A Cooperative Dictionary Learning and Semi-supervised Learning Framework for Sea Clutter Suppression of HFSWR

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Abstract. High-frequency surface-wave radar (HFSWR) has been applied in searching targets and maritime surveillance systems. However, the sea clutter is usually strong and harmful for detecting the targets. In this paper, we explore the sea clutter suppression problem for HFSWR and propose a novel sea clutter suppression method named a cooperative dictionary learning and semi-supervised learning sea clutter suppression framework (CDLSL). The semi-supervised learning can obtain abundant needed sea clutter data for the subsequent dictionary learning. The dictionary learning has ability to capture the features of sea echo and provides a desired clutter estimation. We have applied the proposed framework in the actual HFSWR data. Significant improvements in sea clutter suppression performance are achieved by the proposed method with respect to the state-of-the-art method.

Keywords: Dictionary learning · High-frequency surface-wave radar · Sea clutter suppression · Semi-supervised learning

1 Introduction

Because of the curvature of the earth, traditional microwave radar has the problem of line-of-sight and the detection blind spots. The targets over the horizon are hard to be detected by ground-based line-of-sight radar. High-frequency surface-wave radar (HFSWR) utilizes the surface-wave in the lower half of the high-frequency (HF) band to explore targets and then receives vessel and low-flying aircraft echoes over the horizon. With its own superior performance, the maximum surveillance range of HFSWR can cover Exclusive Economic Zone (EEZ) and also can monitor the ocean dynamic parameters over the horizon, such as the direction of winds and the height of the waves. In the meantime, HFSWR has the advantages of all-weather operability, and thus it is widely used in coastal warning, maritime rescue, marine resource development, and continuous monitoring for military [1–3].

Q. Guo et al. (Eds.): WiSATS 2021, LNICST 410, pp. 593–606, 2022.
https://doi.org/10.1007/978-3-030-93398-2_53

However, the strong clutter and interference severely limit the detection ability of HFSWR. As the most common clutter, sea clutter becomes a crucial problem for the accurate detection of marine targets [4, 5]. Sea clutter is produced from resonance effect between electromagnetic waves and ocean waves. Hence, it is of great importance to design suitable detectors or propose the effective sea clutter suppression methods for improving the detection ability in HFSWR.

2 Research Status Review

From 1970s, a surge of research into clutter suppression field with the development of the HFSWR all over the world. The sea clutter spectrum of shore-based HFSWR is mainly composed of first order and second order components. The first order spectrum is derived from Bragg resonance scattering and its spectrum can be represented as two discrete spectral lines. In particular, the first order Bragg peaks of sea clutter are generated by waves with specific wavelength. In target detection experiment, second-order sea clutter signal and atmospheric noise also can impact the detection effect [6].

At present, the suppression methods of sea clutter mainly include the sea clutter modeling method, cyclic iterative cancellation method [7], subspace estimation method [8, 9], and neural network method [10, 11]. The sea clutter modeling method can be roughly divided into three categories. The first one is the statistical model for describing the amplitude variation of sea clutter in time domain. The second one is the power spectrum distribution model for describing the distribution of sea clutter in the frequency domain. The last one is the sea clutter model based on the radar cross-sectional area scattering principle. It applies the sea surface electromagnetic scattering mechanism to establish a suitable interaction model between the electromagnetic wave and the scattering medium. Finally, building the radar sea surface scattering cross-sectional area equation to achieve the modeling of sea clutter [5].

In the sea clutter modeling method, Ward et al. first proposed a K-distribution model and utilized synthetic modulation to model the sea clutter of high-resolution radar [12]. In 1983, Sekine et al. proposed the Weibull distribution, and the probability density function (PDF) of Weibull distribution lies between Rayleigh and log-normal distributions [13]. In 1997, Farina et al. applied the Weibull distribution for modeling sea clutter [14]. In 2006, based on ice multi-parameter imaging X-band radar clutter data, Greco et al. proposed a generalized K-distribution model to estimate the clutter amplitude distribution. Immediately following this, some models are introduced to explicitly model sea spikes, such as the KA- and KK-distributions. In addition, Rosenberg et al. proposed the Pareto-distribution to model the longer tails in the presence of spikes [15].

In the cyclic iterative cancellation method, the sinusoidal signal is constituted by estimating parameters, and then the sinusoidal signal will be subtracted from the echo to achieve sea clutter suppression. The subspace estimation method can suppress sea clutter by clustering the property of subspace. However, the existing literatures based on subspace estimation suppression may cause the problem of target spectrum peak shift, which affects the target signal detection.

Nowadays, the machine learning has attracted much attention in machine vision and engineering applications. The machine learning approach employs abundant knowledge and information to analyze the characteristic of data and then investigates the techniques to provide a generalized treatment of the input samples and the discrimination algorithms to be applied. As a special kind of machine learning, the deep learning methods are conventionally designed for investigating the big data. In most cases, deep learning methods usually need a lot of training data and a large calculation cost, while the specific sea clutter data and interference data are limited in the experiment.

By analyzing the features of the target, clutter and the interference in Range Doppler (RD) spectrum images, Zhang et al. proposed a lightweight deep convolutional learning network based on a faster region-based convolutional neural networks (Faster R-CNN). By combining a classifier, this network first applies effective feature extraction to detect the clutter and the interference [16].

In actual environment experiment, the low signal-to-clutter ratios on the sea surface is a challenge for the researchers. Li et al. proposed a novel convolutional neural network based dual-activated clutter suppression algorithm. This framework firstly multiplies the activation weights of the last dense layer with the activation feature mapping of the upper sample layer. Then, the class activation maps (CAMs) obtained by last step are correspond to the sea clutter distribution region. By mapping the CAM inversely to the sea clutter spectrum, the framework can obtain the corresponding suppression coefficients [17].

As stated above, it is difficult to make accurate sea clutter estimation in the traditional clutter models, and the error of model estimation depends on the integrating degree of the current clutter and standard model. In the deep learning methods, initially, we still should consider the distribution of the data set, such as the subdivision of labels, multiple features and the distribution of the training and testing samples. Then, beginning the next step to extract the feature needed for suppressing the clutter.

3 Proposed Methodology

Usually, HFSWR echo data contains a large number of targets, sea clutter, ionospheric clutter and interference. Hence, the first task is asking us to accurately select the needed data, which contributes to the distinguish the clutter and the target in the experiment.

Inspired by machine learning, we think about sea clutter estimation and suppression from the perspective of semi-supervised learning. Specifically, we first select some sea clutter data (almost have no target) and the data of target coexists with sea clutter. Then, we label these two different data as labeled training samples set for subsequent classification algorithm. Of course, the training samples set also contains unlabeled samples. Next, we feed the raw radar echoes into the semi-supervised learning classification algorithm (enhanced M-training) and obtain the initial classification results. The sea clutter data and the data of target coexists with sea clutter can be automatically classified into two classes. Hence, we will obtain a large number of the sea clutter data and we only select the sea clutter data for the dictionary learning. With the help of dictionary learning and sparse representation, we will extract sea clutter components in radar echoes. In this section, a clutter suppression method that combines dictionary learning and semi-supervised learning is proposed. Through the cooperation of offline training and real-time processing, this method realizes the improvement of clutter suppression performance and accelerates the calculation speed.

3.1 STEP 1: Semi-supervised Classification – Enhanced M-training

As the classical semi-supervised classification method, Tri-training algorithm has been applied in many fields [18]. As the improvement of Tri-training algorithm, M-training algorithm has validated its effectiveness in semi-supervised classification, such as electronic nose learning technique and hyperspectral image classification. But the original M-training algorithm ignores the diversity of classifier types, which cannot achieve excellent classification results when the number of labeled samples is limited at the initial stage. In order to improve the performance of original M-training algorithm, the improved M-training algorithm with enhanced classifier diversity was proposed and obtained more promising results. Because complementing different kinds of classifiers for each other can avoid the classifier performance deterioration [19].

We set the enhanced M-training algorithm with four classifiers in two different classes, which contributes to increase the diversity of classifiers. In the experiment, we select two support vector machine (SVM) classifiers, two random forest classifiers (RF). SVM is very suitable for dealing with large input spaces and produce sparse solutions. SVM is a supervised nonparametric statistical learning technique, which doesn't rely on prior assumptions about the input samples distribution [20]. In the classification process, SVM is based on linear modeling of the classification boundary utilizing a least squares method.

Otherwise, RF has the advantages in dealing with large scale data set. When the scale of data set enlarges, the performance of RF does not appear over-fitting. Moreover, when the size of the data set is small, RF also has a strong generalization ability. When the data or some characteristic values are partially lost, RF has desired anti-noise ability and better tolerance [21].

Algorithm 2
Enhanced M-training algorithm

Input:

Initial training set: $L = \{(x_i, y_i)_{i=1}^{l}\}$

Initial unlabeled data set: $U = (x_j)_{j=1}^{u}$

Initial iteration times: $t = 0$

the number of iterations: T

While $t \leq T$:

Repeat:

1. Train classifiers C1, C2, C3, C4 by using initial training set L.
2. Choose a classifier as main classifier and others are assistant classifiers.
3. Use U as the test set. When an unlabled sample recieves the same classifiaction labels from one main classifier and three assistant classifiers, this unlabeled sample will be labled by classifiers and put it into new labeled data set $L_1(t)$, and $L_1(t) = \{x \mid x \in U, C_1(x) = C_2(x) = C_3(x) = C_4(x)\}$ (Similarly, when C2, C3, C4 as main classifier, respectively, we denote new labeled data set as $L_2(t)$, $L_3(t)$, $L_4(t)$, respectively.
4. If C1 as main classifier and $e_1(t)|L_1(t)| < e_1(t-1)|L_1(t-1)|$, update the labeled data set and unlabeled data set. $L_1(t) = L_1(t-1) \cup L_1(t)$
5. If C1 as main classifier and $e_1(t)|L_1(t)| \geq e_1(t-1)|L_1(t-1)|$, we randomly select samples as $L_1(t)$ to ensure $e_1(t)|L_1(t)| < e_1(t-1)|L_1(t-1)|$.
6. Update iteration times $t = t + 1$.
7. Until $t > T$

Output: Trained classifiers

Input test samples into the trained classifiers, using majority vote strategy to obtain classification results.

In the experiment, the four classifiers (denoted as C1, C2, C3, and C4) are initially trained by the labeled samples. Each classifier has the equal probability to be the main classifier, in the meantime, the rest of classifiers as assistant classifiers. Then we will calculate the classification error rate of both the unlabeled samples and the labeled samples, respectively. The $e_i(U)$ means the error rate of unlabeled samples. The $e_i(t)$ represents the limitation of the classification error rate for assistant classifiers at t th iteration. Specifically, $e_i(U)$ and $e_i(t)$ can be estimated as:

$$e_i(U) = \frac{(n_i(u) - k_i)}{n_i(u)} \tag{1}$$

$$e_i(t) = \lambda * e_i(L) + (1 - \lambda) * e_i(U) \tag{2}$$

Where $n_i(u)$ represents the number of all the unlabeled samples, k_i represents the number of unlabeled samples with the same labels by the three assistant classifiers. λ is a weighting coefficient that tunes the tradeoff between $e_i(t)$ and $e_i(U)$. ($\lambda = 0, 0.1, 0.2 \ldots 0.9, 1$) $L(t)$ represents the new labeled data set at t th iteration. When an unlabeled sample obtains the same class labels from all the classifiers at the same time, it can be assigned with temporary labels and begin to train classifiers from the next iteration. When the C1 as main classifier, and $e_1(t)|L_1(t)| < e_1(t-1)|L_1(t-1)|$, the original labeled data set is enlarged as $L_1(t) = L_1(t-1) \cup L_1(t)$. When $e_1(t)|L_1(t)| \geq e_1(t-1)|L_1(t-1)|$, the algorithm will randomly select samples from $L(t)$ and these selected samples will compose into $S(S = L_1(t))$. Then, this algorithm applies $L_1(t) = L_1(t-1) \cup L_1(t)$ to retrain classifier C1. Eventually, we apply the majority vote strategy to predict the class of a given unlabeled sample.

3.2 STEP 2: Dictionary Learning

In recent years, dictionary learning is an effective way to acquire more knowledge and information with less resources, which is applied in various practical cases, including visual tracking [23], face recognition [24], and classification [25]. dictionary learning (ODL) algorithm. In the current research, there has been a large amount of research on the dictionary learning. As one of the representatives for classical DL algorithms, at each iteration, K-means singular value decomposition (K-SVD) deals with the entire training set in batches. The classical DL algorithms can achieve promising performance but they require the excellent calculation ability. The essential point of dictionary learning algorithm depends on sparse representation, in which a given signal is represented as a combination of several atoms from an overcomplete dictionary [26]. The goal of the dictionary learning is to learn abundant knowledge and formulate a dictionary with less content from a mass of signal training data set. In this way, the time consumption and the cost of data collection can be greatly decreased. In the training data set, each column can contain either an original signal or features extracted from that signal.

When most elements are zero, the vector is sparse. Sparse coding is a kind of representation learning. In the sparse coding, the input data is represented by sparse vectors. By the sparse coding, the input data is broken up into a few basic elements named atoms, and a group of atoms constitutes a dictionary. The input data can be recreated with a linear combination of atoms. The sparse representation of the signal decides the approach of atoms combination for creating the signal. For each type of signal, the relevant dictionary should be established and deterministic and adaptive, such as DCT [22].

We donate $Y \in \mathbb{R}_{+}^{M \times P}$ as sea clutter data set, and each column of sea clutter data set is represented as $y_i \in \mathbb{R}_{+}^{M \times 1}, i = 1, ..., P$ $\boldsymbol{D} \triangleq [\boldsymbol{d}_1, ..., \boldsymbol{d}_k], \boldsymbol{D} \in \mathbb{R}_{+}^{M \times K}$ is donated as clutter dictionary matrix. $\boldsymbol{G} \triangleq [\boldsymbol{g}_1, ..., \boldsymbol{g}_K], \boldsymbol{G} \in \mathbb{R}_{+}^{K \times P}$ represents the sparse representation coefficient. As stated above, the dictionary learning based on sparse representation can be written as:

$$[\boldsymbol{D}, \boldsymbol{G}] = \min_{\boldsymbol{D}, \boldsymbol{G} \geq 0} \frac{1}{2} \|\boldsymbol{Y} - \boldsymbol{D}\boldsymbol{G}\|_{\boldsymbol{F}}^2 + \lambda \|\boldsymbol{G}\|_1 s.t. \|\boldsymbol{d}_i\|_F^2 \leq \alpha_i, \forall i = 1, \ldots, K \tag{3}$$

Where Frobenius norm $\|\cdot\|_{\mathrm{F}}$ is applied to measure the distance of matrix, L_1 norm is applied to represent the sparseness of $\boldsymbol{G}$. It should be emphasized that the sea clutter data set $\boldsymbol{Y}$ is denoised, but $\boldsymbol{Y}$ may contain noise or interference. Otherwise, restraining the sparseness of $\boldsymbol{G}$ and the norm of each column in dictionary also can enhance the stability of algorithm. λ represents the penalty factor and α_i is used to restrain the norm of each column in dictionary. The value of λ and α_i are greater than zero.

We apply the Block Successive Upper Bound Minimization (BSUM) to explore the optimal solution of $\mathcal{D} = \left\{\boldsymbol{D} | \boldsymbol{D} \geq 0, \|\boldsymbol{d}_i\|_F^2 \leq \alpha_i, \forall i\right\}$ and $\mathcal{G} = \{\boldsymbol{G} | \boldsymbol{G} \geq 0\}$. We can obtain the optimal value of $\boldsymbol{G}$ and $\boldsymbol{D}$ by iterative optimization. According to BSUM algorithm, the iteration of $\boldsymbol{G}$ and $\boldsymbol{D}$ is formulated as:

$$\boldsymbol{D}^{(q+1)} = \arg \min_{\boldsymbol{D} \in \mathcal{D}} \left\langle \nabla_{\boldsymbol{D}} \left(\left\| \boldsymbol{Y} - \boldsymbol{D}^{(q)} \boldsymbol{G}^{(q)} \right\|_F^2, \boldsymbol{D} \right\rangle + \frac{\epsilon_d^{(q)}}{2} \left\| \boldsymbol{D} - \boldsymbol{D}^{(q)} \right\|_F^2 \tag{4}$$

$$\boldsymbol{G}^{(q+1)} = \arg \min_{G \in \mathcal{G}} \left\langle \nabla_{\boldsymbol{G}} \left(\left\| \boldsymbol{Y} - \boldsymbol{D}^{(q+1)} \boldsymbol{G}^{(q)} \right\|_F^2, \boldsymbol{G} \right\rangle + \frac{\epsilon_g^{(q)}}{2} \left\| \boldsymbol{G} - \boldsymbol{G}^{(q)} \right\|_F^2 + \lambda \|\boldsymbol{G}\|_1 \tag{5}$$

Where ∇_D represents the gradient along $\boldsymbol{D}$. $\boldsymbol{D}^{(q)}$ represents the solution of the $\boldsymbol{D}$ in q th iteration and $\boldsymbol{G}^{(q)}$ represents the solution of the $\boldsymbol{G}$ in q th iteration. $\langle \cdot, \cdot \rangle$ represents the inner product. $\mathcal{P}_{\mathcal{D}}(\cdot)$ is the projection operator to the convex set $\mathcal{D}$. Moreover, the ϵ_d and ϵ_g should be iterated as following:

$$\epsilon_d^{(q+1)} = \rho_{\max}^2 \left(\boldsymbol{G}^{(q+1)} \right) \tag{6}$$

$$\epsilon_g^{(q+1)} = \rho_{\max}^2 \left(\boldsymbol{D}^{(q+1)} \right) \tag{7}$$

3.3 Proposed Framework

In this section, we propose a cooperative dictionary learning and semi-supervised learning sea clutter suppression framework (CDLSL) to solve the sea clutter problem. Some earlier works have adequately demonstrated the effectiveness of dictionary learning approach. In essence, sparse representation applies an equipped dictionary, and dictionary learning further exploits the crucial information in dictionary. Another approach, which is named semi-supervised learning, can improve the performance by applying the unlabeled samples to increase the quantity of the training samples. To complement dictionary learning and semi-supervised learning for each other. The proposed framework applies enhanced M-training algorithm with different classifiers, sparse representation and dictionary learning to effectually detect the targets and sea clutter in HFSWR.

In our experiment, we will gather huge volumes of data in six days, and then pore over it. From the Fig. 1, HFSWR echo data usually contains a large number of targets, sea clutter, ionospheric clutter and other interference. Hence, the first task for us is that to accurately select the needed data, which contributes to the identify and distinguish the clutter and the target in the experiment. In this paper, we select a semi-supervised learning framework (enhanced M-training algorithm) to select the needed data in our experiment. In enhanced M-training algorithm, we select the sea clutter data (almost have no target) and the data of target coexists with sea clutter to train the four classifiers from A-R-D (Angle-Range-Doppler) data.

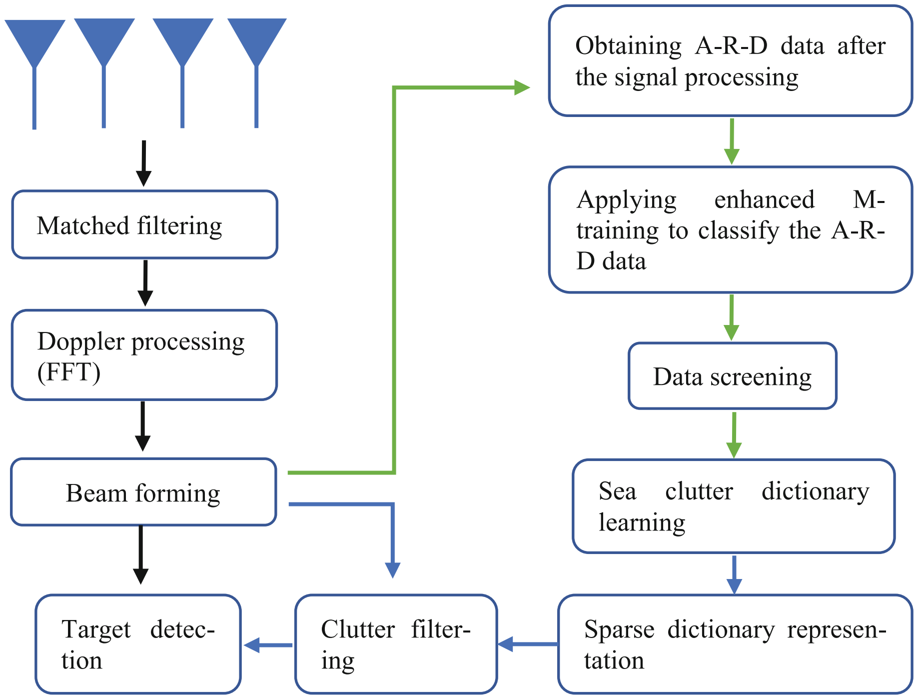

Fig. 1. Flowchart of the cooperative dictionary learning and semi-supervised learning sea clutter suppression framework (CDLSL)

We randomly divide the entire available data into two parts for each class: 50% data are used for training and 50% data are used for testing. And in the training data, we randomly select 60% samples in each class as the initial labeled data, and the remaining samples are used as the unlabeled data. Hence, after training the classifiers, we put the original radar data into the enhanced M-training algorithm. And we obtain the sea clutter data set (almost have no target). We begin to train the sea clutter frequency spectrum dictionary. Then, we will obtain the sea clutter frequency spectrum dictionary and conduct sea clutter dictionary. The above-mentioned steps are conducted in quasi real time mode and we represent the quasi real time steps in green arrows. In the traditional radar signal processing, the echo signals are received by receiving array, then echo signals are matched filtering and conducted by Fast Fourier Transform. After beam forming, the echo signals are directly detected by target detectors. The black arrows describe the above-mentioned procedures. Different from the traditional radar signal procedure, after the beam forming, CDLSL algorithm makes use of dictionary to perform sparse representation of echo and clutter suppression, and then carries out target detection on the echo signal with clutter filtering. The above-mentioned process is represented by the blue line in the Fig. 1.

4 Experimental Data Processing and Experiment Results

4.1 Experimental Data Processing

In Weihai, Shandong province, China, we have collected a large number of the radar echoes from HFSWR system. The receiver of HFSWR constantly collected echo data from August 26, 2020 to August 31, 2020. In the meanwhile, the carrier frequency (f_c) is shifty and f_c = 4–8 MHz. For just a week, the weather is always cloudy, and sometimes be sunny or light rainy. Moreover, aiming at verifying the effectiveness of the proposed framework, we choose the Sparse Dictionary Represented Optimal Filter (SDROF) algorithm as compared methods. By combining the dictionary learning and clutter filter, SDROF effectively suppresses the sea clutter for High-frequency (HF) sky-wave over-the-horizon radar (OTHR). Hence, we applied this outstanding approach in the HFSWR system as compared method.

4.2 Experiment Results

In this experiment, we select 640 samples to train the enhanced M-training and obtain the overall classification accuracy between the sea clutter data (almost have no target) and the data of target coexists with sea clutter is 77.57%. The classification results are shown in Fig. 2.

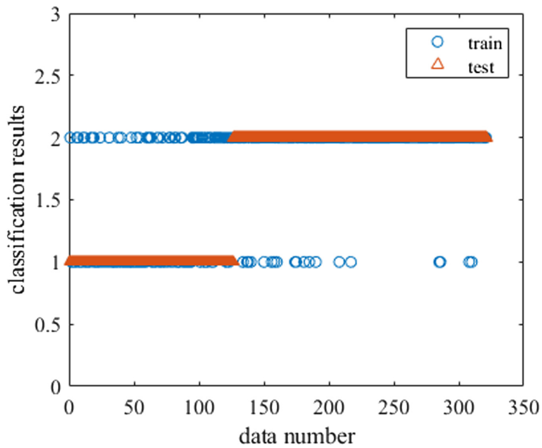

Fig. 2. The classification results of enhanced M-training.

We should emphasize that the sea clutter data is affected by the experimental weather. Hence, when we apply CDLSL framework to suppress the sea clutter, we should utilize a little earlier sea clutter data to train the dictionary. Because the ever-changing weather impacts on the physical character of sea clutter and ionospheric clutter. If we utilize the sea clutter data from a long time ago to train the dictionary, we cannot adequately mine the representative and discriminative information of current the sea clutter. Capturing the underlying patterns of near-term sea clutter is a crucial step for obtaining the adequate detection results.

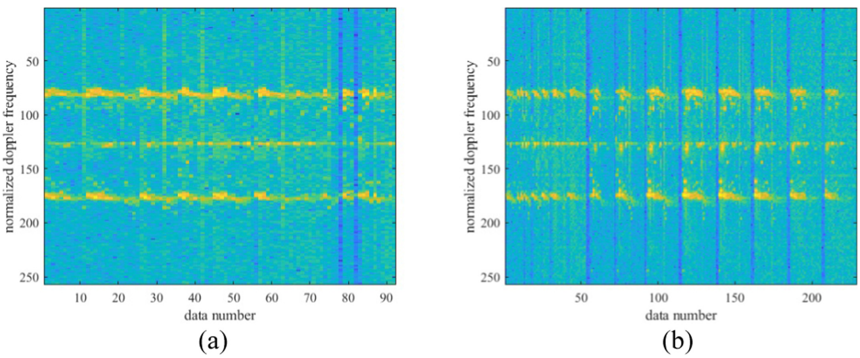

Fig. 3. The classification results of enhanced M-training algorithm (a) the sea clutter data (almost have no target); (b) sea clutter and target data

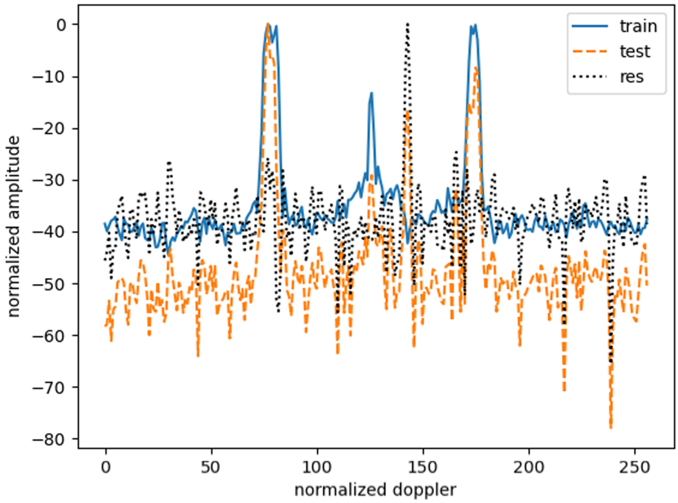

Fig. 4. Results of sea clutter suppression by proposed method (CDLSL)

Compared with dictionary learning, the enhanced M-training algorithm does not need the real-time data. And the classification results of the enhanced M-training algorithm are shown in Fig. 3. We can reserve the sea clutter data (almost have no target) for the subsequent dictionary learning. From the results map of CDLSL (Fig. 4), we can observe that the proposed framework accurately expresses the characteristics of sea clutter. Specifically, the blue curve represents the sea clutter obtained by dictionary learning. The orange curve represents current received sea clutter and will be learned the features. The black curve represents the detection target. As you can observe from the Fig. 4, the blue curve almost overlaps the orange curve which confirms that CDLSL can precisely capture the characteristics of sea clutter and construct optimal sea clutter that are estimated from the dictionary learning. The sea clutter obtained by dictionary learning is more similar to the current real sea clutter echo, the more effective the proposed method is.

We apply the same sea clutter data set to compare the performance between CDLSL and Dictionary Represented Optimal Filter (SDROF) in the HFSWR. Obviously, our proposed framework has better performance by comparing the experiment results in Fig. 4 and Fig. 5. The result obtained by SDROF is shown in Fig. 5 and it indicates that the SDROF doesn't accurately estimate the peculiarity of sea clutter in HFSWR system. The main reason may be that the sky-wave OTHR system can receive a lot of clutter echo when it is started up for daily operation, but most clutter data contains targets and interference. Irrelevant training samples will seriously affect the performance of the model, thus influences the suppression effect of algorithm. And SDROF applies fewer relevant samples, which cannot mine rich hidden sea clutter information. It also demonstrates that the real-time training data set is very important to

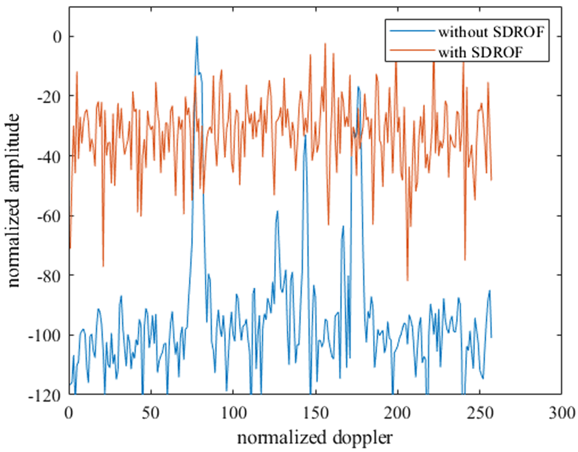

Fig. 5. Result of sea clutter suppression by SDROF

improve the suppression performance. Because our proposed framework can guarantee the accurate and real-time of the training data set for dictionary learning. Different from SDROF, by enhanced M-training algorithm, we can obtain the adequate and required sea clutter train samples for learning the physical characteristics of near-term sea clutter data. Therefore, the dictionary learning can adequately capture different sea clutter in different weather.

5 Conclusion

In this paper, we present a sea clutter suppression method for HFSWR. The proposed algorithm named a cooperative dictionary learning and semi-supervised learning sea clutter suppression framework (CDLSL). Applying enhanced M-training algorithm with different classifiers to obtain vast amounts of sea clutter data that almost contains no target. These pure sea clutter data is applied for the sparse representation and dictionary learning to capture the characteristics of sea clutter. Moreover, with the cooperation of online real time and quasi real time, the proposed framework can accurately detect the targets among the sea clutter. To further evaluate the performance of the proposed framework, we also conduct the previous research named Sparse Dictionary Represented Optimal Filter (SDROF) on the HFSWR in the same experiment setting. The experiment results effectually prove the superiority of our proposed framework (CDLSL) in HFSWR.

Acknowledgments. This work was supported in part by Hainan Province Key Research and Development Project under Grant ZDYF2019195, in part by the National Natural Science Foundation of China under Grant 62031014.

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