A Sea Clutter Suppression Method Based on Machine Learning Approach for Marine Surveillance Radar

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***Abstract*—Marine surveillance radar is widely used in marine monitoring for its ability of observing sea surface all-time and all-weather. However, the radar target detection performance is seriously affected by the existence of sea clutter. In this article, we propose a new sea clutter suppression method based on machine learning approach. We first employ a cyclic structure network with a pair of generative adversarial networks to sufficiently learn the characteristics of sea clutter, which converts the problem of sea clutter suppression as a transformation from the clutter radar data domain to the clutter-free radar data domain. In addition, we propose a target-consistency loss for the cost function of the network to effectively preserve the target information while suppressing the sea clutter. Therefore, the proposed method can not only effectively remove the sea clutter from the radar data but also protect the target information from being damaged during sea clutter suppression, thereby achieving excellent sea clutter suppression performance. Experimental results have shown the superiorities of the proposed sea clutter suppression method on both simulated and measured marine surveillance radar data.**

***Index Terms*—Generative adversarial networks (GAN), machine learning, marine surveillance radar, sea clutter suppression, target-consistency loss.**

I. Introduction

MARINE environment monitoring has great research value in the fields of marine environmental awareness, marine ecological protection, and marine security defense. Nowadays, various types of sensors, such as radar, infrared, and optical sensors, constitute a complex system for all-round monitoring of sea surface. Marine surveillance radar is a microwave sensor system with the capability of observing the sea surface all-time and all-weather. It can monitor the sea surface and detect the targets dynamically and is widely used in both civil and military marine monitoring fields.

When the marine surveillance radar detects the sea surface, not only the target information is included in radar echoes but also the sea clutter, which is the backscattered echo of sea surface [1]–[5]. The generation mechanism of sea clutter is complicated, and its characteristics are affected by the sea surface environmental factors, radar operating parameters, etc. When the radar detects the sea surface targets, especially those with small radar cross section (RCS) such as fishing boats and dinghies, the existence of sea clutter will reduce the signal-to-clutter ratio (SCR) of radar echoes sharply and decrease the final target detection probability. Therefore, the sea clutter will seriously affect and degrade the detection performance of marine surveillance radar. That is reflected in the following: 1) The existence of sea clutter will lead to a lower SCR of radar echoes, especially detecting the targets with small RCS, which may cause missing alarms easily [6]; 2) the echo amplitude of the sea clutter is strong under high state of the sea, which may cause difficulties in distinguishing targets from the background in the detection of the sea surface, resulting in many false alarms in the detection results [7]. Therefore, researches of the sea clutter suppression must be carried out to improve the target detection performance of marine surveillance radar.

In recent years, researchers focused on sea clutter suppression field and have proposed many novel methods to suppress the sea clutter for the marine surveillance radar [8], [9]. There are generally two different sea clutter suppression genres: traditional approach and machine learning based approach. The traditional suppression methods are mainly based on classical signal processing techniques, perform clutter suppression processing on radar echoes in spatial domain, frequency domain, or other transform domains. The spatial domain processing means mostly describe the sea clutter components based on clutter statistical models and eliminate the sea clutter [10]–[12]. The frequency domain processing methods extract the Doppler information of the targets and clutter through Fourier transform or other means and employ the Doppler filters to remove the sea clutter components. Classical frequency domain methods mainly include moving target indicator, moving target detection [13], etc. Subspace-based sea clutter suppression methods [14]–[17] model the clutter components in the subspace and utilize the spatial–temporal correlation of sea clutter to suppress it, which includes eigenvalue decomposition, singular value decomposition (SVD), and so on.

Although the methods mentioned above generally perform well in sea clutter suppression, most of them need to model and estimate the parameters of sea clutter in advance, leading to unavoidable errors in the suppression of complex and changeable sea clutter [18]. Aiming to remedy the shortcomings of the above methods, some research works have been further carried

Manuscript received December 27, 2021; revised March 28, 2022; accepted April 8, 2022. Date of publication April 14, 2022; date of current version May 3, 2022. This work was supported by the National Natural Science Foundation of China under Grant 61901091 and Grant 61901090. *(Corresponding author: Weibo Huo.)*

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Digital Object Identifier 10.1109/JSTARS.2022.3167410

out based on sea surface fractal features [19], [20] and time-frequency analysis [21], [22]. However, the fractal features of sea clutter time series often exist within a period time interval and are influenced by radar parameters, sea states, and resolutions, which could affect the sea clutter suppression performances of these methods.

With the development of artificial intelligence [23], many researchers have proposed new sea clutter suppression methods based on machine learning theory in recent years. The work [24] constructed the boundary between sea clutter and targets using *k*-nearest neighbor and support vector machine algorithms and realized the sea clutter suppression. However, due to the simplicity of the selected models and the need for specific analysis and preprocessing of the radar data, the performance of sea clutter suppression is limited. In order to improve the sea clutter suppression performance, more complex machine learning models have been applied to sea clutter suppression tasks [25]. The works [26] and [27] proposed the clutter suppression networks based on deep convolution autoencoders, and [28] proposed clutter suppression method based on deep convolutional neural networks and achieved good results. In the training phase of these methods, a large number of clutter sample and corresponding clutter-free sample pairs are often needed as training samples. In order to effectively utilize training samples, [29] proposed an unsupervised sea clutter suppression method based on generative adversarial networks (GANs) and applied in the target detection of marine radar plan position indicator images.

Although the existing learning-based sea clutter suppression methods have achieved good performances and shown great potential, there are still two important problems that should be resolved. On the one hand, to achieve effective sea clutter suppression in the complex and changeable sea environment, the suppression method should be able to learn the complex sea clutter characteristics deeply. On the other hand, the interested target echoes coexist with the sea clutter among the echoes of the marine surveillance radar, and the target component is relatively sparser compared with the sea clutter. Therefore, how to completely retain the target information while suppressing the sea clutter, i.e., suppressing the sea clutter precisely, is quite crucial to improve the performance of final target detection.

This article proposes a new method based on machine learning to address these two problems and to improve the sea clutter suppression performance. First, we introduce a cyclic deep network structure, which is based on the cycle-consistent adversarial network (CycleGAN) and composed of two pairs of generators and discriminators, to learn the characteristics of sea clutter effectively. It converts the problem of sea clutter suppression to the transforming between different domains, i.e., transforming the clutter data domain into the clutter-free data domain based on the deep neural network to achieve effective sea clutter suppression. In addition, in order to preserve the target information well while suppressing the clutter, we add target-consistency loss to the cost function of the network, which can ensure that the target will not be damaged during the transforming between different data domains. Thus, these two problems in sea clutter suppression can be effectively resolved with the proposed method. Therefore, the proposed method can achieve satisfactory sea clutter suppression performance.

The main contributions of this article are the following. 1) We utilized a GAN with a cyclic structure for sea clutter suppression, which can learn the characteristics of the sea clutter sufficiently and suppress the sea clutter effectively. 2) We proposed the target-consistency loss, which can preserve the target information while suppressing the sea clutter. 3) The proposed method achieves excellent clutter suppression performance compared with the available methods.

The rest of this article is organized as follows. Section II describes the proposed method in detail. Experiments and analyses are carried out to evaluate our method in Section III. Finally, Section IV concludes this article.

II. Proposed Method

In this section, we will introduce the proposed sea clutter suppression method in detail. First, the overall structure of the sea clutter suppression method is given. Then, the components in the sea clutter suppression network are introduced, including the specific structure of the generators and discriminators. Finally, we present the proposed target-consistency loss for maintaining target information in the clutter suppression network.

A. *Framework of Sea Clutter Suppression Network*

As shown in Fig. 1, we define the process of sea clutter suppression f as the mapping from X to Y: $f : X \to Y$, where X is the clutter radar data domain and Y is the clutter-free radar data domain. The inverse mapping of f is g, which is defined as: $g : Y \to X$. The essence of sea clutter suppression is to learn the mapping relationship f from clutter radar data and realize the transforming from X to Y, and its inverse process g is clutter recovery. The framework of the proposed method includes not only the processing of clutter suppression but also the processing of clutter recovery, which aims to enable the network to deeply learn the sea clutter characteristics and achieve the mutual conversion between clutter and clutter-free radar data domains, thereby improving the final clutter suppression performance.

This method designs the clutter suppression network based on the structure of CycleGAN [30], and the specific network structure is shown in Fig. 2. The structure of the entire network is cyclic and composed of two symmetrical GANs. Among them, each GAN is composed of a pair of generator and discriminator, and these two GANs are used to realize the transformation and inverse transformation of clutter radar data domain X and clutter-free radar data domain Y, respectively. Specifically, it uses the sea clutter suppression generator (SCSG) to extract the characteristics of sea clutter and learn the mapping f. Clutter radar data x passes through SCSG and $f(x)$ is generated, which realizes the clutter suppression of x, where $x \in X$. To make sure $f(x) \in Y$, the discriminator D_Y is used to discriminate the clutter suppression result $f(x)$, so as to guide the SCSG to learn the mapping f from X to Y. Since D_Y can only judge whether the generated $f(x)$ matches the characteristics of radar data in Y, it cannot guarantee that $f(x)$ has a one-to-one correspondence with x. For the purpose of assuring that x and $f(x)$ correspond

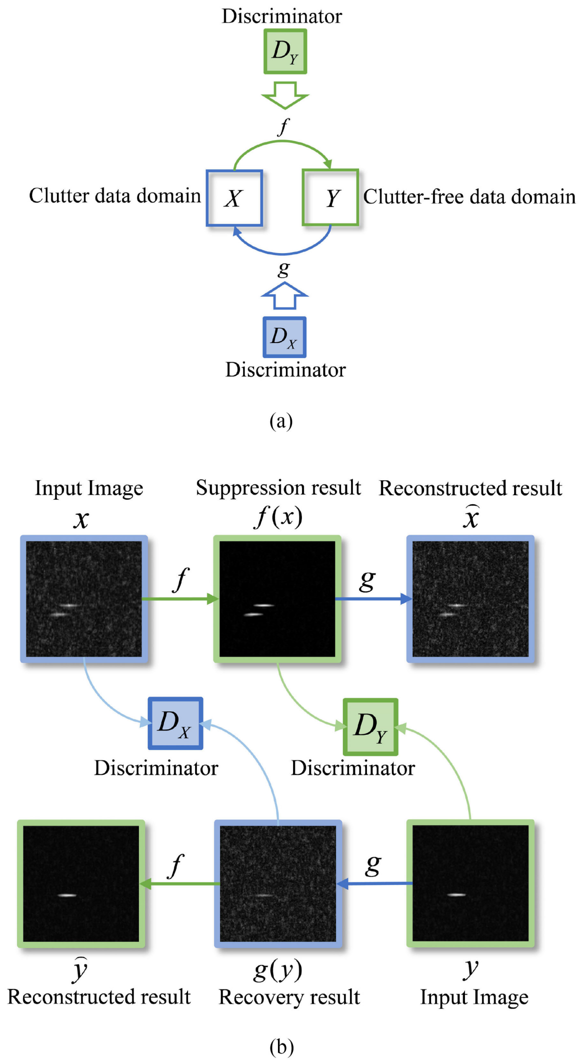


Fig. 1. Sea clutter suppression methodology. (a) General idea of methodology. (b) Flowchart of sea clutter suppression. X and Y refer to clutter radar data domain and clutter-free radar data domain, respectively. Using discriminators D_Y and D_X to guide learning process of f and g, which are used to achieve clutter suppression and recovery.

one-to-one, this network uses the sea clutter recovery generator (SCRG) to learn the clutter recovery mapping g and defines it as $g : f(x) \rightarrow \hat{x}$, that is, $g[f(x)] = \hat{x}$, where $\hat{x} \approx x$. Utilizing the structure of the above network, the proposed method is able to learn the sea clutter characteristics adequately and achieve the one-to-one correspondence between x and $f(x)$ as well as assures a good clutter suppression performance.

The above is the optimization process for obtaining f. In view of the symmetric structure of the network, it is also necessary to learn and optimize the mapping g to realize sea clutter recovery. Similarly, the $g(y)$ generated by SCRG is the result of clutter recovery on y, where $y \in Y$. Then, the discriminator D_X is used to discriminate whether $g(y)$ meets the characteristics of X and recover $g(y)$ with SCSG.

From the basic architecture of the network, we can see that the proposed method can realize the conversion from clutter radar data domain to clutter-free radar data domain and finally realize an effective suppression of sea clutter. Specific modules in the sea clutter suppression network are given in the following discussion.

B. Architecture of Generator

As the core components of the sea clutter suppression network, the generators SCSG and SCRG are used to suppress and recover the sea clutter, respectively. They are both composed of encoding, transformation, and decoding modules. The specific structure is shown in Fig. 3. To achieve effective learning of f and g, we first use the encoding module to learn the characteristics of the input data. Then, the transformation module is used to realize the transformation of the characteristics extracted by the encoding module. Finally, the decoding module reconstructs the features of the output data domain, so as to generate sea clutter suppression or recovery results.

The encoding module is composed of convolutional layers, batch normalizations (BNs) and ReLU activation functions alternately. Transformation module contains a series of ResNet blocks and aims to realize the characteristics transformation between different data domains. Decoding module consists of deconvolutions, BN layers, and activation functions by turns to generate corresponding clutter suppression or clutter recovery results.

C. Architecture of Discriminator

In order to make SCSG and SCRG have good clutter suppression and clutter recovery performances, it is necessary to use discriminators to guide the learning processes of mapping f and g. The sea clutter suppression network contains two discriminators D_X and D_Y and discriminate whether the generated samples meet the data characteristics of each domain. The structure and specific settings of the discriminators are shown in Fig. 4.

The first four layers of the discriminator consist of convolutional layers, BN layers, and leaky-ReLUs in turn, and the final layer only contains convolutional layer. After processed by the first four layers of D_X and D_Y, the input data are converted into a series of feature maps. The final layer is used to transform those feature maps into the output for the decision, and the values in the output are in the range from 0 to 1.

D. Cost Function

In the training phase, the clutter suppression network can eventually converge by training generators and discriminators alternately, and the desired clutter suppression performance can be achieved. The cost function is the index to measure the effect of network learning during training, and the network training process is the optimization process of the cost function. The cost function of the sea clutter suppression network consists of three ingredients: the adversarial loss, the cycle-consistency loss, and the target-consistency loss.

The adversarial losses are used for the training of generators and discriminators, whose effect is to make the generated samples obey the data distribution of the specified domain. For the mapping function $f : X \rightarrow Y$ and discriminator D_Y, the loss

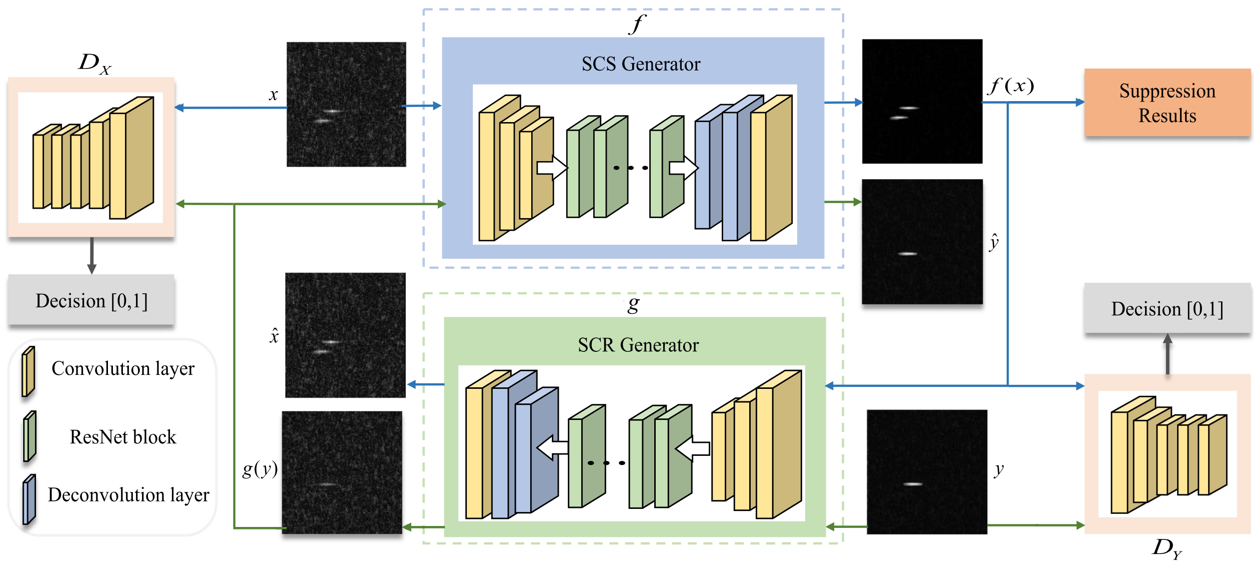


Fig. 2. Overview of sea clutter suppression network. x is radar data with clutter, $f(x)$ is the result of clutter suppression using SCSG for x, and $\widehat{x}$ is data with clutter restored using SCRG $\widehat{x} \approx x$; y is radar data without clutter, $g(y)$ is the result of clutter recovery using SCRG for y, and $\widehat{y}$ is data without clutter restored using SCSG ($\widehat{y} \approx y$).

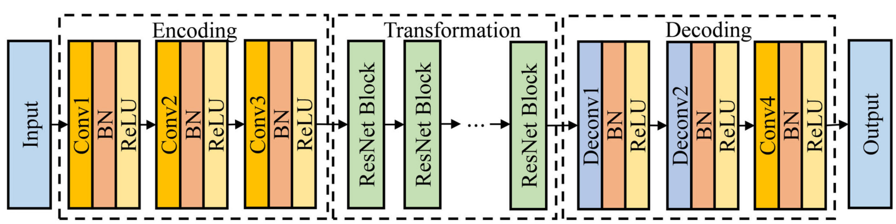


Fig. 3. Architecture of generator. Conv1–Conv4 refer to convolutional layers, BNs represent batch normalizations, ResNet Blocks are built in the same way as in ResNet-34 [31], and Deconv1 and Deconv2 are transposed convolutional layers.

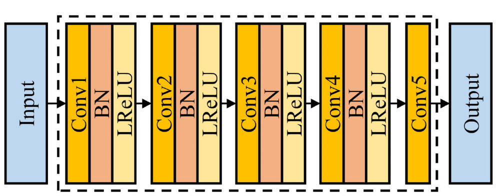


Fig. 4. Architecture of discriminator.

can be expressed as

$$L_{\text{adv\_}f}(f, D_Y, X, Y) = E_{y\sim P_{\text{data}}(y)}\left[\log D_Y(y)\right] + E_{x\sim P_{\text{data}}(x)}\left[\log\left(1 - D_Y\left(f(x)\right)\right)\right] \tag{1}$$

where D_Y is the discriminator that aims to discriminate between y and $f(x)$, and y and x are sampled from Y and X.

For $g : Y \to X$ and D_X, the loss can be expressed as

$$L_{\text{adv\_}g}(g, D_X, Y, X) = E_{x\sim P_{\text{data}}(x)}\left[\log D_X(x)\right] + E_{y\sim P_{\text{data}}(y)}\left[\log\left(1 - D_X\left(g(y)\right)\right)\right] \tag{2}$$

where D_X is the discriminator that aims to discriminate between x and $g(y)$.

The cycle-consistency loss are employed to make sure $g[f(x)] \approx x$ and $f[g(y)] \approx y$, which can be expressed as

$$L_{\text{cyc}}(f, g) = \frac{1}{m}\sum_{i=1}^{m}\left|\left|g\left[f\left(x^i\right)\right] - x^i\right|\right|_1 + \frac{1}{m}\sum_{i=1}^{m}\left|\left|f\left[g\left(y^i\right)\right] - y^i\right|\right|_1 \tag{3}$$

where $g[f(x)]$ and $f[g(y)]$ refer to the reconstructed results of input date from both domains, $\{y^i\}_{i=1}^m$ and $\{x^i\}_{i=1}^m$ are sampled from Y and X, m refers to the batch size in each training step, and $\|\cdot\|_1$ represents the 1-norm.

The sea clutter suppression needs to be improved in two ways: not only suppress the clutter accurately in various marine environments but also preserve target information effectively. Therefore, we propose the target-consistency loss to preserve the target information while suppressing the sea clutter, which can be expressed as

$$L_{\text{tar}}(f, g) = \frac{1}{m}\sum_{i=1}^{m}\left|\left|g\left(x^i\right) - x^i\right|\right|_1 + \frac{1}{m}\sum_{i=1}^{m}\left|\left|f\left(y^i\right) - y^i\right|\right|_1. \tag{4}$$

By adding the target information retention constraint to f and g, target-consistency loss $L_{\text{tar}}(f,g)$ can ensure that SCSG and SCRG do not change the target characteristics in the input data, thus preserving the information in the target region effectively.

Finally, the cost function of the sea clutter suppression network can be expressed as

$$\begin{aligned} L\left(f,g,D_X,D_Y\right) = {} & L_{\text{adv\_}f}\left(f,D_Y,X,Y\right) \\ & + L_{\text{adv\_}g}\left(g,D_X,Y,X\right) \\ & + \lambda L_{\text{cyc}}(f,g) \\ & + \mu L_{\text{tar}}(f,g) \end{aligned} \tag{5}$$

where λ and μ are the weights of $L_{\text{cyc}}(f,g)$ and $L_{\text{tar}}(f,g)$.

The optimization objective function of the network training can be expressed as

$$\begin{aligned} & \min_{f,g} \max_{D_X,D_Y} L\left(f,g,D_X,D_Y\right) \\ & = \min_{f,g} \max_{D_X,D_Y} \left[L_{\text{adv\_}f}\left(f,D_Y,X,Y\right)\right. \\ & + L_{\text{adv\_}g}\left(g,D_X,Y,X\right) \\ & + \lambda L_{\text{cyc}}(f,g) \\ & \left.+\mu L_{\text{tar}}(f,g)\right]. \end{aligned} \tag{6}$$

The training phase of the sea clutter suppression can be regarded as solving a maximum–minimum process. Specifically, we keep the parameters of the generators SCSG and SCRG constant, update the parameters of D_X and D_Y, and maximize the cost function, so that the discriminator can effectively discriminate the input samples and generated samples. Then, keeping the discriminator parameters unchanged, the generator parameters are updated, and the cost function is minimized, accordingly making the distribution of the generated samples and the input samples as consistent as possible.

When the generated data distribution is consistent with the real data distribution, the trainable parameters of the network will learn to their optimal values. In the testing phase, sea clutter suppression can be effectively realized by inputting the clutter radar data into the SCSG.

III. Experiments and Results

In this section, we will assess the performance of the proposed sea clutter suppression network using simulated and measured data. First, the specific setting of the sea clutter suppression network will be introduced. Then, the experimental results based on simulated and measured data will be given, respectively. Finally, we will compare our method with existing clutter suppression methods in terms of their sea clutter suppression performances.

A. Network Architecture Setup

The hyper-parameters of the proposed sea clutter suppression network, including the generator and discriminator, are shown in Tables I and II, respectively. The selection of hyper-parameters is mainly determined by the statistical validation method and trials.

TABLE I
Detailed Architecture of Generator

Layer Names	Feature Maps	Kernel Sizes	Stride Sizes
Conv1	64	7×7	1×1
Conv2	128	3×3	2×2
Conv3	256	3×3	2×2
ResNet Block	$\begin{bmatrix}256\\256\end{bmatrix}$	$\begin{bmatrix}3\times3\\3\times3\end{bmatrix}$	$\begin{bmatrix}1\times1\\1\times1\end{bmatrix}$
Deconv1	128	3×3	2×2
Deconv2	64	3×3	2×2
Conv4	1	7×7	1×1

TABLE II
Detailed Architecture of Discriminator

Layer Names	Feature Maps	Kernel Sizes	Stride Sizes
Conv1	64	4×4	2×2
Conv2	128	4×4	2×2
Conv3	256	4×4	2×2
Conv4	512	4×4	1×1
Conv5	1	4×4	1×1

TABLE III
Radar Parameters Setting for Simulated Dataset

Parameters	Values	Parameters	Values
Beam Width	4°	PRF	$500Hz$
Scanning Velocity	$36^\circ/s$	Carrier Frequency	$10GHz$
Bandwidth	$100MHz$	Polarization Mode	VV

TABLE IV
Training and Testing Sets in Simulated Dataset

Simulated Data	Number of Sample Pairs
Training Set A	4500
Training Set B	2500
Testing Set	500

B. Sea Clutter Suppression Performance on Simulated Data

In this subsection, the simulated dataset used in this experiment will be introduced at first. Then, the clutter suppression network will be trained with the training data. Finally, the performance of the proposed sea clutter suppression method will be verified using the testing data. We construct the simulated sea clutter dataset based on the compound *K*-distribution model, which can fit the sea clutter well and has been widely used [32], [33]. The settings of the radar parameters are shown in Table III. The simulated dataset consists of two training sets, i.e., training set A and B, and one testing set, and the number of the samples in each set is shown in Table IV. The training set A is composed of radar data with single target and at high SCRs, and the training set B contains radar data with more targets and at different SCRs. The testing data include radar samples under various SCRs and different target numbers, which is used for evaluating

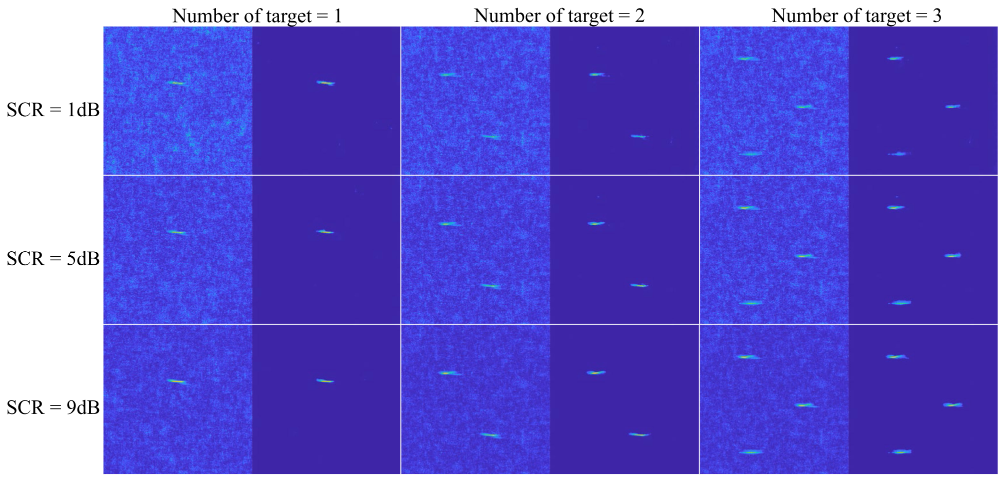


Fig. 5. Sea clutter suppression results under different sea situations.

the sea clutter suppression performance of the proposed method in different sea environments.

In this experimental setup, in order to make the proposed network learn the complex and variable sea clutter characteristics well, we use the method of "pretraining and fine-tuning" to gradually improve the performance of the sea clutter suppression network. In the pretraining stage, the network is trained with training set A, which contains radar samples with single target and under high SCRs, to obtain the basic prototype of the sea clutter suppression network. In the second training stage, in order to further optimize the network parameters, the clutter suppression network is trained with training set B, which is composed of radar samples with more targets and under lower SCRs. Benefitting from the learned sea clutter characteristics in pretraining stage, the clutter suppression network performs well in the learning of sea clutter characteristics in training set B, which is under lower SCRs and more complex situations, so as to enable the sea clutter suppression network to suppress the clutter in different sea situations effectively. In the testing phase, we will evaluate the proposed network on the marine surveillance radar testing data under different situations and test its performance on the simulated dataset qualitatively and quantitatively.

Fig. 5 shows the testing results of the sea clutter suppression performance of the proposed method under different target numbers and SCRs. It can be seen that the sea clutter in the radar samples become more and more obvious as the SCRs of the input data decrease. At the same time, the increase of the target numbers will also bring difficulties to the sea clutter suppression task. However, the clutter suppression method proposed in this article can effectively suppress the sea clutter under different SCRs and various numbers of targets and retain the target information well at the same time.

As mentioned before, the proposed method adopts a cyclic network structure, which can learn the sea clutter characteristics deeply and realize the mapping from the clutter data domain to the clutter-free data domain. The testing results also show that the deep network proposed in this article can effectively learn the sea clutter characteristics and suppress the sea clutter under different situations. In addition, the proposed target-consistency loss can keep the target information while completing the transformation between the clutter radar data domain and the clutter-free radar data domain.

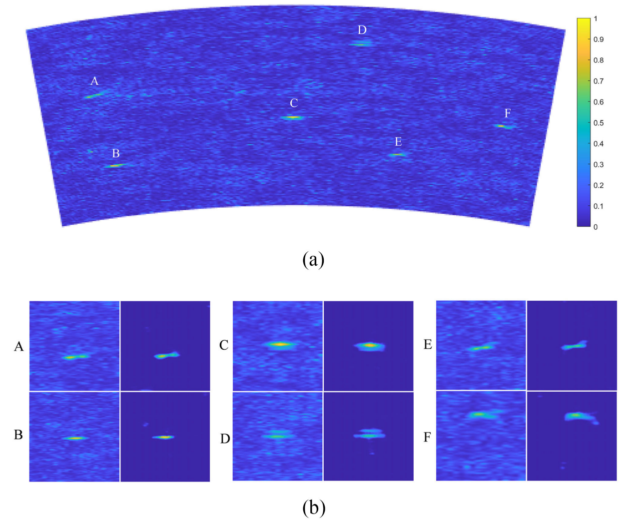


Fig. 6. Sea clutter suppression result on simulated wide scene. (a) Original wide scene. (b) Clutter suppression results.

The sea clutter suppression results on the simulated wide scene are shown in Fig. 6, in which Fig. 6(a) shows the distribution of sea clutter and targets in the original scene and Fig. 6(b) shows the results after clutter suppression. The simulated wide scene in Fig. 6(a) is in polar format. The scanning interval of Fig. 6(a) is $[-10^\circ, 10^\circ]$, and its acquisition time is about 0.56 s. It can be seen from Fig. 6 that the proposed clutter suppression network can effectively suppress the clutter of the sea surface. In addition, the target slices from the sea scene have shown that our method can not only suppress the sea clutter effectively but also maintain the target information well.

The sea clutter suppression improvement factor σ is introduced here to evaluate the clutter suppression performance of the proposed method quantitatively, which can be expressed as

$$\sigma = \mathrm{SCR}_{\mathrm{out}} - \mathrm{SCR}_{\mathrm{in}}, \tag{7}$$

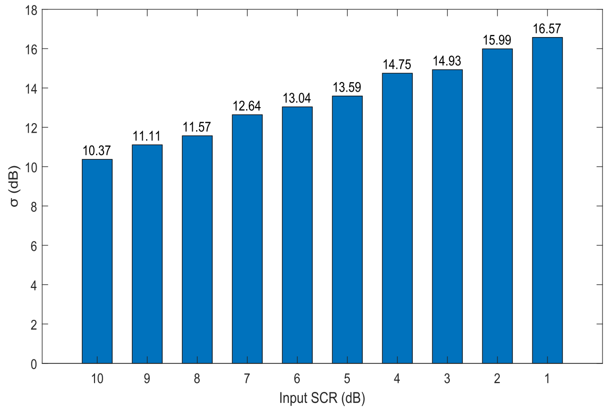
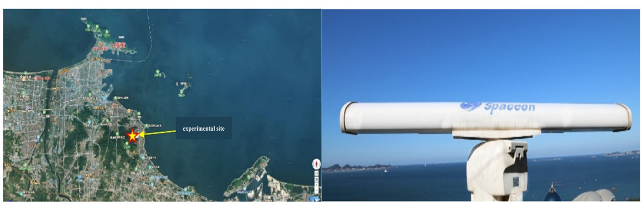


Fig. 7. Statistics of sea clutter suppression results under different input SCRs.



(a) (b)

Fig. 8. Descriptions of experiments [31]. (a) Aerial view of experimental site. (b) Radar used in experiment.

$$\mathrm{SCR} = \bar{P}_t / \bar{P}_c \tag{8}$$

where $\mathrm{SCR_{out}}$ and $\mathrm{SCR_{in}}$ represent the SCR of radar data after and before clutter suppression, respectively, and their unit is dB. $\bar{P}_t$ and $\bar{P}_c$ are the average powers of the target region and the clutter region, respectively.

The quantitative statistical results of the sea clutter suppression network on the testing data with different input SCRs are shown in Fig. 7. We can see that the proposed sea clutter suppression method can effectively suppress the sea clutter under different input SCRs and significantly improve the SCRs of the output radar data.

C. Sea Clutter Suppression Performance on Measured Data

In this subsection, we will train and test the clutter suppression network using measured sea clutter data, so as to assess its sea clutter suppression performance in a more realistic environment. The measured sea clutter data used in this subsection is selected from the sea detection experimental data published in [34] in 2021. Their experiment obtained the data of sea clutter and target echoes under different sea conditions using an X-band marine surveillance radar. The aerial view of the experimental site and the used radar are, respectively, shown in Fig. 8(a) and (b). As shown in Fig. 8, the radar collected the sea surface echoes under the circular scanning mode. The radar parameters are shown in Table V. The target areas in the measured radar dataset are selected for training and testing in our experiment, and the training and testing data are from different sea scenes.

TABLE V
RADAR PARAMETERS SETTING FOR MEASURED DATASET

Parameters	Values	Parameters	Values
Beam Width	$1.2°$	PRF	$1600Hz$
Scanning Velocity	$144°/s$	Carrier Frequency	$9.5GHz$
Bandwidth	$25MHz$	Polarization Mode	HH

TABLE VI
TRAINING AND TESTING SETS IN MEASURED DATASET

Measured Data	Number of Sample Pairs
Training Set	244
Testing Set	24

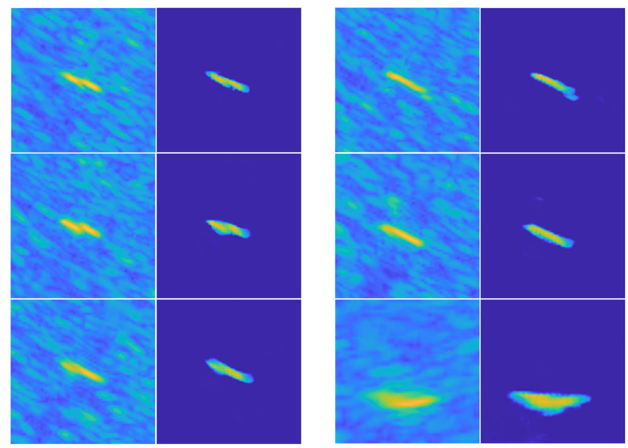


Fig. 9. Sea clutter suppression results on measured data slices.

The specific numbers of the samples in the measured dataset are shown in Table VI.

Based on the good experimental results in the training of simulated dataset in the previous subsection, the measured marine radar data are used to train the proposed deep network sequentially, so as to make the sea clutter suppression network converge. We evaluate the clutter suppression performance of our method on different measured radar data, and the testing results are shown in Figs. 9 and 10.

The clutter suppression results on target slices from different measured scenes are shown in Fig. 9, which confirm that the proposed clutter suppression method has good clutter suppression performance on the measured data. Although the training set and testing set are obtained from different marine environments, it can be seen from the results that the clutter suppression network can still effectively suppress the sea clutter.

The clutter suppression results on another measured scene is also shown in Fig. 10, in which two of the areas containing targets have been marked. The measured wide scene in Fig. 10(a) is in polar format, and its acquisition time is about 2.5 s. The testing results of the target areas show that the proposed sea clutter suppression method can not only suppress the sea clutter effectively but also protect the target information well. Therefore, the good performance of the proposed method has been validated again by the clutter suppression results on the measured scene.

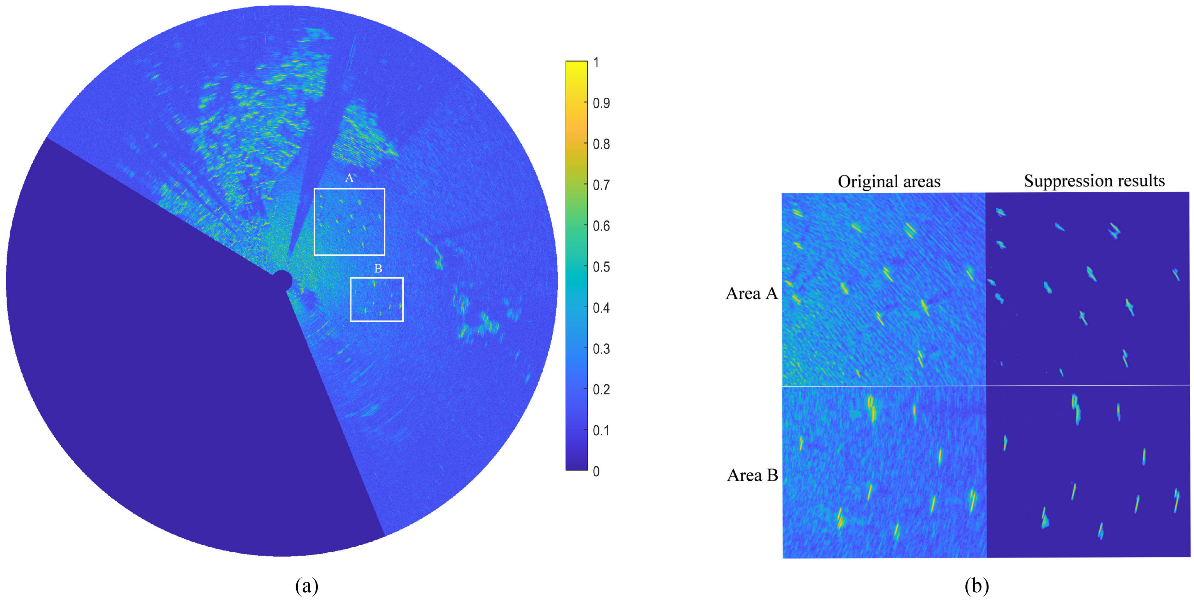


Fig. 10. Sea clutter suppression result on measured scene. (a) Original wide scene. (b) Clutter suppression results.

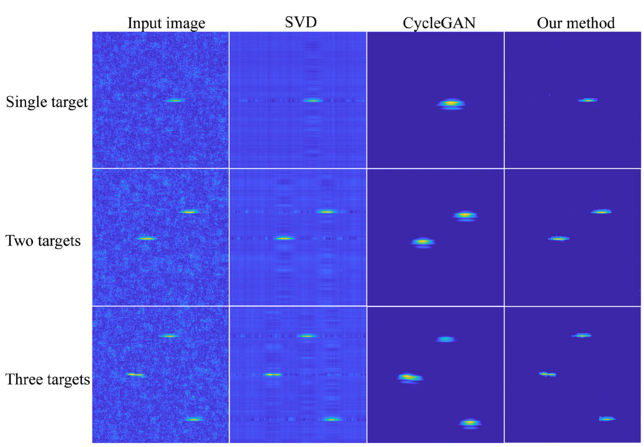


Fig. 11. Suppression performance comparison on simulated data.

D. Suppression Performance Comparison

We compare the proposed sea clutter suppression network with two other methods on both simulated and measured data in this subsection. These methods are SVD [14], [35] and CycleGAN [30]. SVD is a classical algorithm that is widely used in noise or clutter reduction and other fields. It can describe and suppress the sea clutter component based on subspace decomposition. CycleGAN can accomplish image style transfer well and can realize the mutual transformations of two image data domains; here, its network structure is introduced into the field of clutter suppression.

The clutter suppression results of the above methods on the simulated data are shown in Fig. 11. The results show that all of the three methods can suppress the sea clutter, but their clutter suppression performances are different. The clutter suppression abilities of SVD are not good facing the complex and changeable sea clutter because it has not learned the clutter characteristics in advance. CycleGAN is able to suppress the sea clutter well, but due to the lack of constraint on target area, the target information, such as contour and so on, may change while suppressing the sea clutter. Compared with these two methods, the proposed method can learn the characteristics of sea clutter deeply and effectively suppress the sea clutter. Meanwhile, the proposed target-consistency loss ensures that the target information will not be destroyed during clutter suppression. Therefore, the effective sea clutter suppression results can be finally achieved.

Some indexes, including sea clutter suppression improvement factor σ and target structural similarity (SSIM), are used to objectively evaluate the performances of various methods. σ indicates the suppression abilities of different methods. SSIM measures the similarity of target areas before and after clutter suppression and is introduced here to evaluate the capabilities of target information preservation of different methods, which can be defined as

$$\mathrm{SSIM}(t,\hat{t}) = \frac{(2\mu_t\mu_{\hat{t}} + C_1)[2\mathrm{cov}(t,\hat{t}) + C_2]}{(\mu_t^2 + \mu_{\hat{t}}^2 + C_1)[\mathrm{var}(t) + \mathrm{var}(\hat{t}) + C_2]}$$

where t and $\hat{t}$ are the target areas of radar data before and after clutter suppression, μ_t and $\mu_{\hat{t}}$ are the means of t and $\hat{t}$, $\mathrm{var}(t)$ and $\mathrm{var}(\hat{t})$ are the variances of t and $\hat{t}$, $\mathrm{cov}(t,\hat{t})$ is the covariance of t and $\hat{t}$, and C_1 and C_2 are the constants.

The σ and SSIM of various methods on simulated data are shown in Tables VII and VIII, respectively. According to the statistical results in Table VII, as SCR changes, sea clutter suppression improvement factors of all the methods will change accordingly, and the clutter suppression performance of our method is better than the other two comparison methods. In addition, it can be seen from Table VIII that the SSIMs of the proposed method are higher than the other two methods, which shows the superiority of preserving target information of the proposed method in sea clutter suppression.

TABLE VII
SEA CLUTTER SUPPRESSION IMPROVEMENT FACTORS OF VARIOUS METHODS ON SIMULATED DATA

SCR (dB)	σ		
	SVD	CycleGAN	Our Method
1	8.05	16.49	16.57
3	6.79	14.77	14.93
5	5.71	12.88	13.59
7	4.31	9.66	12.64
9	3.71	7.62	11.11

TABLE VIII
STRUCTURAL SIMILARITIES OF VARIOUS METHODS ON SIMULATED DATA

SCR (dB)	SSIM		
	SVD	CycleGAN	Our Method
1	0.48	0.19	0.65
3	0.51	0.18	0.66
5	0.50	0.19	0.68
7	0.50	0.17	0.71
9	0.52	0.18	0.71

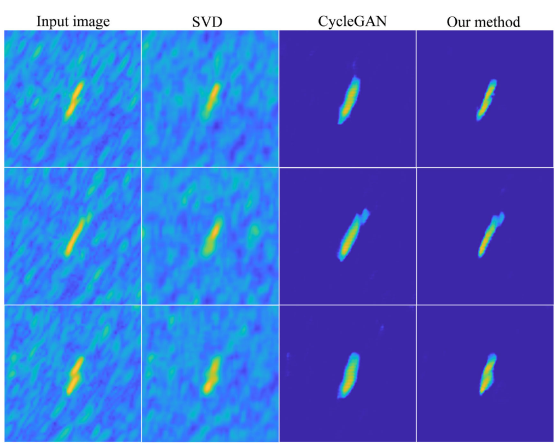


Fig. 12. Suppression performance comparison on measured data.

Fig. 12 shows the comparison experimental results of the three sea clutter suppression methods on the measured data. Similar to the testing results on simulated data, SVD reduces not only the amplitude of the sea clutter but also the amplitude of the targets and could destroy the information of the targets, which cannot perform well. In addition, the target information may change while suppressing sea clutter with CycleGAN. In contrast, the proposed clutter suppression method performs better than the other two methods on the measured data.

The statistical results of comparison tests on measured data are shown in Table IX. It can be seen from the quantitative results that the proposed method has good performances in both clutter suppression and target preservation.

All the above experiments carried out have manifested that the proposed sea clutter suppression network has a good suppression capability on both the simulated and measured datasets and clearly verified the superiority of the proposed sea clutter suppression method.

TABLE IX
PERFORMANCE COMPARISON OF VARIOUS METHODS ON MEASURED DATA

	SVD	CycleGAN	Our Method
σ	1.97	12.7	15.52
SSIM	0.53	0.37	0.63

IV. CONCLUSION

The detection performance of marine surveillance radar can be benefited from sea clutter suppression. It is important to not only remove the clutter effectively but also protect the target information from being damaged during sea clutter suppression. In this article, a novel deep neural network consisting of two GANs has been employed to solving the sea clutter suppression problem. Based on its cyclic structure, the proposed method can learn the clutter characteristics sufficiently and suppress the sea clutter effectively. Besides, the target-consistency loss has also been proposed to preserve the target information; so the performance of the target detection in the next step will not be affected for marine surveillance radar. Extensive experiments have been carried out on both simulated and measured data, and the results have shown that the proposed method can achieve a better suppression performance than existing sea clutter suppression methods.

The subsequent research mainly consists of new clutter suppression networks design and performance improvement under more complex sea conditions. Additionally, we will study clutter suppression method based on complex data to make use of the Doppler information contained in echoes to obtain better sea clutter suppression performance.

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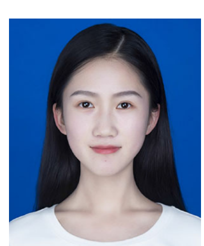

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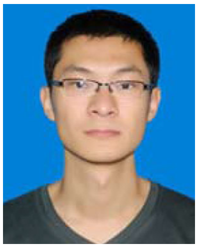

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