



Communication Sea-Land Clutter Classification Based on Graph Spectrum Features

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Abstract: In this paper, an approach for radar clutter, especially sea and land clutter classification, is considered under the following conditions: the average amplitude levels of the clutter are close to each other, and the distributions of the clutter are unknown. The proposed approach divides the dataset into two parts. The first data sequence from sea and land is used to train the model to compute the parameters of the classifier, and the second data sequence from sea and land under the same conditions is used to test the performance of the algorithm. In order to find the essential structure of the data, a new data representation method based on the graph spectrum is utilized. The method reveals the nondominant correlation implied in the data, and it is quite different from the traditional method. Furthermore, this representation is combined with the support vector machine (SVM) artificial intelligence algorithm to solve the problem of sea and land clutter classification. We compare the proposed graph feature set with nine exciting valid features that have been used to classify sea clutter from the radar in other works, especially when the average amplitude levels of the two types of clutter are very close. The experimental results prove that the proposed extraction can represent the characteristics of the raw data efficiently in this application.

Keywords: radar clutter classification; graph feature extraction; support vector machine; average amplitude level

1. Introduction

The radar sends electromagnetic waves to a specific area and receives the target's reflected echoes, which are always mixed with clutter and noise [1–3]. These uninteresting echoes from rain, fog, sea and land are important factors affecting radar performance.

Clutter classification and suppression are important not only in classical radar system design but also in complicated applications such as meteorological radars and satellite systems [4,5]. Sea and land clutter often exist in shore-based surveillance radar or satellite echo, and the task of distinguishing the sea and land clutter should be performed using intelligent technology when the maps cannot be used or updated [6].

Efficient intelligent perception and classification of a clutter environment, and highquality joint feature acquisition are the main problems of clutter classification and target detection [7–9]. A central question of clutter concerns the selection of features, that is, which features are present in radar returns and able to accurately identify each clutter type and be removed from the returns. In [2], the overall quality of the defogged remote sensing image is improved by decomposing the source image and feature enhancement based on the dual self-attention boost residual octave convolution. Preivous literature [3] applied an atmospheric scattering model that is based on the estimated atmospheric light and transmission map to remove clutter from remote sensing images. Many traditional studies have focused on the amplitude statistical properties and spectrum properties of clutter, and some mathematical models have been established to describe clutter in specific situations [10–16].



Citation: Zhang, L.; Xue, A.; Zhao, X.; Xu, S.; Mao, K. Sea-Land Clutter Classification Based on Graph Spectrum Features. *Remote Sens.* **2021**, *13*, 4588. https://doi.org/10.3390/ rs13224588

Academic Editor: Ali Khenchaf

Received: 9 October 2021 Accepted: 12 November 2021 Published: 15 November 2021

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Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). Furthermore, the first-order [17,18] and higher-order representations [7,19] of statistical models and polarization characteristics [20–23] are always extracted and combined with intelligent technologies to realize clutter classification or target detection. These algorithms exhibit superior performance in the evaluation of simulation data, but almost all of them depend on the accuracy of the established model and are quite sensitive to the environment. In many cases, the model is only applicable to specific conditions, and intelligent classifiers and detectors will tend to experience considerable performance loss [21,24–27] and face a high false alarm rate when the model deviates from the actual situation. The different existing solution types mentioned above are compared in Table 1.

Solution Type	Pros	Cons
Clutter Distribution Model Properties	good theoretical foundation and excellent performance when well fit with the environment	difficulty of modeling and parameter estimation and sensitive to the environment
Amplitude Statistical Properties	good theoretical foundation, reflect signal value characteristics	can not reflect the relationship between samples and target moving velocity
Doppler Spectra	reflect the target radial velocity	can not reflect tangential velocity and insensitive to slow targets

 Table 1. Pros and Cons of different feature extraction solutions.

The signal index using graphs is a new information representation framework, and signal processing using graphs extends classical discrete signal processing to the signal index using the vertices of a graph [28,29].

The process includes two stages: the first stage is mapping the signal to a weighted graph. In this stage, the graph should contain the value and relationship information of samples. The second stage is analyzing and processing the graph mathematically in the matrix domain. This technology has been extended to address weak and sparse communication signal detection [30], nonstationary signal classification [31] and target detection within sea clutter [32] by transforming the signals into graphs. In our proposed method, graph features that contain not only signal values but also relationships between samples instead of a distribution model are revealed to represent the characteristics of the clutter to improve the generalization performance. Once the graph is established from sea and land clutter sequences, we focus on analyzing the corresponding Laplacian matrix, spectral radius and maximum degree of the graph instead of the graph connectivity, which is used in [30,32], to characterize the cutter. Finally, we address the classification of sea and land clutter by combining the graph feature extractor and machine learning classifier. The main contributions of this study are summarized as follows:

- 1. We propose a novel framework, namely an undirected graph to represent the sea and land clutter. The graph contains not only the value but also relationship information of samples, and the Laplacian matrix of the graph is used to analyze its properties.
- 2. We present a novel set of features for improving the classification performance, namely Laplacian spectrum radius m(G), the maximum degree D(G) and the minimum degree d(G) of the graph (graph feature). Both the value and relationship information of clutter samples are represented in case the statistical distribution is unknown.
- 3. We present a novel classification system based on the SVM utilizing the graph feature space, and we conduct an in-depth, exhaustive analysis of the proposed methods and compare them against the routine baseline, namely the ELM and variant form RELM and KELM, to observe the generalization and robustness of proposed system.

The remainder of the paper is organized as follows. We review the essential background on clutter models, digital signal processing on graphs, and SVM techniques in Section 2. We then introduce the proposed techniques in Section 3. In Section 4, we discuss the experimental results and analyze the complexity of the proposed algorithm. We finally conclude the paper in Section 5.

2. Related Work

2.1. Clutter Modeling

Using a probability distribution model of radar clutter is an efficient and versatile technique, and the distribution of the amplitude can describe the temporal and spatial variation of clutter. The common distributions for radar clutter include Rayleigh, log-normal, Weibull and K distributions [11,19]. More specifically, the Weibull distribution can be used to describe the land clutter amplitude for L and X band radars, almost mimicking high-resolution radars for land clutter. In this paper, we generate the classic land clutter sequence following a Weibull distribution, and the amplitude probability density function (APDF) of the Weibull distribution is:

$$f(x) = \alpha \delta(x)^{\alpha - 1} \exp(-\delta x^{\alpha}), x \ge 0, \alpha, \delta > 0$$
⁽¹⁾

where δ is the scale parameter, and α is the shape parameter. The Weibull distribution can model land clutter more accurately than the Rayleigh and log-normal distributions over a large range and can be used to model and simulate even undulating land clutter sequences at low grazing angles of the high-resolution radar.

2.2. Discrete Signal Processing Using Graphs

Discrete signal processing using graphs is a novel paradigm of traditional time and image signal representations that was proposed by Sandryhaila [29] in 2013. This paradigm maps the discrete time series or pixels to a corresponding graph that indexes the data using the nodes of the graph and retains the information on both the magnitude and relationship structures of the signals.

Once the graph is established, the Laplacian matrix and adjacency matrix and their eigenvalues can be used to analyze it mathematically. Furthermore, according to Abreu [33], the Laplacian matrix is more intuitive and important than the adjacency matrix; thus, in this paper, we analyze the properties of the Laplacian matrix instead of the adjacency matrix of the graph.

The Laplacian matrix is a representation of a graph in the matrix domain, and its eigenvalues and eigenvectors are mainly used to conduct discrete mathematics, combinatorial optimization and data dimension reduction and to interpret some physical and chemical problems [28]. The eigenvalues form the Laplacian spectrum of the graph and can be considered graph frequencies to analyze the signal.

The most popular eigenvalue of the Laplacian matrix of the graph is the second smallest one, which is also called algebraic connectivity of a graph by Fiedler [34] and has received much more attention. This eigenvalue is usually used to measure how well a graph is connected because the graph is only connected when the algebraic connectivity is not zero, which is not only an immediate consequence of the matrix-tree theorem but also can be obtained from the Perron–Frobenius theorem. The relevant research results have been used in some application areas, such as outlier node detection in wireless sensor networks (WSNs) [35], target detection within sea clutter [32] and image segmentation in computer vision [36]. The maximum eigenvalue, which is also referred to as the Laplacian spectrum radius of the graph, is another important parameter of a graph.

2.3. Brief Review of the SVM

SVM is a supervised learning model that is an intelligent agent aiming to construct a hyperplane in high-dimensional space, the SVM can provide good generalization on classification and detection applications by approximately implementing structural risk minimization, especially in binary classification problems. It has been utilized to detect targets from sea clutter.In [37], three discriminative features, namely the temporal information entropy(TIE), the temporal Hurst exponent(THE) and the frequency peak to average ratio(FPAR), are combined with SVM to design a learning-based detector. In [38], SVM is used to recognize micro-Doppler clutter. In order to verify the effectiveness of the proposed algorithm objectively, the TIE, THE and other five popular time domain features and two Doppler domain features are extracted and compared with the proposed graph features in this paper. Since the effective features of the dataset and an appropriate kernel function are the main factors affecting the performance of the SVM, we build 3D feature space by mapping raw data to the graph spectrum that tends to characterize the relationship between samples and select the radial basis function as the kernel function of SVM to obtain the high-dimensional features and find the hyperplane.

3. Proposed Method

3.1. Overview of the System

The intelligent classification of radar clutter is a major project in radar system design. In this paper, we expect to mine discriminative features and combine them with the SVM to distinguish two types of typical clutter from sea and land surfaces. The algorithm includes five modules: data preprocessing, creating the graph of cluttered data, extracting the features of the graph, training the machine learning model and decision data categories. Figure 1 summarizes these five stages.



Figure 1. Flowchart of the proposed algorithm.

3.2. Preprocessing

Radar clutter from sea and land surfaces is time-varying and nonstationary, so we transfer the data to a piecewise steady signal by separating the entire time series into a number of segments; each segment is referred to as the quasi-steady state of the signal in the short time interval. Then, we select the value of the segment length *d* as in our previous work [39]. For a sampled signal x(t) with a length of *l*, let *d* be the length of each segment, and let the signal x(t) be segmented into *N* frames $\{x_1^d(t), x_2^d(t), \dots, x_N^d(t)\}$. This is an important step in clutter data preprocessing prior to feature extraction.

3.3. Create the Graph of Clutter Data

In general, the sampled signal can be represented as a probability density function (PDF), power spectrum and other time and frequency domain forms. However, almost all forms pay attention to the magnitude or the statistical distribution. In this paper, we explore the relationship between samples to represent sea and land clutter as a graph and extract essential features by analyzing the Laplacian matrix obtained from the corresponding graph.

We construct an undirected graph *G* to represent the clutter dataset. Graph $G = \{V, E\}$ contains a set of nodes V and a set of edges E; the former reflects the magnitude or intensity of the signal, while the latter reveals the relational information between each sample.

We quantify the amplitude of each frame signal and map the quantization levels to the node set. Assuming that the value of the quantization level is an integer **U** and the interval is $\frac{1}{\mathbf{U}}$, we can quantify the signal sequence $x_i^d(t)$ as follows:

$$Q_{i}^{d}(t) = i; if^{(i-1)}/U \le x_{i}^{d}(t) \le i/U$$
(2)

where $i = 1, 2, \dots, U$; therefore, we obtain the node set $\mathbf{V} = \{v_1, v_2, \dots, v_i, \dots, v_U\}$ by mapping each level *i* to each node v_i .

The edge set contains the relationship information between a node and its neighbors. For example, if the change times from node v_m , which reflects the value of quantization level m, to node v_n , which reflects the value of the quantization level n, is not zero, we consider that the edge e_{mn} is connected; otherwise, edge e_{mn} is considered unconnected, and the edge set can be expressed as $\mathbf{E} = \{e_{mn} | (m, n) \in N_U \times N_U\}$, where $N_U = \{1, 2, \dots, U\}$. Consequently, the graph construct is $G = \{\mathbf{V}, \mathbf{E}\}$.

3.4. Graph Feature Extraction

Signals indexed by the nodes or vertex of the corresponding graph are a new representation paradigm of signal processing, and the properties of graphs have recently received much more attention. For example, for the second smallest eigenvalue of the Laplacian matrix of a graph, called by the algebraic connectivity of graph by Felder, if and only if the algebraic connectivity measurement is not equal to zero is the graph connected [33]. Furthermore, the second largest eigenvalue of the Laplacian matrix is often used to determine whether the graph is fully connected because these measurements are sensitive to the sample changing. Connectivity analysis of the graph has been used for band-limited weak signal detection in [30] and small size target detection within sea clutter in [32]. Related research indicates that the graph generated from random clutter and white noise is dense and tends to be fully connected, which corresponds to a situation without a target; however, when a target exists, even if it is small, the graph is sparse. Therefore, the signal detection problem is converted to graph connectivity analysis, which is based on the frequency analysis of the graph. In [28], the graph Fourier transform and spectrum are defined by the eigenvectors and eigenvalues of the graph Laplacian matrix, and the concepts of low and high frequencies on graphs are expressed. In this paper, the task is to identify distinctive distinguishing features from two types of clutter called sea and land clutter acquired under different environmental conditions. Since these two types of clutter are random and unstable, both graphs extracted from them tend to be fully connected according to previous related research work, and we study the Laplacian spectrum radius of the graph instead of the connectivity of the graph.

As mentioned earlier, we have constructed a graph *G* of a quantized signal. For further analysis, if node v_m is connected with node v_n , we register the weight of edge e_{mn} as 1; otherwise, the weight is 0. Then, the adjacency matrix corresponding to this graph is defined as follows:

$$\tilde{\mathbf{A}} = \begin{vmatrix} a_{11} & a_{12} & \cdots & a_{1U} \\ a_{21} & a_{22} & \cdots & a_{2U} \\ \vdots & \vdots & \ddots & \vdots \\ a_{U1} & a_{U2} & \cdots & a_{UU} \end{vmatrix}$$
(3)

The element of the matrix $\tilde{\mathbf{A}}$ is defined as:

$$a_{mn} = \begin{cases} 1 & when \quad e_{mn} = 1; \\ 0 & when \quad e_{mn} = 0; \end{cases}$$

$$\tag{4}$$

The degree matrix of the graph is a diagonal matrix:

$$\tilde{D} = \begin{bmatrix} d_1 & 0 & 0 & \cdots & 0 \\ 0 & \ddots & 0 & \ddots & \vdots \\ 0 & 0 & d_m & 0 & 0 \\ \vdots & \ddots & 0 & \ddots & 0 \\ 0 & \cdots & 0 & 0 & d_U \end{bmatrix}$$
(5)

The diagonal elements of the matrix d_m are the degree of node v_m , which is obtained as:

$$d_m = \sum_{n=1}^{U} a_{mn} \tag{6}$$

Figure 2 represents the degree of one frame clutter graphs from the land and sea datasets.



Figure 2. (a) Degree of the land clutter graph and (b) degree of the sea clutter graph.

Accordingly, the Laplacian matrix of graph *G* can be calculated as:

$$\tilde{L} = \tilde{D} - \tilde{A} \tag{7}$$

The Laplacian matrix is often used to represent a graph and to further analyze the graph signal mathematically.

First, we perform eigenvalue decomposition on the Laplacian matrix of the graph [28]:

$$\tilde{L} = P\Lambda P^T \tag{8}$$

where *P* is the eigenvector matrix $P = \{p_1, p_2, \dots, p_i, \dots, p_U\}$, Λ is the eigenvalue matrix $\Lambda = diag\{\lambda_i\}$ and $i = 1, 2, \dots, U$. The distinct eigenvalues of the Laplacian matrix are called the graph frequencies of the signal and compose the graph spectrum, and eigenvector p_i is the frequency components corresponding to frequency λ_i . Since the graph Laplacian matrix \tilde{L} is a symmetric positive semidefinite matrix, it has a nonnegative real spectrum, and the ordered eigenvalues can be expressed as:

$$\lambda_1 \ge \lambda_2 \ge \dots \ge \lambda_U \tag{9}$$

Note that the larger λ is, the lower the corresponding graph frequency, and the largest eigenvalue λ_0 is called the Laplacian spectrum radius of the graph. Thus, the Laplacian spectrum radius $\mu(G)$, the maximum degree $\Delta(G)$ and the minimum degree $\delta(G)$ of the graph are defined as follows:

$$\mu(G) = \max\{\lambda_i\}\tag{10}$$

$$\Delta(G) = \max\{d_m\}\tag{11}$$

$$\delta(G) = \min\{d_m\}\tag{12}$$

Figure 3 represents the degree of one frame clutter graphs from the land and sea datasets.



Figure 3. (a) $\mu(G)$ of the land clutter graph and (b) $\mu(G)$ of the sea clutter graph.

These three measurement sets acquired from the graph domain provided a new view to describe the signals; in what follows, we will combine this feature extractor with a popular intelligent algorithm called the SVM to verify the effectiveness of these graph features to discriminate sea and land clutter from radar.

3.5. Sea-Land Clutter Classification via an SVM

The proposed sea-land clutter classification scheme shown in Figure 1 is composed of four functional blocks. The first block is data preprocessing, where the raw dataset from one range cell is segmented by windowing. The second block is a graph signal creating block, where each segmented series is normalized and quantified, and the corresponding graph is constructed based on the node set and edge set. Then, the Laplacian matrix and degree matrix of the graph are obtained, and the feature set is mapped in the third block. The widely used robust binary classifier is used to separate the two typical clutters by finding a hyperplane according to the max-margin principle in the fourth function block. For a sample series *s*, we construct the feature set $\mathbf{F} = [\mu_s, \Delta_s, \delta_s]^T$ and the label set $Y : \{+1, -1\}$, where sea clutter (+1) and land clutter (-1). Then, using the least squares minimization technique to find the hyperplane via the SVM, the equation function of the hyperplane has the following form:

$$f(x) = \omega^T x + \mathbf{b} \tag{13}$$

The training process of the SVM determines ω and b by minimizing the sum of squared differences between the support vector and boundary hyperplane. Mathematically, the quadratic program is solved as:

$$\min \frac{1}{2} \| \omega \|^2 + \alpha \sum_{i=1}^{s} \xi_i$$

$$s.t.y_i[k(\omega, F) + b] \ge 1 - \xi_i, \xi_i \ge 0, i = 1, 2, \cdots s.$$
(14)

where ξ_i is the slack variable and α is the penalty parameter, which is used to balance the structural risk of the system and empirical risk.

4. Experiments and Results

In this section, we execute classification experiments on two types clutter sets: a sea clutter set and a land clutter set. We first state the dataset and experimental setting, and then we analyze the impact of the key components of our proposed method, present

the recent comparison results of this method with other machine learning algorithms and compare the proposed feature set against other commonly used features.

4.1. Datasets and Experimental Settings

4.1.1. Datasets

In this paper, we validate the proposed method on the IPIX (Ice Multiparameter Imaging X-Band Radar) radar sea clutter dataset obtained from shores of Lake Ontario in Grimsby, Canada in 1998 by McMaster University [40] and on the simulated land clutter dataset mentioned above because, although the IPIX dataset contains abundant sea clutter data, it has no land clutter. Moreover, we can make the verification more flexible and effective by controlling the average amplitude ratio of the two types of clutter. Therefore, the dataset used for evaluating the proposed method contains 60,000 measurements from IPIX and 60,000 measurements of simulated land clutter following a Weibull distribution.

4.1.2. Experiments Setup

A large number of experiments are used to verify the effectiveness of our approach, including the following:

- 1. Assessing the impact of the quantization level on the classification accuracy by varying the quantization level **U**;
- 2. Testing the generalization performance of the proposed feature extraction method through combining it with different popular classifiers;
- 3. Assessing the significant discrimination performance of the proposed feature set by comparing its performance on other existing popular feature sets;
- 4. Assessing the effectiveness of the proposed feature extraction method through multiple data sets via the SVM.

4.1.3. Evaluation

We evaluate the proposed method using two types of metrics, which are the training time (*TT*) and the testing accuracy (*TA*). *TT* measures the model training time, and *TA* measures the overall classification accuracy of the two types of clutter on the testing dataset. *TA* is defined as:

$$TA = \frac{TP_1 + TP_2}{\Phi} \tag{15}$$

where TP_1 is the true positive sea clutter, TP_2 is the true positive land clutter and Φ represents the overall data of the testing dataset.

4.1.4. Implementation Settings

In all the experiments, the dataset is split at an 8:2 ratio for training and testing. We performed a grid search to select the suitable parameter value of SVM. Dataset 1, which is used to evaluate feature extraction using the graph-based algorithm. In this paper, the dataset contains the sea clutter from an IPIX radar over range R_1 and the land clutter, which is modeled as a Weibull amplitude compound Gaussian distribution. We use the same dataset configuration to study the effects of key components of the proposed method, and we used a computer with an Intel Core-2 processor clocked at 2.30 GHz with 16 GB RAM.

4.2. Experimental Results

4.2.1. Impact of the Quantization Level on Classification Performance

To understand the impact of the quantization level on the classification performance, we varied the level values in the range of $\{5, 8, 10, 20, 30\}$ while extracting the proposed features on the graph using an intelligent classifier. We show the resulting performance in Table 2 and Figure 4.

Quantization Level (U)	Accuracy (%)
5	72.98
8	94.04
10	92.34
20	95.11
30	91.70
100 90 80 70 40 30 20 10 U=5 U=8 U=10 U=20 U=30 Quantization Level Value	FELM $U = 5$ $U = 8$ $U = 10$ $U = 20$ $U = 30$ $U = 30$ $U = 30$ $U = 10$
(a)	(b)

Table 2. Variation of the TA with the Quantization Level.

Figure 4. (a) TA of the ELM in the case of different quantization levels and (b) TT of the ELM in the case of different quantization levels.

As the quantization level increases, the testing accuracy also generally shows an increasing trend. Furthermore, the highest testing accuracy of 95.11% is obtained in the case of U = 20, which indicates that the features on the graph can maintain the high similarity of the same type of clutter and clear distinction of different types of clutter, especially in this case. Therefore, the remainder of the experiments use this quantization level value.

4.2.2. Evaluating Graph Features by Combining Other Classifiers

In this section, we assess the robustness of the performance of the proposed graph features by combining four different machine learning algorithms, namely the extreme Learning Machine (ELM), regularized extreme Learning Machine (RELM), kernel extreme learning machine (KELM) and SVM. We maintained the frame length at d = 512 and the quantization level at U = 20. The results of these experiments are shown in Figure 5.





We take the radial basis function and sigmoid activation function in these four intelligent classifiers and perform a grid search to select suitable parameters of them. The TAs shown in Figure 5a are all above 95%, and the TTs shown in Figure 5b prove that the processing efficiency of the ELM is significantly lower than those of the other three algorithms in this case, and the best overall performance is the proposed feature extractor combined with the SVM.

4.2.3. Evaluating the Graph Features Using Different Dataset Configurations

For a fair comparison, we utilized nine additional datasets as input to the graph feature extraction method and SVM to evaluate the generalizability of our proposed method. Table 3 illustrates the details of the nine datasets, and Figure 6a shows the performance results.

Table 3. The additional nine datasets used to evaluate proposed features.

Dataset	Sea Clutter Component	Land Clutter Component	Average Amplitude Ratio (Sea/Land)
Dataset 1	IPIX radar measurements over region R_1	modelled Weibull series 1	1.0045
Dataset 2	IPIX radar measurements over region R_1	modelled Weibull series 2	1.0455
Dataset 3	IPIX radar measurements over region R_1	modelled Weibull series 3	0.9171
Dataset 4	IPIX radar measurements over region R_1	modelled Weibull series 4	1.1631
Dataset 5	IPIX radar measurements over region R_1	modelled Weibull series 5	0.8734
Dataset 6	IPIX radar measurements over region R_1	modelled Weibull series 6	1.1537
Dataset 7	IPIX radar measurements over region R_1	modelled Weibull series 7	0.8422
Dataset 8	IPIX radar measurements over region R_2	modelled Weibull series 1	0.5442
Dataset 9	IPIX radar measurements over region R_3	modelled Weibull series 1	9.0217

In order to verify the performance of the proposed algorithm when the energies of the two types of clutter are close, we provided more challenging datasets, such as dataset 1 and dataset 7 listed in Table 3, in which the average amplitude ratios are approximately 1.





Figure 6a shows the results on different datasets with a fixed frame length of 512 and a quantization level of 20, and the same intelligent classifier SVM is used throughout the experiment. The results show that the performance of the proposed method on different datasets is almost the same, especially in the former six datasets. They consistently achieved high testing accuracy and consumed less computing time. However, the deviation that appears in dataset 7 is because the graph structure of the signal reflects part of the implicit relationship between each data point on this dataset.

4.2.4. Evaluating the Graph Features by Comparing with Other Valid Features

For a more in-depth assessment of the proposed feature selection, we compare the performance of the time-domain three joint features: relative average amplitude, TIE and THE (RTT), as well as Doppler-domain two joint features: relative Doppler peak height and relative entropy of Doppler spectrum (RPE) with proposed graph features. Figure 7a exhibits Doppler amplitude spectra of a time series of sea and land clutter, and Figure 7b shows TA and TT of these feature sets fed to SVM on the same dataset. Furthermore,

we evaluated the impact of different features on the additional nine datasets shown in Table 3. The existing valid features, such as ECVA features [39] and RTT (relative average amplitude, temporal information entropy and temporal hurst exponent) features in [37], are compared with the proposed graph features on different datasets, and the results are shown in Figure 8.



Figure 7. (**a**) Doppler amplitude spectra of sea and land clutter. (**b**) TA and TT of RTT/RPE/ Graph features combined with SVM.



Figure 8. (a) Testing accuracy of the SVM across different feature sets and different datasets, and (b) training times of the SVM across different feature sets and different datasets

It can clearly be seen that the testing accuracy based on the proposed feature set and ECVA feature set remains higher than that of the RTT. Furthermore, the results on the graph feature set maintain stable performance when the average energies of the two types of clutter are close (dataset 1 dataset 6), which is a challenging task in previous work. As shown in Figure 8b. The training time based on our proposed feature set is also very efficient.

5. Conclusions

Intelligent environment recognition is a challenging problem for radar target detection, and radar clutter classification is an essential operation in many adaptive target detection and radar system designs.

In general, these problems are often addressed using well-formulated statistical models of the clutter types. However, the performance of these algorithms is always highly dependent on modeling effectiveness; in other words, unless the models are data adaptive, they are unlikely to perform very well on classification.

Machine learning-based techniques are known to be data adaptive, and the characteristics of the dataset are the main factor of its performance. In this paper, we proposed new approaches to reveal the underlying relationship of the data to construct feature sets on graphs to classify sea and land clutter via the SVM machine learning classifier, which captures the Laplacian spectrum radius $\mu(G)$, the maximum degree $\Delta(G)$ and the minimum degree $\delta(G)$ of the graph.

The exhaustive evaluation based on a number of mixed datasets showed that the proposed feature set combined with the SVM offers superior classification performance compared to the proposed feature set and compared to other popular classifiers.

Author Contributions: Conceptualization, A.X. and L.Z.; methodology, L.Z.; software, L.Z. and K.M.; validation, S.X. and L.Z.; formal analysis, A.X. and L.Z.; investigation, X.Z. and L.Z.; resources, S.X. and L.Z.; data curation, S.X. and L.Z.; writing—original draft preparation, L.Z.; writing—review and editing, L.Z.; visualization, X.Z. and L.Z.; supervision, A.X. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China of grants' number 61333009 and 61427808.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: This work was supported in part by the National Natural Science Foundation of China under Grants 61333009 and 61427808. The authors thank Tianlei Wang for their assistance in technical discussions.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

SVM	Support Vector Machine
0 1 1 1	

- APDF Amplitude Probability Density Function
- WSNs Wireless Sensor Networks
- IPIX Ice Multiparameter Imaging X-Band Radar
- TT Training Time
- TA Training Accuracy
- ELM Extreme Learning Machine
- RELM Regularized Extreme Learning Machine
- KELM Kernel Extreme Learning Machine
- RTT Relative average amplitude, Temporal information entropy, Temporal hurst exponent

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