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A LIGHTWEIGHT CONVOLUTIONAL NEURAL NETWORK FOR BITEMPORAL IMAGE CHANGE DETECTION

Rongfang Wang, Fan Ding, Jia-Wei Chen, Licheng Jiao, Liang Wang*

Key Laboratory of Intelligent Perception and Image Understanding of Ministry of Education,
School of Artificial Intelligence, Xidian University, Xi'an, China, 710071

ABSTRACT

Recently, many convolution neural networks have been successfully employed in bitemporal SAR image change detection. However, most of those networks are too heavy where large memory are necessary for storage and calculation. To reduce the computational and spatial complexity and facilitate the change detection on edge devices, in this paper, we propose a lightweight neural network for bitemporal SAR image change detection. In the proposed network, we replace the regular convolutional layers with bottlenecks, which will not increase the number of channels. Furthermore, we employ dilated convolutional kernels with a few non-zero entries which reduces the FLOPs in convlutional operators. Comparing with traditional neural network, our lightweight neural network will be faster, less FLOPs and parameters. We verify our lightweight neural network on two sets of bitemporal SAR images. The experimental results show that the proposed network can obtain the comparable performance with those heavy-weight neural network.

***Index Terms*—** Lightweight neural network, Bitemporal SAR images

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, sparse 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 to exploiting 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, it is still an open problem to extract the changed regions from the noisy DI.

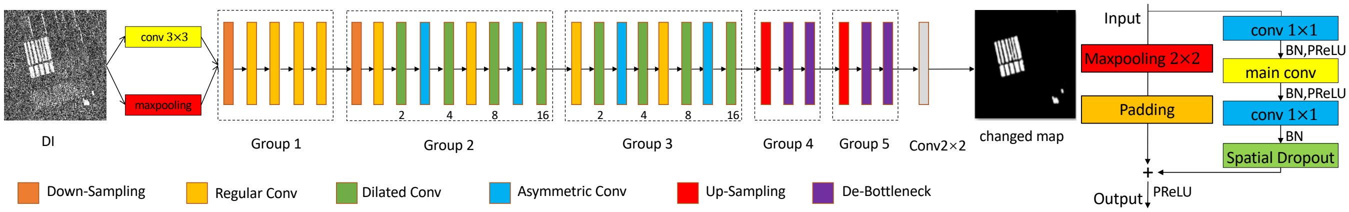
* Corresponding Author: Jia-Wei Chen

On the other hand, He et al. proposed a residual network[7] for image recognition and achieves the state-of-arts results. However, this kind of CNNs are quite heavy, where the large capacity of model parameters can reduce the efficiency of model inference. Recently, several lite networks are proposed to improve the inference efficiency. Howard et al. and Sandler et al. proposed two lite networks MobileNetV1 [8] and MobileNetV2 [9] for visual category. Recently, Howard et al. proposed to search for MobileNetV3 [10]. These three lite networks have been extensively employed to visual category and the experimental results show that they can achieve comparable performance with heavy networks, but with low latency and network capacity.

Nowadays, a large volume of SAR images are acquired by satellites and it is imperative to improve the efficiency of SAR image interpretation. Inspired by this, in this paper, we focus on the application of lite networks in SAR image change detection. To achieve this, we propose a lightweight convolutional neural network for SAR image change detection. In this lightweight convolutional neural network, bottleneck layers are introduced to reduce the number of output channel. Furthermore, the dilated convolutional layers are introduced to enlarge receptive field with a few of non-zero entries in the kernel, which reduces the number of network parameters. 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

In this section, we will propose a lightweight convolutional neural network to exploit the changed regions from the noisy



(a) Network Architecture (b) Bottleneck

Fig. 1: The framework of the proposed network.

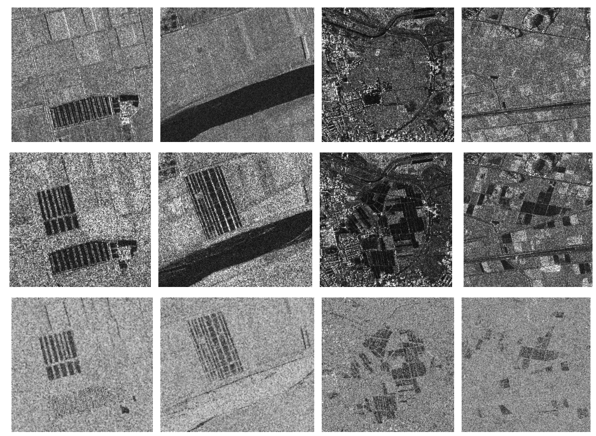
DI. The whole framework of the proposed network can illustrated in Fig.1(a). It is shown that the whole framework consists of a variety of bottleneck layers with variable structures, where the basic structure of bottleneck layer can be illustrated in Fig.1(b). It is shown in the figure that each one is a small residual block, including a maxpooling path and a convolutional path. The convolutional path consists of two 1×1 convolutions and one main convolution. The main convolution will vary with the various function of the bottleneck. It can be a regular convolution, a dilated convolution or an asymmetrical convolution.

All the bottleneck layers are divided into five groups, where three groups are designed for encoder and two groups for decoder. Given bitemporal SAR images, the DI generated by the neighborhood-based LR operator [11] is forwarded to the proposed network as an input. Firstly, the input data go through a regular convolutional layer and a maxpooling layer, respectively and then the outputs are contacted. Next, the data go through the decoder with three groups bottleneck layers. The first group consist a down-sampling bottleneck and four regular convolutional layers . To exploit the spatial context, based on settings of the first group, we insert an asymmetrical convolution and dilated convolution layers with various kernel sizes , where the kernel sizes are set 2, 4, 8 and 16, respectively. In these special layers, the main convolutional layers in the bottlenecks will be replaced by the corresponding dilated convolutional layers or asymmetrical convolutional layer.

Inspired by the idea of U-Net [12], in the decoder, we set a upsampling layer and two bottleneck layers, where the main convolutional layer is replaced by the deconvolutional layer to recover the size of feature map to the original size. Finally, we put a 2×2 convolutional layer to get the probability map of two categories.

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 [13] acquired by the Radarsat-2 satellite in 2008 and 2009, respectively. Their image sizes are 306×291 and 400×350, respectively. Other



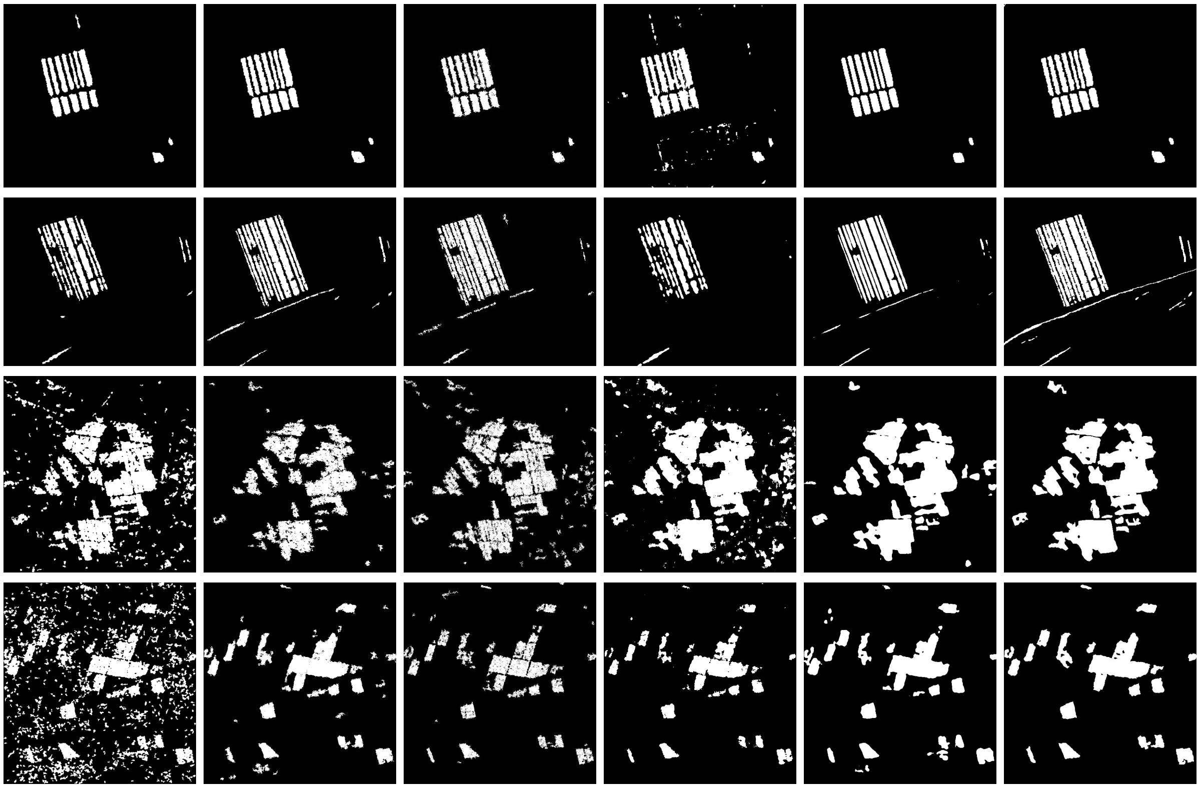
(a) YR-A (b) YR-B (c) Sendai-A (d) Sendai-B

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

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 [14]. Their sizes (Sendai-A and Sendai-B) are 590×687 and 689×734, 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 the unsupervised PCA-Net (U-PCA-Net)[4], the supervised PCA-Net (S-PCA-Net) [5] which achieves the state-of-arts performance on SAR image change detection. We also compare the proposed method with the deep neural network (DNN) method [13] and CNN [15]. Among these methods, DNN and U-PCA-Net are unsupervised methods,while S-PCA-Net, CNN and the proposed method are supervised ones. 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 both S-PCA-Net and our proposed method obtain more clear structures of changed regions on



(a) U-PCA-Net (b) S-PCA-Net (c) DNN (d) CNN (e) Proposed method (f) Reference map

Fig. 3: The visual comparison results.

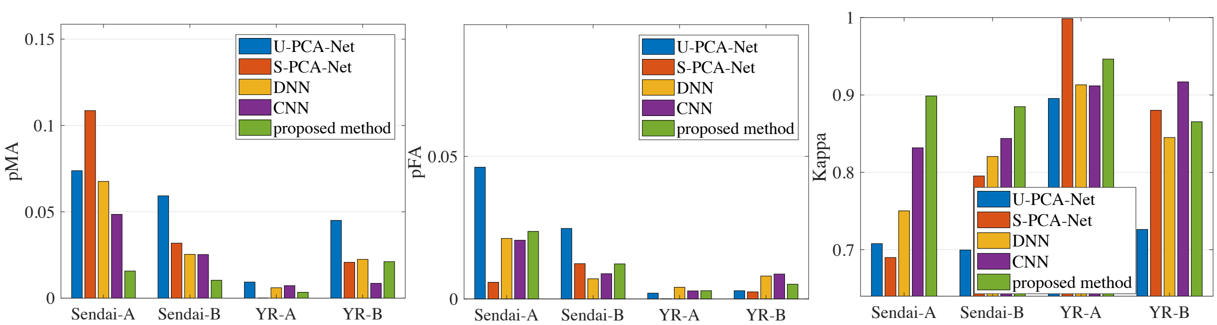


Fig. 4: The quantitative evaluations of compared methods.

four datasets. More specifically, our proposed method get more accurate changed regions than S-PCA-Net except the YR-B dataset. Moreover, we show the quantitative evaluations in Fig.4. It is shown that our proposed method get the lowest pMA on all the datasets and lower pFA on the YR-A, Sendai-A and Sendai-B datasets. Both S-PCA-Net and the proposed method got the comparable pFA on the YR-B dataset. Overall, our proposed method gets the comparable Kappa with S-PCA-Net on the YR-B dataset and the best Kappa on the other three datasets. It is demonstrated that our proposed method outperforms other compared methods.

4. CONCLUSION

In this paper, we develop a lightweight convolutional neural network for bitemporal SAR image change detection. The proposed network consists of groups of bottlenecks layers which exploit the image feature with sparse kernels. 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.

5. ACKNOWLEDGMENT

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