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DEEP LEARNING MITIGATION OF SEA CLUTTER FOR ENHANCED RADAR TARGET DETECTION

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ABSTRACT

This research provides a detailed examination of how deep learning significantly improves radar accuracy. By integrating advanced simulations with real-world tests, the study demonstrates how deep learning enhances the removal of sea clutter, substantially improving target detection in Constant False Alarm Rate (CFAR) algorithms. The results clearly show that deep learning is not just advantageous but critical for advancing radar performance, ensuring a new level of precision and reliability in maritime identification and tracking. The paper highlights deep learning as an essential tool for dealing with the complexities of sea clutter in radar systems. It goes beyond simple improvements, redefining accuracy in target detection and affirming the strength and reliability of radar operations in the chaotic maritime environment. The comprehensive methodology and solid empirical evidence presented emphasize the revolutionary impact of deep learning, marking the beginning of a new chapter in radar technology characterized by unmatched precision, adaptability, and reliability.

KEYWORDS: Convolutional Neural Network; constant false alarm rate; cell under test; clustering algorithm.

التعلم العميق للتخفيف من فوضى البحر لتحسين كشف الأهداف بالرادار

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الملخص

يقدم هذا البحث تحليلاً شاملاً لكيفية تحسين التعلم العميق بشكل كبير لدقة أنظمة الرادار. من خلال دمج المحاكاة المتقدمة مع الاختبارات العملية، يُظهر البحث كيف يُسهم التعلم العميق في تقليل تشويش البحر بفعالية، مما يعزز من كفاءة كشف الأهداف في خوارزميات معدل الإنذار الخاطئ الثابت (CFAR). النتائج تُبرز بوضوح فائدة التعلم العميق في تطوير أداء الرادار، مؤكدةً تحقيق مستوى جديد من الدقة والموثوقية في التعرف والتتبع البحري. تُسلط الورقة الضوء على التعلم العميق كأداة رئيسية لمواجهة تعقيدات فوضى البحر في أنظمة الرادار. يفوق التحسين المعتاد، إذ يُعيد تعريف معايير الدقة في كشف الأهداف ويؤكد على قوة وموثوقية عمليات الرادار في البيئة البحرية الفوضوية. المنهجية المنظمة والأدلة العملية القوية التي نقدمها تُبرز الأثر الكبير للتعلم العميق، ممهدةً الطريق لعهد جديد في تكنولوجيا الرادار يتسم بدقة فائقة، قدرة على التكيف، وموثوقية عالي.

الكلمات المفتاحية : شبكة عصبية تلافيفية، معدل إنذار خاطئ ثابت، الخلية قيد الاختبار، خوارزمية التجميع.

1. INTRODUCTION

Marine environment monitoring is essential for understanding marine ecosystems, ensuring their protection, and maintaining marine security. In modern times, a wide range of sensor technologies such as radar, infrared, and optical sensors, create a comprehensive system for ocean surface surveillance. Among these, marine surveillance radar is a standout as a microwave sensor system, capable of providing consistent, all-weather observation of the sea surface. This technology is crucial for dynamic monitoring of the sea and detecting various targets, making it extremely valuable for both civilian and military marine monitoring purposes.

In the realm of marine surveillance radar systems, the presence of sea clutter poses a significant obstacle to accurately detecting sea surface targets [1], [2]. This clutter, a backscattered echo generated by the sea surface, complexly interacts with radar waves, influenced by both environmental factors and radar operational parameters [3] [4]. It particularly impairs the detection of small radar cross-section (RCS) targets, such as fishing boats and dinghies, by drastically reducing the signal-to-clutter ratio (SCR) [5]. This reduction manifests in two primary challenges: a lowered SCR leading to missed detections of small RCS targets, and in scenarios of high sea states, intense clutter echo amplitudes obscure target recognition, increasing the likelihood of false alarms. Addressing these issues is paramount for enhancing the efficacy of marine surveillance radars [6].

In the field of marine surveillance radar technology, significant advancements have been made in addressing the challenge of sea clutter, which has been a longstanding obstacle in maritime detection. This evolution is marked by the development and implementation of sophisticated techniques aimed at enhancing sea clutter suppression, effectively improving radar performance in marine environments [7].

These advancements can be broadly classified into two categories: traditional methods and those employing machine learning techniques. Traditional sea clutter suppression methods are grounded in classical signal processing. These involve analyzing radar echoes across various domains such as spatial and frequency [8], [9]. In the spatial domain, the emphasis is on using statistical models to characterize and mitigate sea clutter [10, 11]. Frequency domain techniques, on the other hand, focus on separating target signals from clutter by extracting and analyzing Doppler information, primarily through Fourier transforms and Doppler filtering. Methods like the moving target indicator and moving target detection are exemplary of this approach [12,13]. These advancements in sea clutter suppression have greatly enhanced the efficacy of marine surveillance radars. By refining detection capabilities, they enable more accurate and reliable monitoring in maritime environments, thus playing a crucial role in various naval and civilian maritime applications [14].

To enhance sea clutter suppression in radar systems, various approaches have been explored. Traditional methods based on pre-modeling often struggle with the dynamic nature of sea clutter [24]. Recent studies focus on fractal features and time-frequency analysis, but these too face challenges due to the variability in sea conditions and radar settings. This highlights the need for adaptive and innovative solutions in this field [15, 16].

The relentless advancement of artificial intelligence, notably in machine learning, has revolutionized numerous fields, including radar signal processing. Sea clutter, an omnipresent challenge in maritime radar systems, significantly hampers the detection of real targets [17, 18]. Traditional methods, while effective to a degree, have struggled to cope with the dynamic and complex nature of sea clutter. Recognizing this, recent research has pivoted towards leveraging machine learning algorithms for enhanced clutter suppression [19, 20].

Early attempts in this direction, as exemplified in [23], employed algorithms like k-nearest neighbors and support vector machines to demarcate the boundary between sea clutter and actual targets, marking a significant step in clutter suppression. However, these initial models, in their simplicity, encountered limitations, particularly in handling the intricacies of radar data which necessitates detailed analysis and preprocessing [21, 22].

Addressing these shortcomings, more sophisticated machine learning models have been introduced, as noted in [24]. Notable among these are the deep learning-based approaches, including the clutter suppression networks utilizing deep convolution autoencoders [33, 34] and methods employing deep convolutional neural networks [35]. These advanced techniques have demonstrated promising results, chiefly due to their ability to intricately model and mitigate the complexities of sea clutter.

Current progress in learning-based techniques for mitigating sea clutter in marine radar systems is noteworthy, showcasing significant effectiveness and potential. However, this field faces two substantial hurdles. Firstly, the dynamic and complex nature of marine environments demands a suppression method that can deeply understand and adapt to the intricate features of sea clutter. Secondly, and of equal importance, is the necessity to differentiate between crucial target echoes and sea clutter within radar signals. Given that these target signals are often sparse in comparison to the surrounding clutter, it's crucial to develop strategies that not only efficiently suppress sea clutter but also preserve essential target information. Overcoming these challenges is crucial for improving the accuracy and dependability of target detection in maritime surveillance systems.

In recent years, the development of advanced machine learning techniques has significantly revolutionized the field of image processing, particularly in the realms of denoising and clutter reduction. Here, we provide a comprehensive overview of three pioneering approaches that address unique challenges in this area.

A Fast and Flexible Denoising Network (FFDNet), a convolutional neural network designed for image denoising, epitomizes flexibility and efficiency. This model is uniquely crafted to handle different noise levels using a single model, facilitated by an adjustable noise level map as input. This feature allows for effective management of both uniform and non-uniform noise. The network architecture also incorporates a downsampling strategy to enhance training and inference speed while maintaining high-quality denoising performance. Comparative tests have established that FFDNet outperforms existing state-of-the-art methods, affirming its status as an ideal practical solution for image denoising applications [37].

Further contributing to advancements in this field, researchers have developed a deep neural network model employing a residual learning strategy to effectively separate noise from noisy observations. This model integrates batch normalization with residual learning, accelerating the training process and enhancing denoising performance. Unlike traditional discriminative models, this advanced model is capable of blind denoising and effectively handling unknown noise levels. Additionally, it demonstrates the potential to efficiently train a single model to address three general denoising tasks, showcasing its versatility and broad applicability [38].

Additionally, a new model based on Generative Adversarial Networks (GANs), specifically designed for reducing sea clutter in radar Plan Position Indicator (PPI) images, termed SCS-GAN, has been introduced. This model employs residual attention networks and a dedicated sea clutter discriminator, enhancing its clutter suppression capability while fully preserving marine targets within the images. It offers superior performance in complex maritime environments compared to previous methods, highlighting its effectiveness and innovative approach to clutter reduction [36].

Building upon foundational models, our research introduces a unique methodology that integrates Convolutional Neural Networks (CNNs) with CFAR techniques to enhance detection capabilities in maritime radar images. This approach synergistically combines CNNs and CFAR, unlike traditional methods which apply them separately, to achieve robust denoising and clutter suppression. Our study details the development of a CNN designed to filter out clutter from maritime radar PPI images, employing advanced deep learning techniques alongside various CFAR algorithms to demonstrate the impact of noise reduction on target detection accuracy in maritime surveillance systems.

In this paper, we begin by introducing Convolutional Neural Networks and their application in detection using CFAR. Following this, we delve into Data Analysis and Simulation Results, and finally, we conclude with key findings from the study and propose directions for future research.

2.1 Convolutional Neural Network (CNN)

Convolutional Neural Networks, designed for image processing and classification, consist of an architecture featuring convolutional, pooling, and output layers. The convolutional layers use filters to identify features in images, and the pooling layers reduce feature map sizes to manage computational load and avoid overfitting [31], [29]. This process culminates in the output layer, usually comprising fully connected layers, which classify the image based on these features. The structure of CNNs, including the number of layers and filters, along with key parameters such as weights and biases, is carefully determined to optimize performance as shown in the figure.

2.1.1 The training of a CNN

The training of a CNN begins with the careful selection of a diverse array of training and validation samples. This foundational step is crucial for the network to effectively learn from a wide range of data. The CNNs architecture is then initialized, including the setup of various layers, filters, and vital parameters such as weights, biases, and the learning rate. This setup is critical for determining how the network will process and interpret the input data [32].

During training, the CNNs undergoes two main stages: feedforward and backpropagation. In the feedforward phase, the network processes the input image through its layers, extracting and identifying features via convolutional and pooling operations. This leads to the generation of preliminary classification results [28]. The backpropagation stage is essential for refining the network's accuracy. Here, the CNN adjusts its parameters based on the error rate, learning from its performance and iteratively improving. This cycle of feedforward processing and error correction through backpropagation continues until the network's parameters are finely tuned. This rigorous training process is pivotal in ensuring CNN's effectiveness in complex tasks like image recognition or removing clutter [30, 27].

2.2 CFAR Detection

CFAR detection in radar signal processing is a sophisticated technique designed to distinguish targets from background noise. It involves setting a dynamic threshold for target detection to maintain a constant rate of false alarms, regardless of the varying levels of background noise [25]. This effectiveness is heightened when there's a significant contrast between the target signal and the background. The fundamental equations for CFAR include:

*False Alarm Rate (Pf): The false alarm probability is given by:

$$Pf = r\int_{0}^{T} P_B(x)dx \tag{1}$$

where r is a constant, T is the threshold, and $P_B(x)$ is the probability distribution function of the background noise.

*Detection Rate (Pd): This represents the probability of detecting the target, calculated

$$Pd = \int_{0}^{T} P_T(x)dx \tag{2}$$

where $P_T(x)$ is the target signal's probability distribution function.

*Threshold Determination: The threshold T is set such that:

$$1 - Pf = \int_{0}^{T} P_B(x)dx \tag{3}$$

In practical applications, a sliding window technique is used. This method involves moving a window across the image and applying a local threshold at each position. The local threshold for each window position is adjusted based on the statistical properties of the area within the window, ensuring the false alarm rate remains constant across different parts of the image [26].

CFAR algorithms are integral in these processes, with several variants each suited to different radar environments:

*CA-CFAR: This agorithm uses the mean of all available Reference Cells (RCs) for clutter estimation. Its simplicity, however, makes it less effective in nonhomogeneous interference environments. The key formula for the calculation of the threshold multiplier K is:

$$K = N\left(PFA^{-\frac{1}{N}} - 1\right) \tag{4}$$

Here, N is the number of RCs and PFA is the desired probability of false alarm.

*SOCA-CFAR: Suitable for target masking scenarios, it uses the smaller mean of the lagging and leading RCs. The formula for K in SOCA-CFAR is:

$$PFA = 2\sum_{k=0}^{\frac{N}{2}-1}\left(\frac{\frac{N}{2}-1+k}{k}\right)\left(2+\frac{K}{\frac{N}{2}}\right)^{-\frac{N}{2}} \tag{5}$$

This formula is designed to adaptively select the best threshold considering the target masking effect.

*GOCA-CFAR: Effective in clutter edge transition scenarios, GOCA-CFAR estimates clutter using the greater mean of the lagging and leading RCs. The formula for K is:

$$PFA = 2\left(2+\frac{K}{\frac{N}{2}}\right) - 2\sum_{k=0}^{\frac{N}{2}-1}\left(\frac{\frac{N}{2}-1+k}{k}\right)\left(2+\frac{K}{\frac{N}{2}}\right)^{-\frac{N}{2}} \tag{6}$$

This equation accounts for the abrupt changes in clutter at the edges.

*OS-CFAR: This variant improves upon CA-CFAR by using a specific rank of RCs for clutter estimation. The formula for the calculation of K in OS-CFAR is:

$$PFA = k\binom{N}{k} - B(K+N-k+1, k) \tag{7}$$

Here,k is the rank, and B denotes the beta function. This approach enhances the performance in various clutter scenarios, as shown in Fig.1.

Each of these CFAR variants employs its methodology for clutter estimation (PClutter) and threshold calcula- tion, balancing detection accuracy with computational efficiency. The algorithms dynamically adjust detection thresholds based on varying environmental conditions, involving the Cell-Under-Test (CUT), Reference Cells (RCs), and Guard Cells (GCs) in their processes. The CUT is the point of focus for testing, RCs assist in estimating interference, and GCs protect the CUT from direct interference [25].

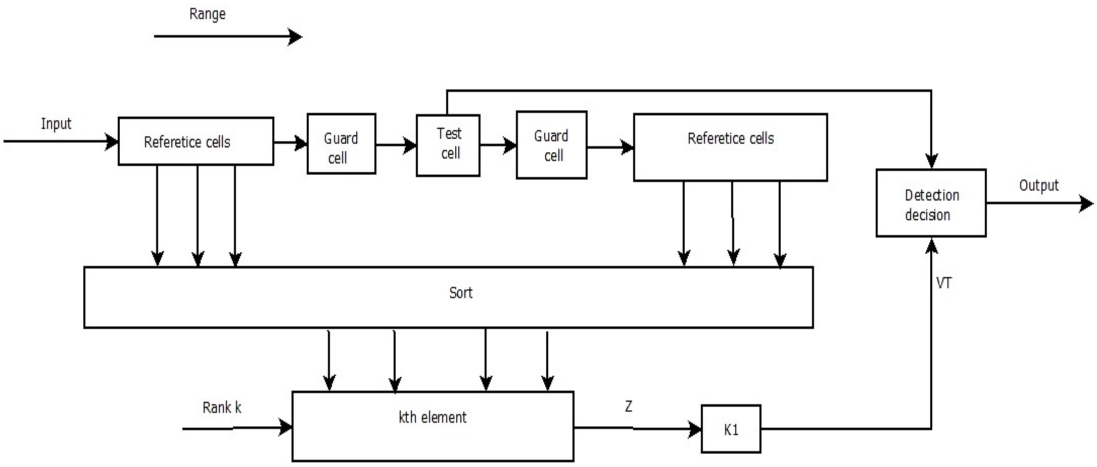

Fig.1: Block diagram of the OS-CFAR implementation

3-Data Analysis and Simulation Results

The dataset comprises 84 pairs of synthetic radar images. Each pair consists of an input image displaying sea clutter along with extended target echoes, and a corresponding target response image that exclusively highlights these target echoes. The images were crafted using radarScenario simulations, incorporating a radarTransceiver and a rotating uniform linear array (ULA), known as software-defined radar. Within each image, two different extended targets are depicted: a small container ship and a larger one. These targets are visualized using point scatterers strategically placed on the surfaces of cuboidal models to ensure they are distinguishable without any overlapping. This dataset is meticulously curated for advanced radar image analysis and interpretation, offering a rich resource for understanding complex radar imagery.

We have implemented a CNN specifically designed for image denoising. The network architecture begins with an `imageInputLayer` tailored to accommodate the spatial size of the input images (626x626 pixels), allowing for direct input of images without the need for reformatting. This is followed by a series of convolutional layers, batch normalization layers, and non-linear activation layers designed to effectively capture and process the image features necessary for denoising tasks.

The network configuration includes:

- An initial convolutional layer with a 5x5 spatial filter, set to maintain the spatial dimensions using 'same' padding and designed to handle one input channel and produce one output channel.

- Batch normalization layers follow each convolutional layer to ensure numerical stability and enhance training speed by normalizing the activations of the previous layer.

- Non-linear activation is achieved through Leaky ReLU layers with a scaling factor of 0.2, allowing small negative values to pass, which helps maintain gradient flow during training. Additionally, subsequent layers include larger 6x6 convolutional filters, increasing to four channels, designed to deepen the feature extraction process without altering spatial dimensions due to the 'same' padding.

- The final output from the convolutional stack is passed through another 5x5 convolutional layer which matches the number of output channels to the desired response, followed by batch normalization and another Leaky ReLU activation.

The output layer of the network is a `regressionLayer`, which evaluates performance using a mean-squared-error (MSE) loss function. This choice is crucial for denoising applications as it directly minimizes the pixel-wise differences between the denoised output and the clean ground truth images.

Our training strategy employs the adaptive moment estimation (Adam) solver, known for its efficiency in handling sparse gradients and its adaptive learning rate capabilities. We trained the network for a maximum of 80 epochs with a mini-batch size of 20, which balances speed and memory usage effectively. The initial learning rate was set to 0.1, and the model was trained using shuffling of data at every epoch to prevent model bias towards order-dependent features.

Table 1 displays the constant transmission and reception specifications for a maritime radar system, including frequency, antenna details, pulse information, and range coverage. While **Table 2** in the document lists the technical specifications of a radar system, including the frequency, pulse length, and the dimensions of the targets it is designed to detect. Table 3 outlines randomized parameters likely used for testing the radar's capabilities, such as varying wind speeds and target movements. These tables are essential for understanding the radar's performance characteristics in different scenarios.

Table 1: Transmission and Reception Characteristics of the Maritime Radar System

Characteristic	Value
Radar System Frequency (X-band)	10.0 GHz
Antenna Polarization	H and H
Antenna Rotation Speed	6.4 rpm
Pulse Repetition Frequency (PRF)	1000 Hz
Radar Pulse Width	80 ns
Azimuthal Range (Coverage)	0U360◦
Azimuthal Resolution	0.28◦
Distance Range (Coverage)	Standard Configuration: 200U2150 m Fast Acquisition: 150Ű1350 m
Range Resolution	7.5 m

Table 2: Radar and Target Parameters

Parameter	Value
Radar System Parameters	
Frequency	10 GHz
Pulse Length	80 ns
Range Resolution	7.5 m
PRF	1 kHz
Azimuth Beamwidth	0.28 deg
Radar Platform Parameters	
Height	55 m
Rotation Rate	50 RPM
Target Parameters	
Small Target Dimensions (LxWxH)	120 x 18 x 22 m
Large Target Dimensions (LxWxH)	200 x 32 x 58 m

Table 3: Randomized Parameters

Parameter Type	Values
Surface Parameters	-
Wind Speed	7 to 17 m/s
Wind Direction	0 to 180 deg
Target Parameters	-
Target Position	Anywhere on the surface
Target Heading	0 to 360 deg
Target Speed	4 to 19 m/s
Small Target RCS	8 to 16 m2
Large Target RCS	14 to 26 m2

Fig.2 displays the original image before clutter removal and the image after noise removal. Through these techniques, targets appear much clearer, regardless of the specific detection method applied, whether OS-CFAR or CA-CFAR. This processing is crucial for enhancing radar signal interpretation and ensuring precise target identification, proving that clutter removal using neural networks is an essential asset in radar technology.

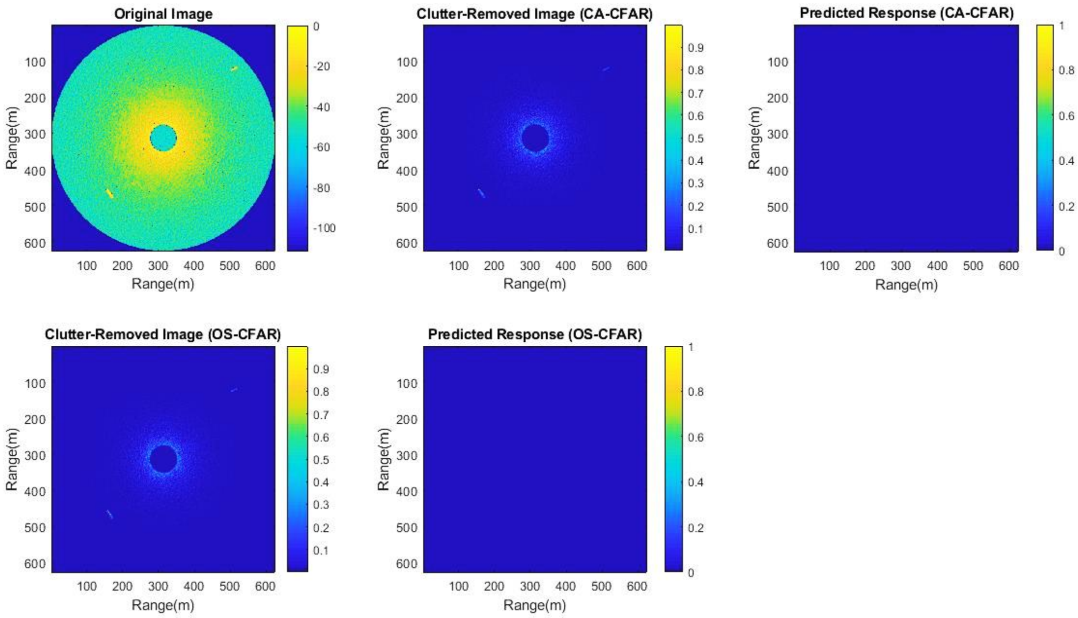

Fig.2: Original Image Before and After Clutter Removal Using CA-CFAR and OS-CFAR

This approach ensures that once the neural network is trained with this dataset, it will be effectively adaptable for the removal of marine clutter. We will conduct tests in scenarios to evaluate detection performance based on the quantity of images used for training. The first scenario involves dividing the dataset into different segments for varied purposes: images 1 to 70 are designated for the training phase, images 71 to 80 are reserved for validation, and the final four images in the set are allocated for the critical task of assessing the network's performance. This is depicted in **Fig.3**. Meanwhile, in the second scenario, the dataset is divided differently: images 1 to 60 are for training, images 61 to 70 for validation, and the last 14 images are set aside for the crucial evaluation of network performance, as shown in **Fig.4**.

Fig.3 illustrates the profound impact of clutter removal on radar image clarity and accuracy. Initially, blue data points depict the detection probability before clutter removal, revealing a near-zero likelihood due to overwhelming noise. In stark contrast, the red data points, representing the post-clutter removal state using the OS-CFAR algorithm, show a significant upward trend. As the SNR improves, the detection probability markedly increases, underscoring the effectiveness of noise mitigation. This clear trend demonstrates that with each increment in SNR, the probability of accurately detecting targets escalates, highlighting the critical role of advanced clutter removal in enhancing the performance and reliability of radar systems.

Moving on to **Fig.4**, it similarly demonstrates the positive impact of clutter removal on network performance evaluation. However, **Fig.4** is more comprehensive, presenting 14 different images related to the evaluation of network performance. These images provide a powerful visual representation of the improvement achieved through clutter removal techniques.

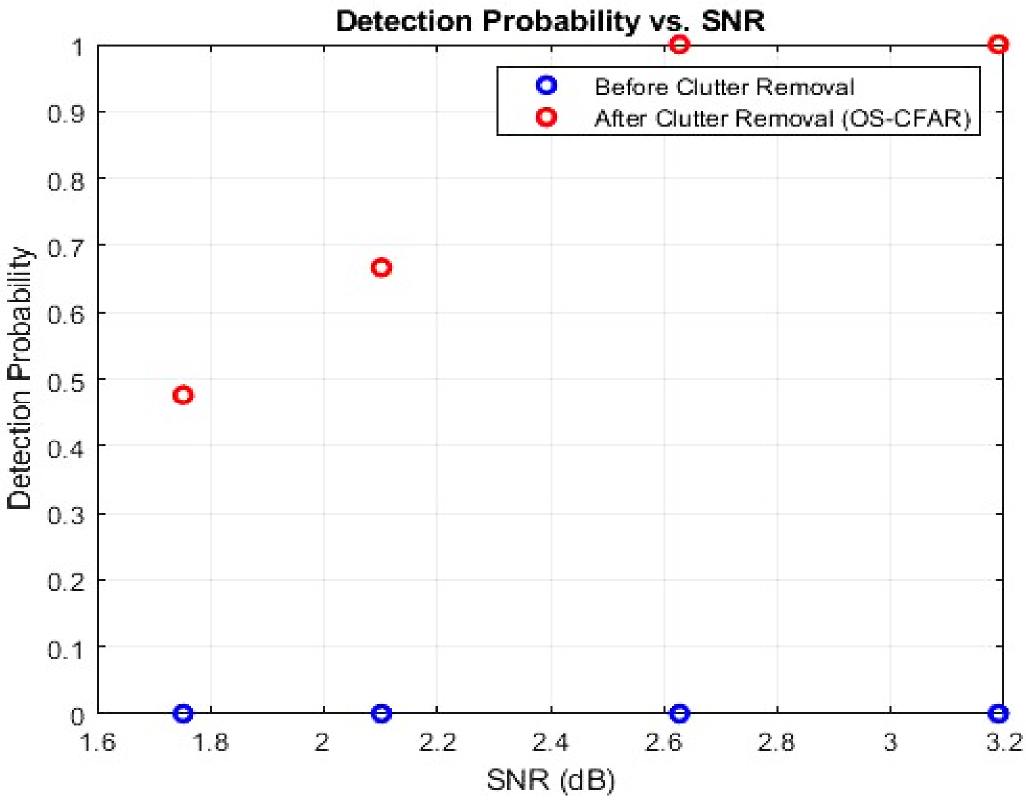

Fig.3: Detection Probability vs. SNR with OS-CFAR, 4 Images Evaluation

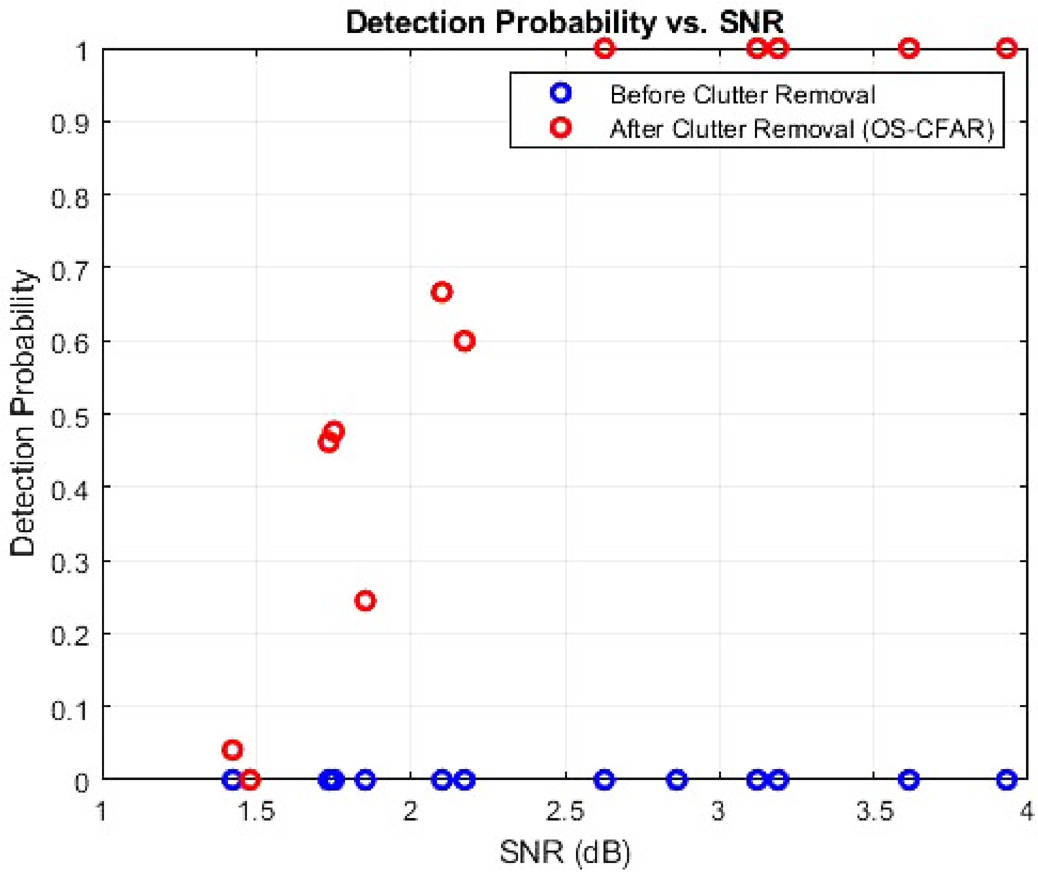

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Fig.4: Detection Probability vs. SNR with OS-CFAR, 14 Images Evaluation.

Conclusions

This research thoroughly investigated the effectiveness of deep learning in improving radar accuracy, specifically in reducing the impact of sea clutter on target detection within various CFAR methods. The study combined simulations and real-world experiments to assess how deep learning can enhance radar systems by removing sea clutter, focusing particularly on its effect on target detection.

The findings from both simulations and empirical tests revealed a significant improvement in target detection across all CFAR methods after the application of deep learning for sea clutter removal. This substantial increase in detection rates after clutter removal, compared to the rates before removal, highlights the pivotal role of neural networks, especially CNN, in advancing radar signal processing. The study not only confirms the practical use of neural networks in real-world situations but also sets the stage for their expanded application in radar image analysis. Moving forward, the research aims to apply this approach to a broader range of radar image datasets and to investigate the capabilities of various neural network models, thereby contributing to the growing field of radar image processing and the improvement of maritime surveillance systems.

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