SAR IMAGE CHANGE DETECTION METHOD VIA A PYRAMID POOLING CONVOLUTIONAL 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. In this paper, we propose a novel mutli-scale average pooling (MSAP) network to exploit the changed information from the noisy difference image. Being different from traditional convolutional network with only an one-scale pooling kernel, in the proposed method, multi-scale pooling kernels are equipped in convolutional network to obtain the spatial context information on changed regions from the difference image. 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; Multi-scale Average Pooling

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.

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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, all the pooling kernels have the same size and pooling operators are usually subsequently employed to exploit a larger range of spatial context. Recently, Zhao et al.[10] proposed a pyramid scene parsing network, which exploits global spatial context information by aggregating various sizes of context through pyramid pooling layers. Kim et al.[11] developed an U-Net with pyramid pooling layers for object segmentation.

Inspired by this idea, in this paper, we propose a multi-scale average pooling (MSAP) convolutional network for SAR image change detection to exploit the changed regions from the noisy difference image. In this network, the MSAP layer is introduced to obtain robust features of changed regions with the spatial context information at various scales. The MSAP layer can facilitate to exploit the structures of changed regions with a shallow network, which can be easily trained. 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. Network Structure

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 MSAP network can be illustrated in Fig.1. Given a set of bitemporal

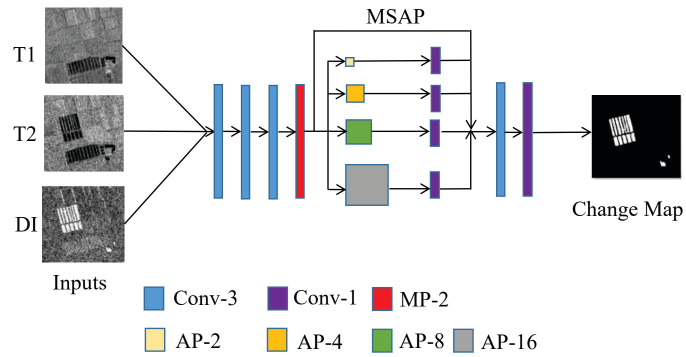


Fig. 1: The illustration of the proposed method.

SAR images, the DI is firstly generated by the neighborhood-based LR ratio [12]. Then both the bitemporal SAR images and the generated DI are taken as the input of the MSAP network. The goal is to elaborate the changed map from the noisy input images.

To perform efficient inference, we extract patches from the group of input images and feed the patches into the MSAP network. As shown in Fig.1, for each group of the input patches, it is sequentially followed by a batch-norm (BN) layer and three convolution layers (Conv-3), illustrated as the blue bars in the figure. The digit in 'Conv-3' indicate the sizes of the convolution kernels are 3×3. Then a max-pooling layer (MP-2) follows the convolution layers to exploit spatial context with a 2×2 kernel as illustrated by a red bars.

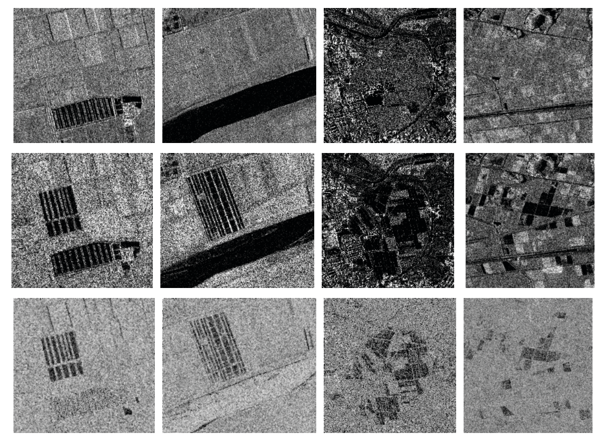
Following the MP-2, a MSAP layer is developed to further exploit the spatial context with various scales of receptive fields. To achieve this, the MSAP layer is designed as a group of parallel convolution layers with the kernel sizes of 2×2, 4×4, and 8×8, which are denoted by AP-2, AP-4 and AP-8 and illustrated by various sizes and colors of blocks, respectively. The spatial context information obtained by the MSAP is integrated into a tensor with multiple channels, followed by a deconvolutional layer recovering the feature maps as the same size as the input patches. In this process, the spatial context obtained by the MSAP will be propagated to pixel levels [13].

As shown above, the proposed network is a lite and shallow one and the most importantly, we exploit the spatial context at the variety of scales by a MSAP layer instead of a fixed size of pooling layer, which reduces the depth of the network.

2.2. Network Training

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] . In this paper, we totally randomly draw 20% samples for training including changed and unchanged category, among which there are 50% the boundary samples.

Moreover, the patchsize of each sample is set as 32×32 and 8 samples are fed in each training step. Additionally, the Adam algorithm [14] is employed to optimize the weights of network in the training stage, where the initial learning rate is set as 0.005. 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.



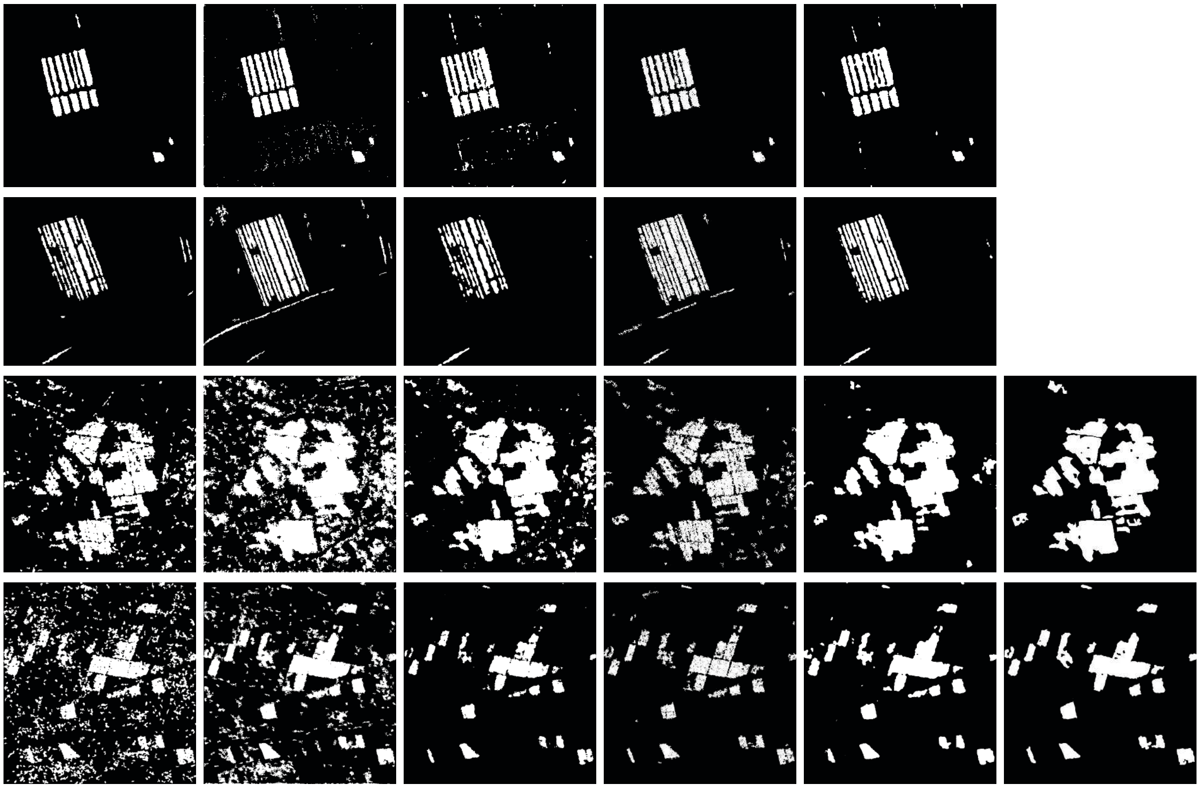
(a) YR-A (b) YR-B (c) Sendai-A (d) Sendai-B

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

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 [15]. 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)[8], the supervised PCA-Net (S-PCA-Net) [9] which achieve the state-of-arts performance on SAR image change detection. We also compare the proposed method with the deep neural network (DNN) method [7] and CNN [16]. Among these methods, DNN and U-PCA-Net are unsupervised methods,while S-PCA-Net, CNN and PSP-Net are supervised ones. The performance of the compared methods is evaluated by probabilistic missed alarm (pMA), probabilistic false



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

Fig. 3: The visual comparison experiments.

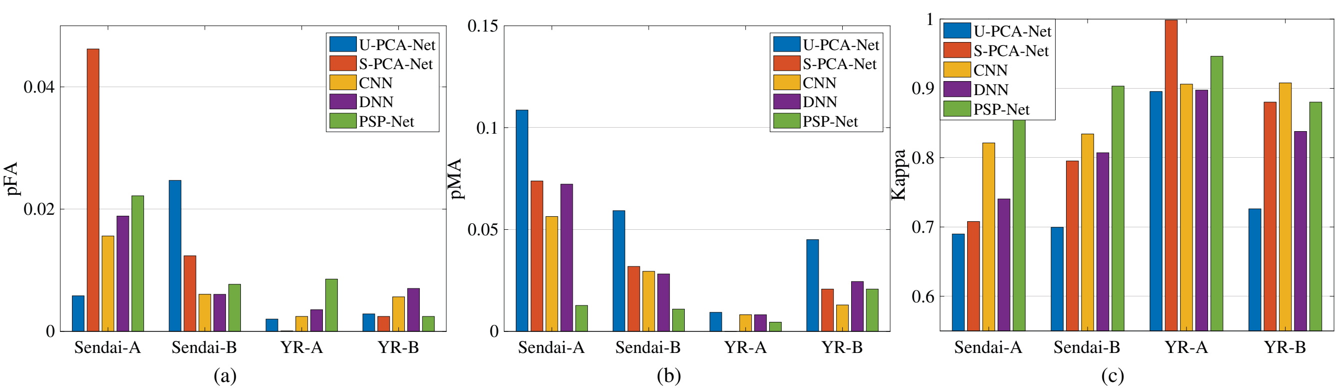


Fig. 4: The comparisons of quantitative evaluations.

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 Sendai-A, Sendai-B and YR-A datasets.

4. CONCLUSION

In this paper, a novel spatial metric learning method has been developed for bitemporal SAR images change detection, where spatial context was considered in building the constraint pairs to reduce the effects of speckle and compensate for unavoidable registration errors. Then the constraint pairs are fed into a metric learning model to train a PSD metric matrix based the max-margin criterion. 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

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