distribution*. In Proceeding Committee on Earth observing Satellites SAR workshop. Toulouse. 1999.
- [21] Choy SK, Tong CS. Statistical Wavelet Subband Characterization Based on Generalized Gamma Density and Its Application in Texture Retrieval. *IEEE Transactions. on Image Processing*. 2010; 19(2): 281-289.
- [22] Zhou SR, Yin JP. Lbp Texture Feature Based on Haar Characteristics. *Journal of Software*. 2013; 8: 1909-1926.
- [23] Frey BJ, Dueck D. Clustering by Passing Messages Between Data Points. *Science*. 2007; 315(5814): 972-976.
- [24] Xiao Y, Yu J. Semi-Supervised Clustering Based on Affinity Propagation Algorithm. *Journal of Software*. 2008; 19(11): 2803-2813.
- [25] Lee JS, Grunes MR, Grandi GD. Polarimetric SAR Speckle Filtering and Its implication for Classification. *IEEE Transactions on Geoscience and Remote Sensing*. 1999; 37(5): 2363-2373.