

Article

Sea Clutter Amplitude Prediction Using a Long Short-Term Memory Neural Network

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Abstract: In the marine environment, shore-based radars play an important role in military surveillance and sensing. Sea clutter is one of the main factors affecting the performance of shore-based radar. Affected by marine environmental factors and radar parameters, the fluctuation law of sea clutter amplitude is very complicated. In the process of training a sea clutter amplitude prediction model, the traditional method updates the model parameters according to the current input data and the parameters in the current model, and cannot utilize the historical information of sea clutter amplitude. It is only possible to learn the short-term variation characteristics of the sea clutter. In order to learn the long-term variation law of sea clutter, a sea clutter prediction system based on the long short-term memory neural network is proposed. Based on sea clutter data collected by IPIX radar, UHF-band radar and S-band radar, the experimental results show that the mean square error of this prediction system is smaller than the traditional prediction methods. The sea clutter suppression signal is extracted by comparing the predicted sea clutter data with the original sea clutter data. The results show that the proposed sea clutter prediction system has a good effect on sea clutter suppression.

Keywords: shore-based radars; sea clutter; long short-term memory neural network; nonlinear prediction; sea clutter suppression

1. Introduction

Radar plays an important role in the field of ocean-based environmental remote sensing and military surveillance. Synthetic aperture radar (SAR) can be used to acquire radar images of oceans, ocean currents, land surface, and other remote targets. Airborne radar has a very important role in the military field by detecting and classifying ships on the sea by detecting backscatter signals on the sea surface. Shore-based radars are usually in a fixed position to monitor sea surface conditions for extended periods of time. The electromagnetic scattering echo received by the radar is called sea clutter [1]. In order to improve the performance of the radar, sea clutter analysis is the focus and hotspot of the research. This paper mainly analyzes the sea clutter amplitude based on sea clutter data collected by different shore-based radars and suggests an approach to suppress sea clutter.

For a long time, the change of sea clutter has been considered as a stochastic process [2], and the changing trend of sea clutter amplitude is difficult to predict. The small target is difficult to be detected

for that it is often submerged in waves when the sea surface is rough [3]. Most of the sea surface target detection methods are based on statistical theory [4–6], which depends on the choice of the sea clutter amplitude probability density function (PDF) and parameter estimation algorithm. The PDF model for sea clutter is related to radar parameters and ocean environment parameters. There are also complex correlations between different parameters, which produce diverse sea clutter. The most commonly used PDF model for sea-clutter is the K-distribution as it captures the bulk of the distribution very well [7]. However, it is difficult to use a uniform amplitude distribution function to detect sea surface targets in different sea areas. Sea clutter amplitude prediction methods can also be used for maritime target detection [8]. The principle of target detection is that when the prediction error is small, the input signal should be sea clutter. On the other hand, the input signal is more likely to be a target for that the dynamic change is usually different from that of sea clutter.

There are qualitative similarities (such as boundedness, broad flat spectrums, and irregular temporal behavior) between chaotic signals and sea clutter [9]. Some key parameters in chaotic systems (such as correlation dimensions) play an important role in the construction of sea clutter training sets for training nonlinear predictors [9,10] of sea clutter amplitude. In most nonlinear prediction methods, the commonly used technique is the radial basis function (RBF) [2,3,9,11]. Leung [2] who has been engaged in sea clutter research for many years used the RBF neural networks (NN) to reconstruct the dynamic of sea clutter, the results show that the appropriate embedding dimension is selected, and the prediction error of sea clutters that are collected by IPIX radar [12] will decrease. Leung et al. [11] considered the prediction of noisy chaotic time series using an optimal RBF neural network, by detecting the dimension of subspace spanned and using the proposed cross-validated subspace method, the number of hidden units of RBF is determined, the minimum prediction mean square error (MSE) of sea clutter was obtained. In 2002, McDonald et al. [9] used RBF network and a local linear technique to predict sea clutter that collected by AN/APS 506 airborne maritime surveillance radar, the prediction errors of these two methods is approximately 0.0032 that it is unclear whether the RBF network predictor is better under the real world detection scenarios. Zhang et al. [13] proposed a decomposition model for sea clutter processing, and used RBF predictor for sea clutter prediction under different sea states, and obtained stable fitting performance.

Other nonlinear methods such as artificial NN (ANN) had also been proposed for sea clutter prediction. In 2009, Shen and Li [14] predicted sea clutter by chaotic NN [15], which obtains better performance than BP NN [16] and discrete Hopfield NN [17]. Mukherjee et al [18] used support vector machines (SVM) to predict chaotic time series generated by the Mackey-Glass delay-differential equation [19] or Lorene differential equation [20], the result shows that the SVM algorithm had better performance than RBF functions and NN, etc. SVM technique was also used for sea clutter prediction by Xia and Leung [8]. In 2018, Xing and Yan [21] modeled sea clutter by a Volterra filter [22], and verified the proposed method on the IPIX radar sea clutter dataset [23], the experimental results show that the targets can be detected based on its relatively large prediction error. Gao and Chen [10] predicted sea clutter based on general regression NN (GRNN) algorithm, this method applying adaptive particle swarm optimization algorithm [24] to optimize GRNN Gaussian width coefficient.

Sea clutter amplitude is affected by many factors, mainly including radar parameters (polarization mode, transmission power, angle of incidence, etc.) and marine environmental parameters (wave height, wave direction, wind speed, wind direction, wave period, etc.). Radar parameters can be set manually. However, the changes of marine environmental parameters are uncertain, which leads to a very complex variation in sea clutter amplitude. Traditional methods (such as SVR and RBF neural network) usually build model structures based on only a small number of sea clutter amplitude samples, which can learn the partial variation of sea clutter amplitude. In addition, the artificial neural network can use a large amount of data for training and use the gradient descent algorithm to update the parameters in the network according to the current sample, which can learn the short-term variation of the sea clutter amplitude.

Recently, recurrent NN (RNN) [25–28] has been widely used in many fields. Since the current input includes the current information and the memory information learned in the previous period, RNN can learn the long-term information of the sequence, and it achieved outstanding results in some areas, especially in speech signal recognition and machine translation. There is a problem with gradient explosion or disappearance during RNN training. To solve this problem, Hochreiter et al. [29] proposed a gradient-based method called “Long Short-Term Memory” (LSTM) in 1997. LSTM improves the hidden layer unit of RNN and can learn the historical variation of sea clutter amplitude time series. In addition, the development of GPUs [30,31] provides a guarantee for improving the training speed of deep learning networks that are running on several deep learning frameworks including the TensorFlow platform [32]. LSTM has also been applied to sea clutter signal processing. For instance, In 2019, Zhao et al. [33] predicting sea clutter power based on LSTM, and achieved lower prediction error than BP NN [16]. Also in 2019, Li et al. [34] identify clutter points after target detection based on LSTM and achieved higher recognition accuracy than SVM.

Inspired by the above methods, a sea clutter prediction system based on LSTM is proposed in this paper. The sea clutter prediction system consists of a sea clutter preprocessing module (including data conversion, pulse compression, input signal extraction, sea clutter extraction, and data normalization) and a sea clutter prediction module (the sea clutter prediction method is LSTM). The prediction method is verified by sea clutter datasets of IPIX radar, UHF-band radar, and S-band radar. The results show that for SVR, ANN, RBF, and LSTM, the mean MSE of the sea clutter of the first range cell collected by all the radars mentioned in this paper is $3.1\text{e-}03$, $7.1\text{e-}04$, $8.3\text{e-}03$ and $5.6\text{e-}04$, respectively. The mean MSE of the sea clutter amplitude except for the sea clutter of the first range cell are $4.6\text{e-}03$, $4.6\text{e-}03$, $1.2\text{e-}01$, and $3.4\text{e-}03$, respectively. Based on the prediction of the sea clutter amplitude by the LSTM, the sea clutter is suppressed in the frequency domain. Experiments show that for the sea clutter without target, which is collected by IPIX radar, the method can reduce the peak power of sea clutter to the average level of the entire power spectrum signal. For the sea clutter with target acquired by IPIX radar, this method can reduce the peak power and Doppler broadening of sea clutter without reducing the Doppler broadening of the target signal. For the UHF-band and S-band sea clutter without a target, the method can reduce the peak power of sea clutter by 18.5 dB and 13 dB, respectively, and significantly reduce the Doppler broadening of sea clutter.

The paper is organized as follows: In Section 2, IPIX radar, UHF-band radar, S-band radar, and sea clutter datasets are introduced. In Section 3, the principle of prediction is described firstly, and then SVM, ANN and RBF NN for sea clutter prediction is introduced briefly, and then the proposed sea clutter prediction system is introduced in detail, and finally the sea clutter suppression method is introduced. Section 4 presents results analysis of sea clutter prediction and suppression. Conclusions are given in Section 5.

2. Materials

2.1. IPIX Radar and Sea Clutter Dataset in Canada

The IPIX radar site is located in Canada at $44^{\circ}36.72' \text{ N}$, $63^{\circ}25.41' \text{ W}$, on a cliff facing the Atlantic Ocean at a height of about 30 m above mean sea level. The placement of the IPIX radar is indicated by the red position marker on the Google map in Figure 1.

The IPIX radar is an X-Band dual-polarized radar. The range resolution of the radar is 30 m, and the IPIX radar dataset collected in November 1993 contains different targets. The database used in this paper contains three staring data sets (19931107_135603_starea17.mat (#17) with a target in the 9th range cell, 19931111_163625_starea54.mat (#54) with a target in the 8th range cell, 19931118_023604_stareC0000280.mat (#280) with a target in the 8th range cell). Each staring data (antenna is staring in a single direction) includes two polarization modes which are HH and VV polarization. The sea clutter data in each polarization mode have 14 range cells, and each range cell has 131072 pulses.

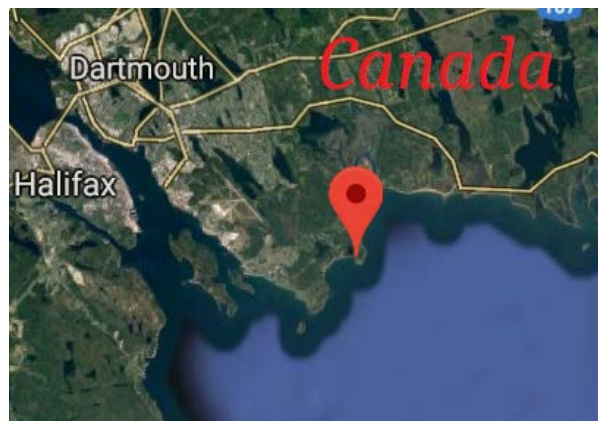


Figure 1. The placement of the IPIX radar.

Table 1 shows the characteristics of IPIX radar data, including the radar information, marine environmental parameters when collecting sea clutter, and the sea clutter information. Figure 2 shows the spatiotemporal distribution of normalized sea clutter amplitude of three datasets. Here, the x-axis denotes the range cell, and the y-axis denotes the pulse number. The brighter the image, the larger the amplitude of the sea clutter.

Table 1. Characteristics of IPIX radar and sea clutter data.

	#17	#54	#280
Radar Transmitting Frequency (GHz)	9.39	9.39	9.39
Pulse Power (Kw)	8	8	8
Polarization Mode	H or V	H or V	H or V
Beam Width (°)	0.9	0.9	0.9
PRF(Hz)	1000	1000	1000
Range Resolution(m)	30	30	30
Pulse Length (ns)	200	200	200
Maximum Wave Height (m)	3.02	0.94	2.9
Average Wave Height (m)	2.01	0.63	1.69
Wind Speed (m/s)	9	19	7
Wind Direction (°)	300	300	220
Range Samples	14	14	14
Pulse Number	131072	131072	131072
Range (m)	2574-2769	2574-2769	2550-2745

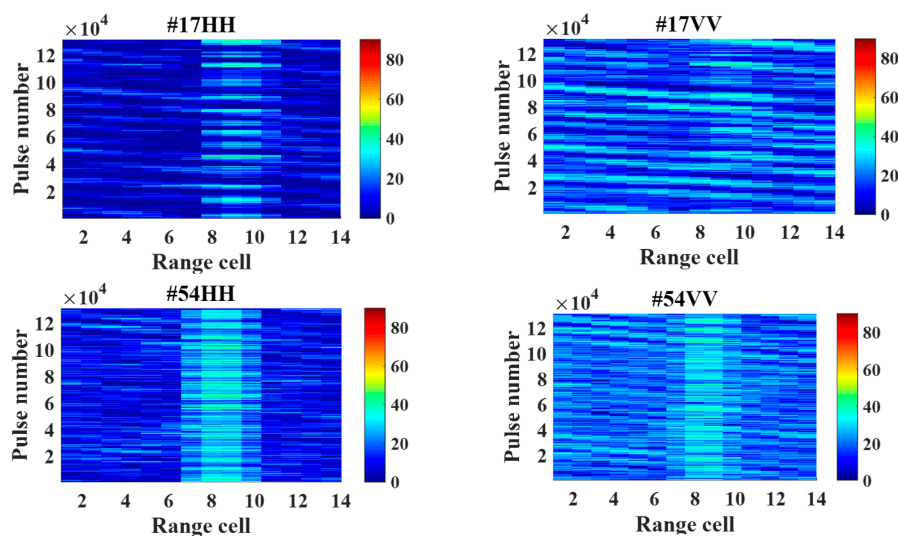


Figure 2. Cont.

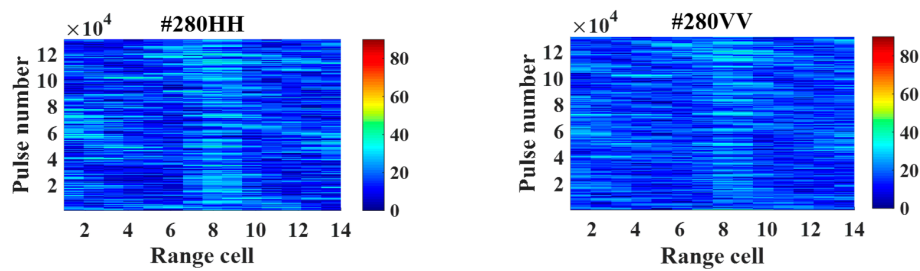


Figure 2. Spatiotemporal distribution of normalized sea clutter amplitude of IPIX radar.

2.2. UHF Radar, S Radar and Sea Clutter Datasets in China

The UHF-band radar is located at 35°45′N, 120°15′E, on a hill on Lingshan Island facing the Yellow Sea of China. The placement of the UHF-band radar is indicated by the red position marker on the Google map shown in Figure 3.



Figure 3. The placement of the UHF-band and S-band radar.

The UHF-band radar sea clutter properties are given in Table 2. The UHF-1 - UHF-4 are four sea clutter datasets without targets. According to the Douglas Sea State Table [1] (p. 16), the UHF-1 - UHF-4 respectively represent the sea clutter of 1–4 sea state levels.

Table 2. Characteristics of UHF-band radar and sea clutter data.

	UHF-1	UHF-2	UHF-3	UHF-4
Radar Transmitting Frequency (MHz)	456	456	456	456
Polarization Mode	HH	HH	HH	HH
Bandwidth (MHz)	1	1	1	1
Pulse Length (us)	10	10	10	10
PRF (Hz)	1000	1000	1000	1000
Beam Width (°)	≤10.2	≤10.2	≤10.2	≤10.2
Wave height (m)	0.3	0.5	1.3	1.9
Wave direction (°)	8.7	80.8	92.9	85.9
Wave period (s)	3.4	3.63	5.4	6.4
Wind speed (m/s)	8.6	7.8	5	8.8
Wind direction (°)	353.9	354.9	51.8	70.4
Range Samples	100	100	150	150
Pulse Number	61001	62001	62002	61001

Spatiotemporal amplitude distribution of four datasets are given in Figure 4. Here, the x-axis denotes the range cell, and the y-axis denotes the pulse number. As can be seen, as the sea state level increases, the amplitude of sea clutter increases.

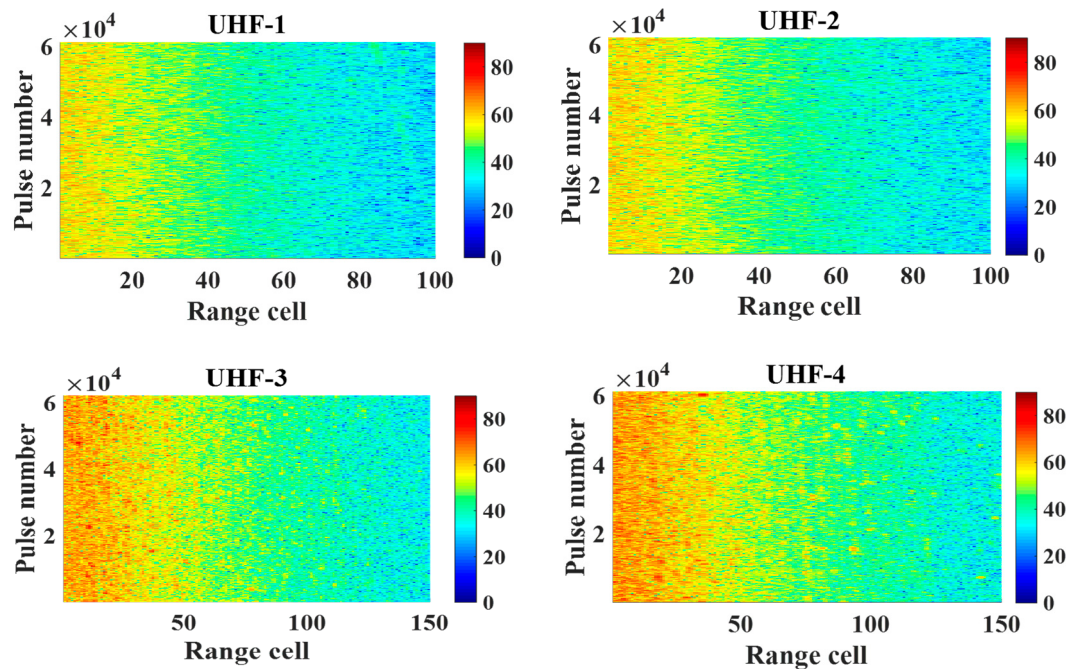


Figure 4. Spatiotemporal distribution of sea clutter amplitude of UHF-band radar.

The S-band radar sea clutter experiments are also conducted at Lingshan Island. Sea clutter datasets without targets of the S-band radar contains 1-4 sea state levels. The detailed information of marine environment parameters, the S-band radar parameters, and sea clutter properties is shown in Table 3. Figure 5 shows the spatiotemporal amplitude distribution of the S1~S4. As can be seen, the sea clutter amplitude of the S-band radar is larger than the UHF-band radar.

Table 3. Characteristics of S-band radar and sea clutter data.

	S1	S2	S3	S4
Radar Transmitting Frequency (GHz)	3.2	3.2	3.2	3.2
Polarization Mode	HH	HH	HH	HH
Bandwidth (MHz)	2.5	2.5	2.5	2.5
Pulse Length (us)	10	10	10	10
PRF (Hz)	1000	1000	1000	1000
Beam Width (°)	≤5.3	≤5.3	≤5.3	≤5.3
Wave height (m)	0.26	0.71	1.3	1.91
Wave direction (°)	66.7	95	91.2	91.1
Wave period (s)	2.5	4	3.7	4.9
Wind speed (m/s)	3.2	1.8	8.5	3
Wind direction (°)	255.4	122	208.6	200.7
Range Samples	100	150	200	250
Pulse Number	21,540	21,540	21,540	21,540

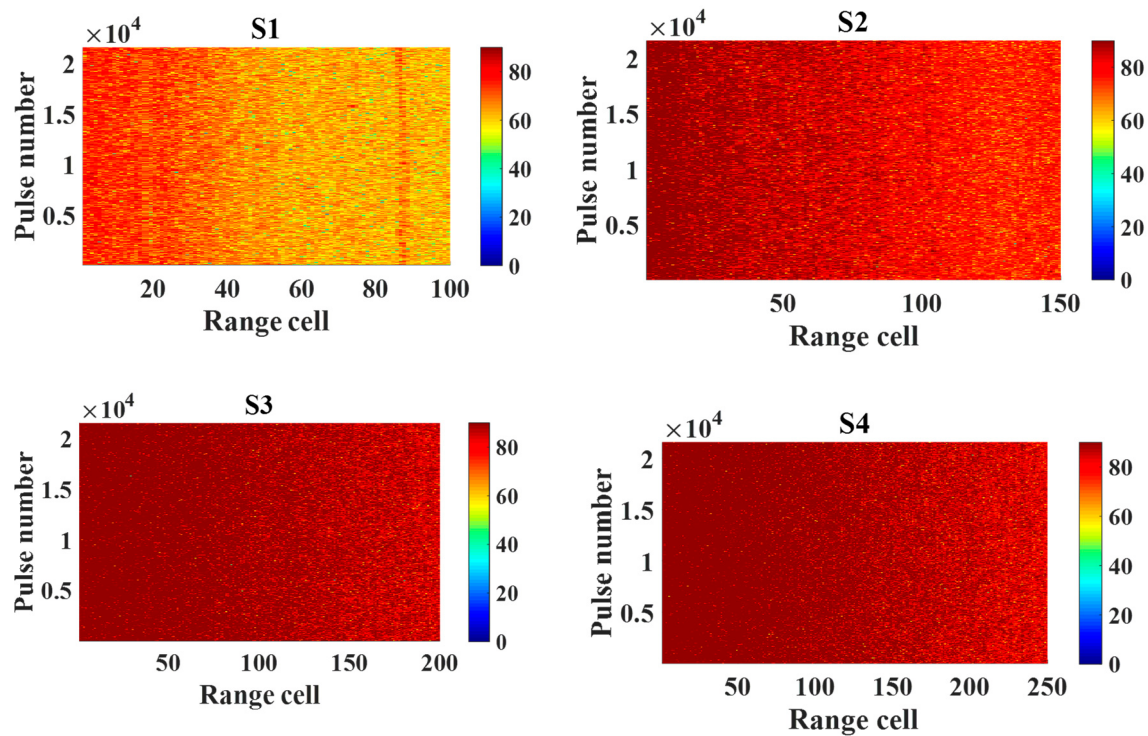


Figure 5. Spatiotemporal distribution of sea clutter amplitude of S-band radar.

3. Methods

Large-scale gravity waves and small-scale capillary ripples are superimposed to form a double superimposition model (DSM), which is a well-known approach for a time-evolving oceanic surface model (TOSM) [35]. Radar backscatter from the sea is derived from a complex interaction between incident electromagnetic waves and the sea surface [1], the sea clutter amplitude is closely related to the sea surface roughness structure. In the same sea area of the same season, the marine environmental parameters such as wave height, wave direction, wind speed, and wind direction can produce different types of sea spectrum which determines the sea surface roughness structure, and these marine environmental parameters often change within a certain range. Therefore, the amplitude of the sea surface scattering echo collected by the same radar also varies within a certain range. By learning the variation law of sea clutter by nonlinear prediction method, the future amplitude of sea clutter can be predicted, and sea clutter can be further suppressed.

The flow chart for sea clutter suppression and target detection is shown in Figure 6. The sea clutter data used in this paper consists of three parts: IPIX radar sea clutter collected with the McMaster University IPIX radar [23], UHF-band radar and S-band radar [36] sea clutter collected by the China Research Institute of Radio-wave Propagation. The radar emits electromagnetic waves through the transmitting antenna to the specific area of the sea surface and is scattered by the sea surface, and then the electromagnetic scattering is received by the radar receiver. The preprocessing of the sea clutter received by the radar is mostly done manually, and then the preprocessed sea clutter time series is input to the sea clutter predictor, the prediction sea clutter data is used to suppress the original sea clutter.

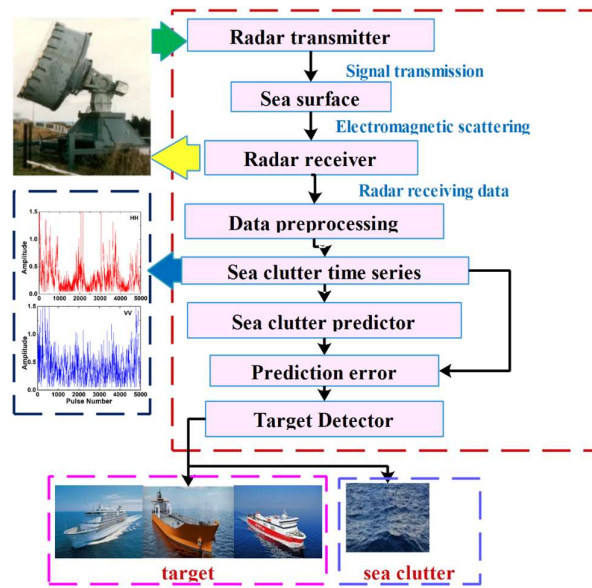


Figure 6. Flow chart of sea clutter suppression and target detection.

3.1. Sea Clutter Prediction Principle

This paper embeds the LSTM network into the sea clutter suppression chart. Schematic visualization for radar collecting electromagnetic scattering (EM) signals on the sea surface is shown in Figure 7. The radar received sea clutter from point O. Training the sea clutter without any interference by the sea clutter predictor in Figure 6, the predictor can learn the dynamic changes of sea clutter. Then, we use the predictor to predict the input signal of other range cells. When a target occurs at point O, the EM signal of the target is different from sea clutter, using the trained predictor to predict the boat's EM, the MSE will increase. Furthermore, the sea clutter suppression signal containing the target is different from the sea clutter suppression signal without any interference in the frequency domain.

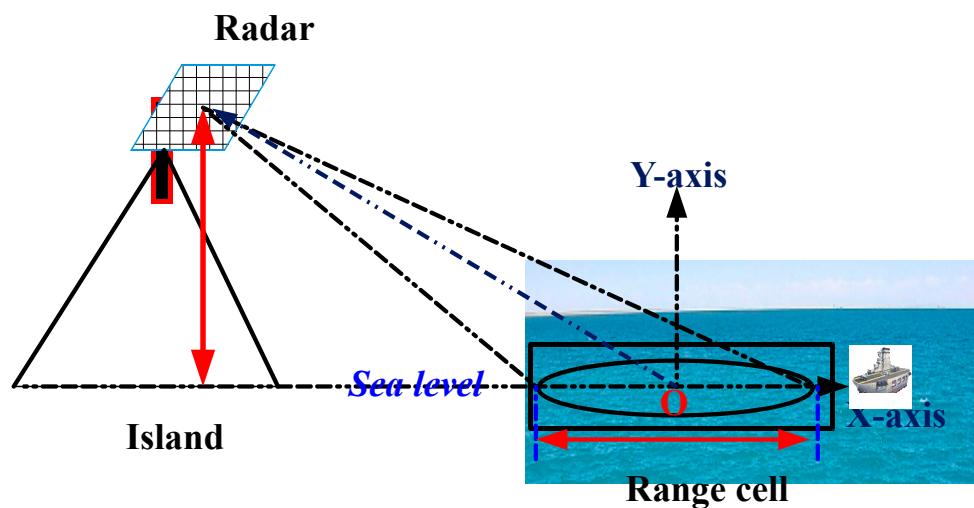


Figure 7. Schematic visualization for radar collecting EM signals.

The sea clutter prediction principle is as follows (Equation (1)):

$$y(t) = H(x(t), h(t-1)) \quad (1)$$

where $x(t)$ is the observation sea clutter amplitude of current step size, $h(t-1)$ is the historical information of sea clutter characteristics, $y(t)$ is the prediction result, and $H(\cdot)$ is a nonlinear model.

3.2. Traditional Prediction Methods

SVM is a significant machine learning approach in data mining. The sea clutter time series is defined as $SC = \{S_i\}_{i=1}^N$, N is the length of the sea clutter time series. The support vector regression (SVR) can be described as follows (Equation (2)):

$$f(x) = w^T \Phi(x) + b \quad (2)$$

where $\Phi(\cdot)$ is the input feature that maps the input vector x to high dimensional space, w and b are the model parameters to be estimated from the sea clutter data.

An ANN structure with three layers is used in this paper. The activation function for the hidden layer and output layer are Rectified Linear Unit (ReLU) and linear function respectively. The prediction output is described as follows (Equation (3)):

$$f(x) = w_o^T (\text{ReLU}(w_1^T x + b_1)) + b_o \quad (3)$$

where x is the input sea clutter amplitude time series. w_1^T and w_o^T are the weight matrices of the hidden layer and the output layer, respectively. b_o and b_1 are the offset vectors of the hidden layer and the output layer, respectively.

The structure of the RBF NN is similar to ANN, the difference is, the input of the hidden layer is the distance between RBF NN input vector and the center vector of RBF, and the radial basis function as the activation function of hidden layer. Gaussian RBF is described as follows (Equation (4)):

$$\rho(x, c_i) = e^{\frac{-1}{2\sigma^2} \|x - c_i\|^2} \quad (4)$$

where, c_i is the i -th center of hidden layer, σ^2 is the variance. c_i and σ^2 are parameters to be estimated of the hidden layer.

The sea clutter prediction output using RBF NN is shown as follows (Equation (5)):

$$\varphi(x) = \sum_{i=1}^m (w_i \rho(x, c_i) + b_i) \quad (5)$$

where, w_i and b_i are the parameters to be estimated from the output layer.

3.3. The Proposed Sea Clutter Prediction System Based on LSTM NN

The LSTM block [37] includes the input gate, forget gate, and output gate. The forget gate is used to discard the information employing the sigmoid function, and the input gate determines the information to be retained at the current time, The LSTM block continuously updates the information at different times, so it is possible to learn the long-term changes of the sea clutter. The structure of the LSTM block is shown in Figure 8.

The update formula for input gate, forget gate and output gate are as follows (Equations (6)–(8)):

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (6)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (7)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (8)$$

The memory cell output is as follows (Equation (9)):

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (9)$$

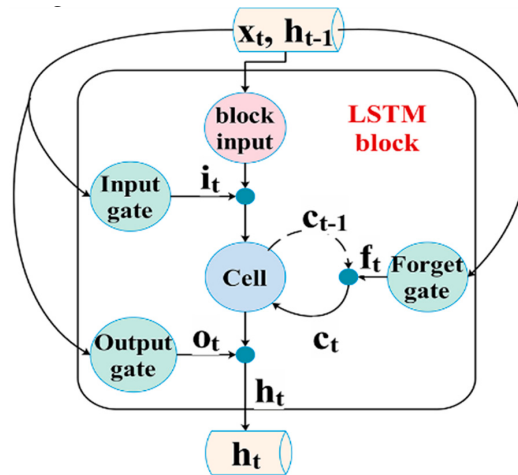


Figure 8. Long short-term memory.

The hidden layer update formula is as follows (Equation (10)):

$$h_t = o_t \odot \tanh(c_t) \quad (10)$$

In Equations (6)–(10): $\odot$ denotes element-wise product. x_t is the sea clutter amplitude at t time step. W_i , W_f and W_o are input weights. U_i , U_f and U_o are recurrent weights. b_i , b_f and b_o are bias weights. These weights are initialized to a number with a mean of 0 and variance of 1; $\sigma(\cdot)$ is the logistic sigmoid function that used as the activation function of gates; $\tanh(\cdot)$ is the hyperbolic tangent which used as the current block input and output activation function.

For UHF-band radar and S-band radar, the proposed sea clutter prediction system including sea clutter preprocessing and the LSTM NN structure is shown in Figure 9. The raw data collected by radar is converted into a binary file, and then the binary file is processed into pulse compressed data using a matched filtering method [38]. Pulse compressed data includes leaked signals, blind spot signals, effective sea clutter data and noise data. To extract the effective sea clutter data, fixed range cells in pulse compressed data are set according to experience. At present, sea clutter data collected by shore-based radars have reached several terabytes, which contain noise and other scattered signals. It takes a lot of time to classify the data, and storing the data consumes a large amount of hardware resources. In order to solve this problem, an Internet of Things (IoT) sea clutter intelligent management system can be established to meet the different needs of sea clutter study by learning from other management architecture [39–41] in the future. The extracted data of the fixed range cells are normalized to improve training speed and prediction accuracy. Normalized sea clutter is then predicted by the LSTM predictor.

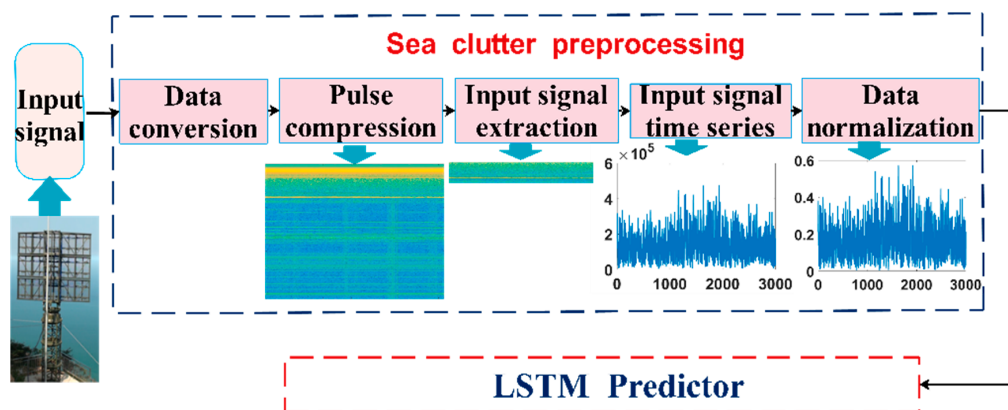


Figure 9. Structure of sea clutter prediction system for UHF-band radar and S-band radar.

For each pulse compressed data, the effective sea clutter data of different grazing angles is extracted and sorted according to the grazing angle from small to large. The sorted grazing angle index is renamed to different range cells. The sea clutter in the first range cell is divided into a training set, a test set, and a validation set, where the proportions of the train set, test set, and the valid set are set as 64%, 20%, and 16%, respectively. The training set is trained using the TensorFlow platform and the Titan V GPU with NVIDIA CUDA8.0 [42], and the test set is tested using the CPU. The trained sea clutter predictor is saved as the sea clutter predictor corresponding to the current radar parameters and marine environmental parameters, and the sea clutter data in other range cells are predicted by the saved predictor.

For IPIX radar, we use the IPIX radar sea clutter datasets provided by McMaster University. Based on the target information provided by McMaster University, we select sea clutter without targets and without target interference. The normalization and prediction methods of the data are the same as the S-band and UHF-band sea clutter.

3.4. Sea Clutter Suppression in the Frequency Domain

In order to improve the detection performance of radar in the future, this paper firstly studies the long-term diversification of sea clutter based on LSTM to predict the sea clutter amplitude. Then the sea clutter is suppressed in the frequency domain for that the Doppler spectrum of sea clutter is different from the target. The equation for sea clutter suppression is as follows (Equation (11)):

$$Z(f) = \text{FFT}(X(t) - Y(t)) \quad (11)$$

where, $X(t)$ is the sea clutter signals received by the radar during a period of time, $Y(t)$ is the sea clutter signals predicted by the LSTM NN during this period, FFT is the Fourier transform, and $Z(f)$ is the sea clutter suppression signal in the frequency domain.

4. Results

The computer system used for sea clutter prediction is a Ubuntu 16.04 LTS, equipped with an Intel(R) Xeon(R) E5-2630 v4 CPU @2.20 GHz and an NVIDIA TITAN V GPU.

4.1. Results and Analysis of Sea Clutter Amplitude Prediction

Based on the datasets introduced in Section 2, different prediction methods are used to predict the sea clutter amplitude of the first range cell firstly, and then sea clutter amplitude of other range cells are predicted afterward using the predicted result of sea clutter of the first range cell.

4.1.1. Sea Clutter Prediction Results in the First Range Cell

In order to increase the convergence speed and improve the prediction accuracy of the prediction model, the sea clutter amplitude of the first range cell is normalized. For SVM and RBF NN, we choose the first 5000 pulses in the normalized sea clutter amplitude of the first range cell. Among them, the training set is the first 3000 pulses, and the subsequent 2000 pulses are used to test the MSE. For other prediction methods, we select all the pulses of the normalized sea clutter amplitude of the first range cell. Among them, the proportion of the train set, test set, and the valid set is set as 64%, 20%, and 16% respectively. Except for SVR, MSE is used as the loss function of the prediction methods, and in the training process, the network structure is adjusted so that the verification error becomes smaller and smaller, the model structure and the weights that minimize the verification error are saved. The network structure is discussed in Section 5.1.

The sea clutter prediction results of the IPIX radar, UHF-band radar and S-band radar based on the following different methods are shown in Figure 10a. For sea clutter without any interference, the lower the MSE, the better the prediction result of the sea clutter time series. From Figure 10a, it can be seen that all prediction methods have the best prediction performance for UHF-band sea clutter,

this is because the normalized sea clutter amplitude of UHF-band radar has the slowest change that shown in Figure 10b. From Figure 10a, we can see that the LSTM is better for sea clutter of IPIX radar and S-band radar, ANN is better for UHF-band radar sea clutter. For different radars, the mean MSE of sea clutter prediction in the first range cell for the SVR, ANN, RBF, and LSTM network are 3.1×10^{-3} , 7.1×10^{-4} , 8.3×10^{-3} and 5.6×10^{-4} , respectively. Both ANN and LSTM perform considerably better than SVR and RBF. This may be due to the fact that when training SVR or RBF NN models, 3000 training samples are used to learn some sea clutter features, while ANN and LSTM used more training samples (for different radar sea clutter, the sample size is 64% multiplied by the pulse number listed in Tables 1–3) to learn more sea clutter features. Overall, the LSTM for sea clutter prediction performs best for IPIX radar, UHF-band radar and S-band radar.

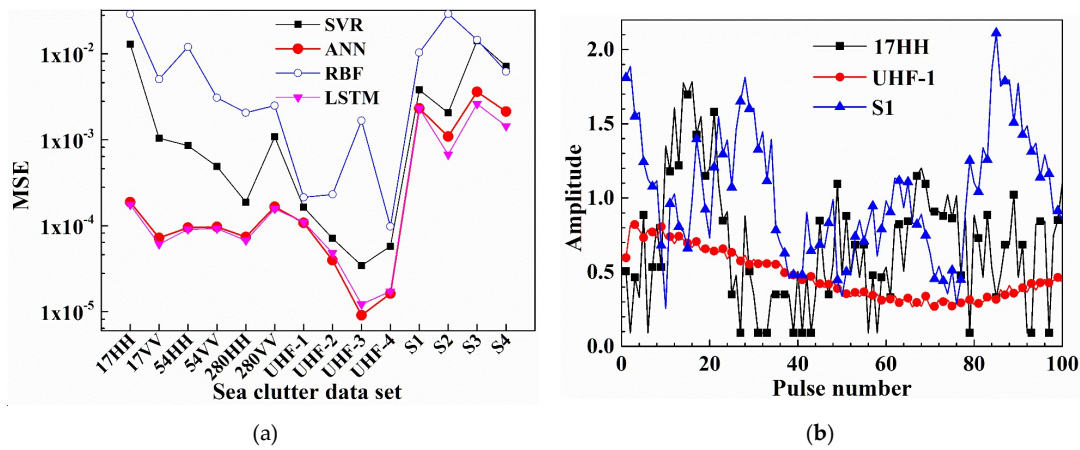


Figure 10. MSE and amplitude of sea clutter of different radars. (a) MSE of sea clutters in the first range cell; (b) Normalized sea clutter amplitude of different radars.

4.1.2. Sea Clutter Prediction Result in Different Range Cells

Mean sea clutter amplitude of each range cell for IPIX radar is shown in Figure 11a, it is easy to see that sea clutter with targets has a higher mean amplitude and the number of range cells affected by the target is also relatively large. As introduced in Section 2, the targets of 17#, 54#, and 280# sea clutter are at the 9th, 8th, and 8th range cell, respectively. This can also be seen in Figure 11a.

The mean amplitude of the sea clutter will increase when the signal hits targets, and the target will affect the sea clutter amplitude of 1 to 2 adjacent range cells. It can be seen from Figure 11b that when the 17#VV polarized sea clutter is predicted by the ANN, MSE at the ninth range cell is the largest. When the 54# sea clutter is predicted, the target information is not obvious. When predicting 280#HH polarized sea clutter, the prediction error starts to rise at the 8th range cell using ANN or LSTM network, and the prediction error is the largest at the 9th range cell. Therefore, when using the sea clutter amplitude prediction method, some target information can be seen, but the target location cannot be accurately predicted.

In order to visually analyze the ability of different prediction methods to detect targets, we calculate the Kullback-Leibler (KL) divergence [43] between the probability distribution of the mean amplitude and the probability distribution of the MSE of different prediction methods, KL divergence is as follows (Equation (12)):

$$D(P||Q) = \sum P(x) \log \frac{P(x)}{Q(x)} \quad (12)$$

where $P(x)$ is the probability distribution of the mean amplitude, $Q(x)$ is the probability distribution of the MSE of sea clutter using prediction method, the smaller the $D(P||Q)$, the closer $P(x)$ and $Q(x)$ are, and the more likely to detect the target.

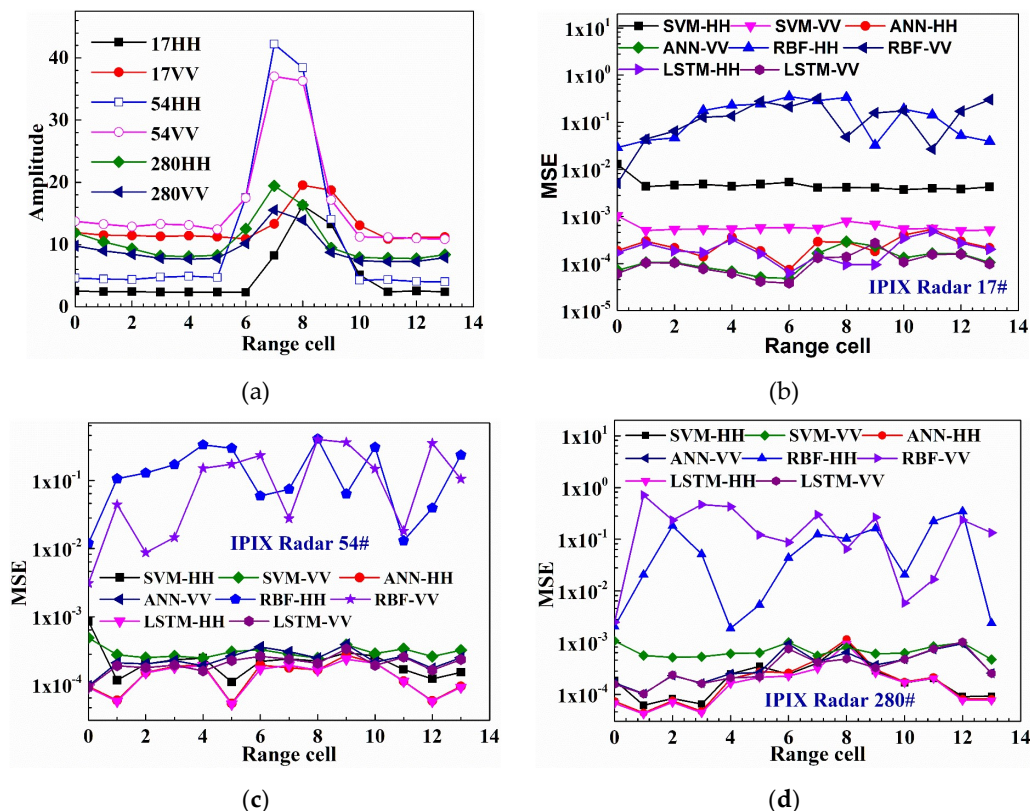


Figure 11. Mean amplitude and prediction results for sea clutter of IPIX radar. (a) Mean amplitude of sea clutter in different range cells; (b) MSE for 17# sea clutter using different prediction methods; (c) MSE for 54# sea clutter using different prediction methods; (d) MSE for 280# sea clutter using different prediction methods.

The corresponding KL divergence of different prediction methods is shown in Figure 12. For #17VV and #280VV sea clutter, SVM prediction results are closest to the distribution of sea clutter amplitude. ANN prediction results are closest to the amplitude distribution of #17HH and #54VV sea clutter. The LSTM network prediction result is closest to the amplitude distribution of #54HH and #280HH. Combine the overall prediction results, targets in #17VV sea clutter is more likely to be detected using the sea clutter time series prediction model.

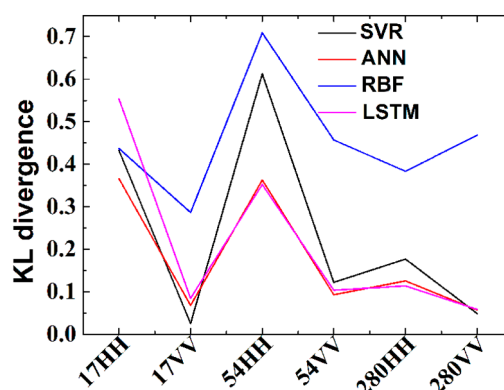


Figure 12. KL divergence of prediction methods for IPIX radar sea clutter.

The prediction results of the UHF-band radar sea clutter amplitude by different methods are shown in Figure 13. As can be seen, for the RBF prediction method, the MSE of the sea clutter amplitude except for the first range cell is relatively large, so it is difficult to predict the sea clutter amplitude of

other range cells based on the prediction result of the first range cell. For other prediction methods, the sea clutter amplitude prediction results of other range cells (near the first range cell) are better; for sea clutter away from the first range cell, the MSE of sea clutter amplitude increases with the increase of distance, this is because, as the distance increases, the variation of the sea clutter of the first range cell is increasingly unsuitable for distant sea clutter.

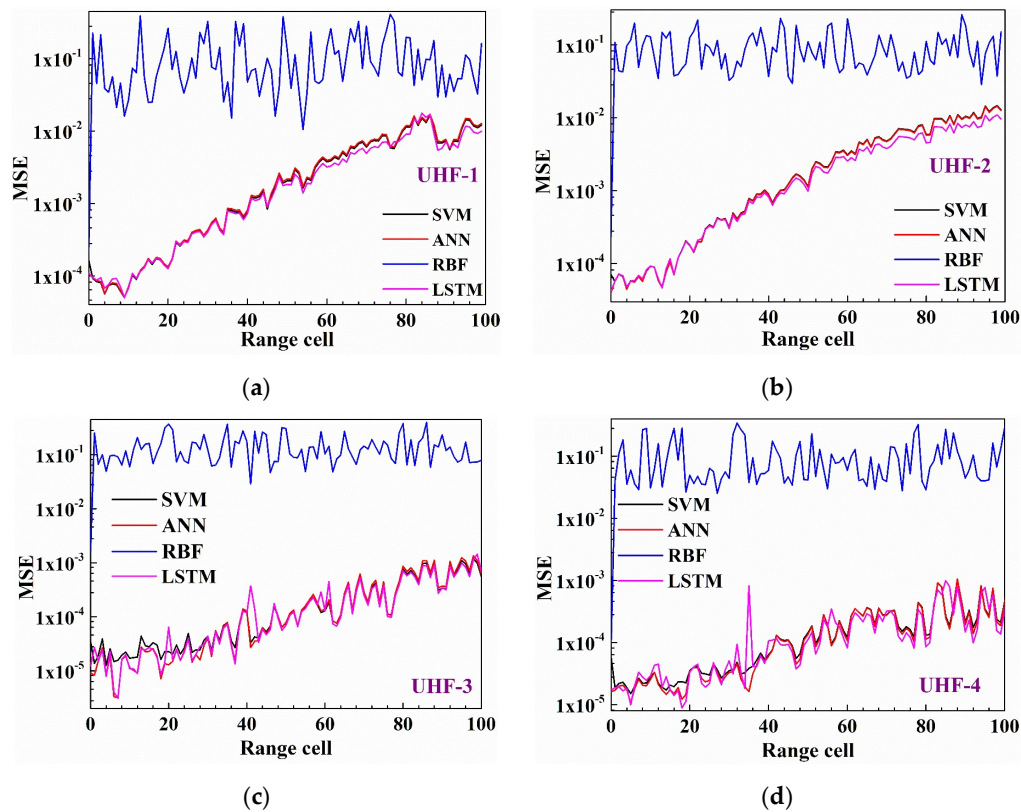


Figure 13. Prediction results for sea clutter of UHF-band radar. (a) MSE of sea clutter of the first sea state level; (b) MSE of sea clutter of the second sea state level; (c) MSE of sea clutter of the third sea state level; (d) MSE of sea clutter of the fourth sea state level.

For S-band radar, the sea clutter prediction results of different methods are shown in Figure 14, as can be seen, LSTM works best in the prediction of sea clutter. The distance resolution of the S-band radar is 60 m (larger than UHF-band radar), and its' prediction error does not increase obviously at a large range cell.

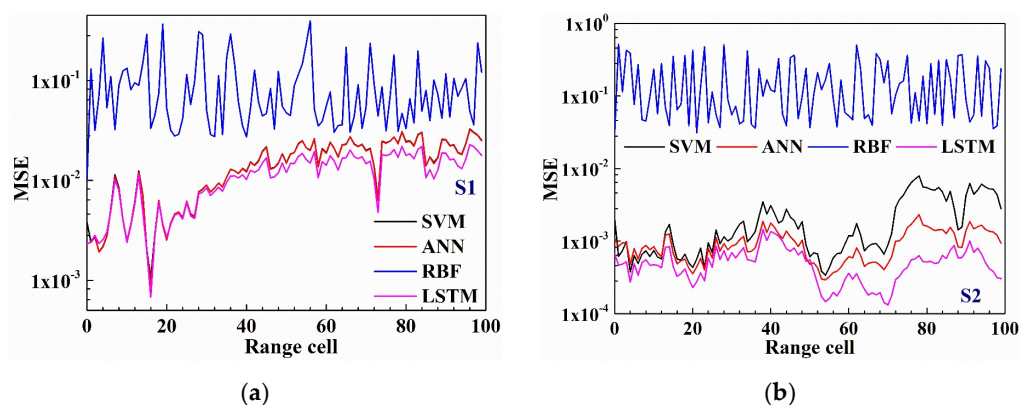


Figure 14. Cont.

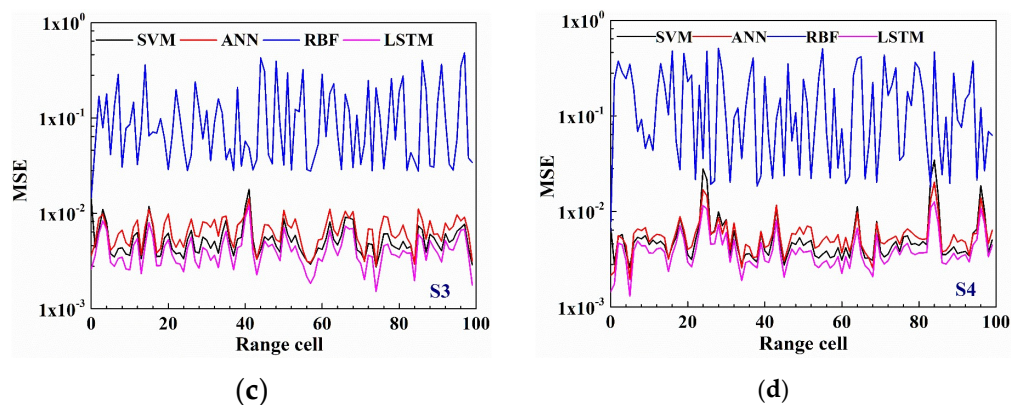


Figure 14. Prediction results for sea clutter of S-band radar. (a) MSE of sea clutter of the first sea state level; (b) MSE of sea clutter of the second sea state level; (c) MSE of sea clutter of the third sea state level; (d) MSE of sea clutter of the fourth sea state level.

From Figures 13 and 14, as can be seen, LSTM has the lowest MSE in the remote range cell overall, this may be because LSTM has learned more about sea clutter change law in the training process. For UHF-band and S-band radars, the mean MSE of sea clutter is shown in Table 4, blackened fonts represent the smallest mean MSE. The smaller the mean MSE, the closer the predicted value is to the original sea clutter and the better the predictor performance. LSTM has the smallest mean MSE for S-band radar sea clutter and UHF-band sea clutter without UHF-4, so it has the best prediction overall. It can also be seen that prediction error for UHF-band sea clutter is smaller than S-band sea clutter.

Table 4. Mean MSE for UHF-band and S-band radar sea clutter.

DATA	MEAN MSE			
	SVR	ANN	RBF	LSTM
UHF-1	0.004	0.0042	0.1113	0.0036
UHF-2	0.0037	0.0036	0.0919	0.0029
UHF-3	0.00023	0.00251	0.1427	0.00215
UHF-4	0.00175	0.00167	0.0965	0.00173
S1	0.0151	0.015	0.093	0.0117
S2	0.0021	0.00947	0.1655	0.00052
S3	0.0055	0.0067	0.1174	0.0043
S4	0.0059	0.0059	0.1591	0.0042

4.2. Sea Clutter Suppression Based on the LSTM Prediction Method

In the frequency domain, based on the 17# sea clutter collected by IPIX radar, the sea clutter corresponding to the first sea state level collected by the UHF-band radar, and the sea clutter corresponding to the first sea state level collected by the S-band radar, the original sea clutter data are suppressed by the prediction results obtained by the LSTM. The sea clutter suppression results are shown in Figures 15 and 16, respectively.

For the IPIX radar, the sea clutter suppression result of the first range cell without the target and the ninth range cell containing the target is as shown in Figure 15, and as can be seen, the frequency shift of the sea clutter is near the 0 frequency. In Figure 15a, the peak power of sea clutter before and after suppression is -67 dB and -86 dB, respectively, and the average power is about -86 dB. As can be seen, the sea clutter suppression result is quite good. In Figure 15b, as can be seen, the peak power of sea clutter is reduced from -62 dB to -75.5 dB, the Doppler broadening is significantly reduced, the peak power of the target is reduced from -77.5 dB to -81 dB, and the Doppler broadening has no obvious change. Therefore, the sea clutter prediction method based on LSTM can significantly suppress sea clutter.

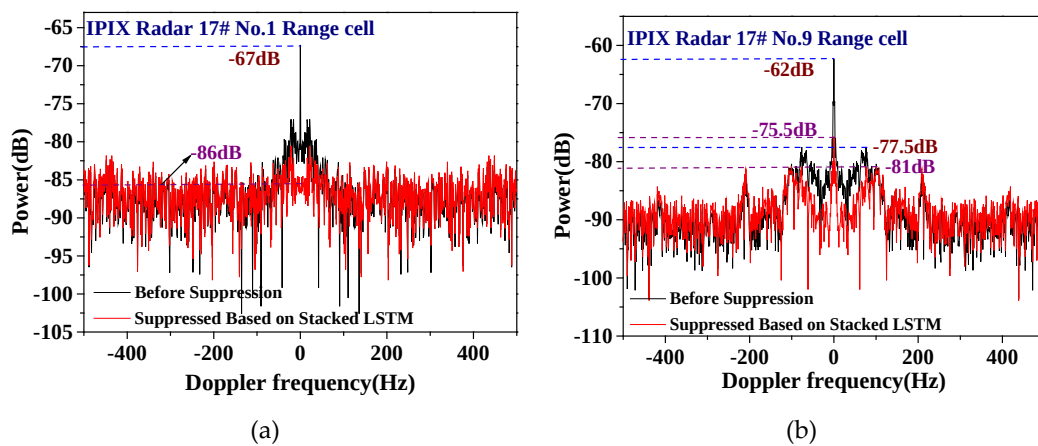


Figure 15. Doppler spectrum of sea clutter suppression signal of IPIX radar. (a) Doppler spectrum of sea clutter suppression signal of 17# in the first range cell; (b) Doppler spectrum of sea clutter suppression signal of 17# in the ninth range cell.

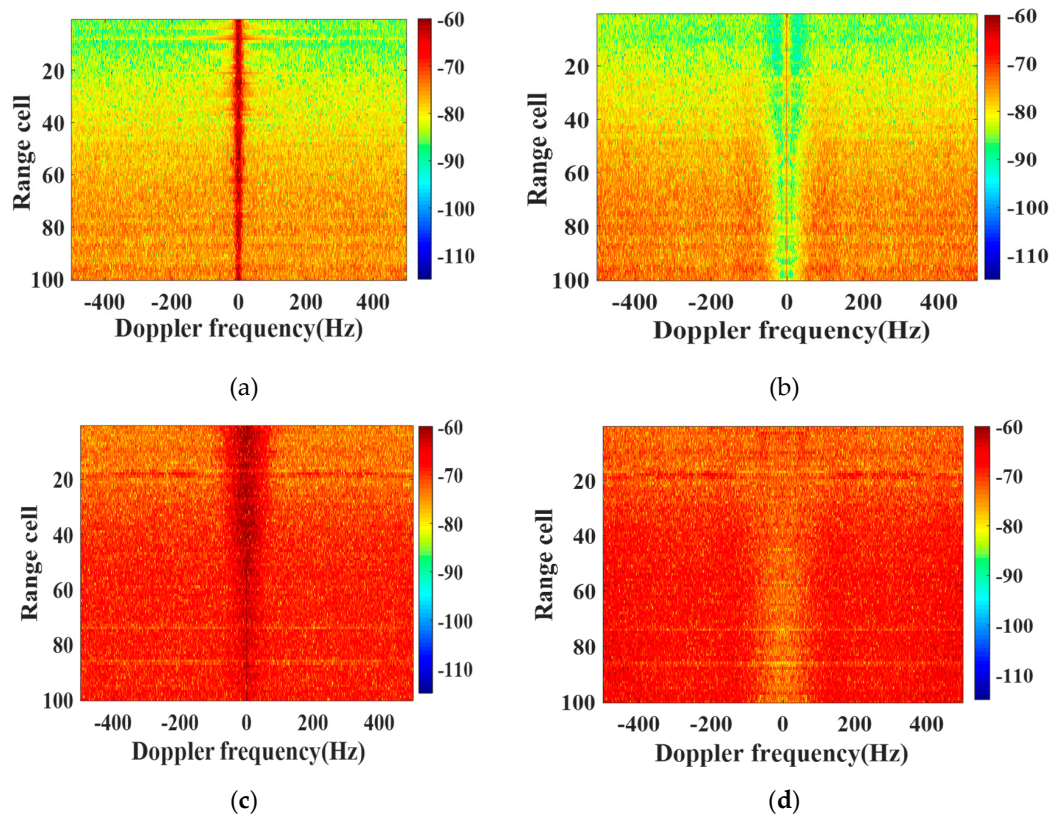


Figure 16. Range-Doppler images of sea clutter of UHF-band radar and S-band radar. (a) Range-Doppler image of sea clutter of UHF-band radar before suppression; (b) Range-Doppler image of sea clutter of UHF-band radar after suppression; (c) Range-Doppler image of sea clutter of S-band radar before suppression; (d) Range-Doppler image of sea clutter of S-band radar after suppression.

Figure 16a,c are the Range-Doppler images of the sea clutter of the first sea state level of UHF-band radar and S-band radar, respectively. As can be seen, the frequency shift of the sea clutter is concentrated near the 0 frequency. Sea clutter suppression results of Figure 16a,c are shown in Figure 16b,d, respectively. As can be seen, the effect of sea clutter suppression is obvious for UHF-band radar and S-band radar, and the sea clutter suppression effect is better in 1–20 range cells, and the sea clutter suppression is excessive after the 20th range cell. Therefore, the LSTM has a good prediction of the sea clutter variation law of the adjacent range cell, and the sea clutter prediction ability of the far

range cell is weakened. This can also be seen in Figure 13a. From Figure 16b,d, as can be seen, the sea clutter suppression capability of S-band radar is stronger than the UHF-band radar.

The sea clutter suppression signals of the first range cell of the first sea state level collected by UHF-band radar and S-band radar are shown in Figure 17a,b, respectively. It can be calculated that the sea clutter powers of UHF-band radar and S-band radar are suppressed by 18.5 dB and 13 dB, respectively, and the Doppler broadening is significantly reduced. This shows that the clutter prediction method based on LSTM can effectively suppress sea clutter.

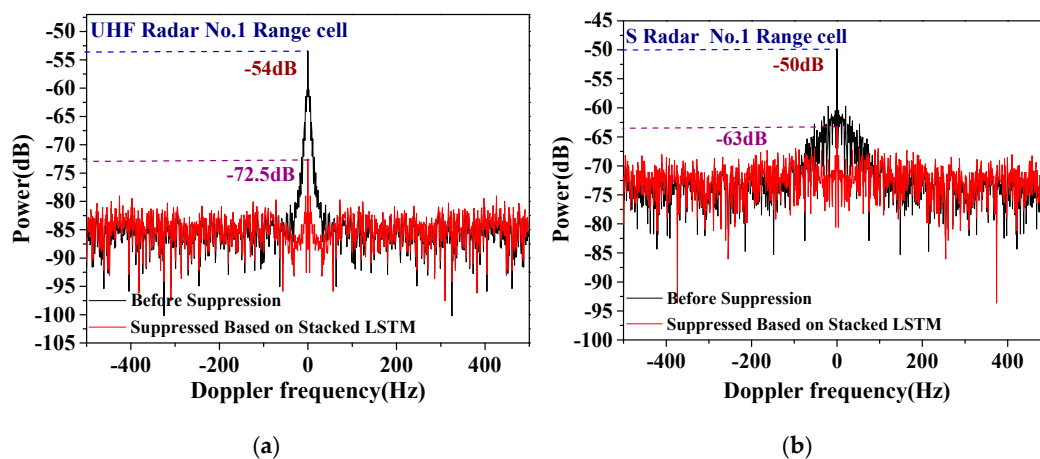


Figure 17. Doppler spectrum of sea clutter of UHF-band radar and S-band radar. (a) Doppler spectrum of sea clutter suppression signal of UHF-band radar in the first range cell; (b) Doppler spectrum of sea clutter suppression signal of S-band radar in the first range cell.

5. Discussion

5.1. The Selection of Parameters in LSTM

The network structure and parameters used in Section 4 are discussed in this section. Taking the prediction results of sea clutter measured by IPIX-band radar as an example, the LSTM NN designed in this paper includes an input layer, a hidden layer using LSTM block and a dense layer. The structure of the LSTM block is introduced in Section 3, the hyperbolic tangent function is used as the activation function of the fully connected layer in this paper, and an output layer with linear activation function.

The MSE changes with the dimension of the input vector are shown in Figure 18. The MSE starts at a relatively small value because we normalize the data. As can be seen, as the dimension of the input vector increases, the MSE exhibits a trend of decreasing first and then increasing, and the MSE reaches a minimum when the input vector dimension is 100.

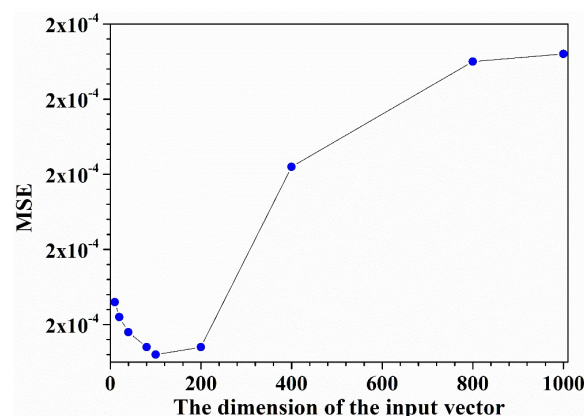


Figure 18. The variation of MSE with the dimension of the input vector.

The larger the batch-size, the faster the calculation. The change in MSE with the batch-size is shown in Figure 19, as can be seen, as the batch-size increases, the MSE gradually increases. When the batch size is greater than 1000, the MSE increases faster, so we choose the batch size to be 1000.

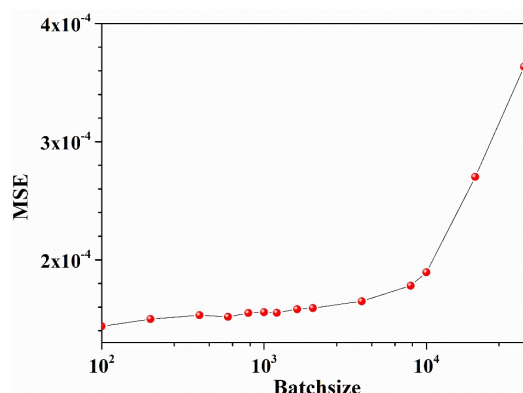


Figure 19. The variation of MSE with the batch size.

The results of neuron's number of the hidden layer of LSTM is shown in Figure 20. As the epoch increases, MSE gradually declines. When the epoch is increased to 25, the MSE remains basically unchanged. When the epoch is greater than 25, and the number of neurons of the hidden layer is 16 or 32, the prediction ability of LSTM is better. The larger the number of neurons, the longer the training time, so the number of neurons in the hidden layer of LSTM is chosen to be 16.

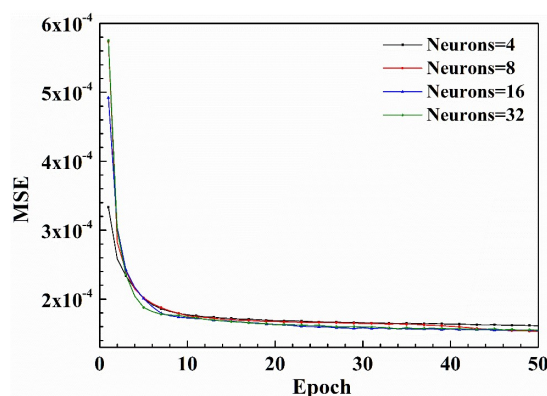


Figure 20. The variation of MSE with the number of neurons in the hidden layer of LSTM and the number of epochs.

According to the above analysis, the input vector dimension of the LSTM of the IPIX radar is 100, the batch size is 1000, and the number of hidden layer neurons is 16.

5.2. Discussion on Sea Clutter MSE of Different Sea State Levels

In this section, we discuss the results shown in Figures 13 and 14 that the MSE does not increase as the sea state level increase. According to the Douglas Sea State Table ([1], p. 16), we can get the range of wind speeds and wave heights corresponding to the sea state levels. When the wave height is low and the wind speed is high, the current sea surface is in a developing state. When the wave height and wind speed are both within the same level of sea conditions, the current sea surface is in a relatively stable state. We observe the wave heights and wind speeds in Tables 2 and 3. For the UHF-band, the sea surface when measuring UHF-4 is relatively stable. For the S-band, the sea surface when measuring S2 is relatively stable.

Our explanation for the increase in MSE of sea clutter amplitude without increasing sea conditions is that for UHF-band radar, when the sea state level is low, the wave height is small and the wind

speed is large; at this time, the sea surface is in an insufficiently developed state, the sea clutter waves change at any time, the variation law of sea clutter amplitudes of different range cell is also different, so the overall prediction error is larger. For S-band radar, the MSE of S2 is the lowest overall because the current sea surface is in a relatively stable state, and the sea clutter difference of different distance gates is relatively small.

This paper used the minimum and maximum values of the sea clutter data to normalize the sea clutter data. To further verify our explanation, the mean and variance curves of the normalized sea clutter amplitude of different sea state levels are calculated, which is shown in Figure 21. In Figure 21a, it is found that the lower the sea state level, the larger the mean value and the variance. Sea clutter in the lower sea state level has higher MSE, so when the sea state level increases, the sea clutter prediction error of other range cells is relatively small, which can be seen from Figure 13. In Figure 21b. As can be seen, the mean and variance of the second sea state level sea clutter are lower, and the prediction effect is also the best. The sea surface of first sea state level is in an insufficiently developed state and the prediction error is also high.

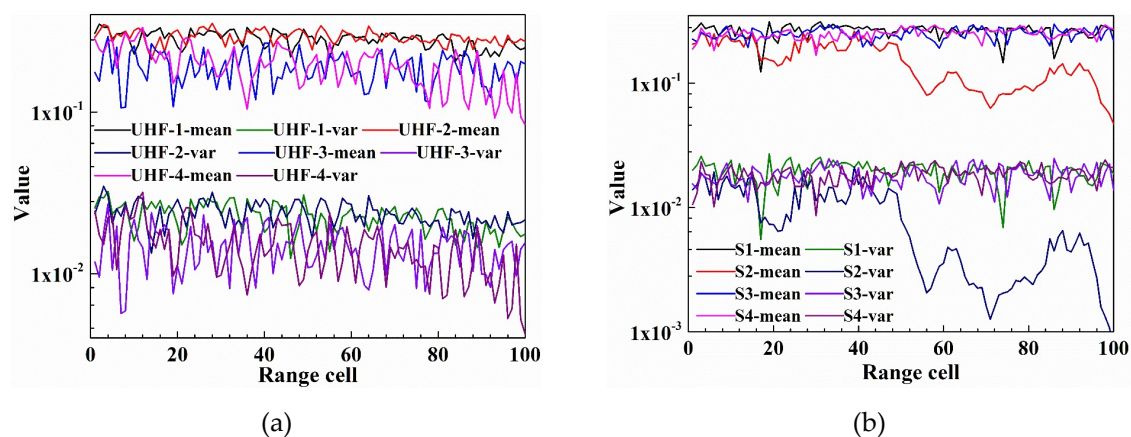


Figure 21. Mean and variance for normalized sea clutter amplitude of UHF-band and S-band radar. (a) Mean and variance for normalized sea clutter amplitude of UHF-band radar; (b) Mean and variance for normalized sea clutter amplitude of S-band radar.

6. Conclusions

In this paper, based on the sea clutter data measured by IPIX radar, UHF-band radar and S-band radar, the sea clutter prediction system using LSTM to predict the sea clutter amplitude is proposed. The sea clutter amplitude prediction results are compared with traditional prediction methods such as SVM, RBF NN and ANN. Experimental results demonstrate that the prediction performance of the LSTM network is generally better. For the UHF-band radar sea clutter, the MSE increases as the distance increases. Due to the high resolution of S-band radar, this phenomenon does not occur in S-band radar sea clutter prediction. For UHF-band radar and S-band radar, LSTM has the best prediction result. For the IPIX radar sea clutter, by calculating the maximum MSE, part of the sea clutter data can reflect the target information. In this paper, we further suppress sea clutter in the frequency domain. Experiments show that the proposed sea clutter prediction system based on LSTM has a good suppression effect on sea clutter collected by different radars.

The sea clutter data is not only correlated in the time domain, but also in the spatial domain. Therefore, the sea clutter data of adjacent range cells will affect each other. This paper only predicts according to the sea clutter time series and does not consider spatial correlation. In the future, based on the spatiotemporal relationship of sea clutter data and deep learning methods, the sea clutter data can be further predicted, and then sea clutter suppression can be performed.

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