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# Artificial Intelligence (AI)-Based Radar Signal Processing and Radar Imaging

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## 1. Introduction to Artificial Intelligence (AI)-Based Radar Signal Processing and Radar Imaging

In recent years, artificial intelligence (AI), especially deep learning, has led to remarkable achievements in image recognition, speech recognition, autonomous driving and many other fields. In the field of radar signal processing, more and more researchers are trying to use deep learning algorithms to solve problems related to radar signal processing, such as radar jamming/clutter recognition and suppression, radar waveform and array design, radar imaging, and automatic target recognition.

(1) Radar jamming/clutter recognition and suppression. With the continuous progress of deceptive active jamming technology, traditional anti-jamming technology cannot guarantee the normal operation of radars under jamming conditions. In light of this, scholars have carried out a series of anti-jamming studies based on deep learning, mainly including jamming signal recognition [1], target recognition under jamming conditions [2], and adaptive anti-jamming strategy optimization [3]. At the same time, the deep learning algorithm provides technical support for suppressing the sea surface and ground clutter. Related research includes target detection in the environment of sea clutter [4] and ground clutter [5].

(2) Radar waveform and array design. In terms of radar waveform and array design, deep learning is mainly used for the following purposes: (1) Transmitting power spectrum design for spectrum sharing, in which the most representative result of this research is of non-interference spectrum interval screening and radar waveform adaptive adjustment technology developed by the DEVCOM laboratory [6]; (2) optimization of MIMO radar transmitting waveform design; and (3) antenna array design, in which the main research focus is MIMO radar design and optimization of sub-array [7].

(3) Automatic target recognition. Deep learning-based radar automatic target recognition technology can mainly be divided into the following categories: (1) automatic target recognition (ATR) based on SAR images [8]; (2) target recognition based on high-resolution range profiles, mainly including the identification of aircraft [9], ground vehicles [10] and ship targets [11]; (3) target identification based on micro-Doppler features, such as human target action recognition [12] and UAV/bird screening [13]; (4) automatic target recognition based on other information (such as target radar cross-section [14]).

(4) Radar imaging. The study of deep learning for radar imaging was first proposed in [15]. The Yazici team designed a recursive autoencoder network structure of the iterative shrinkage threshold algorithm (ISTA) in an optimized manner. This recursive autoencoder network structure has a faster convergence rate and fewer reconstruction errors than ISTA. The radar systems currently used in deep learning for target imaging are 2-D turntable imaging [16], 2-D inverse synthetic aperture radar (ISAR) imaging [17], multiple input and multiple output (MIMO) imaging [18], through-the-wall radar imaging [19], Terahertz

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**Citation:** Feng, W.; Hu, X.; He, X. Artificial Intelligence (AI)-Based Radar Signal Processing and Radar Imaging. *Electronics* **2024**, *13*, 4251. https://doi.org/10.3390/electronics13214251

Received: 16 October 2024
Accepted: 23 October 2024
Published: 30 October 2024

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coded-aperture imaging (TCAI) [20], interferometric ISAR imaging [21], and synthetic aperture radar ground-moving target indication (SAR-GMTI) [22].

## 2. Overview of This Special Issue

This Special Issue, "Artificial Intelligence (AI)-Based Radar Signal Processing and Radar Imaging", attracted the interest of many researchers in the field, and after a double-blind review process, twelve high-quality papers were selected for publication. In this section, a brief overview of these contributions is provided, allowing the reader to explore them in more detail.

The first contribution, by Geng Chen et al., proposes a fast phase-only beamforming algorithm for frequency diverse array multiple-input–multiple-output radar systems. The Kronecker decomposition is used to decompose the desired phase-only weight vector into phase-only transmit and receive weight vectors and decompose the target steering vector into transmit and receive steering vectors. The transmit and receive steering vectors and the transmit and receive weight vectors with the Vandermonde structure are decomposed into Kronecker factors with uni-modulus vectors, respectively. Furthermore, the Kronecker factors are divided into two parts—the interference suppression factors and the signal enhancement factor—to maintain the mainlobe gain and form a deep null at the desired position. The phase-only weights, which effectively form a deep null at the desired position, can be obtained by the proposed strategy.

The second contribution to this Special Issue is a paper by Peng et al. which proposes a synthetic aperture radar (SAR) imaging and detection model of multiple targets at the maritime scene. The sea surface sample is generated according to the composite rough surface theory. The SAR imaging model is constructed based on a hybrid EM calculation approach with the fast ray tracing strategy and the modified facet Small Slope Approximation (SSA) solution. Numerical simulations are performed to calculate the EM scattering and the SAR imaging of multiple cone targets above the sea surface, and the scattering mechanisms are analyzed and discussed. A modified YOLO-v7 neural network with the Spatial Pyramid Pooling Fast Connected Spatial Pyramid Convolution (SPPFCSPC) module, convolutional block attention module (CBAM), modified Feature Pyramid Network (FPN) structure and extra detection head is developed. The results show that the proposed method has a good performance in detecting the targets in complex backgrounds.

The third contribution is an article by Qingkuan Wang et al. that proposes a fast facet-based SAR imaging model to simulate the SAR images of non-cooperative aircraft targets. The scattering coefficient of each facet on the target and rough surface is obtained by combining the iterative physical optics and the Kirchhoff approximation. Next, the radar echo signal of an aircraft target above a rough surface environment is generated, and the SAR images are simulated. A SAR image target detection model is built by combining the YOLO-v5 network with the convolutional block attention module (CBAM) and another detection head. The simulation results demonstrate an obvious improvement in precision.

The fourth contribution is a paper by Xiaoge Wang et al. that proposes a novel interference suppression method based on echo preprocessing to address the smeared spectrum (SMSP) interference. The authors begin by analyzing the pulse compression (PC) and the coherent integration (CI) characteristics of SMSP interference. Then, echo preprocessing and interference suppression are introduced and described in detail. Finally, the SMSP interference is suppressed. Because the proposed method does not involve filtering and reconstruction processing, the energy of the true target is not lost.

The fifth contribution to this Special Issue is a paper by Yongzhe Zhu et al., in which the authors conduct an in-depth analysis of two typical smart noise jamming methods: noise convolution jamming methods and noise product jamming methods. The distribution characteristics of the two jamming methods in both time–frequency dimensions and their internal time–frequency relationships are analyzed. Based on this, a self-defense smart noise jamming suppression method based on pulse frequency stepping is proposed. This method obtains the true distance information of the target based on the phase difference caused by

frequency stepping between adjacent pulses and uses this information to construct a filter for the radar echo, achieving jamming suppression. The effectiveness of this method was verified by simulations.

The sixth contribution of the Special Issue is a paper by Bo Zou et al. that introduces an airborne radar STAP method based on deep unfolding and convolutional neural networks. CNN is used to reduce the requirements of SR algorithms for parameter setting and iterations, increasing their accuracy, and the clutter space–time spectrum obtained by SR is used to reduce the network scale of CNN. Based on the idea of deep unfolding (DU), the SR algorithm is unfolded into a deep neural network, whose optimal parameters are obtained by training to improve its convergence performance. On this basis, the SR network and CNN are trained end-to-end to estimate the clutter space–time spectrum efficiently and accurately. The results of the simulations and experiments show that the proposed method can improve the clutter suppression performance and has a lower computational complexity.

The seventh contribution to this Special Issue is a research article by Ninghui Li et al. It introduces a novel wideband DOA estimation approach utilizing a hierarchical prior based on variational Bayesian inference. To significantly enhance sparsity, the authors propose a novel hierarchical Bayesian prior framework and deduce a novel iterative approach. It is discovered that the iterative approach has a lower computational complexity than most of the existing state-of-the-art algorithms. The proposed approach also achieves a high angular estimation accuracy and sparsity performance by utilizing the joint sparsity of the multiple measurement vector (MMV) models and stabilizes the estimated values between different frequencies or snapshots to obtain a flat spatial spectrum.

The eighth contribution is an article by Huixu Dong et al. that proposes an algorithm for sorting staggered pulse repetition interval (PRI) signals based on the congruence transform. The proposed algorithm transforms the arrival time of the pulse to a fixed value, based on which the staggered PRI signal sorting and the sub-PRI sequence extraction can be achieved. The simulation results show that the proposed algorithm can effectively sort the staggered PRI signals and obtain the sub-PRI sequence directly without sub-PRI ranking, and compared to some typical algorithms, it is less affected by the interfered pulses and the pulse loss.

The ninth contribution to this Special Issue is an article by Zhipeng Liao et al. that introduces an end-to-end robust adaptive beamforming (RBF) approach that utilizes a two-stage convolutional neural network. The first stage includes convolutional blocks and residual blocks without downsampling. The blocks assess the covariance matrix with precision using finite snapshots. The second stage maps the first stage's output to an adaptive weight vector employing a similar structure to the first stage. The two stages are pre-trained with different datasets and fine-tuned as an end-to-end network, simplifying the network training process. The two-stage structure enables the network to possess practical physical meaning, allowing for a satisfying performance even with a few snapshots in the presence of array gain/phase errors.

The tenth contribution to this Special Issue is a paper by Jieyu Huang et al. A joint power and bandwidth allocation algorithm in a collocated MIMO radar based on the quality of service (QoS) framework is proposed for the multi-target tracking problem with different threat levels. Firstly, a posterior Cramer–Rao lower bound (PCRLB) concerning the power and bandwidth is derived. Next, the optimal objective functions of power and bandwidth are designed based on the QoS framework, and the problem is solved using the convex relaxation technique and the cyclical minimization algorithm. The results show that the proposed algorithm has better tracking accuracy and achieves more reasonable resource allocation compared to strategies such as average allocation.

The eleventh contribution is an article by Yongzhe Zhu et al. that proposes a method for suppressing false target jamming with non-uniform stepped-frequency radar. The authors derive the correlation between the phase difference of adjacent pulses and range information and the Doppler frequency when the frequency is uniformly stepped, as well

as the error caused by the Doppler frequency in range estimation. Then, a decoupling method based on waveform design and the corresponding suppression method of range false target jamming are proposed. The simulation results show that the proposed method can effectively suppress the jamming of self-defense range false targets.

Finally, the twelfth contribution to the special issue is a paper by Ziyi Li et al. that uses a cycle-consistency generative adversarial network (CycleGAN) to suppress clutter for millimetre-wave radar. In an unsupervised learning way, their proposed method converts the cluttered range-angle image into a clutter-free one. The generator of CycleGAN is used as the feature extraction network for object detection. The authors use the public dataset CRUW to evaluate their proposed method and compare it with traditional methods and existing deep learning methods. The experimental results show that their proposed method can ensure the integrity and consistency of the target response while effectively removing clutter.

## 3. Conclusions

The Guest Editors of this Special Issue believe that AI-based radar signal processing and radar imaging will remain at the epicenter of scientific interest, and hope that this collection of articles will be helpful to scientists who focus their research efforts on this challenging domain.

**Author Contributions:** Conceptualization, W.F.; writing—original draft preparation, X.H. (Xiaowei Hu); writing—review and editing, W.F. and X.H. (Xingyu He). All authors have read and agreed to the published version of the manuscript.

**Funding:** This work is supported in part by the Youth Talent Lifting Project of the China Association for Science and Technology No. 2021-JCJQ-QT-018 and The Youth Innovation Team of Shaanxi Universities.

**Acknowledgments:** The Guest Editors of this Special Issue sincerely thank all the scientists who submitted their research articles, the reviewers who assisted in evaluating these manuscripts, and both the Editorial Board Members and the Editors of *Electronics* for their overall support.

**Conflicts of Interest:** The authors declare no conflicts of interest.

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