A DEEP GENERALIZED CORRELATION NETWORK FOR BITEMPORAL IMAGE CHANGE DETECTION

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IGARSS 2020 - 2020 IEEE International Geoscience and Remote Sensing Symposium | 978-1-7281-6374-1/20/$31.00 ©2020 IEEE | DOI: 10.1109/IGARSS39084.2020.9324247

ABSTRACT

Recently, many convolution neural networks have been successfully employed in bitemporal SAR image change detection. However, most methods are developed based on the traditional framework that exploits the changed region from a difference image (DI) that is usually subject to the speckle. To essentially solve this issue, in this paper, we propose a deep canonic correlation network for bitemporal SAR image. In the proposed network, bitemporal SAR images and its corresponding DI are taken as the inputs and then three deep neural networks are designed to employ their features, respectively. Then the changed regions are obtained by the exploited features. Finally, we compare the proposed method with other deep learning methods and perform the comparison on four sets of bitemporal SAR images. The experimental results show that our proposed method outperforms other methods.

Index Terms— Neural Network, Bitemporal SAR images, Canonic Correlation Analysis

1. INTRODUCTION

Over past decades, much attention focus on multitemporal synthetic aperture radar (SAR) image change detection, since a SAR is capable of working in all-time and all-weather without the influence of extremely bad weather and the cloud. In a past decade, most traditional SAR image change detection methods are developed based on difference images (DI), which include the information of changed regions. The DI calculated by the log-ratio (LR) [1] is usually subject to the speckle and it is difficult to extract the accurate and clear information on the changed region [2]. To solve this issue, spare learning[3] was recently proposed learning robust features from the noisy DI.

Recently, deep neural networks have been successfully employed to computer vision and remote sensing image analysis due to its ability of exploit essential and robust structural features on categories of objects. With this success, Gao et al. [4] proposed a simple convolutional neural network exploring robust features on the changed regions from the noisy DI. Wang et al. [5] proposed a supervised convolutional neural network (CNN) to improve the performance by carefully collecting typical training samples. Zhao et al. [6] proposed a bitemporal PolSAR image change detection by a joint classification and a similarity measurement. However, most above methods were proposed based on the traditional framework that exploits the changed regions from the DI. Most recently, Wang et al.[7] proposed a novel change detection framework based on metric learning. It has been proven that the novel framework show great advantages over the traditional methods.

In this paper, we propose a novel change detection framework for SAR image change detection based on deep generalized canonic correlation analysis (DGCCA) network. In the proposed framework, we take bitemporal SAR images as well as the corresponding DI as the inputs. Then we develop three deep neural networks for three channels of inputs to exploit the features of each channel image. With the exploited features, we obtain the changed regions through a classifier. Finally, we verify our proposed method on four sets of bitemporal SAR images. Experimental results on two sets of bitemporal SAR image change detection show that our proposed method obtain comparable performance with CNN, while being much more efficient than CNNs.

2. PROPOSED METHOD

2.1. Network Structures

In this section, we will introduce details on our proposed method to exploit the structures of changed regions from bitemporal SAR images. The whole framework of the proposed network can be illustrated in Fig.1.

Given a set of bitemporal SAR images, they are over the same region and are supposed to be aligned. The difference image (DI) is firstly generated based on the neighborhood-based log-ratio (LR) operator [8]. Then we forward both the bitemporal SAR images and the generated DI into the network. For each pixel as the center, the patches of size $n \times n$ are extracted and vectorized to the samples $\mathbf{X}_j \in \mathcal{R}^{d \times n}$,where $d = n \times n$, N is the number of pixels in each image. The value

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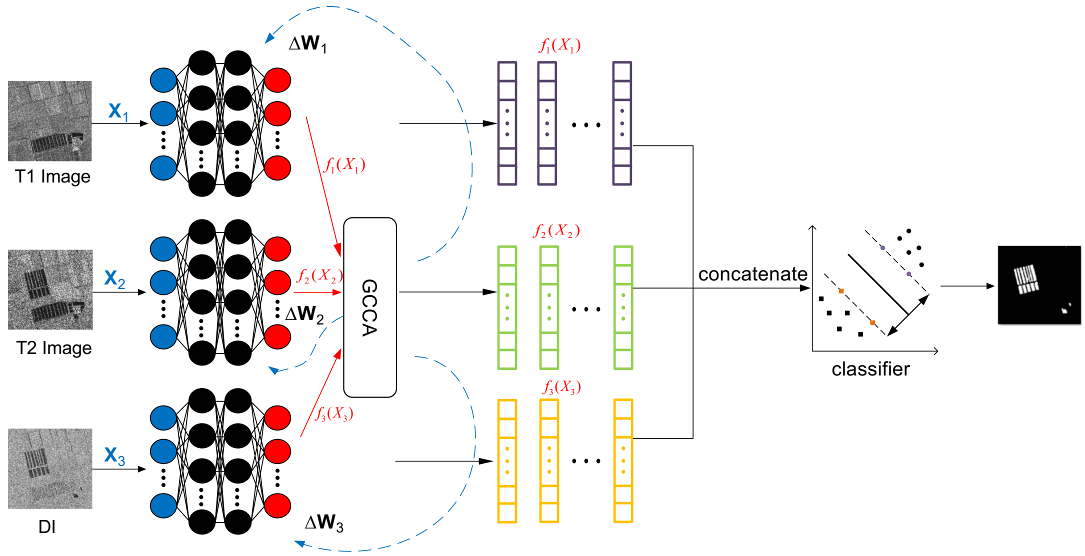
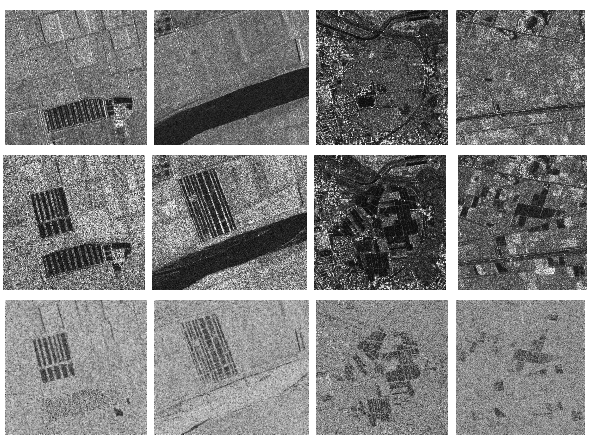


Fig. 1: The framework of the proposed network.



(a) YR-A (b) YR-B (c) Sendai-A (d) Sendai-B

Fig. 2: Four sets of bitemporal SAR images. The first two rows are bitemporal images and the last row is the DIs.

of the reference image corresponding to the central pixel of the patch is used to set the label of each sample.

With the prepared data, we build three fully connected deep neural networks and each one has three hidden layers. The rectified linear units (ReLU) are employed as non-linear activation functions. The output of the *k*th layer is noted as $\mathbf{h}_k^j = \mathrm{ReLU}(\mathbf{W}_k^j \mathbf{h}_{k-1}^j)$, where $\mathbf{W}_k^j$ is the weight matrix. The output of the final layer will be denoted as $f_j(\mathbf{X}_j)$. More specifically, the generalized canonical correlation analysis (GCCA) can be expressed as the following optimization problem:

$$\begin{aligned} \min_{\mathbf{U}_j \in \mathbb{R}^{d_j \times r}, G \in \mathbb{R}^{r \times N}} \quad & \sum_{j=1}^{J} \|\mathbf{G} - \mathbf{U}_j^\top \mathbf{X}_j\|_F^2 \\ s.t. \qquad & \mathbf{G}\mathbf{G}^\top = I_r \end{aligned} \tag{1}$$

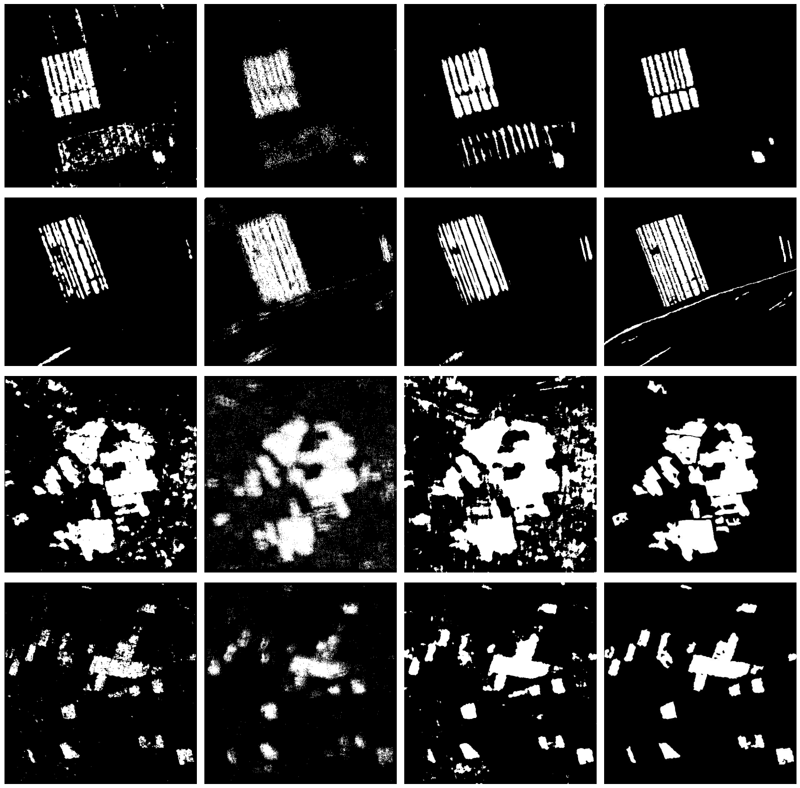
where $\mathbf{G}$ is the shared representation. It aims to seek the weight matrices $\mathbf{W}^j$ with the functions $f_j(\cdot)$ and the linear transformations $\mathbf{U}_j$ of the output of the *j*th network.

2.2. Network Training

We solve the above optimization problem using the Adam algorithm [9] to optimize the weights of network in the training stage. 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 [5]. In this paper, we randomly draw 30% samples from training data, which included all the changed and boundary samples, the others are the unchanged samples. Moreover, the patchsize n of each sample is set as 27×27, and the number of nodes in the input layer is 729. The number of nodes in each hidden layer and output layer are 25, respectively. Additionally, the initial learning rate is set as 0.0001. The training is performed on the Pytorch platform built on the Ubuntu 16.04 installed in a PC with a 16GB DDR memory and an NVIDIA GTX1080Ti Graphics Processing Unit of 12 GB memory.

3. EXPERIMENTAL RESULTS

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 [10] 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 earth-



(a) CNN (b) LRM (c) Proposed method (d) Reference map

Fig. 3: The visual comparison results.

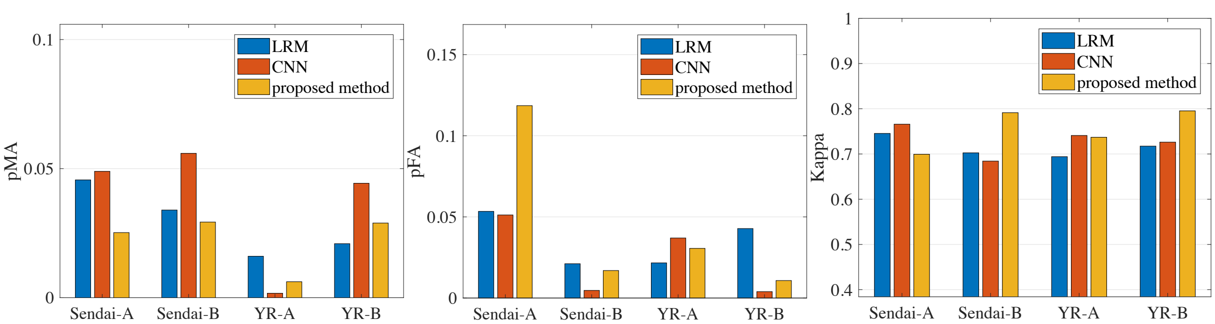


Fig. 4: The quantitative evaluations of compared methods.

quake in Japan [11]. Their sizes (Sendai-A and Sendai-B) are 590 $\times$687 and 689 $\times$ 734, respectively. These four datasets are shown in Fig.2). 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.

To verify the benefits of the proposed method, it is compared with convolutional neural network (CNN)[12] and the change detection based on metric learning (LRM)[7] which achieve the state-of-arts performance on SAR image change detection. Moreover, we verify the performance of the compared methods by the leave-one-out manner. 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 comparison results are shown in Fig.3. It is shown in the figure that for the YR-A and YR-B dataset, both LRM and our proposed method obtain more clear structures of changed regions. For the Sendai-A and Sendai-B datasets, our proposed method get more clear changed regions. Moreover, we show the quantitative evaluations in

Fig.4. It is shown that our proposed method get better kappas, pMAs and pFAs than other methods.

4. CONCLUSION

In this paper, we developed a novel framework for bitemporal SAR image change detection through deep generalized canonic correlation analysis. Being different from the traditional methods only based on DI, our proposed method takes both bitemporal SAR images and the corresponding DI as input and exploit their features via deep neural network. Then we get the changed regions by comparing the exploited features. To verify the benefits of our proposed method, we compare it with several traditional neural networks and the comparisons are performed on fours sets of bitemporal SAR images. The experimental results show that our proposed method outperforms other compared methods on three datasets Sendai-A, Sendai-B and YR-B.

5. ACKNOWLEDGMENT

This work was supported by the State Key Program of National Natural Science of China (No. 61836009), the National Natural Science Foundation of China (No. 61701361, 61806154, 61801124), the Open Fund of Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education, Xidian University (Grant No. IPIU2019006), and the Science and Technology Program of Guangzhou (No. 201904010210).

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