IGARSS 2021 - 2021 IEEE International Geoscience and Remote Sensing Symposium | 978-1-6654-0369-6/21/$31.00 ©2021 IEEE | DOI: 10.1109/IGARSS47720.2021.9554705

SAR IMAGE CHANGE DETECTION VIA A FEW-SHOT LEARNING-BASED NEURAL NETWORK

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ABSTRACT

In synthetic aperture radar (SAR) image change detection, it is quite challenging to exploit the changing information from the noisy difference image subject to the speckle. Although convolutional neural network has been proposed for feature learning, it is necessary to collect numerous of samples to train a perfect model, which is difficult to achieve. In this paper, we propose a few-shot learning-based neural network to exploit the changed information from the noisy difference image. Being different from traditional training method with numerous labeled samples, in the proposed method, fewer samples are used to train a neural network. Finally, we verify our proposed method on four challenging datasets of bitemporal SAR images. Experimental results demonstrate that the difference map obtained by our proposed method outperforms than other state-of-art methods.

Index Terms— Change Detection; SAR Image; Convolutional Neural Network; Few-Shot Learning

1. INTRODUCTION

Synthetic aperture radar (SAR) is a microwave sensor for earth observation working without the limitations of illumination condition. This advantage allows people to perform multiple earth observations at all time with all weather and the acquired multitemporal SAR images give us opportunities to compare the difference of the multi-temporal SAR images on the same scene, which is known as multi-temporal SAR image change detection[1]. In recent years, numerous methods have been developed for SAR image change detection.

Currently, most SAR image change detection methods are developed based on the framework proposed in [2] and [3] by L. Bruzzone and D. F. Prieto, in which the changed regions are detected from a difference image (DI). However, this pixel-wise operator is subject to SAR image speckle and it is quite challenging to exploit the changing information. Zhang et al.[4] proposed a graph-cut method to extract the change regions on the log-ratio difference image through the statistical distributions on the changed and unchanged regions. Li et al.[5] proposed a joint sparse learning model to obtain robust features from difference images.

Recently, fully convolutional neural networks[6] have been successfully employed to image semantic segmentation where the pooling layers can exploit robust features on spatial structures of an image. Inspired by this spirit, they have been extensively employed to exploit the changed regions from the noisy difference image. Gong et al.[7] proposed a deep neural network for the first time to SAR image change detection. Gao et al.[8] proposed a simple convolutional network based on the principle component analysis, known as PCA-Net, to SAR image change detection. Wang et al.[9] proposed a supervised PCA-Net approach, where training samples are selected with the guidance of morphological structures of reference. However, in most traditional convolutional networks, numerous labeled samples are necessarily to collect for training perfect network weights. Recently, few-shot learning methods[10] have been proposed for image classification, where a few samples are needed to train a classifier.

Inspired by this idea, in this paper, we propose a few-shot learning-based convolutional neural network for SAR image change detection to exploit the changed regions from the noisy difference image. In our proposed method, a small number of training samples are fed to train a perfect network. Furthermore, we can conduct a faster inference due to a smaller support dataset. To verify the effects of our proposed method, several methods are compared with our proposed method and the comparisons are performed on four datasets. The experimental results show that the proposed method outperforms the other methods in cross-dataset SAR image change detection.

2. PROPOSED METHOD

2.1. Few-Shot Learning

A SAR image is usually subject to the speckle and it is challenging to exploit a robust feature for its structure. Fortunately, convolutional neural networks are proposed for the feature learning of SAR image. It has been proven that CNN

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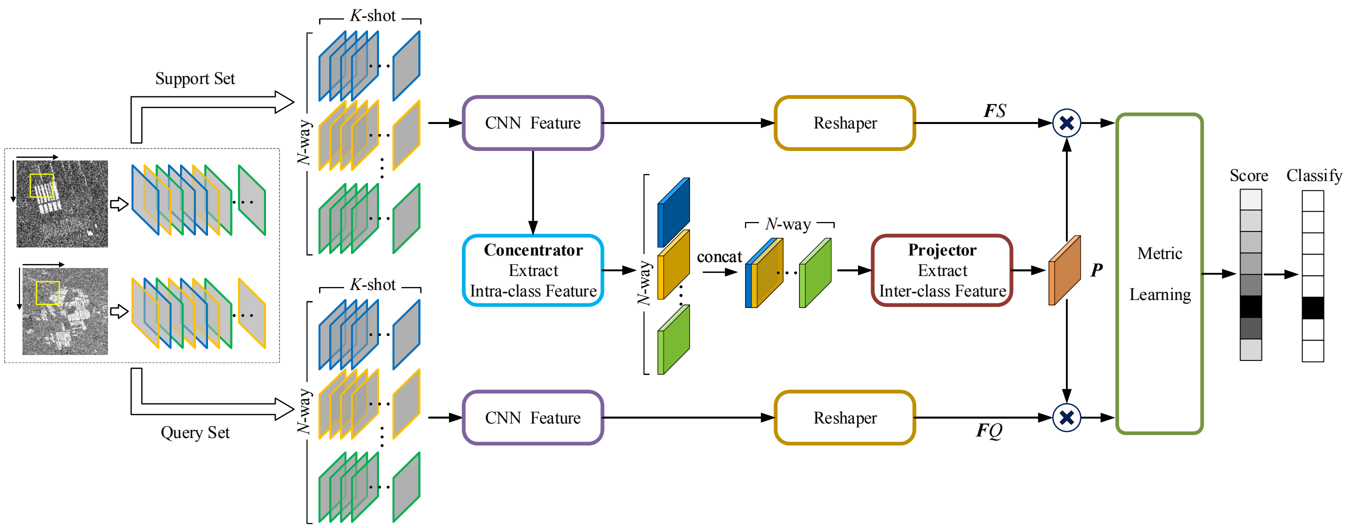

Fig. 1: The framework of the proposed method.

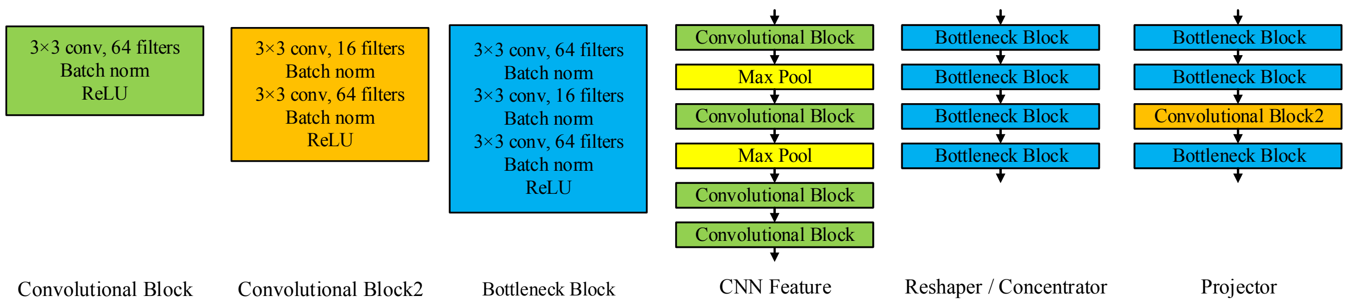

Fig. 2: The illustration of the network architecture.

is successful to bitemporal SAR image change detection [9]. However, CNN-based methods usually need a large number of training sample to train a perfect model, whereas it is quite difficult to get sufficient land-cover labels samples for SAR images. Recently, few-shot learning [10] becomes gradually popular, which exploits the information of each single sample so that less samples are needed in model training.

Inspired by this, in this paper, we proposed a few-shot learning-based bitemporal SAR image change detection, where less training samples are needed to train a model. The whole framework can be illustrated as Fig.1. It is shown in the figure that, there are a concentrator and a projector in the whole framework, which are optimized in model training. The concentrator is designed to extract the intra-class features, while the projector to the inter-class features. Then, in the inference process, given a support dataset with known labels and a query dataset with unknown labels, the features of these two datasets are extracted by the trained backbone network. Finally, we applied the trained projector to the extracted features. By comparing the feature similarity between the query and support dataset, we can get the estimated class of the query dataset.

2.2. Model Training

In this subsection, we will introduce the pipeline of model training. First, the components of the proposed framework can be illustrated as Fig.2. The backbone for the CNN feature extractor consists of 4 convolutional blocks and 2 max-pooling layers, where each convolutional block is defined as a combination of a convolution, a batchnorm and ReLU operator. The concentrator consists of 4 bottleneck layers and each one contains 3 convolutions with 3×3 kernels, 3 batchnorms and a ReLU.

To train the network efficiently, we elaborately collect the samples from training datasets, especially near the boundaries (named as boundary samples), which has been demonstrated that the network can be efficiently trained for SAR image change detection with less training samples [9] . The patchsize of each sample is set as 21×21 and 2 samples are fed in each training step. Additionally, the Adam algorithm [11] is employed to optimize the weights of network in the training stage, where the initial learning rate is set as 0.001. The training is performed on the Pytorch platform built on the Ubuntu 16.04 installed in a PC with a 16 GB DDR memory and an NVIDIA TITAN Xp Graphics Processing Unit of 11

GB memory.

3. EXPERIMENTAL RESULTS AND ANALYSIS

In this paper, the proposed method is verified on four sets of bitemporal SAR images. Two scenes (YR-A and YR-B) are from bitemporal Yellow River SAR images [7] acquired by the Radarsat-2 satellite in 2008 and 2009, respectively. Their image sizes are 306×291 and 400×350, respectively. Other two are parts of TerraSAR-X images acquired prior to (on Oct. 20, 2010) and after (on May 6, 2011) the Sendai earthquake in Japan [12]. Their sizes (Sendai-A and Sendai-B) are 590×687 and 689×734, respectively. These four datasets are quite challenging, such as the linear-shape changed regions in YR-B dataset and complex scene in both Sendai-A and Sendai-B datasets [13].

To verify the benefits of the proposed method (FSNN), it is compared with the CNN [14], Efficient-Net(ENet) [13]. The performance of the compared methods is evaluated by probabilistic missed alarm (pMA), probabilistic false alarm (pFA) and kappa coefficient, where pFA (pMA) are calculated by the ratios between FA (MA) and the number of unchanged pixels (NC).

The visual results are demonstrated in Fig.3. It is shown that the other compared methods obtain noisy changed map especially on Sendai-A and Sendai-B datasets, while our proposed method can get clear and more completed changed area on four datasets. Besides, we also show the quantitative evaluation results in Fig.4. It is shown that our proposed method obtains lower pFA and pMA on Sendai-A, Sendai-B and YR-A datasets. Other compared methods are subject to the speckle and get higher pMA and pFA. Moreover, our proposed method obtains higher Kappas on YR-A and YR-B datasets.

4. CONCLUSION

In this paper, we proposed a few-shot learning-based neural network for bitemporal SAR image change detection. It is shown that less training samples are used for model training. Furthermore, with a small support set, we can achieve a fast inference, which will benefits for large scale remote sensing images. To verify the effectiveness of the proposed method, we compared the proposed methods with other state-of-arts on four challenging datasets. The comparison results show that the proposed method outperforms than the other compared methods.

5. ACKNOWLEDGMENT

This work was supported by the State Key Program of National Natural Science of China (No. 61836009), the Fujian Key Laboratory of Data Science and Statistics (Minnan Normal University) (No.2020L0707).

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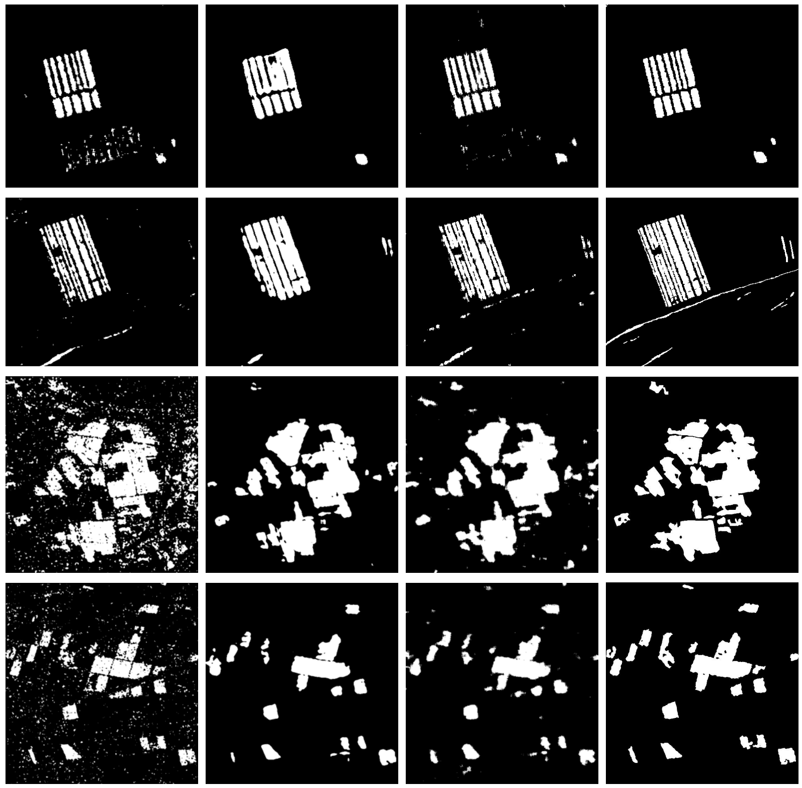
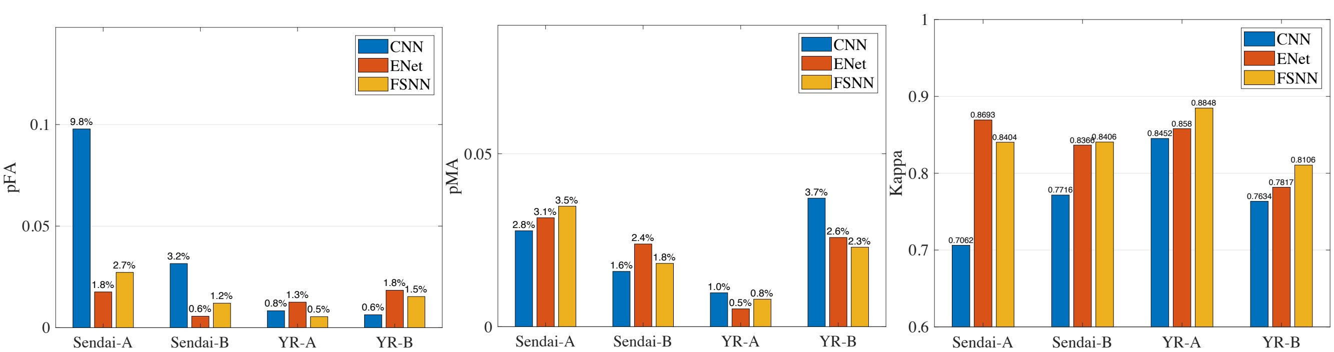


(a) CNN (b) ENet (c) FSNN (d) Reference map

Fig. 3: The visual comparison experiments.



(a) (b) (c)

Fig. 4: The comparisons of quantitative evaluations in terms of (a) pFA, (b) pMA and (c) Kappa.

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