Processing Method of Civil Radar Echo Signal Based on Kalman Filter Algorithm

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Abstract. With the popularization of civil radar application, it has great development potential in the situations of earthquake disasters and engineering accidents, such as personnel search and rescue, medical detection, and urban anti-terrorism. A civil radar echo signal processing method based on Kalman filter algorithm is designed. The Kalman filter algorithm is used to suppress the noise of the acquired radar echo signal. According to the amount of information obtained for the target being explored in different stages, target detection is regarded as the second stage of civil radar echo signal processing. Based on the Faster R-CNN detection framework, the context information and multi-scale Faster R-CNN target detection method are designed to determine the presence or absence of the target based on the denoised signal. Implement reference signal reconstruction, multipath clutter suppression, target location and tracking, and obtain some basic parameters to determine the target. The test results show that the tracking distance error of this method for stationary target, inching target and moving target is small.

Keywords: Kalman Filter Algorithm · Civil Radar · Faster R-CNN · Multipath Clutter Suppression

1 Introduction

The basic working principle of the radar is to send a series of electromagnetic waves to the target to be measured through the transmitter. After the transmission, the electromagnetic waves will collide with the target to be measured, and then part of the electromagnetic waves will be absorbed by the target to be measured, and the other part will be reflected back. Radar is to detect the target to be measured according to the reflected electromagnetic wave. When the target to be measured is detected, the feature information about the moving target to be measured can be extracted from the reflected electromagnetic wave for analysis, and finally some parameters [1] of the target to be measured can be determined. If the emitted electromagnetic wave is completely absorbed by the object, the target will be invisible and cannot be detected by radar. In short, radar is to use the waveform information returned from detection to obtain target information. Based on the working characteristics of radar, radar technology has been widely used in weather, transportation, national defense and other aspects. With the diversification of radar system applications, multi-function speed radar, navigation radar and detection radar have

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sprung up like mushrooms. In the civil field, radar is widely used. For example, weather detection radar can provide timely and accurate meteorological information for weather prediction, and remote sensing detection radar can provide various detailed parameters for the detection of earth resources and the imaging of targets. It can be said that the application of civil radar has penetrated into every corner of people's life.

The performance of radar signal processing is one of the important signs to measure the performance of a radar system. Its main role is to suppress interference as much as possible in complex environments and obtain more important and valuable information [2]. In the radar echo signal, the composition of the radar echo signal is more complex. Clutter, noise and jamming will seriously affect the detection performance of the system, so after obtaining the radar echo signal, the back-end signal processing, target search and other algorithms are particularly important.

A considerable amount of research has been achieved on the processing of radar echo signals. Scholars have proposed the use of wavelet threshold shrinkage to solve the problem of noise interference in the process of ground penetrating radar recording echo signals in a wide frequency band. A preprocessing method for ground penetrating radar echo signals is designed to remove radar echo noise, and the method is implemented through DSP circuits and software. Scholars have also proposed a simulation method for echo generation and signal processing of ground-based radar. Through radar system simulation technology, the echo generation and signal processing of ground-based radar are processed, and the application of the method is achieved through various aspects such as radar system analysis, design, testing, and evaluation. However, the above methods have significant tracking distance errors for stationary targets, micro moving targets, and moving targets, which cannot meet the application requirements of civilian radar echo signal processing.

In order to solve the shortcomings of the above methods, this paper takes the research project of X band Ground Based Radar (GBR) software simulation system proposed by the scientific research contract unit as the background, conducts a more in-depth study on the design and implementation of the echo generation and signal processing simulation subsystem, and proposes a civil radar echo signal processing method based on Kalman filter algorithm, In order to reduce the error in tracking distance during the processing of civilian radar echo signals. The specific research contents are as follows: the working principle and mode of the X band ground-based radar simulation system are introduced, the functions of the echo generation and signal processing subsystem in the entire simulation system are emphatically analyzed, and the overall design of the echo generation and signal processing simulation subsystem is carried out according to the system parameters. Under the application background of the X band ground-based radar simulation system, this paper proposes an implementation scheme of the echo generation and signal processing simulation subsystem, and models, simulates and tests it. The test results prove the rationality of the modeling.

2 Design of Echo Signal Processing Method for Civil Radar

2.1 Noise Suppression

Civil radar signal echo refers to the signal that the electromagnetic waves emitted by the radar system return to the radar receiver after interacting with the target object. These signal echoes carry information about the target object, including its position, velocity, size, and scattering characteristics. Compared with other signal echoes, civilian radar signal echoes have special signal characteristics and target reflection characteristics. Through distance and velocity measurement capabilities, they provide a wide range of application scenarios and play an important role in aviation, navigation, meteorology, geological exploration, and other fields. Therefore, in order to ensure the effectiveness of the radar echo signal, this paper implements noise suppression on the obtained radar echo signal based on the Kalman filter algorithm [3].

If we say random process $\{y_n\}$ Is a q The autoregressive process of order is generally expressed as $AR(q)$, it satisfies the following difference equation:

$$
\begin{aligned}
&y(n) + c(1)y(n-1) + \ldots + c(q)y(n-q) \\
&= \alpha(n)
\end{aligned}
\tag{1}
$$

In formula (1) $c(1), \ldots, c(q)$ Is a constant; $\alpha(n)$ It has a mean of zero and a variance of σ_α^2 Stationary white noise sequence. Next, we will use the AR model to estimate the parameters.

Establish the following model for the acquired radar echo signal:

$$
\beta_y(t) = \beta_s(t) + \beta_N(t) + \omega_1(t) \tag{2}
$$

In formula (2) $\beta_s(t)$ Represents pure signal; $\beta_N(t)$, $\omega_1(t)$ Represents a stationary additive noise signal, assuming that the three are uncorrelated; $\beta_y(t)$ Indicates a noisy signal.

Assuming that the radar echo signal is short-time stable, it can be used q Order AR model. Kalman filter is an optimal estimation method based on Bayesian inference, which can optimally estimate the state of the system under the condition of given observation data. By converting the AR model into the Equation of state and observation equation of Kalman filter, we can take advantage of the advantages of Kalman filter to obtain more accurate and stable state estimation, and can better deal with these nonlinear and non Gaussian situations, improving the adaptability and accuracy of the model.

Which will be used to represent the radar echo signal q The order AR model is transformed into the state equation and observation equation of Kalman filter.

In this method, we first estimate the power spectrum of the observed signal and the power spectrum of the noise, obtain the power spectrum of the pure signal required in the experiment through spectral subtraction, and then calculate the AR coefficients of the noise and the signal through the power spectrum respectively.

The specific parameter estimation process is shown in Fig. 1.

The measurement matrix, state transition matrix, noise covariance matrix of the measurement equation and noise covariance moment of the state equation are obtained according to the AR coefficient obtained above.

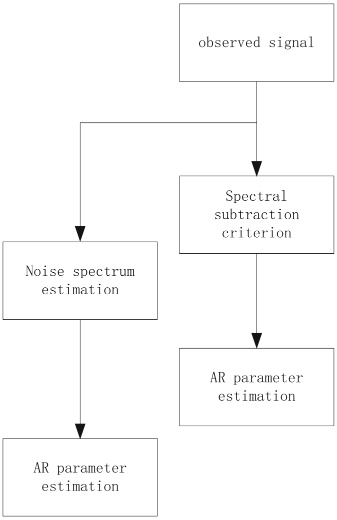

Fig. 1. Specific parameter estimation process

The parameters of Kalman filter are obtained, and then Kalman filter is applied to the signal.

The time update equation and the state update equation are obtained by continuous iteration.

The Kalman filter algorithm requires initial values x (0 | 0) and P (0 | 0). The initial estimated value of x (0 | 0) can be 0 or other values obtained from prior information, and P (0 | 0) can be the identity matrix. In this study, x (0 | 0) and P (0 | 0) are 0 and unit matrices, respectively.

2.2 Object Detection

According to the amount of information obtained from the explored target in different stages, target detection is regarded as the second stage of civil radar echo signal processing, that is, the presence or absence of targets is judged based on the denoised signal. Based on the Faster R-CNN detection framework, a context based and multi-scale Faster R-CNN target detection method is designed. On the one hand, the method uses multi-scale feature fusion, which uses deep semantic features for detection, and also fuses shallow details to enrich the information of the proposed features. On the other hand, the bidirectional GRU in RNN is used to process multi-scale features to achieve reasonable fusion of context information in SAR images, so that the candidate region generation phase and detection phase are assisted by context information. Under the joint action of multi-scale information fusion and context information, more informative target features can be obtained to improve target detection performance [4].

The proposed SAR image target detection framework is shown in Fig. 2. The detection network consists of four parts: feature extraction module, context information fusion module, candidate region generation module, and detection module. Firstly, the feature extraction module uses CNN to extract features from SAR images. At the same time, in order to enrich the feature information, the module also fuses the output features of different levels in the network, so that the final output features include deep semantic information and shallow details. Secondly, the context information fusion module composed of bidirectional GRU network is used to process the output features of the feature extraction module to achieve the fusion and utilization of the context information in the feature map. Then, the candidate region generation module processes the multi-scale context features processed by the context information fusion module, and outputs the classification and regression results of anchor boxes through the convolution operation, so as to select candidate regions. Finally, the detection module processes the corresponding features of the selected candidate region through the full connection layer to obtain the final target category and target location coordinates, and complete target detection in SAR images [5].

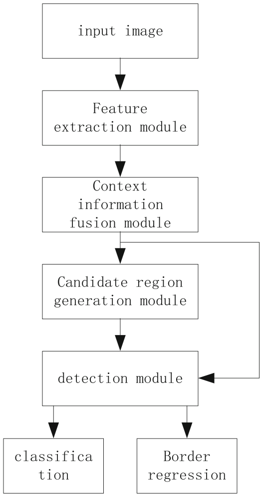

Fig. 2. Target Detection Framework

The network training in the proposed method is in the form of joint optimization. In the training process, after the input image is extracted by the feature extraction module and the context information fusion module, the loss of the candidate area generation module and the loss of the detection module are obtained by the candidate area generation module and the detection module. Add the two losses to get the total loss of the network, and update the network weight through BP algorithm and gradient descent. The specific training process is as follows:

(1) The training data set is generated and expanded. Due to the large size of the original SAR image, it is not conducive to network training. Therefore, it is necessary to cut the large image in the original SAR image dataset to obtain several SAR image sub images, as shown in the following formula:

$$A = \{a_1, a_2, \ldots, a_n\} \tag{3}$$

In formula (3) a_n It refers to the No n SAR image sub images.

And mark them at the target level, including the target category and target border. At the same time, due to the small amount of SAR image data, the sub images obtained by clipping are expanded by adding noise, filtering, rotating, and flipping. Among them, Gaussian noise and salt pepper noise with additive mean of 0 and variance of 0.01 are used for noise addition; Median filter, Gaussian filter and mean filter are adopted for filtering; Rotate to rotate at three angles, 90°, 180° and 270° respectively; The flip mode is horizontal; At the same time, rotate the horizontally flipped pictures by 90°, 180° and 270° respectively. Integrate the sub images obtained after the above processing to obtain the final training dataset;

(2) Load the pre training model. In order to accelerate the model convergence and improve the final performance, the weight parameters of the network are initialized by loading the pre training model. Because the feature extraction network part of the feature extraction module uses the structure of. VGG16, the VGG16 network parameters trained by ImageNet dataset for classification tasks are loaded onto the feature extraction network, while the feature fusion part uses random initialization to initialize the parameters; The weight parameters of context information fusion module, candidate area generation module and detection module are initialized randomly;

(3) Get multi-scale context features. The training data set is input into the network, and the image is processed by the forward calculation of the feature extraction module to obtain multi-scale features. Input the obtained multi-scale features into the context information fusion module, and get the multi-scale context features through operation;

(4) Generate the candidate region and obtain the loss of the candidate region generation module. The multi-scale context features are input into the candidate region generation module for processing, and the regression prediction values [6] of the foreground background prediction probability and position of the preset anchor frame on the feature map are obtained respectively. The loss of the candidate region generation module is calculated by using the category label, the position label of the target box and the prediction value in the training data, and several candidate regions are selected as the input of the detection module according to the prediction results. Several candidate regions selected according to the prediction results are as follows:

$$H = \{h_1, h_2, \ldots, h_m\} \tag{4}$$

In formula (4) h_m It refers to the No m Selected candidate regions.

(5) The selected candidate areas are detected to obtain their category information and location coordinates, and the loss of the detection module is calculated at the same time. Label the selected candidate area according to the image tag, and input the selected candidate area and multi-scale context features into the detection module to obtain the fine regression value of the target category prediction probability of the candidate area and the target rectangular box coordinates, so as to obtain the interested target and complete the detection. At the same time, the loss of detection module is calculated according to the target detection results and the labels of candidate regions;

(6) Update the network parameters and complete the training. Add the loss of candidate area generation module and the loss of detection module as the overall loss of the

network. BP algorithm and gradient descent method are used to optimize the loss of the network and update the parameters. After one update, repeat the process from (3) to (6) to update the network parameters iteratively. When the training times reach the preset training times, the network completes the training [7].

Use the trained model to test the test data. During the test, the original SAR image of a large scene is tested, so the test process is as follows:

(1) For the SAR test image in a large scene, the original SAR image is clipped from left to right and from top to bottom by sliding window capture, the original SAR test image is divided into several test sub images, and the corresponding position coordinates of the cut test sub images on the original large image are recorded;
(2) Input the cut test subgraphs into the target detection network after training, and obtain the target detection results of each subgraph through forward calculation of network parameters;
(3) Set the threshold of classification confidence f The test results will be further screened, that is, the test results meeting the following formula will be retained as the test results of each sub graph.

$$Z > f \tag{5}$$

In formula (5) Z It refers to classification confidence.

(4) According to the position of each sub image on the original SAR image, the detection results on the sub image are mapped back to the original image to obtain the detection results on the original large image;
(5) The overlapping duplicate boxes in the obtained large scene detection results are further filtered, that is, the overlapping target boxes in the original large scene SAR image are removed by the NMS method, and the final detection results are obtained.

The overall structure of the network and the process of training and testing are described above. Next, the feature extraction module, context information fusion module, candidate region generation module and detection module in the network structure are described and introduced in detail.

The feature extraction module is the basic part of the proposed SAR image target detection network. This module extracts SAR image features through a series of convolution and pooling operations, and fuses features at different scales. While using deep semantic features for detection, it also fuses shallow details, making SAR image feature information more abundant. The feature extraction network structure in this module is based on VGG1618.

The module includes a feature extraction network composed of five convolutions and a feature fusion part composed of four convolutions. Among them, the five convolution parts include a total of 13 convolution layers, 13 ReLU layers and 4 maximum pooling layers. The first convolution part and the second convolution part respectively include two convolution layers, each of which is followed by a ReLU layer, and at the same time, the last of each convolution part is followed by a maximum pooling layer. The third to fifth convolution sections respectively include three convolution layers, and each convolution layer is also connected with a ReLU layer. In addition, a maximum pooling layer is connected at the end of the third and fourth convolutions. In the network structure of this part, the size of the convolution kernel is 3 × 3, and the step size is 1. In order to avoid reducing the size of the feature map, the convolution layer is filled with 1 pixel. The step size of the maximum pool layer is set to 2, and the pool area size is 2 × 2 [8]. The detailed network structure parameters are shown in Table 1.

Table 1. Structure parameters of feature extraction network

Convolution part	Hierarchy name	Convolutional core/pool Sizing	Number of input channels	Number of output channels	step
Conv1	Conv1_1	9 × 9	1	64	3
	Conv1_2	9 × 9	32	64	3
	Max-pooling1	4 × 4	32	64	1
Conv2	Conv2_1	9 × 9	32	128	3
	Conv2_2	9 × 9	64	128	3
	Max-pooling2	4 × 4	64	128	1
Conv3	Conv3_1	9 × 9	64	256	3
	Conv3_2	9 × 9	128	256	3
	Conv3_3	9 × 9	128	256	3
	Max- pooling3	4 × 4	128	256	1
Conv4	Conv4_1	9 × 9	128	512	3
	Conv4_2	9 × 9	256	512	3
	Conv4_3	9 × 9	256	512	3
	Max- pooling4	4 × 4	256	512	1
Conv5	Conv5_1	9 × 9	256	512	3
	Conv5_2	9 × 9	256	512	3
	Conv5_3	9 × 9	256	512	3

In the table, only the network parameters of the feature extraction network part in the module are given, and the activation function layer is omitted. By default, each convolution layer is connected to a ReLU layer.

The context information fusion module is the core part of the proposed method. In SAR images, the environment in which targets appear is not random, and different targets often appear in specific scenes. For example, vehicle targets generally appear in roads, parking lots and other scenes; aircraft targets generally appear in airport scenes, and ship targets often appear in the ocean and near shore. It can be seen that there is a certain dependency between the target in the SAR image and the surrounding environment. This relationship is the context information of the target. In the target detection task, the reasonable use of the target context information can better distinguish the target and background in the detection process, reduce the error results, and improve the target detection performance. After extracting features from SAR images, the context information of the target is reflected in the dependency between feature pixels. Because RNN can learn the dependency between sequence data elements well, it can be used to fuse the context between feature pixels, so as to achieve the fusion of context information around the target. Therefore, this module uses the bidirectional GRU network in RNN and the corresponding convolution layer to achieve the fusion of context information in SAR image features.

The composition of context information fusion module is shown in Table 2.

Table 2. Composition of context information fusion module

S/N	structure	number
1	Two way GRU network	4
2	Convolution layer	2
3	ReLU layer	1

The module first inputs the SAR image features obtained by the feature extraction module into the bidirectional GRU network 1 and bidirectional GRU network 2, respectively, to obtain the horizontal context information feature map and the vertical context information feature map. Secondly, after splicing the two along the channel dimension, the context feature 1 can be obtained by feature fusion through 1×1 convolution operation. Then input context feature 1 into two-way GRU network 3 and two-way GRU network 4 respectively, and repeat the same operation as two-way GRU network 1 and 2. Finally, the output features of bidirectional GRU networks 3 and 4 are concatenated with the original SAR image features in the channel dimension. After 1×1 convolution and ReLU activation layer processing, the context feature 2 can be obtained, which is used as the output of the context information fusion module to complete the fusion of the context information in the SAR image features.

The candidate region generation module is an important part of the proposed method, which is used to extract the possible target regions in SAR images, and calculate the loss of the candidate region generation module required for network training.

In the candidate region generation module, in order to generate a region of interest that may be the target, after inputting multi-scale context features, the module will use a small network for sliding window processing. The sliding window size in the small network is nxn. The sliding small network will process the features in the sliding window and get the output vector by activating the function layer. The output vector will continue to be input into two parallel full connection layers, one of which is used to predict the target and background classification of the candidate area, and the other is used to predict the regression value of the target box position of the candidate area. By combining the results of classification and regression, candidate regions that may be targets are obtained. It is worth noting that since this small network processes the feature map through a sliding window, and the parameters of the small network are shared during the sliding process, this structure can actually be regarded as an nxn convolution layer. The convolution step is the sliding step of the sliding window, and the full connection layer of the subsequent processing output vector can also be regarded as a 1×1 convolution operation. Therefore, the candidate region generation module is essentially a full convolutional network.

The composition of candidate region generation module is shown in Table 3.

Table 3. Composition of candidate region generation module

S/N	structure	One
1	Convolution layer	Three
2	ReLU layer	

The detection module is the key part of the proposed method to realize the detection function. The module uses multi-scale context features and the proposed candidate area to obtain the multi-scale context features corresponding to the candidate area through the RoI Align operation. The candidate area features are classified and finely adjusted in the target category and position through the corresponding full connection layer.

2.3 Parameter Extraction

The acquisition of some basic parameters of the target is regarded as the final stage of radar signal processing, and one of the key issues is the reconstruction of reference signal. First, the signal starting point is determined synchronously, then the multipath effect is removed by channel estimation and equalization. Then, according to the civil radar signal standard, the pure code stream is obtained through constellation mapping and channel coding, and then the coding and modulation process at the transmitter is repeated, including channel coding, constellation mapping, OFDM modulation, and framing to obtain the reconstructed signal. Synchronization, channel estimation and equalization and channel decoding are the key steps.

Synchronization plays an important role in SDPR, and its performance directly affects the subsequent reference signal extraction. SDPR system synchronization mainly includes the following three aspects: symbol synchronization, carrier synchronization and sampling rate synchronization.

Symbol synchronization refers to finding the starting point of OFDM symbols in the sampled data, that is, determining the DFT window position during demodulation. It is the first step of subsequent carrier frequency offset estimation and sampling rate synchronization. In the SDPR system, the synchronization starting point is usually the clutter suppression starting point, corresponding to the arrival time of the direct wave, which directly affects the estimation of the target bistatic distance. Conventional adaptive filtering method is used for clutter suppression. If the estimation of symbol synchronization start point is inaccurate, that is, the reconstructed reference signal may not be causal with some multipath clutter in the monitoring signal, and multipath clutter may not be completely suppressed, affecting target detection [9].

Carrier synchronization refers to the estimation and compensation of the deviation between the local carriers between the transmitter and the receiver. For SDPR, because the transmitter is not controlled, the crystal oscillators at the transmitter and receiver cannot match completely. Therefore, the carrier frequency offset is relatively common in SDPR, and it is necessary to estimate and compensate the signal at the receiver in real time. In the OFDM modulation system, if the frequency offset is normalized to the subcarrier spacing, the frequency offset obtained is as follows:

$$\xi = \psi + \zeta \tag{6}$$

In formula (6) ψ It refers to integer octave offset; ζ It refers to decimal octave offset. Among ψ It will not cause ICI, but will cause 50% error probability of the information that is called out. and ζ The sampling point will not be at the vertex of the subcarrier, thus destroying the orthogonality of the subcarrier and introducing ICI. Therefore, the receiving end must ψ And ζ Estimate and compensate.

Sampling rate synchronization is to estimate and compensate the sampling time deviation between the transmitter and receiver. Considering that the transmitter and receiver usually use the GPS module to provide a highly stable clock source, the impact of sampling rate deviation is small and can be ignored.

Generally speaking, rough symbol synchronization is performed first to find the approximate position of the synchronization signal, and then fractional octave offset is estimated using the synchronization signal, and then integer octave offset is estimated using the compensated synchronization signal, and finally fine symbol synchronization is performed.

In order to meet the real-time requirements of the SDPR system, in addition to considering using the GPS module to provide a highly stable clock source, in signal processing, carrier frequency offset estimation and symbol fine synchronization can be done once per frame, and this processing can also eliminate the cumulative error caused by sampling frequency offset.

Channel estimation is implemented based on pilot symbols. The channel estimation method based on pilot symbols is to use known discrete pilot symbols to calculate the impulse response of subcarriers at discrete pilots, and then estimate the channel response at data subcarriers through interpolation algorithm according to the arrangement rule of discrete pilots in the frequency domain direction. Finally, the estimated subcarrier channel response is used to equalize the subcarrier data in the frequency domain.

Let the received signal be expressed as $R(k)$, the channel response at the pilot is:

$$\tilde{F}\left(k_p\right) = \frac{R(k)}{G(k)} \tag{7}$$

be based on $\tilde{F}\left(k_p\right)$ The linear interpolation method is used to obtain the k_p+1 Subcarrier response at $\tilde{F}\left(k_p+1\right)$. Finally, the channel response at the pilot is averaged in the frequency domain for each subcarrier.

The constellation is focused directly according to the signal modulation mode to obtain the reconstructed reference signal.

Multipath clutter is a type of interference signal in radar systems, which is the echo signal generated by the reflection, refraction, and scattering of signals emitted by radar when encountering obstacles, terrain, buildings, etc. during the propagation process. These echo signals propagate through different paths to the radar receiver and are superimposed with the main direct signal, forming multiple echo signals with different time delays. Multipath clutter introduces additional time delay, which expands the time-domain characteristics of the echo signal, resulting in strength measurement errors of the target and reducing the detection performance of the radar system. And due to the different path lengths of multipath propagation, the phase of the echo signal may change. This can cause phase distortion in coherent processing and reduce the target resolution ability of the radar system.

Therefore, this article is based on the frequency domain subcarrier multipath clutter cancellation method to achieve the suppression of multipath clutter. The frequency domain multi-path clutter cancellation method is based on the principle that multi-path clutter is completely correlated on the same subcarrier, while the target is suppressed by multi-path clutter due to the existence of Doppler frequency shift and its non correlation.

After acquiring the monitoring signal after carrier frequency offset compensation, the channel response of multipath clutter is estimated through the least square algorithm $E(w)$, the frequency domain monitoring signal after clutter suppression can represent:

$$D_0(w) = D(w) - C(w)E(w) \tag{8}$$

In the above formula $D(w)$ Is the monitoring signal after carrier frequency offset compensation; $C(w)$ Is the frequency domain reference signal vector [10].

Finally, by locating and tracking the target, some basic parameters to determine the target are obtained. The target is located by TDOA positioning method [11]. For the convenience of expression, the problem of target location on a two-dimensional plane is considered. Assume that the coordinate position of the target is:

$$\chi = \left[x, y\right]^{\nu} \tag{9}$$

In the above formula ν Represents the coordinate threshold; x, y Represents its coordinate value.

The coordinate position of the transmitting station is:

$$\delta_x = \left[x_0, y_0\right]^{\nu} \tag{10}$$

In the above formula x_0, y_0 Represents its coordinate value.

The coordinate positions of the N receiving stations are:

$$\begin{cases} \varepsilon_{x_i} = \left[x_i, y_i\right]^{\nu} \\ i = 1, 2, \ldots, N \end{cases} \tag{11}$$

In the above formula x_i, y_i Represents its coordinate value.

Calculate the baseline distance between the transmitting station and the receiving station according to the above formula, and calculate the bistatic distance of target P measured by the receiving station [12].

After obtaining the position and motion state of the target, it can be regarded as the secondary measurement value as the input of the tracking process [13]. At this time, the common tracking methods such as Kalman filter and Bayesian theory can achieve target tracking.

3 Experimental Research

3.1 Experimental System and Platform

For the civil radar echo signal processing method designed based on Kalman filter algorithm, the method is tested through the designed experimental system and platform. The experimental equipment used includes the UWB radar system with NVA-6100 as the core and a laptop computer. The working mode of the selected transmitter is IF transmission, and the bandwidth is 0.85–9.55 GHz, meeting the ultra wideband standard. The radar data is connected to the notebook computer through the USB interface and the signal is preprocessed.

The experimental system is shown in Fig. 3.

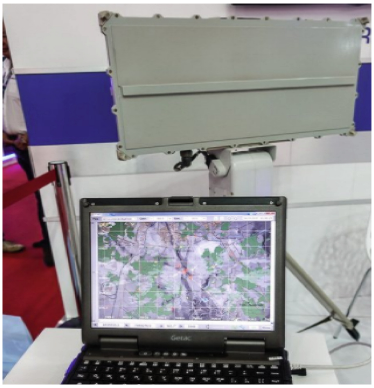

Fig. 3. Experimental System

In order to verify the effectiveness and accuracy of this method, an experimental platform is built. The platform is mainly composed of the track system and the target are composed of two parts. The track system is 5m long and 3m wide, and the two long rails are connected through a transmission rod to achieve synchronous movement. At the same time, the track system is equipped with a track control box, which can move the track to a fixed distance or conduct regular movement, and can carry out standardized detection of the accuracy of the radar system test distance.

3.2 Comparison Method Design

The echo signal pre-processing method of ground penetrating radar and the echo generation and signal processing simulation method of ground-based radar are used as the comparison method to test together, and are represented by method 1 and method 2 respectively.

3.3 Static Target Experimental Verification

First, carry out the static target related experiments on the experimental platform. During the experiment, the radar system is placed on a table 0.85 m from the ground, the target is facing the radar system, and the target is moved on the slide rail to five different positions 1 m, 2 m, 3 m, 4 m, 5 m from the radar by controlling the power motor of the track, and the position is marked and tested by the radar system. The distance test error results obtained are shown in Table 4.

Table 4. Test Results of Distance Error of Static Target

group	Set Distance (m)	Distance error (m)		
		Design method	Method 1	Method 2
A	1.0	0.025	0.056	0.052
B	2.0	0.012	0.056	0.041
C	3.0	0.001	0.039	0.046
D	4.0	0.011	0.041	0.035
E	5.0	0.021	0.035	0.050

According to the range error test results of stationary targets in Table 4, when the target is stationary, the range error of the design method is less than that of Method 1 and Method 2, indicating that its signal processing effect is better and more suitable for civil radar applications.

3.4 Experimental Verification of Inching Target

In order to verify the tracking and extracting ability of the design method for the micro moving target, the micro moving target experiment is conducted on the experimental platform. In the experiment, first move the target to five different positions at 1 m, 2 m, 3 m, 4 m and 5 m, then control the track motor to make it move at a constant speed in the direction of the radar system at a speed of 0.5 cm/s. The distance test error results obtained are shown in Table 5.

Table 5. Test results of range error of inching target

group	Set Distance (m)	Distance error (m)		
		Design method	Method 1	Method 2
A	1.0	0.038	0.075	0.063
B	2.0	0.032	0.068	0.078
C	3.0	0.028	0.068	0.082
D	4.0	0.030	0.063	0.064
E	5.0	0.039	0.071	0.063

According to the distance error test results of micro moving targets in Table 5, when the target is a micro moving target, the distance error of the design method is still significantly smaller than that of Method 1 and Method 2, indicating that its signal processing effect is better than that of Method 1 and Method 2.

3.5 Experimental Verification of Moving Targets

In order to verify the tracking and extraction ability of the design method for moving objects, the experimental platform is used for moving object experimental testing. In the experiment, first move the target to five different positions at 1 m, 2 m, 3 m, 4 m and 5 m, and then control the track motor to make it move at a constant speed of 30 m/min towards the radar system. The distance test error results obtained are shown in Table 6.

Table 6. Distance Error Test Results of Moving Target

group	Set Distance (m)	Distance error (m)		
		Design method	Method 1	Method 2
A	1.0	0.068	0.098	0.086
B	2.0	0.063	0.092	0.094
C	3.0	0.069	0.090	0.096
D	4.0	0.064	0.096	0.092
E	5.0	0.067	0.092	0.088

According to the distance error test results of moving targets in Table 6, when the target is a moving target, the distance error of the design method is higher than the distance error between the stationary target and the inching target, but still less than the distance error of Method 1 and Method 2, indicating that its signal processing effect is better than that of Method 1 and Method 2. However, the difference between the distance error of the design method and the distance error of Method 1 and Method 2 is significantly smaller.

4 Conclusion

In order to reduce the tracking distance error in the processing of civil radar echo signal, this paper proposes a civil radar echo signal processing method based on Kalman filter algorithm. The AR model is converted into the Equation of state and observation equation form of Kalman filter. Based on the Faster R-CNN detection framework, a target detection method based on context information and multi-scale Faster R-CNN is designed, and the multi-path clutter is suppressed based on the frequency domain subcarrier multi-path clutter cancellation method to achieve the processing of civil radar echo signals. And through experimental verification, the tracking distance error of this method is small, and the signal processing effect is good. In the following research, the focus will be on the transmission process of civilian radar echo signals to improve the practical application effect of civilian radar.

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