Automatic Detection of Airport Runway Area Based on Super-Pixel PolSAR Image Classification (EN-A-072)

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Outline

- Introduction
- Basic Theory and Methods
- The Proposed Method
- Experiment Result
- Conclusions
Airport runway is an important facility both for civil application

Automatic detection is used in:

- Emergency rescue
- Terrestrial monitoring
- Aircraft navigation
- etc.
Synthetic aperture radar (SAR) is a microwave imaging system

- All day, all weather
  ----isn’t influenced by lighting condition, raining, frog….
- Strong penetration
  ----isn’t influenced by the distance of imaging
- Widely used in many civil applications such as disaster monitoring, target detection, recognition and other imager interpretation fields
Comparing with single-polarization SAR, polarimetric SAR (PolSAR) can obtain target polarization scattering characteristics much better. More detail features of the terrains in PolSAR image can be shown.
Introduction (4/5)

- State of art runway detection based on SAR image

- Pixel-based image classification
  - the computation complexity and time cost is very high when image size is large.

- Wishart classifier is often used
  - it is sensitive to initial clustering center and easy to fall into a local optimum
Our work in this paper

- Unsupervised classification based on super-pixel image
- Automatically determine the number of feature categories and have a faster calculation speed
- Spectral clustering method is used instead of other classifiers
- Structural feature of airport runway
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Polarimetric SAR Data and Pauli Decomposition

The polarized SAR data records the polarization scattering information of each pixel. For PolSAR, the complex relationship between the incident wave and the scattered wave is usually expressed by the Sinclair matrix

$$S = \begin{bmatrix} S_{HH} & S_{HV} \\ S_{VH} & S_{VV} \end{bmatrix}$$

Where $H$ and $V$ respectively represent the horizontal and vertical polarization states, when $S_{HV} = S_{VH}$, Pauli eigenvector can be expressed as follows:

$$k = \frac{1}{\sqrt{2}} [S_{HH} + S_{VV}, S_{HH} - S_{VV}, 2S_{HV}]$$
In practical use, the polarization coherency matrix is commonly used to represent the scattering process in order to clearly represent the physical meaning:

\[
T = \langle k \cdot k^* \rangle = \begin{pmatrix}
|k_1|^2 & k_1 k_2^* & k_1 k_3^* \\
|k_2|^2 & k_2^* k_1 & k_2 k_3^* \\
|k_3|^2 & k_3 k_1^* & k_3^* k_2
\end{pmatrix}
\]

\[
= \begin{pmatrix}
\langle |X|^2 \rangle & \langle XY^* \rangle & \langle XZ^* \rangle \\
\langle X^*Y \rangle & \langle |Y|^2 \rangle & \langle YZ^* \rangle \\
\langle X^*Z \rangle & \langle Y^*Z \rangle & \langle |Z|^2 \rangle
\end{pmatrix}
\]

Where \( X = S_{HH} + S_{VV} \), \( Y = S_{HH} - S_{VV} \), \( Z = 2S_{HV} \), \( \langle \cdot \rangle \) denotes the time or space set averages, and assumes that the random medium is isotropic.
Super-pixel refers to a small area in which pixels of similarity are merged according to gray scale, color, texture, etc.

SLIC (simple linear iterative clustering) segmentation method, which can obtain the result quickly and effectively for both optical image and SAR image according to the distance similarity of color and pixel location, while preserving image details and useful information, greatly reduce the subsequent processing task of computational complexity and stability.
SLIC Super-pixel Segmentation Method

The basic idea is to describe the RGB space using CLELAB color space and pixel location information, which are 5 dimensional feature vectors. To calculate the color difference, space distance and similarity between pixel i and j.

First, we set the number of super-pixels K, for an image with N pixels, the size of each super-pixel is $N/K$ therefore pixels. Then, N seed points are evenly distributed on the image and labels are assigned to each seed point, so the interval between each seed point is $S = \sqrt{N/K}$. In order to avoid placing seed points at an edge or choosing a noisy pixel we move them to the lowest gradient position in a $3 \times 3$ neighborhood.
SLIC Super-pixel Segmentation Method

According to the equations below, the similarity between the seed points within $2S \times 2S$ area around the super-pixel center (seed point) is obtained. Finally we complete SLIC super-pixel segmentation by calculating the similarity between the seed point and the adjacent pixel, merging the pixels with similar similarity and assign the label of the nearest seed point repeatedly.

$$d_{lab} = \sqrt{(l_i - l_j)^2 + (a_i - a_j)^2 + (b_i + b_j)^2}$$

$$d_{xy} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

$$D_i = d_{lab} + \frac{m}{S} d_{xy}$$

Where $d_{lab}$ is the color distance between the pixels in LAB color space, $d_{xy}$ is the plane distance between pixels and $D_i$ is the sum of the lab distance and the xy plane distance normalized by the grid interval $S$. 

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**Basic Theory and Methods (6/9)**

- **SLIC Super-pixel Segmentation Method**
  - Set the number of super pixels
  - Initialize clustering center
  - Calculate the color difference and space distance
  - Iterate and optimize results
  - Results

  - K, super-pixel size is N/K for an image with N pixels
  - Set K seed points, we move them to seed locations corresponding to the lowest gradient position in a 3 × 3 neighborhood
  - Calculate the color difference, space distance and similarity between pixel i and j in 2S × 2S searching area of CIELAB color space
  - Merge the small areas to make the super pixel more neat
  - Obtain super-pixel images
VAT and DBE Algorithm

VAT (visual assessment of cluster tendency) and DBE (dark block extraction) methods are used to estimate and visualize the potential clustering information of data. The basic steps of the algorithm are in the following example:

(a) shows the randomly generated three types of data points scatter plot. (b) shows the reordered VAT image after calculating the Euclidean distance dissimilarity of the three types of data. (c) shows the projection signal, the ordinate represents the projection value. (d) shows the first-order derivative of the projection signal, where the number of red circle are the estimated class number and the position are the cluster centers.
Spectral clustering is a clustering method based on spectral graph theory. Compared with the traditional clustering method (e.g., k-means, Wishart classifier), it has the characteristics of clustering in any shape data space and converging to the global optimal. Nyström method is used to reduce the time and space cost of spectral clustering, the detailed steps are as follows:
Spectral clustering algorithm

- **Step 1**: Construct affinity matrix $W_{n \times n}$ with a measure.

- **Step 2**: Calculate the Laplacian matrix $L_{\text{sym}} = D^{-\frac{1}{2}}(D - W)D^{-\frac{1}{2}}$, where $D$ is the diagonal matrix, whose diagonal elements are $D(j, j) = \sum_{i=1}^{n} W_{i,j}$, that is the sum of all the column elements of the matrix $W_{n \times n}$.

- **Step 3**: Calculate the eigenvalues of the Laplacian matrix $L_{\text{sym}}$ and arranged in order from large to small, then feature vectors corresponding to the first $k$ eigenvalues to construct the matrix $V_{n \times k} = \{v_1, v_2, \ldots, v_k\}$.

- **Step 4**: Cluster the row vectors of $V_{n \times k}$ using $k$-means algorithm. Complete spectral clustering by dividing the $n$ $k$-dimensional data into $k$ class finally.
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The flowchart of the proposed method
Super-pixel image construction

PauliRGB image is formed by Pauli decomposition, we construct the super-pixel image according to the method mentioned above. Firstly the number of super-pixels $K$ is set, which determines the complexity and execution effect of the latter classification. BR (boundary recall) and computing time are often used to evaluate the effect of super-pixel segmentation, so we choose $K=10000$ as a standard for the experiment according to following pictures.
The Proposed Method (3/6)

Classification processing

After the super-pixel image I is obtained, the gray scale information contained in I is used as the feature to measure the pairwise dissimilarity by Euclidean distance of pixel gray value, then the VAT and the DBE algorithm are used to estimate the class number c. Finally we construct the dissimilarity $w(i, j)$ between super-pixels with distance of by the Gaussian kernel function for performing spectral clustering, as is shown in Equation:

$$w(i, j) = \exp\left(\frac{-\left\| \overline{T_{si}} - \overline{T_{sj}} \right\|^2}{2\sigma^2}\right)$$

$$\overline{T_s} = \frac{1}{n} \sum_{i=1}^{n} T_i$$

Where $\sigma$ is the scaling parameter and $\left\| \overline{T_{si}} - \overline{T_{sj}} \right\|$ is the Euclidian distance between super-pixels i and j, $n = N/K$, $n$ represents the pixels number in each super pixel.
The Proposed Method (4/6)

- **Suspected ROI extraction and identification**
  - **Topologic feature**: It is characterized with Euler number $E$, which is the difference between the number of connected area labeled as “1” and the number of holes labeled as “0” in binary image. Here holes mean the area which are surrounded by pixels labeled as “1”.
  - **Parallel straight line feature**: Straight line is a typical features of runway contour profile. It can be obtained by performing Hough transform on the ROI. If the difference of slopes between two arbitrary straight lines satisfies certain error, they can be considered as a pair of parallel line. If the parallel line spacing meet the standards of runway width, they are identified as runway.
The Proposed Method (5/6)

- Suspected ROI extraction and identification

After obtaining the spectral clustering results:

- Calculate and compare the average power of each class.
- Pixels in the class with minimum power are labeled as “1”. Others are labeled as “0” to form a binary image.

The flowchart of identification

1. Binary Image of ROI
2. 8-connected component labeling
3. Independent suspected runway region
4. Topologic feature < E
   - Yes: Parallel lines spacing < Dis
     - Yes: Airport runway
     - No: Non-airport runway area
   - No: Non-airport runway area
Suspected ROI extraction and identification

- The areas formed by the pixel labeled “1” area called suspected airport runway which is the region of interest (ROI).

- Runway structural features such as parallels, topologic property are utilized to identify which region is the true runway area.
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Experiment Result (1/5)

- **Experiment presentation: San Andreas Fault area**

  - The four-look real PolSAR image data of San Andreas Fault area collected by NASA/JPT UAVSAR system at L band in 2009. The azimuth and range resolution are 7.2m and 4.9m respectively.
  
  - The image size is $1051 \times 1151$ pixels.
Experiment Result (2/5)

- $K = 10000$, Morphological filter threshold $Th_0=450$, the number of Euler $E$ and parallel line spacing $Dis$ are 0 and 10 respectively.
Experiment Result (3/5)

(a) Super-pixel image
(b) Class number estimation result \( (k=9) \)
(c) The classification result
(d) Extraction of minimum power
(e) Extraction of ROI
(f) Detection Result
Experiment Result (4/5)

(a) The Proposed Method

(b) The Experiment Result in [3]

(c) The Experiment Result in [18]

compare to our previous work...
The proposed method needs less time cost, about 4 percent of the method in [3], 30 percent of the method in [18], and has a lower false alarm.

<table>
<thead>
<tr>
<th>Method</th>
<th>Time Cost</th>
<th>False alarm</th>
<th>Missing alarm</th>
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<tbody>
<tr>
<td>Proposed method</td>
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<td>No</td>
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<td>Method in [3]</td>
<td>8786.2s</td>
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<td>Method in [18]</td>
<td>3316.6s</td>
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Experiment Result (1/5)

- Experiment presentation: Gulf Coast area

- The four-look real PolSAR image data of Gulf Coast area collected by NASA/JPT UAVSAR system at L band in 2009. The azimuth and range resolution are 7.2m and 4.9m respectively.

- The image size is $1000 \times 800$ pixels.
$K = 10000$, Morphological filter threshold $Th0=450$, the number of Euler $E$ and parallel line spacing $Dis$ are $0$ and $10$ respectively.
Experiment Result (3/5)

(a) Super-pixel image
(b) Class number estimation result (k=7)
(c) The classification result
(d) Extraction of minimum power
(e) Extraction of ROI
(f) Detection Result
Experiment Result (4/5)

(a) The Proposed Method
(b) The Experiment Result in [3]
(c) The Experiment Result in [18]
The proposed method needs less time cost, about 4 percent of the method in [3], 12 percent of the method in [18], and has a lower false alarm.

<table>
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<th>Method</th>
<th>Time Cost</th>
<th>False alarm</th>
<th>Missing alarm</th>
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<tbody>
<tr>
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<td>Method in [3]</td>
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<td>Method in [18]</td>
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</tr>
</tbody>
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Conclusions

✔ The proposed algorithm can detect the airport runway area more accurately with less calculation time, and the false alarm rate is low.

✔ The algorithm need less priori information and need not to set the class number artificially before classification, also, it is insensitive to speckle noise, which means more robust and higher efficiency.
Conclusions (Cont)

Thank You!

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