Semi-supervised classification method of SAR images using spectral clustering in contourlet domain

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Abstract: A new based on Semi-supervised classification theory for SAR images in contourlet domain is proposed, in this paper. Attempting to get better and faster performance, the PSO algorithm (Particle swarm optimization algorithm) and contourlet domain is proposed to instead of traditional k-means algorithm. PSO is used to find the global optimum by performing a global search in the whole solution space. And then, contourlet is applied in front of construct the similarity matrix to extract more effective eigenvalues. In section five, the proposed algorithm got better classification results than the traditional k-means algorithm which is proved by experimental results show that in terms of running time, classification accuracy and Kappa coefficient.

1. Introduction
Clustering analysis$^1$ is an important data mining method, image recognition, in essence is a process of image classification or division$^2$. Spectral clustering$^{3-5}$ is a popular clustering method which is used widely in computer vision$^6$, image understanding$^7$, speech separation$^8$ and pattern recognition$^9$. To divide the data easily, we decomposed Laplacian matrix to obtain a simpler data space firstly. By adopting some grouping method, clustering result is achieved, secondly, such as k-means method$^{10}$ to get a discrete solution from eigenvectors.

2. Principle of our algorithm
Contourlet were developed as an improvement over wavelets in terms of the inefficiency in presenting geometrical smoothness. The resulting transform has the multiscale and time-frequency-localization properties of wavelets, but also offers a high degree of directionality and anisotropy. It employs a double filter bank structure. First of all, the Laplacian pyramid (LP) is used to generate a multiscale representation of an image to capture the point discontinuities. Subsequently, subband images from the multiscale decomposition are processed by a directional filter bank (DFB) to link point discontinuities into linear structures at each specific scale level. Due to this cascade structure, multiscale and directional decomposition stages in the contourlet transform are independent of each other. One can decompose each scale into any arbitrary power of two’s number of directions, and different scales can be decomposed into different numbers of directions. Also, its basis functions have elongated supports.
rather than square supports as with 2-D wavelets, which make it more efficient in describing curvature details along smooth contours. The contourlet transform is illustrated in Figure 1.

Figure 2 shows an example of the contourlet relationships which are happened by the interaction.

Hence, we use the feature vectors to instead of pixels which is proposed to increase the accurateness, when the similarity matrix structure. Mean that, advanced features is used to alternative low-level features make more accurate segmentation. PSO algorithm makes operations and convergences easier and faster; it also processes multiple particles simultaneously. The search region is much bigger than traditional k-means algorithm, because particle’s movement in PSO algorithm is random. The local and global search capacity is regulated, in order to achieve the global optimum solution. And then, semi-supervised theory is proposed to apply find the initial clustering centers, because the initial particles are randomly which make false initial clustering centers.

3. Semi-supervised Spectral Clustering Algorithm in Contourlet Domain
We use the feature vectors to instead of pixels which are proposed to increase the accurateness. When the similarity matrix structure, advanced features is used to alternative low-level features make more accurate. So all of the pixels \( X = \{ x_1, x_2, \ldots, x_n \} \in \mathbb{R}^m \) in a SAR image are instead by the feature vectors as \( X = \{ X_1, X_2, \ldots, X_n \} \in \mathbb{R}^n \) clustered into \( K \), one feature vectors correspond to one particle. And the ith particle is expressed as location \( X^i = (x_{1i}, x_{2i}, \ldots, x_{ni}) \) and \( v^i = (v_{1i}, v_{2i}, \ldots, v_{ni}) \) velocity, we assume that \( i = 1, 2, \ldots, n \).

\[
\begin{align*}
v_{id}^{k+1} &= \omega v_{id}^k + c_1 r_1 (I_{best} - X_{id}^k) + c_2 r_2 (g_{best} - X_{id}^k) \\
X_{id}^{k+1} &= X_{id}^k + v_{id}^{k+1}
\end{align*}
\]

Hence, \( X_{id}^k \) is the current location. \( v_{id}^k \) is the velocity of the ith particle. \( X_{id}^{k+1} \) is the next location. \( v_{id}^{k+1} \) is the velocity of the ith particle. \( I_{best} \) is the current optimal location of the ith particle.
In the d dimensional search space, we assume $g_{\text{best}}^d$ is the current optimal location of the swarm. $\omega$ is the inertia weight. The influence of the former velocity to the latter velocity is controlled by $\omega$. $r_1$ and $r_2$ are assumed to be the random numbers which are distributed uniformly in the range of (0,1),

$$\omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{\text{Maxiter}} \times \text{iter}$$  \hspace{1cm} (3)

So, $\omega_{\text{min}}$ and $\omega_{\text{max}}$ is the maximum value and the minimum value respectively. $\text{iter}$ is the current iteration number. $\text{Maxiter}$ is the maximum iteration number.

Semi-supervised strategy is applied to get the initial clustering centers, by using a small amount of labeled data as supervised information. Then, the small amount of labeled data is treated as a seed which set S. It is assumed that each class contains at least one labeled sample in this paper. Then the set is divided to get accurate clustering centers by make sure that each class already gets one clustering center. The flow chart is shown in figure 1. The steps are shown as follows:

1) All of the pixels $X = \{x_1, x_2, ..., x_n\} \in \mathbb{R}^n$ are instead by the feature vectors as $X = \{X_1, X_2, ..., X_n\} \in \mathbb{R}^n$ clustered into $K$.

2) The similarity of all pixels is calculated, which $A \in \mathbb{R}^{n \times n}$:

$$A_{ij} = \begin{cases} f(X_i, X_j), & i \neq j \\ 0, & i = j \end{cases}$$ \hspace{1cm} (4)

And, $f(X_i, X_j)$ is the similarity function,

$$f(X_i, X_j) = \exp(-\|X_i - X_j\|^2 / 2\sigma^2)$$ \hspace{1cm} (5)

$\|\|$ is the Euclidean distance, $\sigma$ is the scale parameter;

3) Construct the Laplacian matrix

$$L = D^{-1/2} A D^{-1/2}$$ \hspace{1cm} (6)

Where, D defined as

$$D_{ii} = \sum_{j=1}^{n} A_{ij}$$ \hspace{1cm} (7)

which is a diagonal matrix.

4) The k biggest eigenvalue $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_k$ are corresponding eigenvectors in matrix $L$.

$$F = [f_1, f_2, \ldots, f_k] \in \mathbb{R}^{n \times k}$$ \hspace{1cm} (8)

Where, k is the group number. To get $\bar{F}$ as follow:

$$\bar{F}_{ij} = f_i / (\sum_{j=1}^{k} f_j^2)^{1/2}$$ \hspace{1cm} (9)

5) Repeat the following steps until convergence; Compute the final clustering centers by the distance between each point in $\bar{F}$. Figure 2 shows the flow chart of the proposed algorithm.
4. Experimental Results and Comparison Analysis

Matlab software development tool in operating system of Windows 7 is the software experimental platform. PC is Lenovo of Intel I3 CPU, and memory is 4.00GB.

Where, we use the same data sets in the proposed algorithm and the traditional k-means algorithm respectively for experiment. In this paper, the value 2 is assumed to $c_1$ and $c_2$. The value 0.5 and 0.7 are assumed to parameters $r_1$ and $r_2$ respectively for the proposed algorithm.

4.1 Real SAR image experiment

Fig. 4. (a) original image 1; (b) results of spectral clustering with k-means; (c) results of the proposed algorithm

Fig. 5. (a) original image 2; (b) results of spectral clustering with k-means; (c) results of the proposed algorithm

Fig. 6. (a) original image 3; (b) results of spectral clustering with k-means; (c) results of the proposed algorithm
Table 1 Comparison of spectral clustering with k-means and the proposed algorithm

| SAR image | Figure 4 (a) 219x220 | Figure 5 (a) 256x256 | Figure 6 (a) 256x256 |
|-----------|----------------------|----------------------|----------------------|
| **Spectral clustering algorithm with k-means** | | | |
| Running time (s) | 23.923 | 33.939 | 34.919 |
| Number of error | 6154 | 7956 | 5798 |
| Total accuracy (%) | 83.56 | 83.94 | 92.02 |
| Kappa | 0.7693 | 0.7937 | 0.8337 |
| **The proposed algorithm** | | | |
| Running time (s) | 19.326 | 30.131 | 30.094 |
| Number of error | 5325 | 6002 | 4293 |
| Total accuracy (%) | 90.15 | 90.84 | 93.46 |
| Kappa | 0.8192 | 0.8356 | 0.8871 |

4.2 Comparison analysis

Fig. 7. Total accuracy of the proposed algorithm under different sampling rate

Fig. 8. The run time of the proposed algorithm under different sampling rate

The figure 7 and figure 8 show that, in the case of the less known classification pixels, the higher classification accuracy of proposed algorithm. And the running time of the algorithm does not increase significantly along with the number of known classification pixels increase.

5. Conclusion

At the end, by several experiments, the results of classification by the proposed algorithm were compared with the traditional k-means algorithm. The proposed algorithm is better than the traditional k-means algorithm not only by the running time but also by classification accuracy.

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