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Feature Selection and Construction Based Sea-Surface Weak Target Detection

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SUMMARY: *Aiming at weak sea-surface target detection, this paper proposes a detector based on feature selection and construction. Firstly, multi-dimensional features were extracted from multiple dimensions such as polarization domain, phase domain, time domain, frequency domain and time-frequency domain, and the SHAP value analysis method was used to quantitatively evaluate the importance of multi-dimensional features, and the three features with the highest importance were selected to reduce the dimension of the feature space and the computational complexity. Secondly, to fully utilize information from the polarization domain, the normalized importance of each feature under different polarization modes is used as a linear weighting coefficient for constructing polarization-based features. This effectively compresses high-dimensional polarization features into a 3D feature vector. Finally, anomaly detection using the XGBoost algorithm is applied on these obtained 3D features to obtain corresponding results. Experimental results on a measured database demonstrate that our proposed phase feature detector outperforms existing three-feature detectors.*

KEYWORDS: *Feature selection; Feature construction; Sea clutter; Weak target detection*

1 Introduction

The challenge of identifying minute targets amidst complex sea clutter has persistently represented a fundamental hurdle in radar-centric detection, monitoring, and identification systems [1, 2]. The identification capabilities for small, slow-moving targets with low Radar Cross Section (RCS) floating on the sea surface are substantially limited by the non-Gaussian and dynamic behavior of sea clutter. Within the complex marine setting, the intense backscatter of electromagnetic waves from sea clutter frequently overwhelms target signals in radar echoes, primarily due to pronounced sea peaks induced by waves, hindering their detection [3, 4]. Therefore, in practical applications, traditional detectors that rely on target strength and sea clutter frequently encounter a significant false alarm rate (FAR), posing a formidable challenge for effectively detecting small targets within the ocean environment.

To address the challenge of detecting dim and small targets in sea clutter, extensive research has been conducted by researchers. A groundbreaking discovery made by Martorella et al [5] demonstrated that fractal processes can accurately model the reflection of sea clutter from a turbulent sea surface, establishing a crucial theoretical foundation for subsequent target detection investigations. Hu et al. [6] and Luo et al. [7] further exploit fractal-based properties to quantify the difference between target echoes and sea clutter, resulting in the development of a customized fractal-based detector. However, this single-feature detector has limitations in

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utilizing echo information and adapting to changing detection environments. To address this obstacle, Shui and their team [8] devised an innovative three-feature detection framework, selectively incorporating pivotal attributes such as relative mean amplitude (RAA), relative Doppler peak height (RPH), and the relative entropy derived from the Doppler magnitude spectrum (RVE). This strategic choice was based on a meticulous analysis of the temporal and Doppler domain signatures inherent in radar sea echo signals, effectively enhancing the framework's capability to distinguish targets amidst complex oceanic environments. This detection framework reframes the challenge as a classification task within a multi-dimensional feature space, leading to a notable enhancement in detection efficacy. As research progresses, detectors based on multi-dimensional features continue to emerge including time-frequency (TF)-based detectors, polarimetric detectors, phase-based detectors, and eigenvalue detectors [9-12]. These detectors fully exploit the multi-dimensional information present in radar echo signals while further improving the ability to detect dim and small targets. It is noteworthy that the advancement of deep learning technology has significantly contributed to its application in sea target detection due to its swift development. For instance, detectors based on CNN, Faster R-CNN, improved Faster R-CNN, graph mapping and graph convolutional network (GCN), LSTM, etc. [13-19], have been employed for target detection and recognition. By leveraging deep learning models, the sea clutter sequence can be effectively modeled and analyzed to achieve robust detection of weak and small targets. Despite achieving commendable outcomes in object detection, the aforementioned methods solely concentrate on extracting features from time-frequency representations, neglecting other potential sources of information. However, in the ocean, sometimes the sea clutter and the target will extract similar features in the time-frequency map, which leads to errors in the classification results [20, 21]. To address these issues, various enhancements have been proposed, such as considering the complementarity between multiple feature domains [22] and employing bidirectional Long Short-Term Memory (Bi-LSTM) networks [23, 24], which can effectively capture both positive and backward correlations. Furthermore, Xu et al.'s [25, 26] detector based on polarization three features and Shi et al.'s [27] detection method of sea surface small targets based on multi-domain and multi-dimensional feature fusion both leverage the complementarity between different features to enhance the detection performance. However, multi-dimensional feature detection methods also encounter challenges. As the feature dimension increases, designing high-dimensional classifiers becomes more complex and difficult. How to balance the increase of dimensional information and the difficulty of designing high-dimensional classifiers while ensuring good detection performance is one of the current research projects focuses [28-30]. Of course, with the development of radar technology, various techniques of image detection [31-34] and infrared detection [35-38] of sea surface targets have been further developed.

This letter proposed a small target detection method based on feature selection and construction, which aims to extract multi-dimensional features from multiple dimensions such as polarization domain, phase domain, time domain, frequency domain and time-frequency domain, to expand the dimensional information. Through feature selection based on feature importance in feature domain and feature construction based on normalized feature importance in polarization domain, multi-dimensional features are compressed into 3D space, and XGBoost algorithm is used to realize anomaly detection decision. It is verified that the proposed detector has good performance based on IPIX measured data.

The innovations of this paper are mainly as follows:

(1) Feature selection: Considering that different features have different contributions to maritime target detection, this paper employs the SHAP value to analyze the significance of multiple dimensions of features, and selects the features with larger contributions for classification. The aim is to balance the high classification complexity caused by the excessive

number of features and the accuracy degradation problem caused by reducing the number of features.

(2) Feature Construction: Due to the varying echo of the target in different polarization modes, the contribution of the same feature to classification differs across these modes. Therefore, considering computational efficiency as a prerequisite, we construct features based on polarization modes by utilizing identical features under different polarization modes. The importance of features under different polarization modes was determined by using the SHAP value analysis method, and then it was standardized to feature coefficients.

2 Polarization Feature

2.1 Anomaly detection model

When the radar directs a coherent series of pulses in the form of a beam towards the ocean's surface, each range cell receives an echo time series of length N, denoted as $z = [z(1), z(2)..., z(N)]$.are divided into fragments in the form as $z(n) = z(m\bullet(n-1)+1 : m\bullet(n-1)+l)$. In which m represents the distance separating consecutive fragments, while l signifies the extent of each individual fragment. In the clutter unit, the echo signals consist of scattered echoes and noise originating from the sea surface, while in the target unit, they comprise both target echoes and scattered echoes from the sea surface along with noise. The vital aspect of detection is to ascertain whether the echo signal harbors a constituent matching the target echo. Thus, object detection on the sea surface can be modeled as a binary classification problem.

$$\begin{cases} H_0 \begin{cases} z(n) = c(n), & n = 1,2,3...,N \\ z_p(n) = c_p(n), & \text{p} = 1,2,3...,P \end{cases} \\ H_1 \begin{cases} z(n) = s(n) + c(n), & n = 1,2,3...,N \\ z_p(n) = c_p(n), & \text{p=1,2,3...,}P \end{cases} \end{cases} \tag{1}$$

In this scenario, the hypothesis H_0 implies that the fragment under test (FUT) is categorized as a sea clutter fragment, whereas H_1 suggests that the FUT belongs to the category of target fragments. $z(n)$, $s(n)$, $c(n)$ are the radar echo, target echo and sea clutter respectively. N is the received echo sequence length and P is the reference cell around the cell to be estimated.

The radar reflections encompass both sea clutter echoes and target echoes within the target fragments. Nevertheless, the echoes in the sea clutter fragments stem exclusively from the scattering of the sea surface. Furthermore, in contrast to the consistent presence of sea clutter fragments, the appearance of target fragments is intermittent and unforeseeable. Therefore, the challenge of object detection can be reframed as an anomaly detection endeavor.

2.2 Feature Select

Different aspects of the signal exhibit diverse properties in terms of various features. The effectiveness of different features for target and sea clutter classification varies, necessitating the selection of features that significantly impact classification to achieve improved results with a consistent number of features. In this paper, the SHAP value analysis method is used to select some features, and the more important features are used for classification.

At present, there are many multi-dimensional and multi-domain features generated by time series analysis, and only six of them are selected for testing in this paper. In practice, more features can be selected or CNN can be used to get more features to select.

2.2.1 Feature Introduction

(1) Number of Phase Zero Crossing (NPZC)

The instantaneous phase of radar echo $x(n)$ is as follows:

$$\phi(n) = angle[x(n)] \tag{2}$$

"angle" serves as a function designed to determine the phase angle of a complex variable

$$\{\lambda_m \mid \phi(\lambda_m) \bullet \phi(\lambda_m + 1) < 0, m = 1,2,3..., M\} \tag{3}$$

where λ_m denotes the mathematical phase zero crossing, and m represents the total count of NPZC (non-periodic zero crossings) within the fragment. which is defined as the first phase feature T_1 that is,

$$T_1(x) = M \tag{4}$$

(2) Time domain Hurst exponent (Hurst)

We first utilize the concept of the fractal theory to define a feature in the time domain. Let $z(n)$ be a time sequence formed by the amplitudes of returned echoes, which can be modeled as the following fractal process.

$$F(m) = (\frac{1}{N-m}\sum_{n=1}^{N-m} | z(n+m) - z(n) |^2)^{\frac{1}{2}} \propto m^{H(2)} \tag{5}$$

where F denotes the fluctuation function, $H(2)$ represents the time domain Hurst exponent (TD Hurst), and m signifies the duration of the time interval. For a more vivid comprehension let's log both sides of (5).

$$\begin{aligned} \log_2 F(m) &= \log_2((\frac{1}{N-m}\sum_{n=1}^{N-m} | z(n+m) - z(n) |^2)^{\frac{1}{2}}) \\ &= H(2)\log_2(m) + const \end{aligned} \tag{6}$$

where $\log_2 F(m)$ is linearly dependent on $\log_2(m)$ in the log domain. The Hurst exponent feature is derived by utilizing a first-order polynomial approximation via least squares fitting on a logarithmic scale.

(3) Relative Power Spectral Entropy (RPSE)

Power spectrum entropy and spectral entropy both reflect the randomness and complexity of a signal to some extent. However, power spectrum entropy focuses more on the complexity of the signal's energy distribution in the frequency domain.

For a signal $x(n)$ of length N, the power spectrum sequence $S(k)$ is obtained by n-point discrete Fourier Transform (DFT).The energy distribution $P(k)$ is calculated for each frequency component based on the power spectral sequence $S(k)$, that is:

$$P(k) = S(k) / \sum \mathrm{S(i)}, \quad \mathrm{i=0,1...,N/2} . \tag{7}$$

Using the formula of information entropy, the power spectrum entropy is calculated as follows:

$$H(S) = -\sum p(k) \cdot \log(p(k)), k = 0,1...N/2\ . \tag{8}$$

There into $S(k)$ are presents the power value of frequency component k, and $\sum S(i)$ represents the sum of the power values of all frequency components.

(4) Other Features

At present, there are many multi-dimensional and multi-domain features generated by time series analysis, such as, Doppler Peak is High (DPH), Relative Average Amplitude (RAA), Relative Vector Entropy (RVE) etc.

2.2.2 Feature Select

In this study, an XGBoost algorithm was adopted to construct a classification model, and SHAP (Shapley Additive explanations) values were combined for feature importance analysis to achieve feature selection. This method obtained high-precision classification performance through gradient boosting decision trees, and quantified the contribution of each feature to the prediction results using Shapley values in game theory, providing feature importance explanations at both global and local levels.

Firstly, let's introduce the XGBoost algorithm in detail. XGBoost (Extreme Gradient Boosting) is a machine learning algorithm based on Gradient Boosting. It is widely used in classification and regression tasks. It performs exceptionally well in many practical problems, especially when dealing with large-scale data and complex issues, due to its efficiency, accuracy, and powerful model optimization capabilities. XGBoost constructs multiple decision trees to gradually reduce errors and eventually form a powerful predictive model. The key innovations of XGBoost include:

(1) Regularization: By introducing L1 and L2 regularization terms, it controls the complexity of the model and prevents overfitting;

(2) Parallelization: XGBoost supports parallel computing, significantly improving the training speed;

(3) Accelerated training: It supports GPU acceleration training, which is particularly suitable for large datasets;

(4) Support for handling missing values: It can automatically handle missing data, avoiding cumbersome preprocessing.

The advantages of XGBoost lie in its high accuracy and efficiency, making it the preferred algorithm in many machine learning competitions and practical applications.

Secondly, let's introduce SHAP values. SHAP values (Shapley Additive Explanations) are related to feature importance analysis. SHAP values are a method for explaining model outputs, especially suitable for complex machine learning models such as XGBoost. SHAP values originate from the Shapley value in game theory. They can assign an importance value to each feature, measuring the contribution of that feature to the model's prediction results. SHAP values have several key characteristics:

(1) Fairness: SHAP values can reasonably allocate the contribution of each feature to the model's prediction, avoiding the potential biases that may exist in traditional methods (such as feature importance).

(2) Local interpretability: SHAP values not only provide a global ranking of feature importance but also can explain individual prediction instances, helping to understand the specific prediction result of a certain sample.

(3) Consistency: If the importance of a feature changes in different models, SHAP values

can ensure the consistency of the explanation.

In the XGBoost model, the analysis of feature importance is achieved by calculating SHAP values. SHAP values reveal the specific impact of each feature on the model's output, which is crucial for understanding the decision-making process of the model. For instance, in medical diagnosis problems, SHAP values can help explain how a certain feature (such as age, blood pressure, etc.) affects the prediction results, thereby providing a more transparent model.

Finally, the process of combining XGBoost with SHAP values is introduced.

(1) Training XGBoost model: Firstly, using the XGBoost algorithm, a classification model is constructed on the training set. This model will generate a prediction model based on decision trees.

(2) Calculating SHAP values: After the model training is completed, the SHAP library is used to interpret the XGBoost model. Through the calculation of SHAP values, the contribution size of each feature in each prediction can be understood.

(3) Ranking of feature importance: SHAP values can generate a global ranking of feature importance based on the influence degree of features on the model output. This ranking helps us identify which features are most critical for the prediction. For example, a certain feature may have a significant impact in most samples, while another feature may only play a role in a few samples.

(4) Visual analysis: SHAP values are usually presented through graphical means.

In this way, SHAP values can provide transparency for the prediction process of the XGBoost model, and reveal the importance of features and the relationships among them. Finally, by analysis, features with better performance under the same circumstances can be selected. Here, taking the #31 data as an example, SHAP value analysis is conducted and features are selected. Fig.1 shows the six features importance of data #31 under HV polarization, and the three features with higher importance can be selected for classification through the data, which can achieve the effect of improving efficiency.

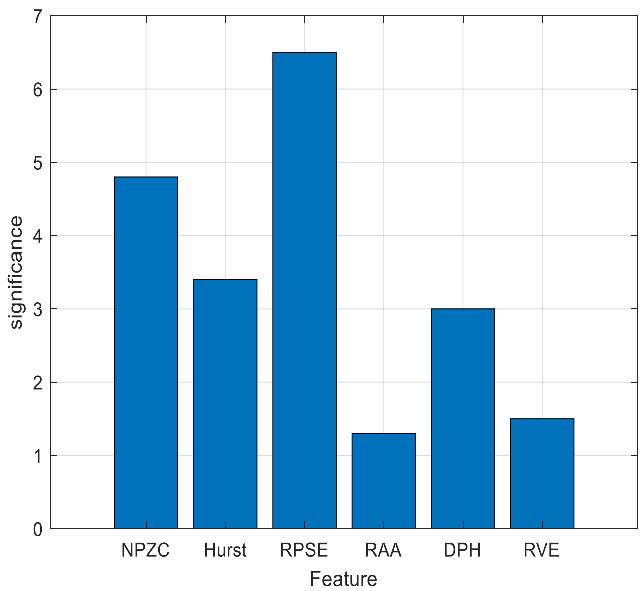

Figure 1: Feature importance in HV polarization mode for IPIX dataset #31.

2.3 Polarization Feature

In this paper, the dimensionality reduction technique utilizes the construction of polarization features, taking advantage of the complementarity between these features, specifically designed for the radar echo signal's polarization mode. However, there are various dimensionality reduction techniques, including PCA, LDA, t-SNE, and others. Because these methods are based on different principles, their performance varies with different datasets. For instance, PCA is effective only for linear data and may not perform optimally with complex, nonlinear data. The LDA method, being linear, is suitable for cases where the data is linearly separable. However, if the data has a nonlinear class distribution, LDA may not yield good results. t-SNE is particularly effective at preserving the local structure of the data, meaning that similar samples will be as close as possible in the reduced-dimensional space. Its performance is sensitive to hyperparameters, such as learning rate and iteration count, which require careful tuning. Due to the nonlinear characteristics of sea clutter, PCA and LDA algorithms may not be suitable, and t-SNE is not suitable for too much calculation. Therefore, more new dimensionality reduction algorithms will be considered in the future, and algorithms that are more adapted to the characteristics of radar signals may emerge.

2.3.1 Polarization Feature Construction

When the radar operates in different polarization modes, there is a significant alteration in the characteristics of sea clutter and target echoes. Generally, HH and VV co-polarization exhibit a lower signal-to-clutter ratio (SCR) compared to HV and VH cross-polarization. Furthermore, the sea clutter spectrum also undergoes changes with respect to the polarization mode. Therefore, in this study, utilize the available data to extract multi-dimensional features independently for each polarization channel and subsequently integrate diverse features within the same polarization domain. This approach aims to mitigate the computational burden associated with high dimensionality while obtaining multi-dimensional information of superior fidelity

Based on the polarization mode and feature domain, a feature fusion method is proposed, which converts the detection problem from multi-feature domain to less feature domain, and then solves the problem of multi-feature domain decision region design. The features: the number of phase zero-crossing, the Hurst exponent in time domain, and the relative power spectrum entropy are selected, and these three features are named as features 1, 2, and 3. The polarization features of these three features are constructed.

$$\begin{cases} T_1 = A_{1HH}T_{1HH} + A_{1HV}T_{1HV} + A_{1VH}T_{1VH} + A_{1VV}T_{1VV} \\ T_2 = A_{2HH}T_{2HH} + A_{2HV}T_{2HV} + A_{2VH}T_{2VH} + A_{2VV}T_{2VV} \\ T_3 = A_{3HH}T_{3HH} + A_{3HV}T_{3HV} + A_{3VH}T_{3VH} + A_{3VV}T_{3VV} \end{cases} \tag{9}$$

T_i (i=1,2,3) is the new polarization-based feature constructed; A_{iHH} , A_{iHV} , A_{iHV} , A_{iVV} (i=1,2,3) is the corresponding feature coefficient; T_{iHH} , T_{iHV} , T_{iVH} , T_{iVV} (i=1,2,3...) is the extracted features under different polarization modes.

2.3.2 Characteristic Coefficient

After constructing the polarimetric features, determining the coefficients becomes a crucial task. In this study, we adopted the same method as the aforementioned feature selection to determine the coefficients, that is, by using SHAP values to analyze the corresponding feature importance values of the known data. The importance degrees of different polarization patterns belonging to the same feature were classified into one group. that is:

The importance of feature 1 is: Z_{1HH} , Z_{1HV} , Z_{1VH} , Z_{1VV} .

The importance of feature 2 is: Z_{2HH} , Z_{2HV} , Z_{2VH} Z_{2VV} .

The importance of feature 3 is: Z_{3HH} , Z_{3HV} , Z_{3VH} , Z_{3VV} .

The importance degree of the same group is normalized to obtain new data, and the new data is used as the coefficient. that is:

$$A_{iHH} = Z_{iHH} / (Z_{iHH} + Z_{iHV} + Z_{iVH} + Z_{iVV}) \text{ , (i=1,2,3...)} \tag{10}$$

The obtained coefficients were put into the features based on polarization mode, and the new features based on polarization were obtained. Fig.2 shows the normalized importance of a set of polarization features.

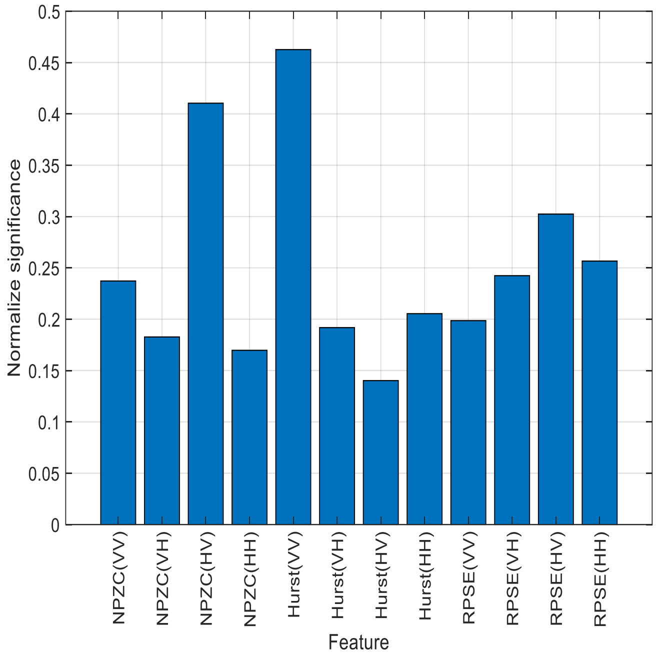

Figure 2: Normalized importance of polarization features for IPIX dataset #31

2.4 Target Detection

Generally, sea clutter data can be obtained in large quantities. However, it is difficult to obtain many echo data from small targets on the sea surface due to their sparse spatial distribution, military confidentiality, and variability with sea state. Therefore, maritime target detection is mostly classified as an anomaly detection problem. In anomaly detection, a large amount of sea clutter is considered normal samples for obtaining a decision region with controllable false alarms, while echoes containing targets are regarded as abnormal samples. At this point, the detection problem transforms into designing a single classifier in the high-dimensional feature space domain.

Fig.3 shows the flowchart based on feature selection and detector construction. Unlike conventional feature detectors, this paper simultaneously processes echo data across four polarizations and extracts multidimensional features in the phase domain, time domain, frequency domain, time-frequency domain, and polarization domain. Additionally, the high-dimensional polarimetric feature space is reduced to a 3D feature space through linear fusion of the polarization and feature domains, effectively addressing the challenge of designing classifiers with high dimensions while preserving crucial dimensional information. Within this 3D feature space, a XGBoost algorithm is employed for classification purposes. If the fusion feature vector of the detection unit falls outside the decision region, it is determined that target echoes are present; otherwise, it is concluded that no targets exist.

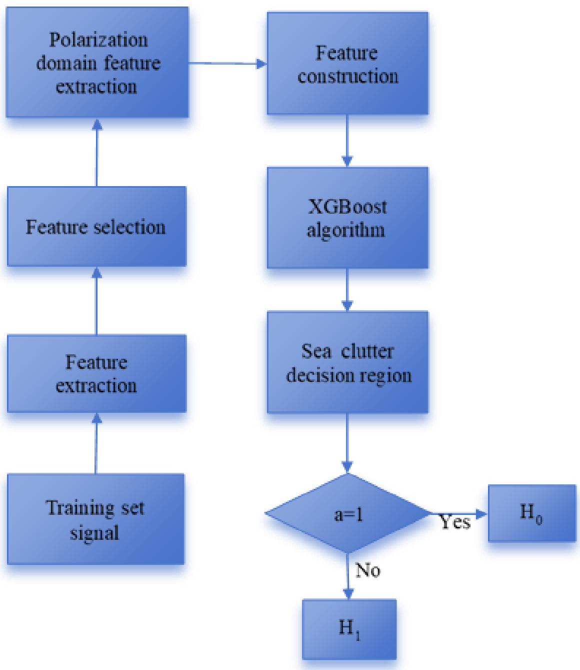

Figure 3: Structure of the detector based on feature selection and construction

3 Results

3.1 Data

The X-band radar dataset from the IPIX database is used in this paper. The IPIX dataset from 1993 comprises datasets numbered #17, #26, #31, #30, #40, #54, #280, #310, #311 and #320. Notably, dataset #17 belongs to sea state class 3-4, whereas the remaining datasets fall within class 2-3. Each of these datasets incorporates radar measurements captured with a shallow grazing angle. Table 1 provides a comprehensive overview of the specific technical details pertaining to the IPIX radar data. Fig4 presents the calculated average signal-to-clutter ratio (SCR) for these ten IPIX datasets, uncovering a manageable average SCR span of 0 to 18 dB.

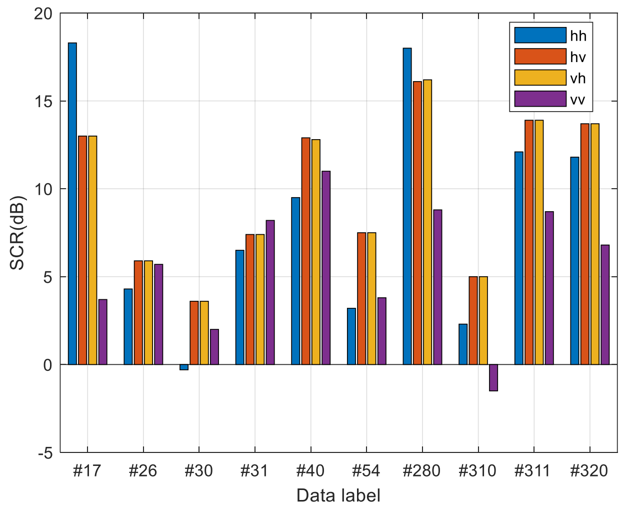

Figure 4: Average SCR of sea clutter for the ten datasets.

Tablel 1: IPIX Data Specification

Label	Data File Name	Sea state level	SWH(m)	WS (km/h)	Primary	Secondary
1	#17	4	2.2	9	9	8,10,11
2	#26	3	1.1	9	7	6,8
3	#30	2	0.9	19	7	6,8
4	#31	2	0.9	19	7	6,8,9
5	#40	2	1.0	9	7	5,6,8
6	#54	2	0.7	20	8	7,9,10
7	#280	3	1.6	7	8	7,9,10
8	#310	2	0.9	33	7	6,8,9
9	#311	2	0.9	33	7	6,8,9
10	#320	2	0.9	28	7	6,8,9

3.2 Detection Performance Analysis

In this section, the experimental results are used to verify the performance of the proposed detector. A comprehensive set of ten datasets is utilized for both the training and evaluation of the proposed detection framework. Before proceeding with the experiment, we need to determine the choice of d and D. In which d represents the distance separating consecutive fragments, while D signifies the extent of each individual fragment. The size of d is inversely proportional to the number of samples, which means as the number of samples increases, the size of d decreases. The value of D will affect the eigenvalues. Investigate how D and d impact detection precision, we choose data number #31 for the experiment, where D=512, 1024; d=32, 64, 128. The outcomes of the experiments are displayed in Table 2. Upon analyzing the data presented in the table, it becomes evident that as the observation vector of the target unit increases in size, both the target feature and the clutter feature tend to accumulate simultaneously. So as D gradually increases, the detection accuracy also gradually increases, but the computational burden also increases. Additionally, increasing the sample size will improve the model's training effectiveness, and it is advisable to choose a lower value for d. Given the balance between the detector's performance and computational demands, we have opted to set d at 32 and D at 1024 for the purpose of carrying out the following experimental procedures.

Tablel 2: The Detection Accuracy of Data #31 for Different D and d

	32	64	128
512	0.8626	0.8616	0.8561
1024	0.8866	0.8837	0.8813

Given an observation time of 1.024 seconds, target detection is conducted across ten groups of IPIX data, with each group containing information from four polarization channels. A comparative analysis is undertaken to assess the detection performance of the proposed sequence-feature detector against the established benchmarks of the three-feature detector [8], the time-frequency feature detector [9], and the phase-feature detector [11]. The results are shown in Fig. 5. As can be seen in Fig. 5, for datasets #17, #26, #30, #31 and #40, the detection probability of feature detectors based on feature selection and construction is significantly higher than that of existing detectors. In addition, for #54, #280, #310, #311 and #320 datasets, the detection performance of the proposed detector, TF feature and phase feature detectors is similar and much better than that of the three-feature detector. It can be seen from Table.3 that the average value of the proposed detector is 0.9309, which is much higher than the other three detectors. Finally, the results further confirm the importance of feature selection and construction for improving object detection accuracy and improving generalization ability, and show that the proposed method has certain advantages in practical applications.

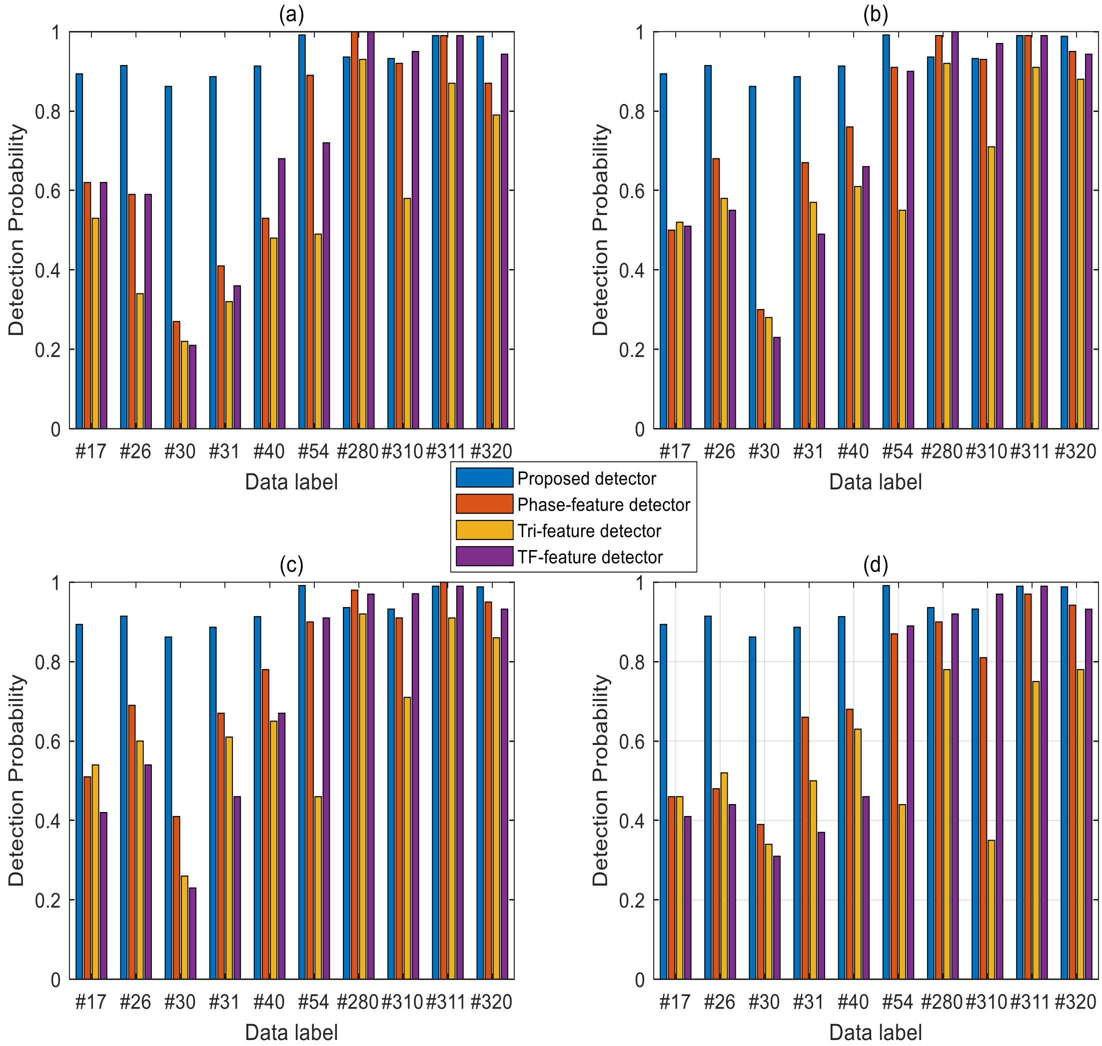

Figure 5: The performance precision of the novel detector, in comparison to three preexisting detectors, has been assessed across ten distinct datasets obtained from the IPIX database an observation period set to 1.024 seconds. HH(a), HV(b), VH(c), VV(d).

Table 3: The average accuracy rate shown in Fig. 5

	HH	HV	VH	VV
proposed detector	0.9309			
Phase-feature detector	0.6512	0.7338	0.7500	0.6563
Tri-feature detector	0.5338	0.6337	0.6438	0.5262
TF-feature detector	0.6725	0.6738	0.6575	0.5687

4 Conclusions

Aiming at the problem of small target detection in high-resolution sea clutter background, this paper proposes a detection method based on feature selection and construction. The above experiments have demonstrated that the proposed method improves the accuracy and generalization ability of object detection to a certain extent. This improvement confirms that different features contribute differently to object detection. By selecting features with high contribution rates, the accuracy of object detection can be improved under the same conditions, which fully demonstrates the crucial role of feature selection in enhancing model performance. In addition, the feature construction process also achieves results, which not only improves the accuracy of object detection, but also enhances the generalization ability of the model. This promotion verifies the complementarity between features in the polarization domain. Through these features occupy different proportions in the polarization domain, and after balanced fusion, the whole model shows robust performance. Therefore, in the future, extracting multi-dimensional features from more domains for selection and fusion or continuing to explore strategies and methods for multi-dimensional feature fusion will be beneficial for improving the detection performance of small targets at sea. This will further enhance the application effect of object detection technology in various complex scenes.

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