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Efficient High-Precision Classification Algorithm for Radar Deceptive Jamming via Array Detection

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ABSTRACT: In complex electromagnetic scenarios where multiple deceptive jamming signals are simultaneously aliased in the time-frequency domain, conventional single-channel electronic detection systems struggle to effectively separate and classify overlapping jamming sources. To address this limitation, this paper investigates an array detection-based classification scheme for multi-source jamming. First, due to the spatial degrees of freedom offered by array systems, the Direction-of-Arrival (DOA) of each jamming source is precisely estimated using the MUSIC algorithm. Then, the adaptive digital beamforming (ADBF) filters are designed based on the estimated DOA parameters, enabling spatial-domain extraction of individual jamming signals. Finally, the DOA information is integrated into the Pulse Description Word (PDW) of each separated jamming measurement, which can facilitate adaptive K-Means clustering with enhanced class separability. Simulation results demonstrate that the proposed method achieves a 22.4% improvement in classification accuracy compared to existing single-channel detection approaches, while maintaining computational efficiency.

1. INTRODUCTION

Deceptive jamming [1] represents a sophisticated electronic warfare technique that significantly disrupts radar systems' target detecting and tracking capabilities through the generation of false targets or sophisticated manipulation of target parameters, thereby compromising the radar's decision-making processes. This advanced countermeasure technology has evolved to a highly refined stage. Among these techniques, repeater jamming [2] emerges as a particularly advanced jamming method, integrating both suppression and deception functionalities through the application of Digital Radio Frequency Memory (DRFM) technology. This approach enables the precise capture, processing, and subsequent retransmission of radar signals, generating highly realistic jamming signals that closely mimic authentic radar echoes. The implementation of such advanced jamming techniques not only substantially degrades the radar's signal-to-noise ratio but also severely disrupts its target identification processes, thereby delivering a comprehensive and sophisticated impact.

Radar pulse signal classification [3] is a fundamental and indispensable technology in contemporary radar reconnaissance systems. This process entails the meticulous analysis of composite pulse streams, the precise extraction of critical signal parameters, and the systematic classification of pulses according to their respective radar emitters. Pulse classification methodologies can be broadly delineated into two distinct paradigms: single-parameter classification and multi-parameter clustering classification [4]. In the early stages of electromagnetic warfare, constrained by technological limitations, radar signals were marked by low pulse stream density and a restricted diversity of signal types. Signal classification primarily hangs on the analysis of pulse repetition interval (PRI) [5] as the key discriminative feature. However, with the exponential growth in the number and variety of radar systems, the pulse stream density within the spatial electromagnetic environment has experienced a dramatic escalation. This evolutionary progression has precipitated a paradigm shift towards more advanced multi-parameter clustering classification, which leverages the full range of multi-dimensional pulse parameters to achieve enhanced dilution effect and superior classification efficiency. Multi-parameter clustering classification exploits the inherent disparities across diverse pulse characteristics, including pulse width (PW), carrier frequency (CF), direction of arrival, and other salient features, to effectively segregate PDWs exhibiting substantial dissimilarities while concurrently aggregating those with pronounced similarities. The degree of similarity between feature parameters is typically quantified through the application of distance metrics. Prominent clustering algorithms utilized in this domain encompass K-Means clustering, fuzzy clustering, and density-based clustering.

As the number of jamming sources increases and complex jamming scenarios emerge, the inherent limitations of conventional single-channel electronic detection systems in radar pulse signal classification have become progressively more pronounced. Conventional single-channel detection systems are generally limited to identifying only the fundamental feature parameters of pulse streams, lacking the capability to resolve more intricate signal characteristics. However, under non-ideal conditions characterized by high pulse density and severe signal overlap, accurately separating and classifying jam-

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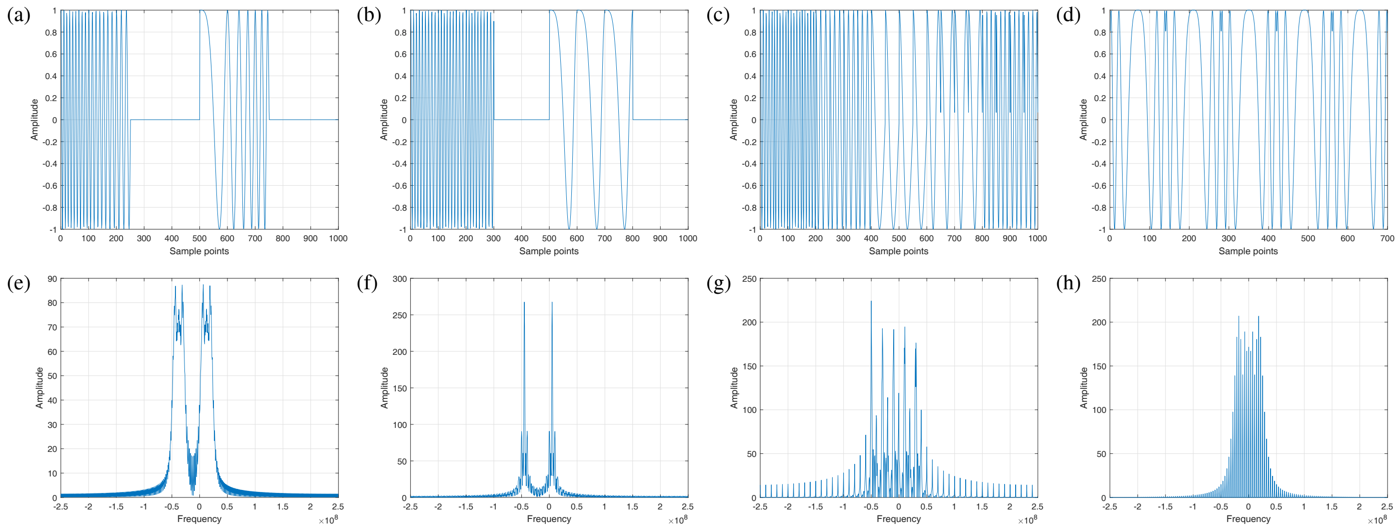

FIGURE 1. The time-domain waveforms (a)–(d) and spectra (e)–(h) for various types of jamming: (a), (e) ISDJ, (b), (f) ISRJ, (c), (g) C&I, and (d), (h) SMSP.

ming sources poses a formidable challenge [6]. To mitigate these limitations, array detection technology has been introduced as a viable solution. Array detection systems leverage spatial filters, meticulously designed based on estimated DOA parameters, to effectively extract jamming signals from multiple spatial directions. This allows for the precise measurement of PDWs for each individual jamming source signal. Although array detection excels in extracting signal features, the subsequent challenge resides in the accurate and efficient classification of these extracted pulse signals. The traditional K-Means clustering algorithm, through widely used, has several limitations. It heavily relies on the predefined number of clusters and the initial placement of the clustering centers [7, 8], and it is additionally vulnerable to the influence of noise points and isolated points [9]. To overcome these issues, this paper introduces an adaptive K-Means clustering algorithm. By incorporating a distance threshold [10], the algorithm significantly mitigates the impact of noise and outliers on the clustering results. Furthermore, it dynamically optimizes the number of clusters through the elbow method [11], ensuring a more precise and efficient classification of radar pulse stream signals.

2. RADAR DECEPTIVE JAMMING MODELING

In this paper, four jamming methods are adopted, namely Interrupted Sampling Repeater Direct Jamming (ISDJ), Interrupted Sampling Repeater Repeated Jamming (ISRJ), Chopping and Interleaving (C&I) Jamming and Smeared Spectrum (SMSP) Jamming.

Assuming that the captured radar signal is represented as $s(t)$, an ideal rectangular pulse train is employed as the interrupted sampling pulse. Interrupted Sampling Repeater Direct Jamming (ISDJ) entails the direct retransmission of the signal following interrupted sampling, bypassing any signal splicing or additional processing, which can be expressed as:

$$j(t) = \sum_{m=1}^{M} \text{rect}\left(\frac{t-(2m-1)\tau}{\tau}\right) s(t-\tau) \tag{1}$$

where M is the number of slice pulses, and τ is the width of each slice pulse.

For comprehensive details on the principles of other jamming methods, readers are referred to [12] and [13].

Figure 1 illustrates time-domain waveforms and frequency-domain spectra for various types of jamming, utilizing a Linear Frequency Modulation (LFM) signal as the radar transmitting signal. The parameters for the LFM signal are configured as follows: the bandwidth B is 50 MHz; the pulse width T_p is 2; the carrier frequency f_0 is 10 GHz; and the sampling rate f_s is 500 MHz.

3. ARRAY-BASED DETECTION OF MULTI-SOURCE DECEPTIVE JAMMING

3.1. DOA Estimation of Each Jamming Source

In a multi-source deceptive jamming environment, precise estimation of the DOA for each jamming source is crucial to effectively separating the jamming signals. Assuming that the array signal detection model receives signals from M directions at a given time, the received signal [14] can be expressed as:

$$X(t) = AS(t) + N(t) \tag{2}$$

where $X(t)$ is the received signal vector, A the steering matrix of the array, $S(t)$ the signal source vector, and $N(t)$ the noise vector, typically modeled as additive white Gaussian noise.

The covariance matrix of the array data, which incorporates contributions from both the signal and noise components, can be expressed as:

$$R = E\left[XX^H\right] = AE\left[SS^H\right]A^H + \sigma^2 I = AR_S A^H + \sigma^2 I \tag{3}$$

where R_s is the covariance matrix of the signal, AR_SA^H the signal component, σ^2 the variance of the noise, and $\sigma^2 I$ the noise component.

Performing eigenvalue decomposition on the data covariance matrix yields:

$$R = U\Sigma U^H = U_S\Sigma_S U_S^H + U_N\Sigma_N U_N^H \tag{4}$$

where $U = [U_S, U_N]$, U_S is orthogonal to U_N, $\sum = diag(\sigma_1^2, \cdots, \sigma_M^2)$; U_S denotes the signal subspace, composed of eigenvectors corresponding to the larger eigenvalues, while U_N denotes the noise subspace composed of eigenvectors corresponding to the smaller eigenvectors.

Therefore, the noise subspace vector U_N is obtained by performing eigenvalue decomposition on the covariance matrix R.

To estimate the DOA of the jamming sources, the Multiple Signal Classification (MUSIC) algorithm [15] is employed. This algorithm exploits the orthogonality between the signal subspace and noise subspace, determining the DOAs of signal sources by minimizing the energy in the noise subspace. The spatial spectrum function of the MUSIC algorithm is defined as:

$$P_{music}(\theta) = \frac{1}{\alpha^H(\theta)U_N U_N^H \alpha(\theta)} = \frac{1}{\left\|U_N^H \alpha(\theta)\right\|^2} \tag{5}$$

By computing spatial spectrum across various angles θ, the peak values within the spectrum correspond to the estimated DOAs of the signal sources.

3.2. Adaptive Signal Extraction Based on Estimated DOAs

In a multi-source jamming environment, directly estimating the covariance matrix from the received data may result in signal cancellation, primarily due to the mutual interference among signals [16]. To address this problem, different ADBF filters can be designed leveraging known DOA information to efficiently extract each individual jamming source [17].

To accomplish this objective, this paper adopts an adaptive beamforming technique grounded in the Linearly Constrained Minimum Variance (LCMV) criterion [18]. The LCMV criterion optimizes the weight vectors to ensure that the target signal from a specific direction is effectively extracted while concurrently suppressing interference from other directions, maintaining distortionless reception of the transmitting signal. Assuming the k-th signal represents the target signal arriving from a specific direction characterized by a steering vector $a(\theta_\kappa)$, the filter weight vector W_k must adhere to the following constraints:

$$\begin{cases} \min_{W_k} P_{out} = \min_{W_k} W_k^H \overline{R}_k W_k \\ s.t. W_k^H a(\theta_k) = 1, \quad a^H(\theta_k) W_k = 1 \end{cases} \tag{6}$$

where $\bar{R}_k$ is the covariance matrix derived after excluding the target signal, mathematically formulated as:

$$\bar{\mathbf{R}}_{\mathrm{k}} = \sum_{i=1, i\neq k}^{K} \mathbf{a}(\theta_{\mathrm{i}})\mathbf{a}(\theta_{\mathrm{i}})^H + \sigma^2\mathbf{I}, \ i = 1, \ldots, K \text{ and } i \neq k \tag{7}$$

where σ^2 is the noise power, and I represents the unit matrix.

To guarantee distortionless reception of the target signal while simultaneously minimizing the total output power of the beamformer, the optimum weight vector $W_{\dot{\kappa}}$ can be derived through the application of the Lagrange multiplier method:

$$W_{\dot{\kappa}} = \frac{\bar{\mathbf{R}}_{\dot{\kappa}}^{-1}\mathbf{A}_{\dot{\kappa}}}{\mathbf{A}_{\dot{\kappa}}^H \bar{\mathbf{R}}_{\dot{\kappa}}^{-1}\mathbf{A}_{\dot{\kappa}}} \tag{8}$$

By designing distinct ADBF filters, jamming signals from specific directions can be efficiently extracted from the complex pulse stream, thereby achieving robust separation of jamming signals in multi-source environments.

4. EFFICIENT CLASSIFICATION ALGORITHM FOR DECEPTIVE JAMMING COMBINED WITH DOA

4.1. Adaptive K-Means Clustering Algorithm

The K-Means clustering algorithm, a widely-used unsupervised clustering technique, iteratively optimizes the assignment of data points to their closest centroids within a feature space. In the context of jamming signal classification, K-Means utilizes the multidimensional feature set of radar signals to cluster signals with similar characteristics, enabling precise differentiation of jamming sources in complex electromagnetic environments.

To address the challenges of autonomously determining the number of clusters and sensitivity to outliers, this paper proposes a hybrid approach that combines the elbow method with a distance threshold. The elbow method provides an elegant solution for automatically identifying the optimal number of clusters by analyzing the Sum of Squared Errors (SSE) as a function of number of clusters [19]. As the number of clusters increases, the SSE gradually decreases. However, beyond a certain point, the rate of decline diminishes sharply, forming a distinct "elbow" in the graph. The optimal number of clusters corresponds to this point. Mathematically, the SSE is expressed as:

$$\text{SSE} = \sum_{k=1}^{k_{optimal}} \sum_{x_i \in C_k} \left\|x_i - \mu_k\right\|^2 \tag{9}$$

where μ_k is the centroid of the k-th cluster, x_i a data point, and C_k the set of data points belonging to the k-th cluster.

The key steps of the adaptive K-Means clustering algorithm are as follows:

(1) For a given dataset, test different numbers of clusters k, calculate the SSE for each k, and determine the optimal number of clusters $k_{optimal}$ by identifying the number of clusters corresponding to the "elbow" on the SSE curve.

(2) Randomly select $k_{optimal}$ samples from the dataset as the initial cluster centers $\{\mu_1, \mu_2, \ldots, \mu_{k_{optimal}}\}$.

(3) Compute the Euclidean distance from each sample to the cluster centers, and assign it to the nearest cluster center, thereby forming $k_{optimal}$ clusters. The Euclidean distance is

calculated as:

$$d\left(x_i,\mu_k\right)=\sqrt{\sum_{j=1}^{m}\left(x_{ij}-\mu_{kj}\right)^2} \tag{10}$$

where x_i is the i-th sample; m represents the spatial dimension; x_{ij} and μ_{ij} are the j-th attributes of the sample and cluster center, respectively.

(4) Update the cluster centers by recalculating its centroid as the mean of all assigned samples. Concurrently, detect and eliminate outliers by removing data points whose distance to their respective cluster centers exceeds a predefined threshold.

(5) Iteratively execute steps (3) and (4) until convergence is achieved, which occurs when either: (i) the cluster centers remain unchanged between iterations, or (ii) the change in cluster center positions falls below a predefined tolerance threshold.

The adaptive K-Means algorithm inherits the convergence property of conventional K-Means algorithm, namely each iteration monotonically decreases the bounded SSE. Specifically, step (3) minimizes SSE for fixed centroids through assignment, while step (4) updates cluster centers and removes outliers. Since SSE has a lower bound and decreases monotonically, the algorithm provably converges when cluster centers stabilize.

The computational complexity of the proposed algorithm is primarily governed by the elbow method and adaptive clustering. The former's overhead becomes negligible for large datasets when the maximum k is significantly smaller than the sample size. After determining $k_{optimal}$, the algorithm maintains traditional K-means algorithm complexity while eliminating the manual optimal cluster number specification that is a key advantage in practice applications.

4.2. Classification Algorithm for Radar Deceptive Jamming Based on DOA Information

In complex electromagnetic environments characterized by multi-source deceptive jamming, conventional single-channel detection methods often struggle to effectively separate and classify overlapping jamming sources. As a result, improving the accuracy of jamming classification has emerged as a critical area of research. To tackle this challenge, this paper proposes a novel classification algorithm for deceptive jamming that leverages DOA information. The flowchart of this algorithm is illustrated in Fig. 2.

The algorithm proceeds as follows: First, the DOAs of mixed jamming pulses are estimated by leveraging the spatial degrees of freedom provided by the array. Next, adaptive beamforming filters are designed to extract jamming signals arriving from different directions. Afterward, the extracted jamming signals are detected, and their key parameters like pulse width and bandwidth are measured. These parameters are then combined with the estimated DOA information to construct a multi-dimensional feature vector. Finally, an adaptive K-Means clustering algorithm is applied to classify PDWs. During the clustering process, pulses with similar characteristics are grouped together based on the similarity of their DOA, pulse width, and bandwidth. This method not only efficiently mitigates misclassification caused by time-frequency domain aliasing but also significantly enhances the ability to distinguish between different types of jamming sources. By integrating spatial, temporal, and spectral features, the algorithm achieves robust classification performance in complex environments.

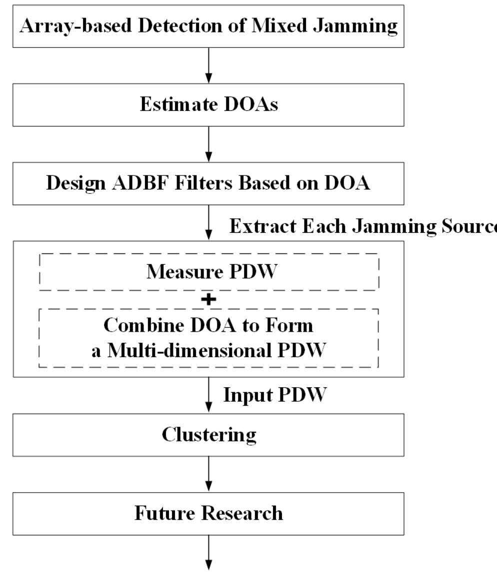

FIGURE 2. The flowchart of the proposed algorithm.

5. EXPERIMENTAL RESULTS AND ANALYSIS

To verify the feasibility of the proposed algorithm, this section presents a series of simulation experiments. The simulation parameters are detailed in Table 1. The radar transmitting signal is modeled as an LFM signal, while the jamming signals are assumed to be far-field signals. Furthermore, the jamming signals and noise are considered uncorrelated. For the simulation, the sampling rate is set to 500 MHz and the jamming-to-noise ratio set to 20 dB. These parameters ensure a realistic and challenging environment for evaluating the performance of the proposed algorithm.

TABLE 1. Main simulation parameters of jamming signals.

Types of jamming	Bandwidth/MHz	Direction of arrival/Degrees
ISDJ	50	25
ISRJ	22	−30
C&I	24	10
SMSP	55	45

The DOA estimation for each jamming source in the simulated mixed jamming pulse stream is presented through the MUSIC spatial spectrum. As demonstrated in the spectrum, the DOA estimates derived by the algorithm exhibit strong alignment with the predefined incident angles.

By leveraging the known DOA information, multiple ADBF filters are designed to effectively extract jamming signals arriving from different directions. The corresponding antenna patterns, which illustrate the beamforming performance are depicted in Fig. 3. These patterns highlight the capability of the

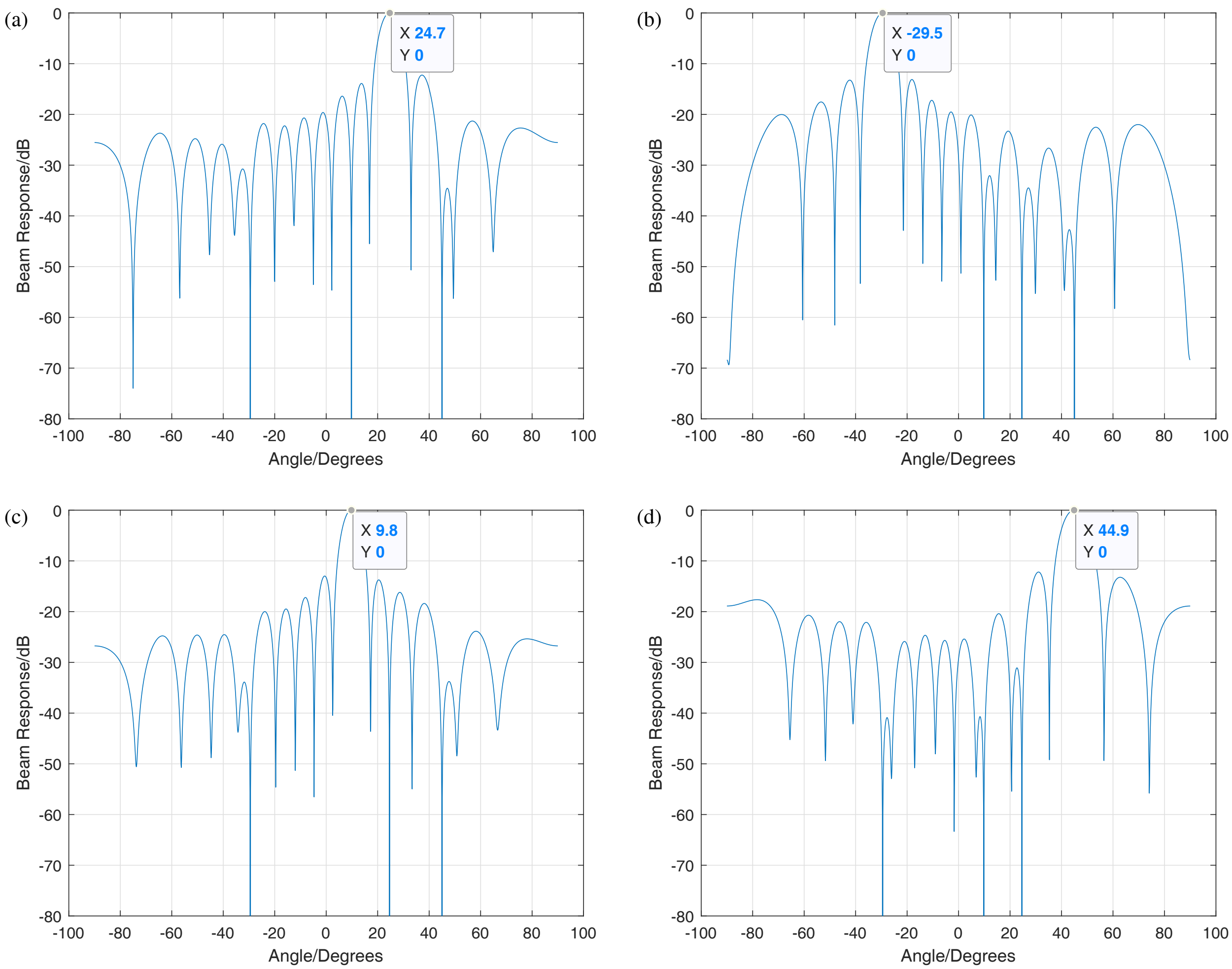

FIGURE 3. The antenna patterns for different target DOAs, namely (a) 24.7°, (b) -29.5°, (c) 9.8°, (d) 44.9°.

ADBF filters to precisely steer beams toward the desired directions while suppressing interference from other directions, ensuring accurate extraction of jamming signals.

The bandwidth and pulse width of each jamming source are measured, and the previously acquired DOA information is integrated to construct a comprehensive PDW. Subsequently, the adaptive K-Means clustering algorithm is applied to jamming signal classification. A comparative analysis between single-channel detection approach and the proposed approach is presented in Fig. 4.

As illustrated in Fig. 4(a) and Table 2, the single-channel detection approach successfully classifies four types of jamming, achieving a minimum classification accuracy of 64%, a maximum classification accuracy of 85.7%, and an overall accuracy of 76.8%. Meanwhile, the approach identifies two additional clusters, corresponding to mixed jamming 1 and 2, respectively. Specifically, mixed jamming 1 is generated by the time-domain aliasing of all types of jamming, and mixed jamming 2 is formed by the aliasing of ISDJ and C&I in the time domain. Furthermore, the adaptive K-Means clustering algorithm effectively filters out data points whose distance from their respective cluster center exceeds a predefined distance threshold, which primarily originate from inaccurate PDW measurements. Therefore, this method exhibits a notable limitation: it fails to effectively distinguish mixed jamming signals caused by time-frequency domain aliasing, which substantially degrades classification accuracy.

In contrast, as demonstrated in Fig. 4(b) and Table 3, the proposed approach successfully clusters the data into four categories, effectively separating and accurately classifying overlapping jamming sources with a classification accuracy exceeding 97.8%. The presence of outliers further demonstrates that the adaptive K-Means clustering contributes to improving the robustness of the clustering results. These findings highlight the superior performance of the proposed method in handling complex jamming scenarios, overcoming the limitation of conventional single-channel detection methods.

The traditional K-Means clustering algorithm requires a predefined determination of the number of clusters, presenting substantial practical limitations in complex electromagnetic environments. In contrast, the proposed adaptive K-Means algorithm incorporates the elbow method to autonomously identify the optimal number of clusters, which ensures that classification results better align with the actual distribution characteristics of jamming signals, as illustrated in Figs. 4(c) and 4(d). In operational scenarios involving multi-source jamming, the

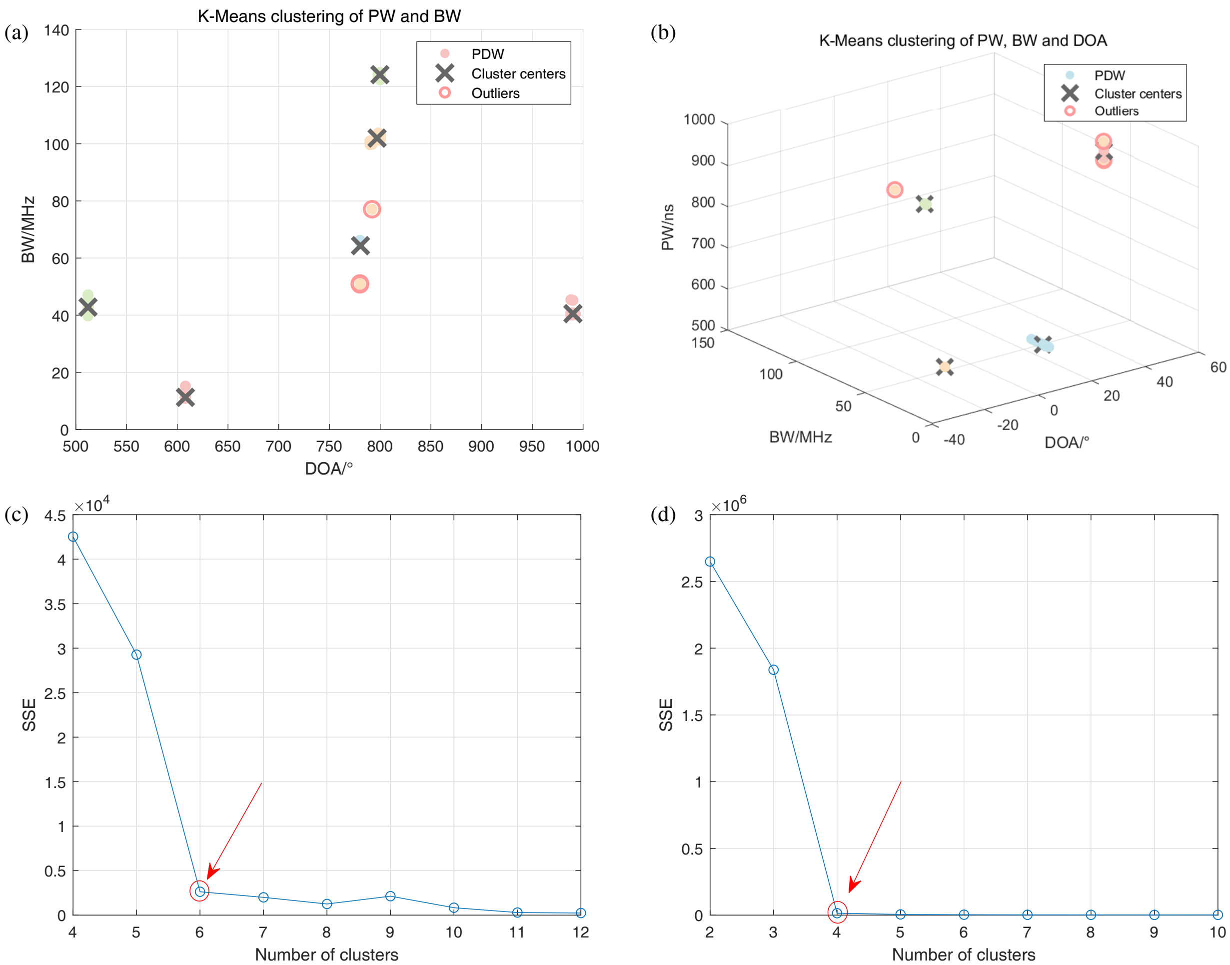

FIGURE 4. Comparison of classification results (a)–(b) and optimal number of clusters (c)–(d) between single-channel detection approach and the proposed approach. (a), (c) Single-channel detection approach. (b), (d) The proposed approach.

TABLE 2. The classification results of the single-channel detection approach.

Cluster number	Corresponding jamming type	Number of predefined pulses	Number of classified pulses	Classification accuracy
1	ISRJ	120	100	83.3%
2	SMSP	140	120	85.7%
3	ISDJ	140	100	71.4%
4	C&I	100	64	64%
5	Mixed jamming 1	20	15	/
6	Mixed jamming 2	20	17	/
/	Outliers	/	4	/

TABLE 3. The classification results of the proposed approach.

Cluster number	Corresponding jamming type	Number of predefined pulses	Number of classified pulses	Classification accuracy
1	SMSP	140	137	97.8%
2	ISDJ	140	140	100%
3	C&I	100	99	99%
4	ISRJ	120	120	100%
/	Outliers	/	4	/

acquired data frequently contain noise-corrupted samples and outliers, to which the traditional K-Means algorithm exhibits marked sensitivity. The proposed adaptive K-Means algorithm effectively filters out data points whose distance from their respective cluster center exceeds a predefined distance threshold, which primarily originate from inaccurate PDW measurements, as evidenced in Figs. 4(a) and 4(b).

When the classification performances of the two approaches are compared, the proposed approach obviously outperforms the conventional single-channel detection approach under identical jamming parameters. This significant improvement is primarily attributed to the design of adaptive beamforming filters based on DOA, which effectively extracts jamming sources from different directions, which mitigate the effects of time-frequency domain aliasing, and consequently enhance classification accuracy.

6. CONCLUSION

In this paper, the multi-source jamming classification algorithm via array interception is investigated, which firstly estimates the DOAs and designs adaptive beamforming filters to extract jamming signals from different directions. Subsequently, it integrates the estimated DOA information into the PDW of each extracted jamming source, constructing a multi-dimensional pulse feature vector. Finally, the adaptive K-Means clustering algorithm is employed to achieve the separation and classification of jamming sources. While the proposed algorithm has been validated through comprehensive simulation experiments, its performance on real-world measured data has not yet been tested. Notably, the current framework presumes independence and non-coherence among jamming sources, disregarding their potential spatial correlations. In real electromagnetic environments where correlated jammers prevail, this may cause DOA estimation biases and compromise classification accuracy. To enhance the algorithm's practicality and robustness, future work will focus on validation using real-world data and further optimization to address practical operational conditions, exploring improved strategies to effectively handle spatially correlated jamming sources.

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