Applying Particle Swarm Intelligence in PolSAR Image Clustering

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Abstract. The clustering problem of polarimetric SAR image is an optimization problem with high dimension and large amount of data. Aiming at the problem that the classical unsupervised classification methods for High Resolution Polarimetric SAR images are difficult to find the global optimal solution. The Particle Swarm Optimization (PSO) algorithm was proposed in High Resolution PolSAR images clustering. For the first beginning, the scattering eigenvalues of PolSAR data were used for initial classification, and then followed by the computation of clustering center and initialization of PSO algorithm, finally the particle swarm are introduced in the iterative steps to reduce noise effect and improve the classification results. The performance of this novel method is demonstrated in experiments using L-Band PolSAR image of San Francisco Bay.

Keyword. Particle swarm optimization; PolSAR; unsupervised classification.

1. Introduction
Unsupervised classification is one of the major applications of the automatic analysis and interpretation of PolSAR (Polarimetric Synthetic Aperture Radar) data [1]. Due to its complexity of measured information from four multiple polarimetric channels and multiplicative speckle noise, the global best centroids of the clustering problem of PolSAR image are hardly found [2]. Over the past two decades, there have extensive research in the area of the classification algorithms for the PolSAR data [3-5]. However most the unsupervised classification methods are based on the scattering mechanisms and their statistical characteristics or some clustering approaches which can automatically exploiting information contained within the data. Thus, most traditional methods unfortunately exhibit the common shortcomings: (1) inability to apply a global search and easily to fall into the local optimum, (2) inability to combining complex information from the PolSAR multiple channels with low dimensional clustering algorithms.

Therefore, in this paper, a methodology aims to solve the above problems of high dimensional PolSAR image clustering problem within the proposed PSO clustering framework. The PSO algorithm are used to accomplish a wide range of tasks in various areas of research on optimizing the complicated problems that are non-linear, and non-differentiable, including function optimization [6], neural networks [7], and pattern classification [8]. In this study, the proposed clustering process based on PSO techniques is applied to automatically optimize the clustering centroids of PolSAR image in the high-dimension polarimetric space instead of just RGB feature space. The performance of the proposed PSO clustering algorithm is evaluated based on PolSAR data of the San Francisco Bay acquired by the NASA/Jet Propulsion Laboratory Airborne SAR (AIRSAR) [9].
2. Data and Distance Measurement
According to the principles of fully polarimetric SAR measurement, the fully polarimetric SAR data is in the form of scattering matrix $S$.

$$ S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix} $$  \hspace{1cm} \text{(1)}

where $S_{HV}$ is the scattering volume transmitted horizontally and received vertically [3]. It is indicated that every element in matrix $S$ is complex form. Therefore, a PolSAR pixel and the centroid of the clustering problem can both be set as Equation (2):

$$ C = \begin{bmatrix} s_{1HH} \, s_{1HV} \, \cdots \, s_{1VH} \, s_{1VV} \\ s_{2HH} \, s_{2HV} \, \cdots \, s_{2VH} \, s_{2VV} \\ \cdots \\ s_{MHH} \, s_{MHV} \, \cdots \, s_{MVH} \, s_{MVV} \end{bmatrix} $$  \hspace{1cm} \text{(2)}

It indicates that the cluster centroids of an $M$-class classification is a matrix containing $M$ 8-dimensional vectors, which also can be the 'position' attribute of the PSO, as Equation (3):

$$ P_i = \begin{bmatrix} s_{i11} & s_{i12} & \cdots & s_{i18} \\ s_{i21} & s_{i22} & \cdots & s_{i28} \\ \cdots \\ s_{iM1} & s_{iM2} & \cdots & s_{iM8} \end{bmatrix} $$  \hspace{1cm} \text{(3)}

where $P_i$ is the position matrix of the $i$th particle in swarm. Then the distance measurement $d_{ik}$ and the 'fitness' measurement $\text{Fit}(P_i)$ of PSO algorithm can be determined as equations (4), (5):

$$ d_{ik} = \sqrt{\sum_{m=1}^{8} (s_{im} - c_{km})^2} $$  \hspace{1cm} \text{(4)}

$$ \text{Fit}(P_i) = \sum_{n=1}^{N} d_{nx} $$  \hspace{1cm} \text{(5)}

where $s_{im}$ is every element of the matrix $S$ of the $i$th pixel, $c_{km}$ is every element of the centroid matrix of the $k$th class, and the $d_{nx}$ in Eq. (5) indicate the distance between the $n$th pixel and the cluster center of the class to which the pixel belongs.

3. PolSAR Image Clustering Based on PSO Algorithm
Similar to other evolutionary algorithms, PSO also learns from the cluster intelligence of nature [10]. By simulating the natural intelligence of birds foraging, the PSO algorithm takes multiple individuals to search the global optimal solution in the feature space, which called "particles". The optimal degree of an particle is called "fitness". The "position" attribute of particle indicates a solution in the feature space, and the "velocity" attribute determines how to update the position. And how to calculate velocity is determined by two groups of factors called "global optimal record" and "individual optimal records".

The process of the novel clustering method of PolSAR image based on PSO can be described as follows:

1. After preprocessing the full polarimetric SAR data, the correlation matrix and related eigenvalues are calculated;
2. Initializing the classification with polarimetric parameter $H$ and $\alpha$ [9];
3. The results of 2) are used to initialize the particle swarm, and the initial cluster centroid is assigned to the position of the particles;
4. The fitness values of all particles are calculated according to equation (5), and then global optimal record of the swarm and the individual optimal record of each particle are updated;
5. Update the velocity and position of all particles according to equation (6) [10];
\[ X_i = X_i + V_i; \]
\[ V_i = \omega \cdot V_i + c_1 \cdot r_1 \cdot (p_i - X_i) + c_2 \cdot r_2 \cdot (g - X_i) \] (6)

(6) Calculated fitness of each particle after classified each pixel by comparing the distance from the pixel to every class centroid which determined by the position of the particle;

(7) If the specified number of iterations are reached, the global optimal solution is outputted as the clustering result and the operation exits, otherwise, return to 4) to continue.

4. Experiment and Discuss
In the experiment part, the novel clustering algorithm with PSO of PolSAR data was applied in AIRSAR image of the San Francisco Bay. The population of PSO and the maximum number of iterations were set to (50,50) after much times test considering both speed and accuracy.

The RGB image of the San Francisco Bay generated by polarization decomposition from PolSAR data was shown in figure 1a, which represents the Ocean by blue, vegetation by green, urban construction area by gray and bare soil by dark gray. The classification results of RGB K-means and proposed PSO clustering were shown in figures 1b and 1c. Overall, by means of visual comparison, it is obviously that the classification result of the bare soil between ocean and urban area by the proposed PSO clustering is more accurate than the RGB K-means, no matter on the left side of the land or on the top side. Furthermore, in the polo field with an oval shape, lots of red speckle which represents the urban area more likely can be seen in classification result of RGB K-means. On the contrary, the same part is almost pure yellow which indicates a higher classification accuracy in the PSO clustering.

![Image of RGB composite image, RGB K-means, and PSO clustering](image)

Figure 1. RGB image and Classification results of AIRSAR data.

After referring to the ground true image [9], the above two classification results were combined to get four main feature categories, and calculated the accuracy, as shown in table 1.

| Algorithm       | Vegetation | Urban area | Ocean  | Bare Soil | Accuracy |
|-----------------|------------|------------|--------|-----------|----------|
| RGB-Kmeans      | 82.44%     | 86.65%     | 90.17% | 76.13%    | 83.94%   |
| PSO Clustering  | 90.83%     | 98.36%     | 98.20% | 91.33%    | 94.87%   |

From table 1, it can be seen that the proposed PSO clustering algorithm is superior to K-means method in both every categories and overall accuracy. This is mainly because the PSO algorithm has the
ability to find the optimal solution in complex space. Even when the initial conditions are not good, the algorithm can still find the global optimal solution by studying with the global optimal and local optimal.

5. Conclusion
The algorithm proposed in this paper effectively combines the advantages of the PSO algorithm and polarimetric parameters performs well in PolSAR image clustering problem. In this method, the initial clustering center is calculated by using the initial classification with polarimetric parameters, and then the particles in the PSO algorithm can be initialized. Finally, the initial classification results are optimized through the iterative process of the PSO algorithm, so as to improve the classification effect. The experimental results show that the method is effective in full polarimetric SAR data classification.

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