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To cite this article: Wen Nie et al 2021 J. Phys.: Conf. Ser. 2026 012024

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# A Region-Based Deep Reinforcement Learning Classification Method for GF-3 PolSAR Imagery Classification

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Abstract. The C-band GF-3 satellite is the first fully polarimetric synthetic aperture (PolSAR) designed by China, which has multi-polarization image modes and been used in various applications. Land cover classification is an effective approach in PolSAR image interpretation and further application. However, conventional classification methods are mostly pixel-based and are easily affected by inherent speckle noise. In addition, the feature selection of PolSAR image and the amount of training samples are also critical to the performance of classifiers. To solve these problems, in this paper, we propose a region-based PolSAR image classification method, which uses reinforcement learning method altogether with statistical region merging algorithm to improve the classification performance. The contributions of our method are mainly reflected in three aspects: First, the T3 matrix is considered as the only feature set in our method, including image segmentation and classification. Second, the region is produced via statistical region merging algorithm. Finally, a deep reinforcement learning model is used to obtain PolSAR image classification result. To evaluate the performance of the proposed method, two real GF-3 images are performed in the experiments, and the experimental results illustrate that the proposed method outperforms the conventional methods (support vector machine, random forest, and convolution neural network) in terms of accuracy and achieves the state-of-art results. Keywords. GF-3; PolSAR; region-based image classification; deep reinforcement learning.

#### **1. Introduction**

The launch of the Chinese GF-3 satellite provided plenty of polarimetric synthetic aperture radar (PolSAR) images and it has been widely used in crop classification [1], target automatic recognition [2], land cover classification [3], and forest type identification [4]. For the purpose of land cover classification, PolSAR image has the potential to identify different land cover types from the target's structure and physical scattering information. In recent years, amounts of machine learning-based methods [5-7], such as support vector machine (SVM) [8], random forest (RF) [9], and convolution neural networks (CNN) [10] have been proposed and successfully performed in PolSAR image classification. However, a common limitation remains in many methods is requiring complicated feature selection and the result map is also affected by speckle noise.

To address these problems, in this study, a region-based deep reinforcement learning classification method, namely DQN, is proposed. The main contributions of this study are list as follows: (1) Only the coherent matrix T3 of PolSAR data are collected as the input of the model to avoid the feature selection process and to improve the generalization of the proposed method. (2) Integrating the advantage of reinforcement learning (RL) with statistical region merging (SRM) algorithm to reduce the impact of speckle noise and to improve the classification accuracy of PolSAR image. The main workflow of this

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study is list as follows. First, a refined Lee filtering is used to reduce the speckle noise of GF-3 PolSAR image. Second, image segmentation result of GF-3 data is produced by statistical region merging (SRM) algorithm. Finally, the generated region-based GF-3 data are fed into the proposed RL-based neural network to generate the final classification result.

The remainder of this paper is organized as follows. Section 2 presents the proposed methodology of PolSAR image classification. Section 3 shows the experiment results on GF-3 PolSAR image over Beijing and Chizhou. Finally, a brief conclusion is discussed in section 4.

### 2. Methodology

#### 2.1. SRM Segmentation

The SRM algorithm has the advantage of coping with significant noise interference while not rely on data distribution, and therefore widely used in image segmentation [11]. The two basic elements of SRM are merging predicate and merging order, which respectively defines the whether and the order of the regions merging. The mathematical expression of merging predicate is list as [12]:

$$P(\mathbf{R}, \mathbf{R}') = \begin{cases} ture & \max_{k \in \{R, G, B\}} \left| \overline{R'_k} - \overline{R_k} \right| \le \left( b^2(\mathbf{R}) + b^2(\mathbf{R}') \right)^{1/2} \\ false & otherwise \end{cases}$$
(1)

$$b(R) = g\left(\frac{1}{2Q|R|}\right)^{\frac{1}{2}} ln \frac{|R|R|}{\delta},$$
(2)

Where k refers to the channel of image,  $\overline{R_k}$  is the observed average for channel k in the region R,  $R_{R/R}$  stands for the set of regions with R pixels, and  $\delta$  is the maximum probability when P(R, R') = false.

The gradient function *f* defined as:

$$f(p,p') = \max_{k \in \{R,G,B\}} |p'_k - p_k|,$$
(3)

where  $p'_k$  and  $p_k$  are the pixel values of an adjacent pixel's pair for channel k.

### 2.2. PolSAR Image Classification Based on DQN

In this study, the RL-based PolSAR image classification task can be generalized as the neural network interacts with the training dataset through a sequence of states, actions, and rewards, and finally aims to map the input states to the actions with the highest cumulative rewards (denote as *Q*).

Specially, for each training sample (denote as *s*), the neural network selects an action (denote as *a*) follow the current strategy (denote as  $\pi$ ), and then a reward (denote as *r*) will generate from environment to optimize the model. In brief, the model training phrase can be expressed as the following optimization problem, defined in (4), to find an optimal policy  $\pi$  to maximize the cumulative rewards for each action selection.

$$Q^*(s,a) = max_{\pi} Q^{\pi}(s,a)$$
<sup>(4)</sup>

where  $Q^{\pi}(s, a)$  is the cumulative reward value of choosing the action *a* for the state *s* following the policy  $\pi$ , and  $Q^{*}(s, a)$  indicates the optimal cumulative reward value for the state-action pair.

The optimal policy solving process obeys an important identity, known as Bellman Equation, given in (5), which uses an iterative updating mechanism to consider the value of action in the long run. In (5),  $r_s^a$  is the reward value for the state-action pair (s, a),  $\gamma \in (0,1)$  is the discount factor for the next iteration.

$$Q_{i+1}(s,a) = \mathbb{E}\left[r_s^a + \gamma \max_{a'} Q_i(s',a')/s,a\right]$$
(5)

In this study, the optimal action value function is parameterized and estimate by a deep neural network as  $Q(s,a;\theta) \approx Q^*(s,a)$ , in which  $\theta$  is the parameter of the model, and the loss function  $L_t(\theta_t)$  is given as follows.

$$L_{t}(\theta_{t}) = \frac{1}{2} \left[ r_{t} + \gamma \max_{a_{t+1}} Q^{*}(s_{t+1}, a_{t+1}; \theta_{t-1}) - Q(s, a; \theta_{t}) \right]^{2}$$
(6)

where  $Q(s,a;\theta_t)$  is the prediction value for iteration t.

# 2.3. The Workflow of the Proposed Method

The pipeline of the proposed method is given in figure 1, mainly including GF-3 PolSAR imagery preprocessing, segmentation from T3 matrix via SRM method, model training, and GF-3 PolSAR image classification. Notably, different from the comparison methods RF, SVM, and CNN, in the proposed DQN method, the training samples are not directly used to train the model, but are used to generate numerous experience data through randomly explore and exploit for experience replay.



Figure 1. The procedure of this study.

# 3. Experimental result and Analysis

# 3.1. Experimental datasets description

To evaluate the performance of the proposed method, two C-band GF-3 PolSAR images are used in this study: (1) the data of Beijing acquired on December 9, 2017, the image size is  $482 \times 482$  pixels and the incidence angles range from 19.9° to 22.4°. (2) The data of Chizhou city acquired on August 17, 2017, this image has a size of  $1182 \times 1182$  pixels and the incidence angle ranges from  $35.3^{\circ}$  to  $37.0^{\circ}$ . These two study areas covered by building, water, bare land, forest, and farmland. The Pauli-RGB images and corresponding ground truth maps are shown in figure 2.

# 3.2. Pre-processing

The GF-3 PolSAR image in this study only pre-processed through a Refined Lee filter [13] with a window of  $7 \times 7$  to reduce the speckle noise and to smooth the image and maintain spatial resolution in

regions of heterogeneity. In addition, to validate the performance of the proposed method, 300 sample points per class are randomly selected from reference map for model training, and all the rest of samples are as test samples.



**Figure 2.** (a)-(b) are the Pauli-RGB image and reference map of Beijing GF-3 dataset; (c)-(d) are the GF-3 data of Chizhou area.

## 3.3. Experiments

For the GF-3 PolSAR image in Beijing, the experiment image is classified using the SVM, RF, CNN, and the proposed method, and classification results and the corresponding accuracy evaluated by Kappa coefficient and overall accuracy (OA) are respectively presented in figure 3 and table 1. Similarly, the Experimental results of Chizhou dataset are presented in figure 4, and the accuracy for each class, Kappa coefficient, OA is shown in table 2. Accordingly, the experimental results from the two datasets show that the proposed region-based PolSAR image classification method can effectively reduce the impact of noise, and compared with the results from CNN, SVM, and RF, the proposed DQN method achieves the best performance both in accuracy and visual classification map in same training samples.



**Figure 3.** Classification result of Beijing using different methods: (a)-(d) are respectively the results of CNN, SVM, RF method, and the proposed method.



**Figure. 4.** Classification result of Chizhou using different methods, (a)-(d) are respectively the results of CNN, SVM, RF method, and the proposed method.

#### **2026** (2021) 012024 doi:10.1088/1742-6596/2026/1/012024

Classes	CNN	SVM	RF	DQN
Forest	0.72	0.81	0.97	0.96
Water	0.86	0.99	0.91	0.90
Building	0.77	0.69	0.89	0.92
Bare land	0.19	0.60	0.71	0.78
Farmland	0.40	0.49	0.87	0.84
Kappa	0.44	0.63	0.86	0.88
OA	0.62	0.75	0.91	0.92

**Table 1.** The accuracy of the classification results in Beijing data.

Table 2. The accuracy	of the classification	ation results in	Chizhou data
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Classes	CNN	SVM	RF	DQN
Water	0.70	0.74	0.73	0.93
Forest	0.61	0.76	0.84	0.77
Farmland	0.78	0.72	0.92	0.89
Building	0.21	0.46	0.46	0.47
Kappa	0.46	0.56	0.71	0.71
OA	0.63	0.71	0.80	0.80

## 4. Conclusion

A region-based deep reinforcement learning classification method for GF-3 PolSAR image is proposed. This method only uses nine elements from T3 matrix and no more complex feature extraction operation are required. The proposed method combined the advantages of reinforcement learning and region-based classification can reduce the effect of speckle noise on classification results. The experimental results from two GF-3 PolSAR images illustrate the effectiveness of the proposed method.

### Acknowledgments

This work is supported in part by National Natural Science Foundation of China, under Grant 41501382 and 41771377. Hubei Provincial Natural Science Foundation of China, under Grant 2016CFB246.

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