remote sensing

Editorial

Synthetic Aperture Radar (SAR) Meets Deep Learning

Tianwen Zhang [1], Tianjiao Zeng [2,3] and Xiaoling Zhang [1,*]

1 School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China
2 Electrical and Electronic Engineering, University of Hong Kong, Hong Kong 999077, China
3 School of Aeronautics and Astronautics, University of Electronic Science and Technology of China, Chengdu 611731, China
* Correspondence: xlzhang@uestc.edu.cn

1. Introduction

Synthetic aperture radar (SAR) is an important active microwave imaging sensor. Its all-day and all-weather working capacity makes it play an important role in the remote sensing community. Since the launch of the first SAR satellite by the United States [1], SAR has received extensive attention in the remote sensing community [2], e.g., geological exploration [3], topographic mapping [4], disaster forecast [5,6], and marine traffic management [7–10]. Therefore, it is valuable and meaningful to study SAR-based remote sensing applications [11].

In recent years, with the rapid development of artificial intelligence, deep learning (DL) [12] has been applied to all walks of life, such as face recognition, automatic driving, search recommendation, internet of things, and so on. The DL represented by convolutional neural network (CNN) is promoting the evolution of many algorithms and the innovation of advanced technologies. At present, scholars are exploring the application value of DL in SAR remote sensing field. Many SAR remote sensing application technologies based on DL have emerged, such as land surface change detection, ocean remote sensing, sea-land segmentation, traffic surveillance and topographic mapping.

Aiming to promote the application of DL in SAR, we initiated this Special Issue and collected a total of 14 papers (including 12 articles, 1 review and 1 technical note) covering various topics, e.g., object detection, classification and tracking, SAR image intelligent processing, data analytics in the SAR remote sensing community and interferometric SAR technology. The overview of contribution is in the following section.

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2. Overview of Contribution

On the topic of object detection, classification and tracking, Li et al. [13] summarized the dataset, algorithm, performance, DL framework, country and timeline of DL-based ship detection methods. They analyzed the 177 published papers about DL-based SAR ship detection and attempted to stimulate more research in this field. Xia [14] proposed a visual transformer framework based on contextual joint-representation learning referred to as CRTransSar. CRTransSar combined the global contextual information perception of transformers and the local feature representation capabilities of convolutional neural networks (CNNs). It was found to produce more accurate ship detection results than other most advanced methods. Note that the authors also released a larger-scale SAR multiclass target detection dataset called SMCDD. Feng et al. [15] established a lightweight position-enhanced anchor-free SAR ship detection algorithm called LPEDet. They designed a lightweight multiscale backbone and a position-enhanced attention strategy for balancing detection speed and accuracy. The results showed that their method achieved a higher detection accuracy and a faster detection speed than other state-of-the-art (SOTA) detection methods. Xu et al. [16] presented a unified framework combining triangle distance IoU loss

(TDIoU loss), an attention-weighted feature pyramid network (AW-FPN), and a Rotated-SARShip dataset (RSSD) for arbitrary-oriented SAR ship detection. Their method showed superior performance on both SAR and optical image datasets, significantly outperforming the SOTA methods. Xiao et al. [17] proposed a simple, yet effective, self-supervised representation learning (Lite-SRL) algorithm for the scene classification task. Note that they successfully evaluate the on-board operational capability of Lite-SRL by transplanting Lite-SRL to the low-power computing platform NVIDIA Jetson TX2. Kačan et al. [18] explored object classification on a raw and a reconstructed Ground-based SAR (GBSAR) data. They revealed how processing raw data provides overall better classification accuracy than processing reconstructed data, and revealed the value of this method in industrial GBSAR applications where processing speed is critical. Bao et al. [19] proposed a guided anchor Siamese network (GASN) for arbitrary targets of interest (TOI) tracking in Video-SAR. GASN used a matching function for returning the most similar area, followed by a guided anchor subnetwork to suppress false alarms. GASN realized the TOI tracking with high diversity and arbitrariness, outperforming SOTA methods.

On the topic of SAR image intelligent processing, Tan et al. [20] proposed a feature-preserving heterogeneous remote sensing image transformation model. Through decoupling network design, the method enabled enhancing the detailed information of the generated optical images and reducing its spectral distortion. The results in SEN-2 satellite images revealed that the proposed model has obvious advantages in feature reconstruction and the economical volume of the parameters. Zhang et al. [21] proposed a self-supervised despeckling algorithm with an enhanced U-Net called SSEUNet. Unlike previous self-supervised despeckling works, the noisy-noisy image pairs in SSEUNet were generated from real-world SAR images through a novel generation training pairs module, making it possible to train deep convolutional neural networks using real-world SAR images. Finally, experiments on simulated and real-world SAR images show that SSEUNet notably exceeds SOTA despeckling methods. Habibollahi et al. [22] proposed a DL-based change detection algorithm for bi-temporal polarimetric SAR (PolSAR) imagery called TCD-Net. In particular, this method applied three steps as follows: (1) pre-processing, (2) parallel pseudo-label training sample generation based on a pre-trained model and the fuzzy C-means (FCM) clustering algorithm, and (3) classification. TCD-Net could learn more strong and abstract representations for the spatial information of a certain pixel, and was superior to other well-known methods. Fan et al. [23] proposed a high-precision, rapid, large-size SAR image dense-matching method. The method mainly included four steps: down-sampling image pre-registration, sub-image acquisition, dense matching, and the transformation solution. The experimental results demonstrated that the proposed method is efficient and accurate, which provides a new idea for SAR image registration. Zhang et al. [24] proposed A low-grade road extraction network Based on the fusion of optical and SAR images at the decision level called SDG-DenseNet. Furthermore, they verified that the decision-level fusion of road binary maps from SAR and optical images can significantly improve the accuracy of low-grade road extraction from remote sensing images.

On the topic of data analytics in the SAR remote sensing community, Wangiyana et al. [25] explored the impact of several data augmentation (DA) methods on the performance of building detection on a limited dataset of SAR images. Their results showed that geometric transformations are more effective than pixel transformations and DA methods should be used in moderation to prevent unwanted transformations outside the possible object variations. The study could provide potential guidelines for future research in selecting DA methods for segmentation tasks in radar imagery.

On the topic of interferometric SAR technology, Pu et al. [26] proposed a robust least squares phase unwrapping method called PGENet that works via a phase gradient estimation network based on the encoder–decoder architecture for InSAR. Experiments on simulated and real InSAR data demonstrated that PGENet outperformed the other five well-established phase unwrapping methods and was robust to noise.

3. Conclusions

Recently, as many SAR systems have been put into use, massive SAR data are available, providing important support for exploring how to apply DL to SAR fields. A large number of SAR data coupled with the DL methodology jointly promote the development of SAR fields. The Special Issue shows innovative applications in object detection, classification and tracking, SAR image intelligent processing, data analytics in the SAR remote sensing community and interferometric SAR technology. There is no doubt that applying DL to more SAR fields (such as terrain classification, SAR agriculture monitoring, SAR imaging algorithm updating, SAR forest applications, marine pollution, etc.) is of great significance for earth remote sensing. In addition, we welcome scholars who are interested in applying DL to SAR to contribute to the scientific literature on this subject.

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