results show that the proposed RSA algorithm based on real-time and efficiency optimization is superior to the traditional AES algorithm and the RSA algorithm in terms of efficiency and encryption performance.

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PolSAR Image Classification Based on Deep Convolutional Neural Network

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Abstract
For introducing the advantages of feature learning and multilayer network in the interpretation of Polarimetric synthetic aperture radar (PolSAR) image, a classification algorithm based on deep convolutional neural network is proposed, and is used for PolSAR image classification. Firstly, a special convolutional neural network (CNN) for PolSAR image is constructed, secondly, a large number of PolSAR training data is introduced into the multilayer network, and the CNN network is trained adequately, thirdly, the test data is imported into the multilayer network, and the classification of polarimetric SAR images is realized. Experimental results on the first batch of PolSAR data show that the proposed algorithm can achieve higher classification accuracy rate.
Key words: POLSAR IMAGE CLASSIFICATION, DEEP LEARNING, CONVOLUTIONAL NEURAL NETWORK

1. Introduction

Synthetic aperture radar is a kind of microwave remote sensing imaging system, which can acquire a lot of ground information around the clock[1]. The traditional single polarimetric SAR can only obtain the target scattering information on a certain polarization state, while PolSAR can extract target polarimetric scattering information under different polarization states, therefore, the target information obtained by PolSAR is more abundant, which provides a possibility for further information mining. PolSAR image classification is an important part of the remote sensing image classification, and is widely used in the field of topographic mapping, marine monitoring, city planning, etc.. With the continuous development of SAR remote sensing system, the research on how to effectively implement the SAR image classification and target recognition is of great significance.

Hinton [2] published an article on the top academic journal «science» in 2006, and proposed the concept of deep learning on the first time, which opens application climax of deep learning in academia and industry. Deep learning is a new field of machine learning research, and it has excellent feature learning ability. The learned features can depict the data more essentially, so as to facilitate the visualization and classification. Since 2006, the research of deep learning continues to heat up, and shows its great potentiality in the application field of speech recognition, image recognition, natural language processing, search advertising, CTR predictive, and so on[3].

There are two problems when introduce deep learning to solve the classification problems of PolSAR images, as follows: (1) the SAR image is a kind of special microwave image[4]. Only the regions with the same backscattering coefficient can produce the same grayscale on the image, but the regions with the same grayscale on the image are not necessarily the same on their optical properties, so a simple reference to the current deep learning method applied on optical model is not suitable for SAR image; (2) Polarimetric SAR can obtain several SAR images in different channels. However, the original deep learning models are established on the single channel data, which cannot fully use the rich information of objects in the polarization SAR image.

In order to solve the above problems, an algorithm based on deep convolutional neural network is proposed, the main innovations is: In order to make full use of the rich object information contained by PolSAR image, a special CNN network is constructed for feature extraction and classification[6], which can process multi-channel data for the same object. The traditional CNN network is introduced and improved suitable for PolSAR image classification.

2. Related works

2.1 Classification mode

The general classification mode of the traditional methods is feature extraction + classifier. According to the different methods of feature extraction and classifier learning, the classification methods can be divided into the following three modes, as shown in Figure 1: (1) general artificial feature + general classifier, such as 'sift' or 'Hog'+ SVM classifier, etc. (2) feature and classifier are learned together in a black box at the same time, such as CNN network. (3) features and classifier are learned separately, feature extraction network is trained by the approximate image data set of target image, namely the features is learned from one data set, while the classifier is trained by another data set[7]. This kind of classification model not only makes full use of the benefits of feature learning, but also overcomes requirements for the number of training data.

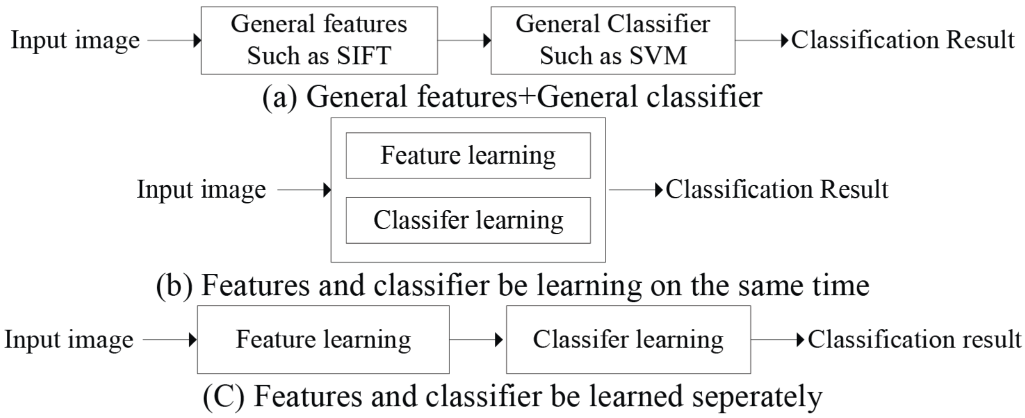

Figure 1. The general classification mode of the traditional classification methods

2.2 Summary of classification methods of PolSAR images

Through colligating present domestic and foreign existing PolSAR image classification methods, the classification methods for polarimetric SAR image can be divided into the following categories: (1) The classification method based on statistical distribution and Bayes theory, the two most common distribution are the complex Gauss distribution and the complex Wishart distribution. For example, Kong et al. proposed the complex ML classification method based on the Gauss distribution for single-look PolSAR image. Out of the need of data compression or speckle filtering, the SAR image sometimes need to be carry on multilook or average processing. In view of this situation, Lee J S proposed multilook (ML) classification method based on Wishart distribution[8]. At this point, Kong and Lee have established two kinds of classic Bayes optimal classification schemes based on polarimetric statistical distribution, and the following algorithms all directly or indirectly used these two schemes. (2) The classification method based on feature extraction + classifier. The features for the classification of polarimetric SAR images mainly include:

(a) The polarimetric decomposition features, the main target polarimetric decomposition methods include: Pauli, SDH, Cameron, Huynen, Holm, Cloude, Barns, Fourcomponent, OEC, Freeman, and so on.

(b) Texture features, for example, Pierce et al had extracted texture variance features from PolSAR image, and put forward a kind of PolSAR image classification algorithm based on knowledge. While He Chu et al combined wavelet polarimetric information and sparse code for the classification of polarimetric SAR image. The classifiers used for classification of polarimetric SAR image mainly include: (a) the Wishart classifier, for example, in 1999, Lee J S proposed a kind of classification method based on polarimetric decomposition and Wishart classifier for the polarimetric SAR image; (b) SVM, it is a machine learning method developed at the end of twentieth Century , and shows many unique advantages in solving the classification problem of small samples, for example, in 2001, Fukuda et al used SVM[9] to classify PolSAR image for the first time. (3) Classification method based on neural network and fuzzy reasoning, neural network need not consider the statistical distribution model, and can be trained to classify the image directly. In 1991, Pottier used a multi-layer perceptron of neural network to classify the polarimetric SAR images for the first time, and the method adopts the back propagation algorithm to train the network.

The classification framework of PolSAR image based on deep convolutional neural network

Convolutional neural network (CNN) is a deep learning model with a particularly high learning efficiency, which can extract implicitly features by training, and is widely used in image classification and recognition. CNN has many advantages in two-dimensional image processing, so CNN is choosed to classify PolSAR image.

The classification framework of PolSAR image based on statistical distribution unit and CNN is shown in Figure 2, firstly, a large number of PolSAR images are collected, secondly, 4 SAR images in HH,HV,VH,VV state is introduced into the CNN network, thirdly, through the training and learning of CNN on the 4 SAR images in different state, the classification results will be achieved.

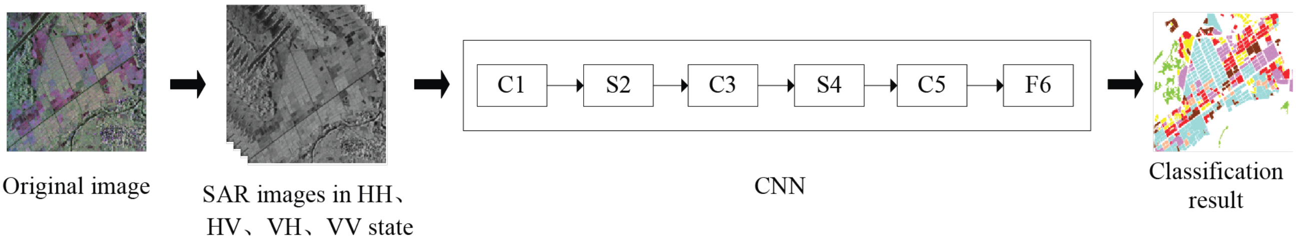

Figure 2. The classification framework of PolSAR

As shown in the figure2, a 6 layer CNN network is used, which consists of input layer, convolutional layer (C), sampling layer (S), fully connected layer(F) and output layer, wherein the convolutional layer and the sampling layer appear alternately. The main task of convolutional layer is to select the features in each angle from the previous layer feature map. Each feature map of convolutional layer is related with several feature maps of the previous layer. The calculation process of neuron X of convolutional layer C are shown in formula (1):

$$x_j^l = f(\sum_{i \in M} x_i^{l-1} * k_{ij}^l + b^l) \quad (1)$$

Where x_j^l represents the j feature map data of l layer, M_j represents the j feature map, k represents the convolutional kernel, b represents the bias term.

The main function of sampling layer is to eliminate the deviation and distortion of the image through the reduction of the spatial resolution of the image. down( ) represents the sampling function, so the calculation formula of neurons X of the sampling layer S is as formula (2):

$$x_j^l = f(w_j^l down(x_j^{l-1}) + b^l) \quad (2)$$

Suppose that C represents the number of categories, N represents the number of training samples, so Mean Square Error of the whole sample set is shown as formula(3), where t_k^n represents the k-th dimension data of target output of the n-th sample, and y_k^n represents the k-th dimension data of actual output of the n-th sample.

$$E^N = \frac{1}{2}\sum_{n=1}^{N}\sum_{k=1}^{C}(t_k^n - y_k^n)^2 \quad (3)$$

Experiment and Discussion

4.1 Experiment Data

The experimental data used in this paper is an airborne X-band PolSAR data of Lingshui county in Hainan Province, which is obtained by thirty-eighth institute of Chinese Electronics Group. The ground truth of the image is manual annotated by using ARCGIS software.

The image size of dataset1 is 2200 pixels * 2048 pixels, and the resolution is 1m*1m. The image is divided into 10 categories: Mango1, Mango2, Mango3, Betel nut, Longan, Forest, Building, Farm1, Farm2, Farm3. Mango is divided into 3 different types according to the breed of Mango, and farmland is divided into 3 different types according to the crop in the farmland. The original image of dataset1 is shown in fig.3(a), and the corresponding ground truth is shown in fig.3(b).

4.2 Experiment Setting

There are 6 layers in CNN, so there are 8 layers in the classification network, the specific parameter settings of Experiment are shown as Tab.1.

To choose the appropriate initial Patch_size of CNN network, we have tested the influence on experimental results produced by the sliding window size. We have changed the size from 9×9, 17×17, 28×28, 35×35 to 43×43 and found that the accuracy had a 1.28% increase for the proposed algorithm, from 9×9 to 28 ×28. However, continuing to 43×43, the accuracy is slowly decreased 0.61%. Thus, in the experiments, we take 28× 28 pixels as the initial patch_size.

Table 1. Parameter Settings of Experiment

Parameter name	Parameter value
CNN layers	6
Initial Patch_size of CNN	28 x 28
Filter_size of CNN	3x3

In order to verify the effectiveness of the proposed method in PolSAR image classification, three contrastive experiments are carried out on the same PolSAR data:

Contrastive experiment 1, it is a classical classification method for SAR, which is based on complex Wishart distribution. Supposed that each type of object obey Wishart distribution of a particular parameter, Maximum Likelihood estimation is used to classify objects. Through finding the category with the minimum Wishart distance, the ML classifier can realize the image classification.

Contrastive experiment 2, the classification method is based on textural features: firstly, GLCM(Gray Level Co-occurrence matrix) features is extracted from the SAR image, secondly, the features are introduced into SVM classifier[9], and classification results are achieved.

Contrastive experiment 3, the classification method is based on the Decomposition+SPM (spatial pyramid model): firstly, several target polarimetric decompositions are implemented on the PolSAR data, including: Pauli, SDH, Cameron, Huynen, Holm, Cloude, Barns, Fourcomponent, OEC, Freeman, and 31 dimensional polarimetric features can be achieved after polarimetric decomposition, secondly, the features are introduced into a 3 layers spatial pyramid model, finally, SVM is used for classification.

4.3 Experiment results

The classification results of the proposed algorithm and the three contrastive experiments on the dataset are shown in Figure 3 and Table 2. It's not hard to see that the classification accuracy of Wishart distribution is lowest, and the average classification accuracy is only 65.20%. The classification accuracy of the contrastive experiment2 improved somewhat compared with the contrastive experiment1, and the average classification accuracy is 71.56%. The average classification accuracy of the contrastive experiment3 is 72.37%, and the average classification accuracy rate of the proposed algorithm is the highest, reaching 75.08%.

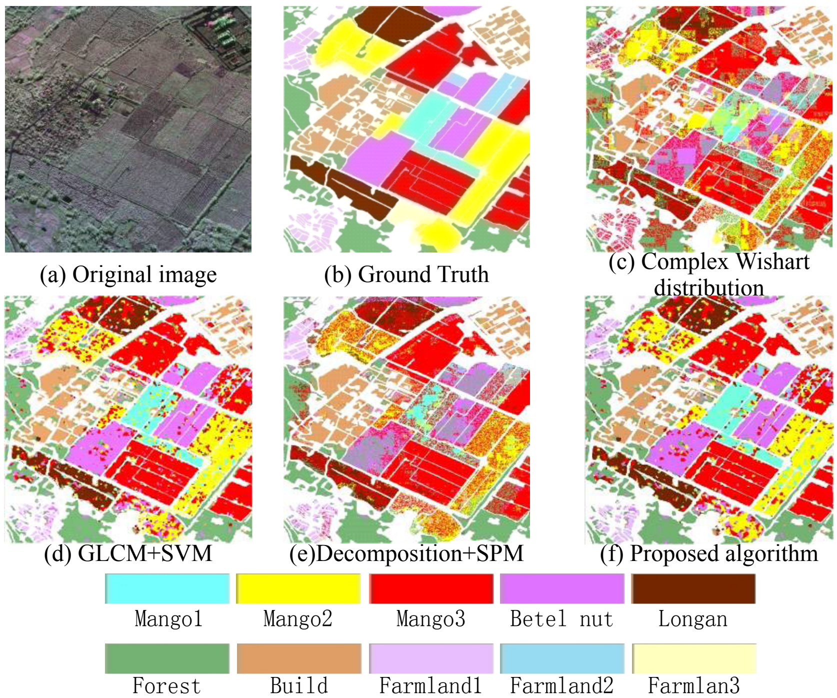

Figure 3. Experiment Results on dataset

Table2. Classification accuracies on dataset

Category	Wishart	GLCM+SVM	Decomposition+SPM	Proposed
Mango1	54.58%	78.39%	61.33%	81.18%
Mango2	62.50%	64.56%	55.83%	66.78%
Mango3	76.83%	82.13%	86.64%	85.12%

Betel nut	54.16%	80.01%	58.00%	80.98%
Longan	57.24%	65.34%	59.00%	69.46%
Forest	71.35%	82.39%	88.47%	88.94%
Build	75.04%	71.27%	84.60%	71.87%
Farmland1	47.49%	58.35%	81.47%	60.35%
Farmland2	50.11%	23.14%	51.29%	23.18%
Farmland3	49.30%	15.98%	49.27%	16.08%
Average	65.20%	71.56%	72.37%	75.08%

4.4 Experiment analysis

For the results of the proposed algorithm and the three contrastive experiments, four contents can be concluded as follows: (1) Although the classification method based on complex Wishart distribution can depict the statistical features of the covariance matrix of polarimetric SAR images much well, in practical classification problems, the method cannot ensure that the complex Wishart distribution can fit completely the distribution of objects, so the results of contrastive experiment1 are almost the worst. (2) Although GLCM features is the common textural feature in optical field, the feature extraction method can only aim to the single image, which cannot use the rich information of ground objects completely. So the classification results of contrastive experiment 2 are relatively poor. (3) Polarimetric decomposition is a specifically decomposition method for PolSAR image, which can depict the PolSAR image to a certain extent, while, the classification situation of the experiment datasets is much complex and the number of training dataset is relatively smaller, therefore, the structural risk of SVM will become larger, resulting that the classification accuracy of contrastive experiment2 is not high. (4) The proposed algorithm uses a large number of training data to train CNN parameters, and 4 SAR images for the same object in different state are all used for classification, so the CNN network can be trained sufficiently and the learned features can depict the PolSAR data more essentially. So the proposed algorithm achieved relatively higher classification accuracy rate.

5. Conclusions

This paper presents a classification algorithm based on deep convolutional neural network, which is used for the classification of PolSAR images, and the three contrastive experiments prove the effectiveness of the proposed algorithm. Firstly, in order to solve the problem that deep learning cannot be directly used for classification of SAR image, the traditional CNN network is updated to process the multi-channels data ; secondly, in order to take full advantage of PolSAR data, the four SAR images in different state are used for CNN training; finally, the proposed method is applied to the classification of the first X-band polarimetric SAR data, and the experimental results show that the deep learning also has great potential in the field of classification of PolSAR image.

Acknowledgements

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