Synthetic aperture radar target recognition of incomplete training datasets via Siamese network

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Abstract: Synthetic aperture radar (SAR) target recognition can provide effective target category information and becomes the key part of SAR image application. Machine learning and deep learning are two main methods of target recognition. Normally, through the massive image features learning, the trained model can be used to infer the possible categories for various new target images, but the overfitting problem caused by limited data samples always makes the trained model unusable. In order to solve this case, the authors introduce a dual-input Siamese convolution neural network to the small samples oriented SAR target recognition. The training method looks like a kind of data enhancement method, but there are some differences between them. In the experiments, only 15 training samples are used to complete a three-class tank classification task. It means each category has just five samples while the number of corresponding testing data is 195. As a result, the recognition accuracy of the authors’ method outperforms the support vector machine, A-ConvNet, and 18-layers ResNet by 31, 13 and 16%, respectively. Siamese network has a good performance in small samples classification and the results prove the validity of the network.

1 Introduction

Synthetic aperture radar (SAR) is an all-weather and all-day method for obtaining ground data in a wide range with high resolution and high penetration, which has high civilian and military value. Due to microwave imaging and sophisticated electromagnetic scattering characteristics, the SAR image representation is vastly different from the human visual system. SAR image interpretation, including pixel-wise classification, target detection and recognition, has gradually become a hot topic in the SAR application [1, 2]. Compared with optical imagery, the SAR images have the characteristics of high acquisition cost and lower quantity. Therefore, the SAR target recognition research under incomplete training data sets is more practical for boosting the SAR image application [3, 4].

The image processing technologies based on machine learning and deep learning are the mainstream methods in target recognition. Normally, the supervised learning is used to identify targets, which mainly include the feature extraction and classification. Feature extraction is generally used to obtain the greyscale features, texture features and contour features of the target in SAR images. The existing methods are principal component analysis (PCA) [5], 2D-PCA [6], histogram of oriented gradient (HOG), local texture features based on Gabor filter [7] and so on. The classification methods mainly include the nearest classification K-NN, Bayesian classifier, support vector machine (SVM), sparse representation classification [8] and so on. In the machine learning-based methods, PCA-based feature extraction and SVM classifier are the most used basic methods, which can derive many other methods. PCA can not only extract features from SAR images but also reduce noise. SVM is a classifier designed based on the Vapnik-Chervonenkis dimension (VC) dimension theory of statistical learning theory and structural risk minimisation theory, and it has a good performance in dealing with small samples problem.

Due to the limited computing resource in the early stage, traditional machine learning methods are more effective and faster than neural networks in SAR target recognition. With the improvement in the computing resource, deep learning achieves better recognition performance, such as the method of multi-aspect-aware bidirectional LSTM networks [9], which can achieve the accuracy of 99.9% in MSTAR SAR data. However, most of deep learning methods get a high accuracy by providing a large amount of data for training. For deep neural networks, e.g. the 152 layers of ResNet or 161 layers of DenseNet [10], the demand for training data is very large for avoiding overfitting. For those networks with a small structure, such as A-ConvNet [11] and 18 layers ResNet, the data requirement is only slightly better than the deep networks. Of course, there are some ways to change the network structure to improve the classification accuracy and performance under small sample conditions, e.g. ensemble model [12] and PCANet [13].

Incomplete training datasets will result in overfitting and make neural networks unable to present its extraordinary advantages in accuracy. In this paper, we introduce a new method to classify small samples SAR tank targets based on Siamese network [14]. The experimental results prove that it has a better performance than other methods in small samples condition.

2 Siamese network

Although some good methods have been proposed for the classification of SAR images, these different methods have their own shortcomings. One of the common shortcomings is the disappointing result in small samples classification. In order to promote practical use of SAR in civilian and military, and make scientific researches meet practical needs. We introduce a new method to get a high classification accuracy with simulating real condition that we cannot get enough training samples. The key to this approach is the Siamese network.

Siamese network is a dual-input neural network, the two inputs share the same weights. It can be divided into two parts, feature extraction and classification. When we extract features, we make input image pairs pass through four convolution layers and one full connection layer. Then we get two feature maps about the input pairs. The following, we flatten each feature map into one-dimensional arrays. When we make a classification, we calculate L1 norm of the two one-dimension arrays and put it in a full connection layer, and there is only one output for the full connection layer. Finally, we get the result by a sigmoid activation function. Obviously, the output is not a category. It’s a possibility about whether the input pairs are the same or not. The structure of Siamese network is shown in Fig. 1.
and the next two are turned into 3 × 3 size. Such a setting does not make the receptive field too small to ignore the relevance of the few images we select two images to form input pairs. According to the rule of thumb, the input pairs are the same category or not by the difference in the output of the second full connection layer before the features are extracted. This training process is more complex and time-consuming than it is in generating neural networks.

By the previous introduction, the Siamese network output is the similarity possibility of the input image pairs, in order to use the network to do classification works. We need to provide a support set with labels. The support set includes three categories tanks, and we give each category some samples as classification references. Its role is to form an input pair with the test target to be classified and help us get the most likely one as the target category.

When we test, we make input pairs from the test target and each category reference in support set. According to the label of the classification reference with highest similarity possibility to test target, we determine category of the test target.

4 Experimental results

The requirements for our experiment is not stringent. The system is Windows 7 Professional Service Pack 1. The basic hardware is Core i5-4590 CPU @ 3.30 GHz, 8G RAM and NVIDIA GeForce GTX 750, and our code is realised in Keras with tensorflow backend. The version of Keras is 2.1.5 and the version of tensorflow is 1.3.0.

With the implementation of the Siamese network, we train it on seven different sizes of training sets, and verify the effectiveness of the network on three support sets. Training and testing data comes from MSTAR SAR data. What is more, we make comparative experiments with method based on HOG feature extraction and SVM classifier, A-ConvNet and 18 layers ResNet in the same condition. The results are shown in Table 1.

The experimental results show that the Siamese network perform significantly better than other methods when the training data number of each category is 3, 5 and 10. The classification accuracy in the condition of 20, 30 and 40 samples and support set size of 5 is only after 18 layers ResNet, and in 50 samples condition, the accuracy is lower than A-ConvNet and ResNet, but it is not a big difference.

From Table 1, we can draw a conclusion that accuracy in support set of size 5 is better and the result in 20 samples is abnormal. So it is obviously that not only training and testing data can affect classification accuracy but also support set can do that. The abnormal accuracies of 20 samples in three sizes of support sets are almost similar and testing data is the same. So the abnormality is not caused by support sets and testing data. The only reason is 20 samples training data. In a word, the network over fit the 20 samples training data. Even though overfitting happened, the classification accuracy is still higher than that of A-ConvNet.

5 Conclusion

Recognition of small samples has driven the development of artificial intelligence-based SAR application technology. Small sample problem is more common in practice, especially the SAR image interpretation. Although this problem is difficult, it is worthy of continuous research. The experimental results show that the Siamese network has a good performance in the complete training data condition. However, its unique training and inference methods limit the training and inference speed. Moreover, the full connection layers in Siamese network will lead to a huge size of network model. We will try to solve the above two questions for better application in the future works.

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