уделено авторскому методу формализации модели в геоинформационном пространстве параметров, связанном с ГИС системами. Предложен метод трансформации модели из этого пространства параметров в классический бихроматический граф, для которого известны решения задачи оптимизации топологической наблюдаемости системы. Реализован предложенный метод на примере математической модели нормализации микроклимата в шахтах.

Научная новизна. Впервые предложен метод определения топологической наблюдаемости МПРС, основанный на формализации модели этой системы в геоинформационном пространстве ее параметров с последующей трансформацией в классический бихроматический граф, позволяющий не только определить уровень наблюдаемости МПРС, но и найти оптимальный вариант усовершенствования модели, который обеспечит полную наблюдаемость этой системы.

Практическая значимость. Использование данного метода определения наблюдаемости многосвязных пространственно-распределенных систем позволит быстро и эффективно проводить оптимизацию их систем сбора и обработки информации, добавлять и удалять приборы контроля и наблюдения, совершенствовать модель системы и осуществлять другие меры по обеспечению полной наблюдаемости.

Ключевые слова: *наблюдаемость системы, геоинформационные системы, геоинформационное пространство параметров, многосвязная система, бихроматический граф, паросочетание*

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AN EFFICIENT METHOD OF CLASSIFICATION OF FULLY POLARIMETRIC SAR IMAGES

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ЕФЕКТИВНИЙ МЕТОД КЛАСИФІКАЦІЇ ПОВНІСТЮ ПОЛЯРИМЕТРИЧНИХ РСА-ЗОБРАЖЕНЬ

Purpose. Synthetic Aperture Radar (SAR) can be used to acquire high-resolution images of ground targets during night as well as day or in good weather as well as inclement weather, so it plays an important role in the national economy and defense. However, according to the characteristics of SAR imaging mechanisms, a geometric distortion and a form of multiplicative noise, known as coherent speckle, generally corrupt the resulting image. SAR image classification is the foundation of SAR image interpretation. For the existing of speckle, traditional image classification technologies cannot work well. In this paper, in order to further improve the effect of polarimetric SAR image classification, an efficient classification method of fully polarimetric SAR image that is based on polarimetric features, the scattering intensity information, and Fuzzy C-Means (FCM) Algorithm is proposed.

Methodology. Combining the scattering properties of fully polarimetric SAR image with the scattering intensity information, the total scattering power, based on $H/\alpha/A/SPAN(H$, Entropy; α, Scattering angle; A, Anisotropy degree; SPAN, the total power of polarization), we obtained the initial classification result of polarimetric SAR image. Then with FCM Algorithm, the result of the polarimetric SAR image classification was achieved.

Findings. The experimental results show that the proposed method is superior to the traditional methods of fully polarimetric SAR images classification.

Originality. The proposed method not only considers the scattering properties of fully polarimetric SAR data but also combines the statistical characteristics information. The proposed method provides good result of classification of polarimetric SAR image and, to some extent, keeps the scattering properties.

Practical value. The experiments have proved that the proposed algorithm can keep the texture and details of SAR image better, can give better classification result to the traditional classification methods of fully polarimetric SAR image. The proposed method is useful in SAR image interpretation.

Keywords: *polarimetric SAR, coherent speckle, image classification, H/α/A/SPAN, complex Wishart distance, Fuzzy C-Means*

Introduction. Polarimetric Synthetic Aperture Radar (PolSAR) sends and receives Radar signal with different polarimetric mode, by which the Radar system can obtain abundant information of scattering properties of the ground object targets. Compared with the conventional SAR system, polarimetric SAR can obtain complex polarimetric scattering matrix according to electromagnetic scattering characteristics of different targets which can reflect objective inherent characteristic (fully polarimetric mode corresponding to fully polarimetric scattering matrix, double polarimetric mode corresponding to double polarimetric scattering vector). Based on the polarimetric complex scattering matrix, the target feature is analyzed, extracted and inversed. Therefore, the research on polarimetric SAR has important significance and has very broad remote sensing application prospects in both military and economy [1–2].

At present, classification of polarimetric SAR image has become the important content of remote sensing data processing. Fully polarimetric SAR data contains more abundant information, and the form of scattering matrix is mainly adopted. The scattering matrix can more completely record scattering echo information feature in four polarimetric states, *HH, HV, VV, VH,* which reflect the polarimetric characteristics of ground objects. For fully polarimetric SAR images, because the corresponding distribution of real object sometimes cannot be gotten, and the training samples with effective features are often difficult to select. Therefore, the focus in the research on polarimetric SAR image classification is un-supervised classification. The decomposition methods, which are frequently used at present, are Krogager decomposition, decomposition of Cameron, Cloude-Pottier decomposition and Freeman decomposition, etc. [1]. Among them, the Cloude-Pottier decomposition method is the most common, with which, based on H-α plane through the entropy H and scattering angle $\boldsymbol{\alpha}$, the fully polarimetric SAR data is divided into eight categories [2]. Combined with $H/\alpha/A$ and maximum likelihood estimation based on complex Wishart distribution, Pottier proposed the Wishart-$H/\alpha/A$ unsupervised classification method [2], which is currently the most widely used in fully polarimetric SAR data classification at present. However, this method cannot remain polarimetric characteristics of ground objects well, and the classification accuracy can still be improved. In solving the problem about classification of polarimetric SAR image, Stefan Uhlmann, and others, extract powerful color features from pseudocolor images corresponding to Polarimetric synthetic aperture radar (PolSAR) data to provide additional data for a superior terrain classification. They introduce and perform in-depth investigation of the application of color features over the Pauli color-coded images besides SAR and texture features. The classification results show that the additional color features introduce a new level of discrimination and provide noteworthy improvement in classification performance (compared with the traditionally employed PolSAR and texture features) within the application of land use and land cover classification [3]. Lang Fengkai proposed a method of polarimetric SAR data classification with Freeman entropy and anisotropy analysis. Firstly, the parameters, H_f and A_f are used to extract shadow and water, and other pixels are divided into 3 categories according to their scattering mechanism. Each category is divided elaborately again with H_f and A_f. Finally, with clustering and iterative classification based on the distribution of Wishart, the final classification results are obtained [4]. Pierre Formont, and others, presents a general approach for high-resolution polarimetric SAR data classification in heterogeneous clutter, based on a statistical test of equality of covariance matrices. The Spherically In-variant Random Vector (SIRV) model is used to describe the clutter. Several distance measures, including classical ones used in standard classification methods, can be derived from the general test. The approach provides a threshold over which pixels are rejected from the image, meaning they are not sufficiently "close" from any existing class. A distance measure using this general approach is derived and tested on a high-resolution polarimetric dataset acquired by the ONERA RAM-SES system. Results show that the new approach rejects all pixels from heterogeneous parts of the scene and classifies its Gaussian parts [5]. Xiaoshuang Ma and others propose an innovative objected-oriented technique that combines pixel-based classification and a segmentation approach for the classification of polarimetric synthetic aperture radar (PolSAR) images. In the process of the pixel-based classification, a soft voting strategy is utilized to fuse multiple classifiers, which can, to some extent, overcome the drawback of majority voting. The experimental results are presented for two quad-polarimetric SAR images. The proposed classification scheme improves the classification accuracies after assembling the multiple classifiers and provides the classification maps with more homogeneous regions by integrating the spatial information when compared with pixel-based classification [6]. In synthetic aperture radar (SAR) images, speckle conceals spatial dependencies, and segmentation algorithms suitable for optical images may become ineffective. Ciro D'Elia and others tackled the problem through the joint use of information-theoretic (IT) SAR features, of a segmentation algorithm based on tree structured Markov random fields (TS-MRFs), and of object-oriented classification achieved through learning vector quantization (LVQ) [7]. Peter Yu and others proposed a region-based unsupervised segmentation and classification algorithm for polarimetric synthetic aperture radar (SAR) imagery that in-corporates region growing and a Markov random field edge strength model. This algorithm is an extension of the successful Iterative Region Growing with Semantics (IRGS) segmentation and classification algorithm, which was designed for amplitude only SAR imagery, to polarimetric data. The incorporation of an edge penalty in the spatial context model improves segmentation performance by preserving segment boundaries that traditional spatial models will smooth over. Evaluation of PolarIRGS with Flevoland fully polarimetric data shows that it improves upon two other recently published techniques in terms of classification accuracy. To classify PolSAR image well, Maryam Salehi and others used three main steps to address this task: 1) feature extraction in the form of three categories, namely original data features, decomposition features, and SAR discriminators; 2) feature selection in the framework of the single and multi-objective optimization; and 3) image classification using the best subset of features. Based on that, a new method is proposed to perform an efficient land cover classification of the San Francisco Bay urban area based on the multi-objective optimization approach. The experimental results on Radarsat-2 fine-quad data show that the proposed method outperforms the single objective approaches tested against it, while saving computational complexity. In addition, the proposed method has a better performance than the SVM (Support Vector Machine) with full set of features and the Wishart classifier, which is based on the covariance matrix [8]. Shuiping Gou and others proposed a novel polarimetric synthetic aperture radar (POLSAR) image classification approach by exploiting coherency matrix eigenvalues for polarimetric information representation and understanding. The approach consists of two parts. Initially, the statistical distributions of eigenvalue for homogeneous areas are analyzed by taking eigenvalues as the features of polarimetric information. The Bayesian classification method is applied to verify the feasibility of distinguishing different homogeneous areas. An eigenvalues-based local operator is defined to overcome the insufficient of the similar pixels by introducing a similar measure and eigenvalues-based texture information. The method is tested on three POL-SAR datasets, in which the average classification accuracy of eight categories for the Flevoland data from our method reaches nearly 90% [9]. Chu He and others proposed a nonlinear compressed sensing-based LDA Topic (NCSLT) model for the classification of polarimetric synthetic aperture radar (PolSAR) images. The CS theory shows that when a signal is sparsely rendered on some basis, it can be recovered exactly by a relatively small set of random measurements of the original signal. In this paper, such notion is applied to a more general case to analyze nonlinear PolSAR data. Therefore, the NCSLT model is presented with the following two objectives: 1) to capture the nonlinear structure of PolSAR data on a manifold surface using the CS theory and 2) to provide a generative explanation for the relationship between the image pixels and high level complex scenes for image classification by establishing a Texture-CS-Topic model [10].

Although there have been some good results of the polarimetric SAR image classification based on only polarization characteristics, the function of that kind of classification methods is still very limited [1–10]. In some cases, the polarization characteristics of some non-similar targets may be very similar, and polarization characteristics of some similar tar-gets may be very different. Therefore, just with the polarization characteristics, the polarimetric SAR image classification accuracy is very limited. In this paper, in order to further improve the effect of polarimetric SAR data classification, we takes into account not only the scattering properties of fully polarimetric SAR data, but also combines the intensity information, a new unsupervised classification algorithm of fully polarimetric SAR image based on initialization of *H/α/A/SPAN* and FCM algorithm is proposed.

H/α/A method. Target data in fully polarimetric SAR measurement can be represented as Sinclair scattering matrix (S) matrix, the matrix is

$$S = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} . \quad (1)$$

In fully polarimetric SAR imaging system, the four complex data can be obtained. General spaceborne polarimetric SAR is single station form, which means that in receiving and transmitting radar signal, the same antenna is used. Under the condition of satisfying the reciprocity, $S_{hv} = S_{vh}$. According to the knowledge of the group theory, Pauli is chosen to vectorize the basic scattering matrix to get k.

$$k = \frac{1}{\sqrt{2}} \left[\mathrm{S}_{hh} + S_{vv} \quad S_{hh} - S_{vv} \quad 2S_{hv} \right] \cdot \quad (2)$$

Considering that the vast majority of terrain targets will be randomly distributed targets, they has multiple scattering centers, and the total signal is gotten by coherent superposition, so spatial statistical average processing is often used to smooth the coherence of electromagnetic wave. Polarimetric coherent matrix is often represented as

$$T = \left\langle k \cdot k^H \right\rangle = \frac{1}{N} \sum_{i=1}^{N} k_i \cdot k_i^H \cdot \quad (3)$$

Where, N is the number of looks, ki is the regard scattering vector of look i, and superscript H expresses conjugate transpose. According to the knowledge of matrix theory, coherence matrix T is 3x3 positive semidefinite Hermite matrix, and it can be decomposed into the sum of three separate coherent matrixes. T has nonnegative real eigenvalues and orthogonal eigenvectors, and it can be expressed as the following form:

$$T = U \sum U^{-1} = \sum_{i=1}^{3} \lambda_i T_i = \sum_{i=1}^{3} \lambda_i u_i \cdot u_i^H . \quad (4)$$

Where, λ_i is the real eigenvalue, u_i is the normalized vector corresponding to the eigenvalue i. T_i expresses independent coherence matrix whose rank is 1, respectively expresses a scattering mechanism, and its corresponding eigenvalue expresses the strength of scattering mechanism. The size of the three eigenvalues and their difference nature are directly related to the earth's surface electromagnetic wave scattering process. For example, Chen Tigang and others give the general form of the eigenvalues under the assumption on horizontal symmetrical orientation of scattering target, and point out that the first eigenvalue represents the total polarimetric intensity of *VV* and *HH,* not including the coherence between them. The second eigenvalue represents the coherent strength of *VV* and *HH*. The third eigenvalue gives the depolarimetric effect aroused by the medium. The general form of the u_i is given by Cloude.

In 1997, Cloude and others gave the entropy H and scattering Angle α of target on the basis of characteristics decomposition of the polarimetric coherent matrix T [1]. H and α can be respectively defined as the follows

$$H = \sum_{i=1}^{3} - P_i \log_3 P_i ; \quad (5)$$

$$\alpha = \sum_{i=1}^{3} P_i \alpha_i . \quad 6)$$

Where $P_i = \frac{\lambda_i}{\sum_{i=1}^{3} \lambda_i}$ and $\sum_{i=1}^{3} P_i = 1$.

According to information theory, the scattering entropy (0≤H≤1) expresses randomness of scattering medium from isotropic scattering (H=0) to a completely random scattering (H=1). If H value is very low, which is that the difference of three eigenvalues is bigger. For that, it can be thought that depolarimetric characteristics of target is weak, the dominant scattering matrix part of target is the eigenvector corresponding to the maximum eigenvalue, and other eigenvectors is ignored. If H=0, it is indicated the target is pure scattering one, and the rank of coherent matrix is 1. If the value of H is very high, which is that the size of three eigenvalues is very close. For that, it can be thought that depolarimetric characteristics of target is very strong, which means the target scattering presents high randomness, which is in that target scattering is mainly composed of body scattering of target. What is able to identify scattering component information is α, and α has the characteristics of rotation invariance along radar wave beam direction and associates with physical mechanism in the process of scattering, corresponding to the change of scattering from the surface scattering (α=0°), to body scattering (α=45°) , and to the dihedral angle scattering (α= 90°). So the *H*-α plane is often used for unsupervised classification, or the initial classification is done based on *H*-plane, etc. Cloude and Pottier used *H* and α to form a two dimensional feature space. Cloude and others gave the category boundary of the plane of the *H*-α on the basis of a large number of experiments. With the *H*-α plane, fully polarimetric SAR data can be divided into eight categories.

There is a case in which scattering mechanism can't distinguish the two parameters, polarimetric entropy *H* and scattering angle α , which is that influence of λ_2 can't be ignored according to the size difference of λ_2 and λ_1. In that condition, the relative relationship of λ_2 and λ_3 should be considered, therefore, Pottier proposed a new parameter in 1998. The degree of anisotropy, as the supplement of *H*-α plane, the definition of the anisotropic degree is the following

$$A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3}\ . \tag{7}$$

Anisotropy degree A expresses anisotropy degree of target scattering. When polarimetric entropy *H* is larger (*H*> 0.7), *A* can characterize the influence degree of the two scattering mechanism that do not dominate to the scattering result. The second larger value *A* indicates that only the second scattering mechanism has significant effect on scattering results. The smaller value *A* indicates that the influence of the third kind of scattering mechanism should be also considered. *H, α*, and *A* form the three dimensional feature space. Through the three dimensional feature space, the classification of the fully polarimetric SAR data also increases to 16 classes.

Because *H, α*, *A,* the three parameters characterize scattering of pixel in the size of the relative strength and scattering mechanism type. They did not provide the strength information of the scattering mechanism among the pixels. In general, the strength of the scattering mechanism among the pixels is very effective for keeping image detail structure and image resolution, and the detailed structure and resolution of the image will directly affect the performance of the classifier. Considering that the total polarimetric power SPAN is effective parameter of characterizing scattering mechanism intensity information among the pixels, SPAN is introduced into initialization in this paper, and its expression formula is as the following.

$$\mathrm{SPAN} = \mathrm{Tr}(\mathrm{SS}^{\mathrm{H}}) = |\mathrm{S}_{\mathrm{hh}}|^2 + |\mathrm{S}_{\mathrm{hv}}|^2 + |\mathrm{S}_{\mathrm{vh}}|^2 + |\mathrm{S}_{\mathrm{vv}}|^2 = \lambda_1 + \lambda_2 + \lambda_3. \tag{8}$$

What SPAN describes is the size of the scattering intensity corresponding to the pixels; it contains the more detailed structure of the image. In general, pixels whose scattering intensity are bigger may correspond to the secondary scattering, and pixels whose scattering intensity are smaller may correspond to the first scattering. Therefore, SPAN can be used to further distinguish three different scattering mechanisms: (1) the larger SPAN value corresponds to the strong scattering, such as construction, forest; (2) the medium SPAN value corresponds to the mixed scattering mechanism, such as crop area; (3) the smaller SPAN value corresponds to the strong scattering, such as water, flat surface.

The complex Wishart distance based on ML. Sinclair scattering matrix is decomposed through Pauli base, and the scattering vector *h* complying with multiple complex Gaussian distribution can be gotten. Considering the correlation matrix corresponding to *h* is *T.* According to the literature [1–2], by multi-look processing of *T*, polarimetric correlation matrix *T* of complex Wishart distribution can be gotten. Considering that Vm is the clustering center of a class, according to the rule of maximum likelihood (ML), the distance between a pixel and a cluster center can be gotten

$$d(\langle T\rangle, Vm) = n\left[\ln|Vm| + \mathrm{tr}(\mathrm{V}_{\mathrm{m}}^{-1}\langle T\rangle)\right] - \ln\left[P(m)\right]. \tag{9}$$

Where, *P (m)* is the prior probability of the category *m*. In the absence of prior knowledge, it is considered that the prior probability *P (m)* of m categories are equal, so the formula (9) can be simplified as

$$d(\langle T\rangle, Vm) = \ln|Vm| + \mathrm{tr}(\mathrm{V}_{\mathrm{m}}^{-1}\langle T\rangle). \tag{10}$$

Therefore, when the polarimetric coherent matrix *T* of a pixel satisfies

$$d(\langle T\rangle, V_m) \le d(\langle T\rangle, V_j), \quad \mathrm{j} = 1, \ldots, \mathrm{M}, \quad m \ne j. \tag{11}$$

The pixel is classified as category *m*. For fully polarimetric SAR data, the formula (10) is a more rational method of calculating the distance between a pixel and a clustering center. Compared with the traditional Euclidean distance, the advantage of this approach is that it is based on the scattering mechanism, and the polarimetric information of the data is better used.

Fuzzy C-means Clustering Technique (FCM). The concept of Fuzzy Clustering Algorithm is proposed by Bedeck firstly, and the algorithm is an important branch of unsupervised pattern recognition. Fuzzy Clustering Algorithms have a wide range of applications in image segmentation, compression, recognition because of their numerous advantages.

Among Fuzzy clustering algorithms, the theory of Fuzzy C-means algorithm is the most mature, and it is one of the representative clustering algorithms. The basic idea of FCM is that through an iterative optimization to represent the objective function of similarity among the image pixels and the centers of FCM, when the maximum value of the objective function is obtained, the optimal clustering result is gained.

Definition of membership matrix. A two-dimensional matrix *U* is used to represent the membership matrix. In a set, if the data point of the element *j, xj* belongs to group i, then the element in the membership matrix, *uij* is given value 1, otherwise, the element value is 0. When the class determines its center point of the clustering, given that the center point of the clustering is *ci,* then the degree of the element membership can be expressed with the following formula

$$u_{ij} = \begin{cases} 1, & k \neq i, \text{if } \|x_j - c_i\|^2 \leq \|x_j - c_k\|^2 \\ 0 & \end{cases} . \quad (12)$$

It can be seen from the above formula that if a cluster center is the nearest cluster center for the element *xj,* then the element *xj* belongs to group i, but every given element in the set can only belong to one group, so the membership matrix *U* has the following property

$$\sum_{i=1}^{c} u_{ij} = 1, \forall j = 1, \cdots n . \quad (13)$$

Definition of fuzzy C-means clustering objective function. In Fuzzy C-Means clustering algorithm, the n vectors (*j* =1,2, ..., *n)* is divided into c fuzzy groups, and the values of the cluster centers of the fuzzy groups are calculated, which makes the objective function of the non-similarity index minimum. By representing dissimilarity index between a vector and corresponding cluster center with Euclidean distance, its objective function can be defined as follows:

$$J = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} (\sum_{k, x_k \in G_i}^{C} \|x_k - c_i\|)^2 . \quad (14)$$

In the above formula, J_i is the objective function in the fuzzy group i, so its value depends on the geometric characteristics of G_i and the location of each cluster center.

Because the sum of the membership matrix of the data set is 1, an objective function of the fuzzy C-means clustering algorithm can be expressed as

$$J(U, C) = \sum_{i=1}^{c} J_i = \sum_{j=1}^{n} \sum_{i=1}^{c} (\mu_{ij})^m \|x_j - c_i\|^2. \quad (15)$$

Among them, c_i is cluster center, $\|x_j - c_i\|$ represents the Euclidean distance between the cluster centers i and the data point *j, m* is the weight index, and its range is [1, ∞]. If m=1, the fuzzy C-means clustering becomes hard C-means clustering. In practical applications, usually it is more appropriate that the value of m is given 2.

Cluster centers and membership matrix. In order to make the objective function *J (U, C)* least in (15), Lagrange multiplier method can be used to find the extremer, the constraint condition is *j* = 1*...n,*

$$\bar{J}(U, c_1, \cdots, c_c, \lambda_1, \cdots, \lambda_n) = J(U, c_1, \cdots, c_c) + \sum_{i=1}^{n} \lambda_j (\sum_{j=1}^{c} u_{ij} - 1). \quad (16)$$

The necessary conditions for the minimum of *J (U, C)* are the following

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}{}^m x_j}{\sum_{j=1}^{n} u_{ij}{}^m} ; \quad u_{ij} = \frac{1}{\sum_{k=1}^{c} (d_{ij} / d_{kj})^{2/(m-1)}} . \quad (17)$$

The basic steps of FCM algorithm. Fuzzy C-Means clustering algorithm is the process of continuously adapting and modifying cluster centers and membership matrix by iteration, it is a dynamic unsupervised clustering. Its main clustering steps are the following:

(1) Initialize the value of the center of every cluster, set the category number of clustering, *c*, and the iteration stop threshold of the algorithm, *ε*, and reset the iteration counter *τ*.

(2) Update the membership matrix.

(3) Update the cluster center value.

$$c_i^{(T)} = \frac{\sum_{j=1}^{n} u_{ij}{}^m x_j}{\sum_{j=1}^{n} u_{ij}{}^m} . \quad (18)$$

(4) If $|J_m(T) - J_m(T+1)| < \varepsilon$, stop iteration and output the circulation membership matrix and the cluster center value by loop, otherwise return to step (1) and continue to run iteration of the loop.

After the end of the repeated iteration of the loop of the above four steps, one of the best membership matrix and the corresponding cluster center value *C* of the matrix can be gotten, then determine the optimal cluster divided according to the maximum degree of membership, and the final clustering result is gotten.

By learning fuzzy C-means clustering algorithm, it is known that the algorithm starts from any cluster initial value, and then through the iterative convergence, the local minimum of the objective function is gotten. By summing up, the Fuzzy C-Means clustering algorithm is excellent in a variety of clustering algorithms; it has relatively high efficiency, and has been applied in many areas. However, this algorithm still has several deficiencies, which are in that the number of categories of the clustering algorithm is artificially determined but not be determined automatically, which leads that a good application in a relatively high degree of automatic SAR image processing system cannot be gotten.

The unsupervised classification method of PolSAR data based on H/α/A/SPAN and FCM. The steps of the unsupervised classification method of PolSAR data based on H/α/A/SPAN and FCM are as the follows:

(1) By preprocessing the PolSAR data (speckle filtering on PolSAR data), polarimetric coherent matrix T is gotten.

(2) Feature decomposition is done on *T*, the eigenvalues and eigenvectors are gotten based on the formula (4). Through formulas (5) to (8), *H, α, A,* and SPAN are calculated.

(3) With the classification method based on H/α/A/ SPAN, the initial classification of the whole polarimetric SAR data is done: (a) according to the value of the SPAN, the SAR data is divided into three classes with three equal number of samples, these three categories correspond to high amplitude value, medium amplitude value and low amplitude value; (b) With the *H/α*, data in each of the three categories are further divided into 8 classes; (c) with *A,* data in each of the 24 classes existing is further divided into two classes. On this basis, the clustering centers of the all classes are calculated.

(4) According to the result of step 3, the parameters corresponding to the FCM clustering are initialized.

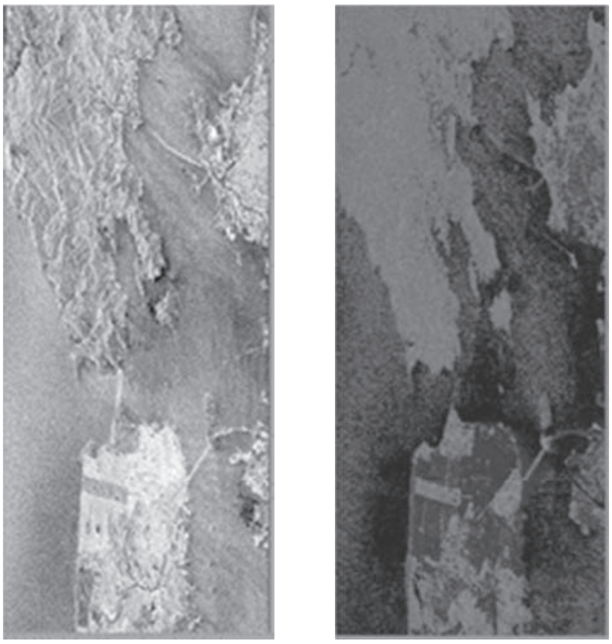
(5) According to the known information in step 4, through iterative, category centers and the class type that each

pixel belongs to in FCM are updated. Each time, the data of two classes whose centers are the nearest among all the clustering centers, is combined, and the combined clustering center of the two classes is calculated. For that, the whole class number and class centers are also changed, and the parameters corresponding to the FCM clustering are also updated.

(6) According to the above steps, if the corresponding error value of global classification meets the requirements, or the times of iterations reach the specified number, the current classification result of the fully polarimetric SAR data is output, and the operation exits. Otherwise, the operation should return step 5 and continues to execute.

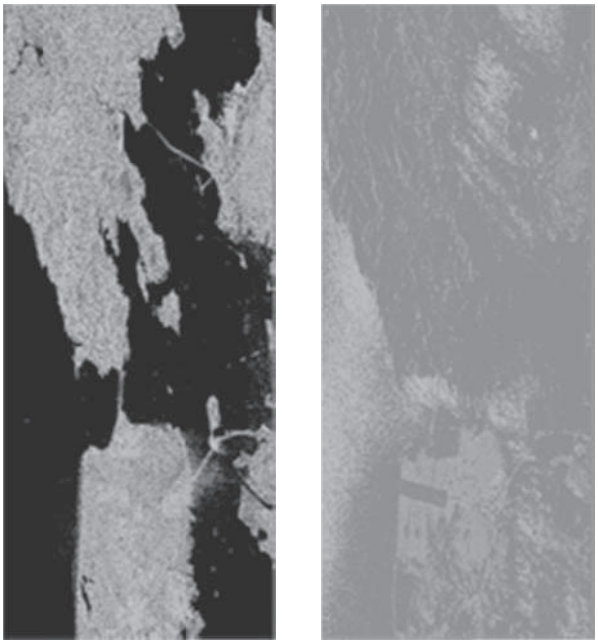
The experiment results and analysis. In order to verify the effectiveness of the proposed method in this paper, we use the 2008 San Francisco Bay area RadarSat-2 l-band data to do classification experiment, the data size is 6670 pixels * 2820 pixels. Firstly, with the improved Lee filter algorithm, 3x3 filter processing on fully PolSAR data is done to reduce speckle. The experimental data is decomposed with Pauli base. The scattering total power image (SPAN) of the original PolSAR data is shown in the fig. 1, *a*. The results of different classification methods are shown in the fig. 1, *b* (H/α classification result), fig. 2, *a* (H/A classification result), fig. 2, *b* ($H/\alpha/$ Span classification result), and fig. 3, *a* (Wishart-$H/\alpha/A$ classification result).

With the classification method based on $H/\alpha/A/SPAN$, the initial classification of the fully polarimetric SAR data is done. Thus, the classification result of 48 classes is gotten, and FCM algorithm is used to do iterative classification. The result of classification using the proposed method is shown in the fig. 3, *b*. Compared with the results of other methods, some typical targets in PolSAR image shown in fig. 3, *b*, such as mountain area, sea and city building are classified better.



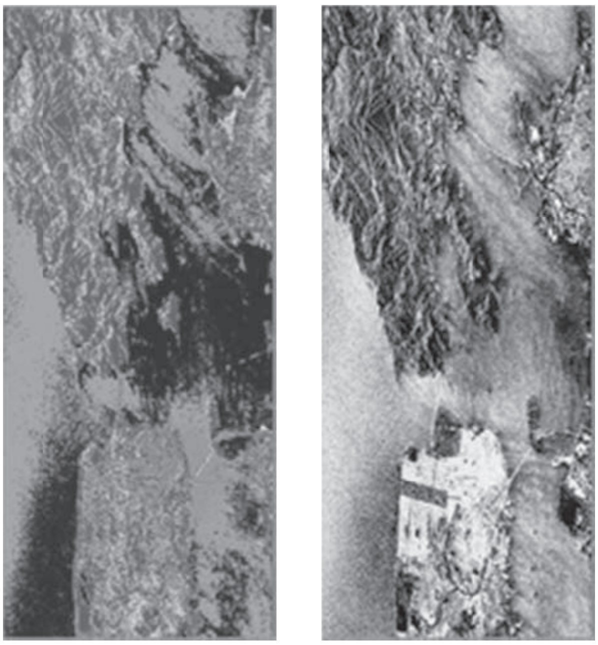
a *b*

Fig. 1. The result images: a – the Scattering total power image (SPAN) of polarization SAR, b – H/α classification result



a *b*

Fig. 2. The result images: a – H/a classification result, b – $H/\alpha/Span$ classification result



a *b*

Fig. 3. The result images: a – Wishart-$H/\alpha/A$ classification result, b – the classification result received with the proposed method

It can be seen from the fig. 3, *b*, that the classification result based on $H/\alpha/A/SPAN$ generally reflects the basic features of ground objects. Compared with the actual objects, the main target categories are recognized. The clustering centers calculated by $H/\alpha/A/SPAN$ classification result are already close to the actual target values. Therefore, when the FCM algorithm is used to classify SAR image, the initial clustering centers obtained can be as a reference, based on which iterations are done. For that, better PolSAR image classification result can be obtained.

Conclusion. A new unsupervised classification method of fully polarimetric SAR data based on polarimetric features and FCM is proposed in this paper. With the result obtained by *H/α/A/SPAN* classification method to initialize the clustering parameters in FCM, the iterative classification of PolSAR data is carried on. In the process of operation, complex Wish-art distance based on maximum likelihood criterion is introduced to improve the performance of classifiers. The Experiments show that the proposed algorithm can keep the texture and details of SAR image better, and its classification result is superior to the traditional classification methods of fully polarimetric SAR classification.

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Мета. Радіолокатор синтезованої апертури (РСА) може бути використаний для отримання знімків високого розділення наземних об'єктів (цілей) незалежно від часу доби та погодних умов, що є важливим для потреб національної економіки й оборони. Проте, згідно з характеристикам механізму побудови РСА-зображень, геометричні спотворення та, свого роду, мультиплікативний шум, відомий як когерентне оптичне випромінювання, часто спотворюють отримане зображення. Класифікація РСА-зображень є основою їх інтерпретації. Із-за впливу спекл-шуму традиційні технології класифікації зображень працюють недостатньо добре. У статті описано запропонований нами ефективний метод класифікації поляриметричних РСА-зображень, що ґрунтується на поляриметричних властивостях, даних про інтенсивність розсіяного випромінювання та методу нечіткої кластеризації С-середніх.

Методика. Поєднавши розсіюючі властивості повністю поляриметричного РСА-зображення й дані про інтенсивність розсіяного випромінювання, ми отримали результат попередньої класифікації РСА-зображення. Остаточний результат класифікації поляриметричного РСА-зображення був отриманий за допомогою алгоритму нечіткої кластеризації С-середніх.

Результати. Експериментально доведено, що запропонований метод перевершує традиційні методи класифікації повністю поляриметричних РСА-зображень.

Наукова новизна. У запропонованому методі враховуються не лише властивості повністю поляриметричних РСА-даних, але й інформація про статистичні характеристики. Метод дозволяє отримати гарні результати класифікації поляриметричних РСА-зображень зі збереженням розсіюючих властивостей (у деякій мірі).

Практична значимість. Експериментальні дослідження показали, що запропонований алгоритм зберігає текстуру й деталі РСА-зображення краще, ніж традиційні методи та дає кращий результат класифікації повністю поляриметричних РСА-зображень. Метод може використовуватися для вирішення завдань інтерпретації РСА-зображень.

Ключові слова: *поляриметричне РСА-зображення, когерентне оптичне випромінювання, класифікація зображень, H/a/A/SPAN, розподіл Вішарта, метод нечіткої кластеризації С-середніх*

Цель. Радиолокатор синтезированной апертуры (РСА) может быть использован для получения снимков высокого разрешения наземных объектов (целей) независимо от времени суток и погодных условий, что является важным для нужд национальной экономики и обороны. Однако, согласно характеристикам механизма построения PCA-изображений, геометрические искажения и, своего рода, мультипликативный шум, известный как когерентное оптическое излучение, зачастую, искажают полученное изображение. Классификация PCA-изображений является основой их интерпретации. Из-за влияния спекл-шума традиционные технологии классификации изображений работают недостаточно хорошо. В статье описан предложенный нами эффективный метод классификации поляриметрических PCA-изображений, основывающийся на поляриметрических свойствах, данных об интенсивности рассеянного излучения и метода нечеткой кластеризации С-средних.

Методика. Совместив рассеивающие свойства полностью поляриметрического PCA-изображения и данные об интенсивности рассеянного излучения, мы получили результат предварительной классификации PCA-изображения. Окончательный результат классификации поляриметрического PCA-изображения был получен с помощью алгоритма нечеткой кластеризации С-средних.

Результаты. Экспериментально доказано, что предложенный метод превосходит традиционные методы классификации полностью поляриметрических PCA-изображений.

Научная новизна. В предложенном методе учитываются не только свойства полностью поляриметрических PCA-данных, но и информация о статистических характеристиках. Метод позволяет получить хорошие результаты классификации поляриметрических PCA-изображений с сохранением рассеивающих свойств (в некоторой степени).

Практическая значимость. Экспериментальные исследования показали, что предложенный алгоритм сохраняет текстуру и детали PCA-изображения лучше, чем традиционные методы, и дает лучший результат классификации полностью поляриметрических PCA-изображений. Метод может использоваться для решения задач интерпретации PCA-изображений.

Ключевые слова: *поляриметрическое PCA-изображение, когерентное оптическое излучение, классификация изображений, H/α/A/SPAN, распределение Вишарта, метод нечеткой кластеризации С-средних*

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ANALYSIS AND REALIZATION OF RFID GROUPING-PROOF PROTOCOL BASED ON ELLIPTIC-CURVES CRYPTOGRAPHY

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АНАЛІЗ І РЕАЛІЗАЦІЯ ПРОТОКОЛУ ОБМІНУ СИГНАЛІВ РАДІОЧАСТОТНОЇ ІДЕНТИФІКАЦІЇ НА ОСНОВІ ЕЛІПТИЧНОЇ КРИПТОГРАФІЇ

Purpose. With the wide application of RFID (Radio Frequency Identification) systems, scholars have become highly concerned about the design of efficient and secure grouping-proof protocols. Responding to the problems of privacy protection, security and efficiency of existing grouping-proof protocols, a new ECC (Elliptic Curves Cryptography) based RFID grouping-proof protocol is proposed after the analysis of existing grouping proof protocols.

Methodology. Some ECC-based grouping-proof protocols cannot resist impersonation attack and other common attacks, since there is no reader and verifier authentication or the reader and the verifier can be untrusted, one can also query the tags actively to collect the attack tuple and trick genuine reader and verifier. So we propose a scheme can realize the authorized access and mutual authentication of tags, readers, and verifier.

Findings. This paper attempts to expound on the initialization phase, the authorization phase, the group proof generation phase, and the group proof verification phase of the new grouping-proof protocol, and also make analyses in terms of privacy preservation, untraceability, reader anonymity, tag anonymity, authorization and authentication, etc.

Originality. In comparison to currently available ECC-based grouping-proof protocols, this protocol can realize the authorized access and mutual authentication of tags, readers, and backend servers.

Practical value. Analysis results show that this new project meets the security and privacy requirements of RFID system grouping-proof protocols, demonstrating better scalability and higher efficiency than similar protocols.

Keywords: *grouping-proof protocol, authorization authentication, mutual authentication, Elliptic Curves Cryptography, RFID*

Introduction. In recent years, it was found that RFID systems had to prove that certain items must COEXIST in some applications. There are many application scenarios of this type: A doctor prescribes medicines in the same prescription to reduce dosage risks for his patients; in the pharmaceutical industry, drug manufacturers ensure that drugs and prescriptions are sold together; at airports, boarding pass, passport and baggage are generated as a group to ensure se-