A Novel Change Detection Method of Urban Area Based on Res-UNet with Coherence and Intensity Characteristics of SAR Image Time-Series

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Abstract

Change detection (CD) is to quantitatively analyze and determine the characteristics and process of earth surface change based on remote sensing data in different periods. It is widely used in disaster dynamic detection, urban planning and other fields. With the impact of globalization, Urban change detection analysis provides an effective technological significance for land use and land cover monitoring. In this study, we focus on exploring a new urban change detection method with SAR image time-series and deep learning method. Speckle noise is an inherent problem of SAR images. It greatly influences the performance of change detection using SAR images. The study proposes a change detection method based on an end-to-end U-Net with residual blocks(Res-UNet) model, in which the residual blocks can avoid the gradient disappearance and gradient explosion caused by the deepening of the network[1], and the encoding and decoding structure can improve the robustness to different levels of noise.

Keywords: Urban change detection; Data fusion; Deep learning; SAR;

1. Introduction

Traditional change detection methods are difficult to detect change areas from complex urban ground feature types. The poor generalization ability makes it impossible to get good results in most samples. Compared with traditional methods, deep learning can learn complex and deep features through large networks and are optimized quickly through backpropagation. There are already some studies of change detection based on deep learning. Liao et al.[2] proposed an unsupervised change-detection approach to detect new urban areas from multi-temporal SAR images. The novelty of the proposed approach is the joint use of coherence and intensity characteristics of SAR imagery. In [3], a dual stream U-Net was proposed for the fusion of SAR and optical data. Sun et al.[4] substituted the convolutional layer of U-Net with Conv-LSTM to form a new architecture L-UNet. In this study, we use Res-Net blocks instead of original convolutional blocks, which can learn more in-depth features. Amplitude information and coherent information are entered into the dual stream Res-UNet model.

2. Methodology

A. Res-Unet

Network structure of Res-UNet used for this study are shown in Fig. 1. The architecture consists of an encoder and an decoder. The encoder composed of four Res-Net blocks, each followed by a max pooling operation, is used to extract change features from the input images. Res-Net block is composed of a convolution block and a skip block. Convolution block includes three sequences consisting of a 3×3 convolution (one padding and one stride), a batch normalization, and nonlinearity in the form of ReLu. Skip block includes a 3×3 convolution (one padding and one stride), a batch normalization, and nonlinearity in the form of ReLu. Convolution block and skip block are aggregated by matrix addition. The subsequent max pooling operation uses a 2 × 2 kernel with a stride of 2 (no padding) and consequently reduces its input size by a factor of 2. After extracting change features, a decoder is used to upsample the input back to its original size. The decoder is composed of four sequential blocks of a transpose convolution operation with a stride of 2, each followed by the previously described Res-Net block. Res-UNet uses skip connections between the encoder and the decoder, adding fine-grained shallow features to coarse-grained deep features for precise localization. Finally, a 1 × 1 convolution followed by a sigmoid activation function is used to create a one-band output with values between 0 and 1.

B. Dual stream Res-UNet

The Dual stream Res-UNet is composed of two separate network streams with identical architectures as shown in Fig. 2. The dual stream concept is used to process the SAR intensity images (PWR) and coherence maps (CM) in parallel and then fuse extracted features from different data sources at the final decision stage.

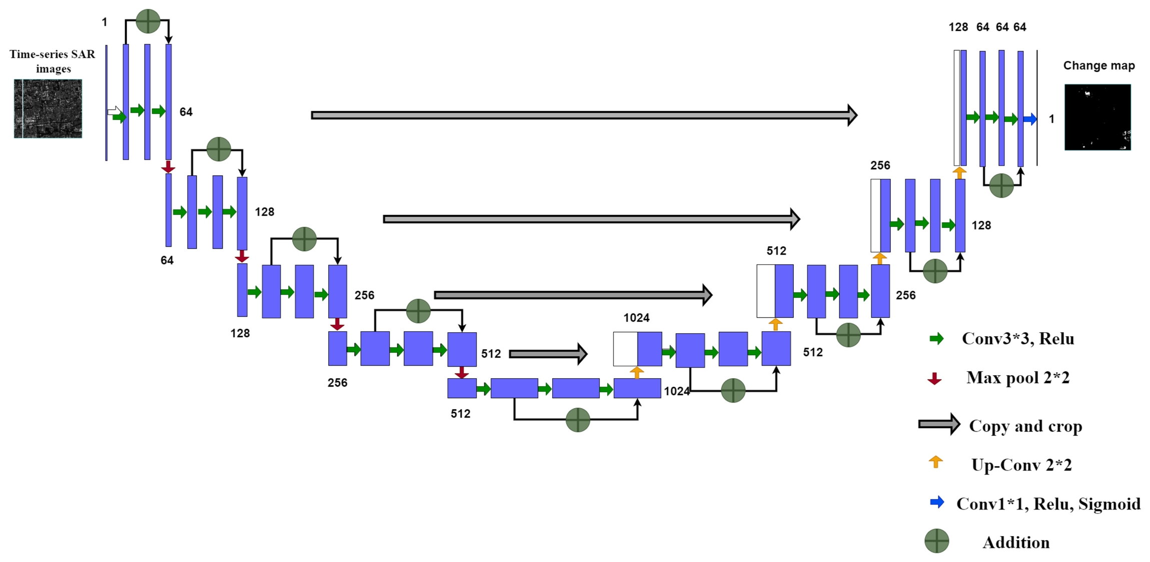

Fig. 1. Network structure of Res-UNet

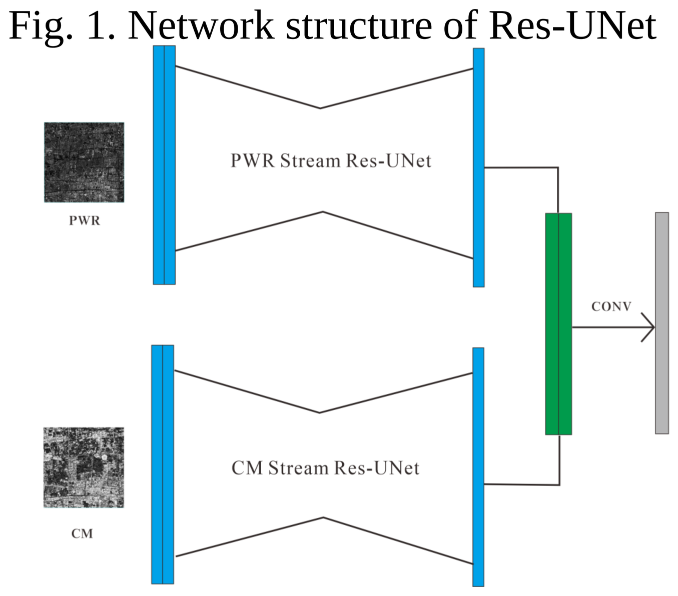

Fig. 2. Network structure of the dual stream Res-UNet. PWR and CM enter the same model with different channel

3. Experiments and results

A. SAR images

This study uses high-resolution TerraSAR-X(TSX) time-series images covering Shanghai. It contains 10 SAR images with a size of 512 × 512. The acquisition time of TSX datasets is from 16 October 2015 to 19 August 2016. Before training the network, we pre-process TSX images to get amplitude information and coherent information. Amplitude information is obtained by pre-processing single look complex (SLC) images, including radiometric correction, multilooking processing and geocoding. Coherent information is obtained by performing interferometry and computing coherence values of interferograms. PWR and CM are shown in Fig. 3.

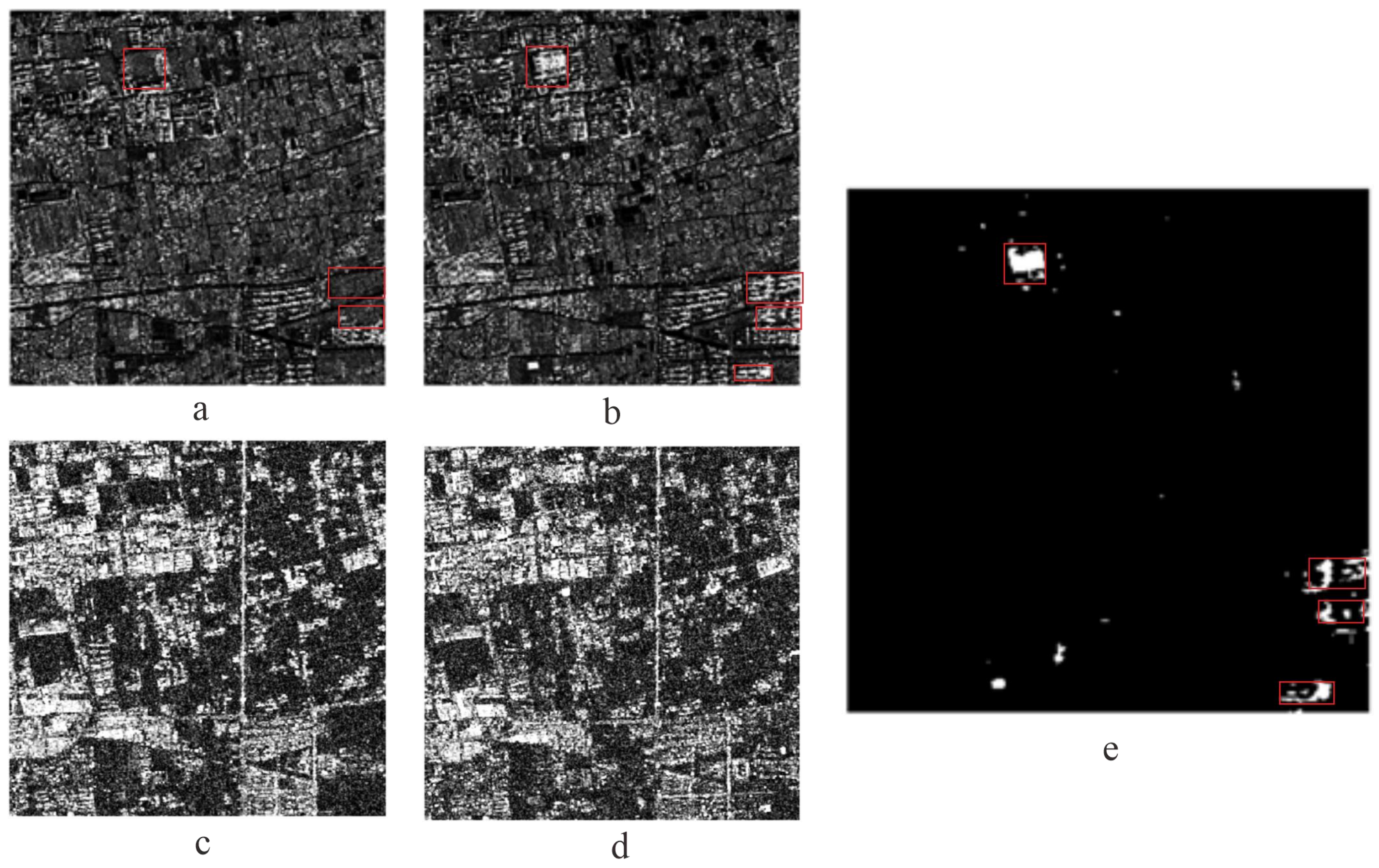

Fig. 3. Data set #1. (a)Pre-event SAR intensity image. (b)Post-event SAR intensity image. (c)Pre-event coherence map. (d)Post-event coherence map. (e) Ground-truth image

B. Result and Accuracy

In this poster, two methods are compared with the proposed Res-UNet. One is conventional U-Net. The other is U^2-Net method, a state-of-the-art supervised change detection method for high-resolution remote sensing images. The U^2-Net method substitutes convolution block with U-Net blocks. It can extract more image features, but the complexity and computation of the network structure will increase greatly. The change detection results are shown in Fig. 4. The results of Res-UNet show better performance than other methods, and the use of coherence maps improves the total accuracy, as shown in Fig. 5. The precision, F1-Score and Accuracy of dual stream Res-UNet are 85.3%, 83.9% and 99.6%, which have the best results. Although the recall of dual stream Res-UNet is a little smaller than that of U-Net, it can still obtain a good accuracy. Therefore, the proposed network architecture is effective in learning multivariate data and fusing their characteristics.

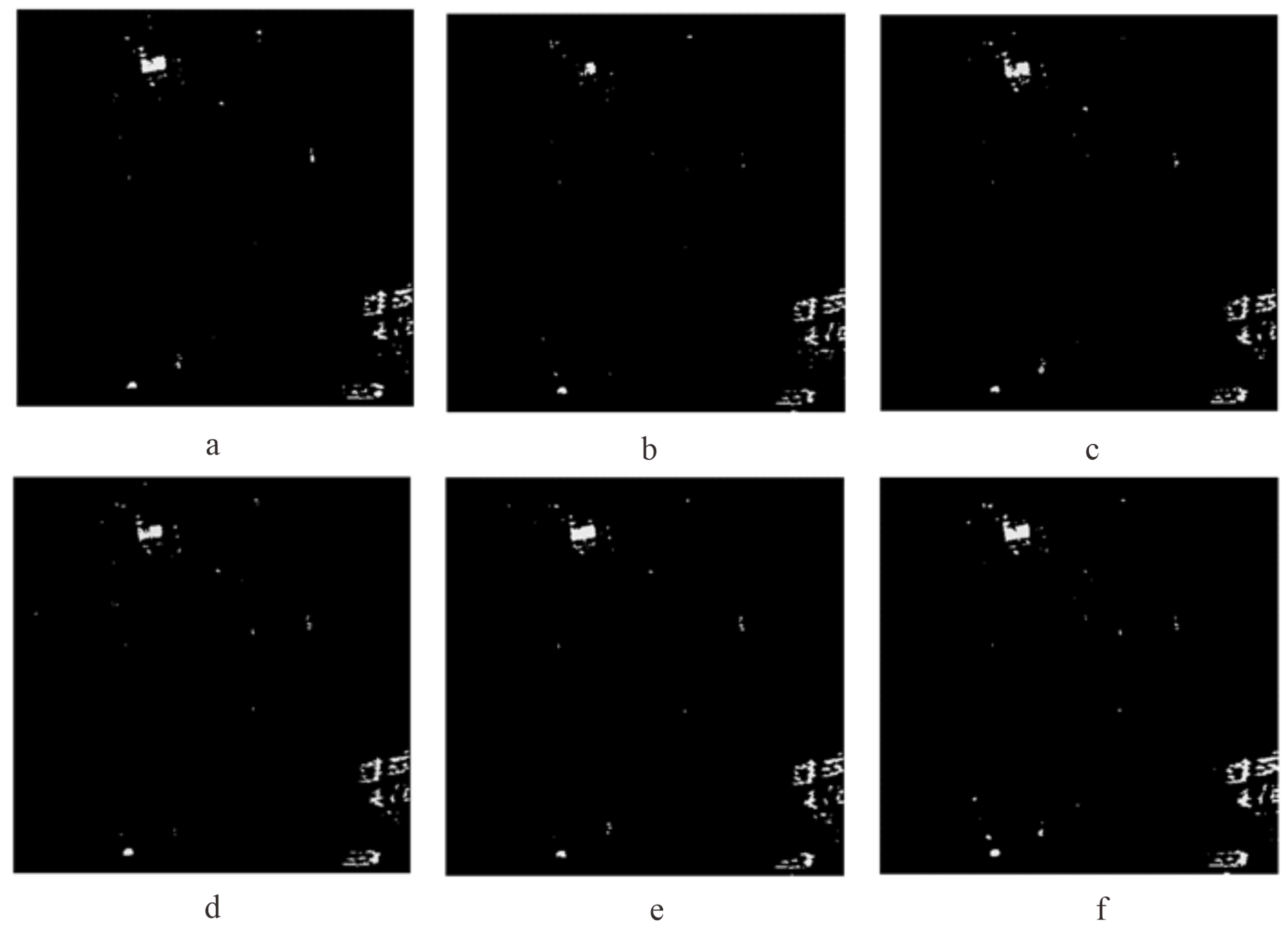

Fig. 4. Change detection result of dataset #1. (a), (c) and (e) are U-Net, U^2-Net , Res-UNet prediction results respectively, backscatter intensity images as input data. (b), (d), (f) are U-Net, U^2-Net , Res-UNet prediction results respectively, backscatter intensity images and coherence maps as input data

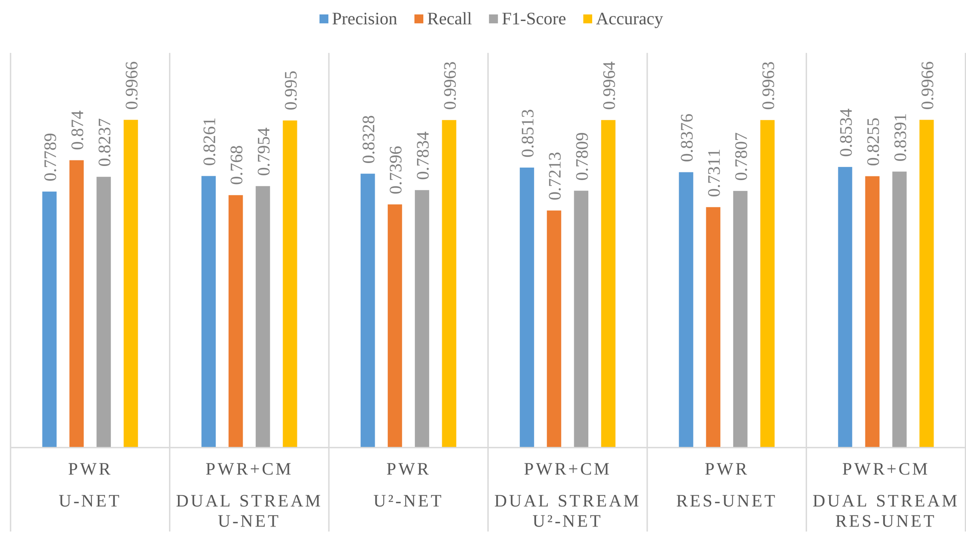

Fig. 5. Comparisons of detection methods based on dataset #1. PWR and PWR+CM represent the different sources of input data

4. Conclusion

In this work, we presented an urban change detection approach that uses a network architecture for the joint use of PWR and CM data. Different from other change detection experiments, this study utilizes CM data that can judge whether the ground objects have changed. Compared with non-artificial objects, urban buildings have very high phase stability characteristics, so the interference coherence provides very reliable information for urban change detection. Besides, for coherent images with long time intervals and short spatial vertical baseline conditions, urban buildings can still maintain high coherence. On the contrary, non-artificial objects may be completely decoherent due to the influence of temporal decoherence. Therefore, SAR coherent information can be introduced into urban change detection. The Dual Stream Res-UNet model aggregates the information of both and extract their features in order to train the network effectively. The results show that the method is reliable in urban change detection and performs better than other advanced change detection methods. Its Precision, Recall, F1-Score and Accuracy reach 85.3%, 82.6%, 83.9% and 99.6% respectively.

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