A Two-Stage Optimization Framework for Radar Jamming Effectiveness Evaluation

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Abstract. *In complex electromagnetic environments, radar signals intercepted by jammers often contain biased data due to factors such as radar mode switching, electromagnetic interference, and receiver noise. To address this challenge, this paper proposes a two-stage optimization framework for jamming effect evaluation from the jammer's perspective. In the first stage, a pre-evaluation is conducted using an entropy-optimized K-means discretization algorithm (KDEOA) to adaptively partition pulse descriptor word (PDW) parameters, enhancing robustness against noise. A GCSAO-LSSVM model is then employed to improve classification accuracy through optimal parameter tuning and a periodic oscillation mutation strategy. In the second stage, an improved entropy weight method (IEWM) integrating Tsallis entropy, kernel density standardization, and game theory is used for objective weighting, followed by an enhanced TOPSIS method (ITOPSIS) incorporating interquartile range standardization and dynamic ideal solution fusion for quantitative scoring. Experimental results demonstrate that the proposed framework achieves the highest pre-evaluation accuracy across all noise levels (up to 50% contamination), with IEWM exhibiting the lowest weight variation rate (0.11–0.23%) and ITOPSIS showing the strongest correlation (0.7290) with baseline scores under high noise. The main limitations include sensitivity to severe signal distortion and assumption of stable radar behavior. This approach enables accurate, non-cooperative jamming assessment and supports robust decision-making in cognitive electronic warfare.*

Keywords

Non-cooperative dynamic adversarial, jamming effect evaluation, improved entropy weight method (IEWM), improved technique for order preference by similarity to ideal solution (ITOPSIS), biased data, K-means discretization based on entropy optimization algorithm (KDEOA)

1. Introduction

Jamming effect evaluation refers to assessing the impact of jamming actions on radar performance by analyzing changes in the radar's behavioral parameters [1], [2]. In cognitive electronic warfare, continuous real-time evaluation of jamming effects is essential to ensure effective and adaptive jamming. By analyzing these effects, the jammer can iteratively optimize its strategies, thereby enhancing the efficacy of electronic countermeasures. This process is critical for jamming strategy formulation and represents a key component of modern electronic warfare [3–5]. At present, the common interference effect evaluation methods are mainly divided into three kinds: evaluation factor method, fuzzy comprehensive evaluation method and intelligent evaluation method.

The evaluation factor method is to select and determine a series of evaluation indicators that can reflect the effect of radar interference, and to obtain an evaluation factor that can objectively analyze the quality of interference from various aspects through mathematical methods, so as to achieve the evaluation of interference effect [6], [7]. This method is relatively simple to implement, but it may lead to the lack of comprehensiveness of the evaluation results obtained because it is difficult for the evaluation factor to cover all the influencing factors in the radar countermeasure process.

Fuzzy comprehensive evaluation method is a combination of fuzzy set theory and comprehensive evaluation method, which is used to deal with the fuzziness and uncertainty between evaluation indexes [8–11]. However, a corresponding membership function needs to be set in the current fuzzy comprehensive evaluation method, and the construction of appropriate membership function and the determination of the weight of different influencing factors still lack clear theoretical support. At the same time, setting the weight artificially may introduce too many subjective factors, resulting in the lack of objectivity of the evaluation results.

Intelligent evaluation method is a kind of interference effect evaluation method based on artificial intelligence and data mining technology. It automatically processes data, extracts features, and uses machine learning algorithms for pattern recognition and prediction to obtain the laws of different influencing factors on the interference effect, so as to realize the intelligent evaluation of the interference effect [12], [13]. However, such methods require

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high quality and accuracy of data. If the data is inaccurate or incomplete, it may affect the accuracy of the evaluation results.

In the simulation research of jamming effect evaluation, traditional jamming effect evaluation methods predominantly adopt a radar-centric approach [14]. These methods typically assume a cooperative relationship between the radar and jammer, assessing jamming effectiveness by comparing pre- and post-jamming radar parameter variations. However, in practical electronic warfare scenarios, the relationship is fundamentally non-cooperative, where the jammer must rely solely on its own observations to obtain limited radar information. Consequently, recent studies have proposed implementing online evaluation from the jammer's perspective.

Huang et al. [15] investigated quantitative assessment and intelligent decision-making methods for multifunctional radar jamming, leveraging artificial intelligence to enhance jamming performance and battlefield survivability. Lei et al. [16] introduced an online evaluation framework based on support vector machines (SVM) and evidence theory, and utilized behavioral characteristics of jammers and radar counter-jamming features for real-time assessment via SVM and basic confidence assignment. Meanwhile, Li et al. [17] proposed a data-driven evaluation method, which combines expert knowledge and data mining to quantify the impact of jamming on radar systems in complex electromagnetic environments. This approach established a unified signal-level evaluation framework for a stable and quantitative jamming assessment. Zhang et al. [18] developed an online evaluation model from the jammer's perspective, incorporating an improved class attribute correlation coefficient (ICACC) method and a probability similarity-based soft output basic belief assignment (BBA) correction technique to enhance evaluation efficiency and accuracy under asymmetric information conditions. Pei et al. [19] presented a radar jamming scheme decision-making approach utilizing an SDAE-SVM algorithm, specifically designed to improve jamming decision precision in active radar guidance scenarios. Complementing these works, Hu et al. [20] investigated online evaluation techniques for radar active anti-jamming effectiveness, and introduced a method based on time-domain criterion, which processes synchronized platform data including radar amplitude timing, parameter timing, and active jamming equipment detection point parameters through buffering, fitting, and situational information generation. In [21], a cooperative jamming effectiveness evaluation method is presented, founded on the improved particle swarm optimization–extreme learning machine (IPSO-ELM). Through optimizing the ELM network with IPSO, the accuracy and real-time performance of the evaluation are significantly improved.

In essence, according to different effect levels, references [15–21] classify and label the information intercepted by the interfering party and then evaluate the effect through the classification algorithm in order to determine the evaluation level. There are limitations in the following aspects. Firstly, there is a lack of optimization and adjustment of classifier parameters. Secondly, in the actual confrontation environment, the interference effect evaluation level may not change before and after the interference action, but the intercepted radar behavior parameters have seen certain changes. Thirdly, in the process of analyzing the intercepted radar signal, due to the switching of radar working mode, electromagnetic interference and receiver noise, the intricate electromagnetic environment leads to an imbalance of radar data acquired by the jamming device, resulting in the deviation of radar information and affecting the accuracy of quantitative evaluation. The comprehensive and objective evaluation of the interference effect and the enhancement of the accuracy of such evaluations have emerged as a focal point of research.

The development of quantitative methods for interference effect evaluation is deeply influenced by information theory and signal processing technology. The early entropy-based feature selection research [22] revealed the discriminative ability of entropy weight in nonlinear systems. At the level of decision-making methods, TOPSIS and its variants have been widely used in mathematics, engineering, science, environment, technology, management, business and other fields [23]. However, the sensitivity of traditional methods to outliers has limited their applicability in complex interference scenarios. In [24], a Hybrid Model-Data-Driven approach is put forward, which integrates the merits of both to enhance the precision and practicality of radar jamming effectiveness evaluation. In [25], a novel approach integrating the Vague set and the TOPSIS method is proposed for the assessment of the jamming effectiveness of impulse signals, which combines the objective weight method based on fuzzy set entropy and the subjective weight method based on set value statistics. Then, these methods are integrated through a game theory-based formula to obtain a comprehensive and balanced set of evaluation weights. An improved TOPSIS method is proposed in [26] in response to the problem that the standard technique for order preference by similarity to ideal solution (TOPSIS) method is affected by data fluctuation and insufficient analysis of data law in radar jamming effect evaluation. This method combines TOPSIS method and grey correlation analysis theory to analyze the original data, and combines the evaluation results of the two methods as the final evaluation results, which makes up for the defects of TOPSIS method in radar jamming effect evaluation.

However, the methods proposed in references [22–26] mainly are limited in three aspects. Firstly, since most of these methods are based on the assumption of good data quality, they fail to fully consider the problem of serious bias (Biased Data) in pulse description word (PDW) data caused by radar mode switching, electromagnetic interference and receiver noise in complex electromagnetic environment, and also their robustness is questionable. Secondly, these methods predominantly involve independent weight assignment or sorting algorithms, so they fail to establish an End-to-End systematic evaluation framework encompassing preprocessing, feature extraction, and final evaluation. Consequently, it is difficult to address the challenge of online rapid evaluation from biased data within non-cooperative adversarial environments. Thirdly, the utilization of local data characteristics is insufficient due to the fact that the evaluation process often relies on the global ideal solution. When the data distribution changes complicatedly due to interference, the accuracy and reliability of the evaluation results will be significantly reduced.

In summary, the existing radar evaluation methods focus either on classification accuracy or on quantitative evaluation instead of integrating the two aspects, so they cannot evaluate the jamming effect comprehensively, objectively and accurately. Different from previous studies, this paper uniquely integrates information theory discretization, parameter optimization LSSVM, game theory weight fusion and clustering-based TOPSIS to build a full-process interference effect evaluation system. Figure 1 illustrates the two-stage jamming effect evaluation framework. In the first stage (pre-evaluation), radar parameters are extracted from both reference databases and unknown radar signals. The KDEOA algorithm discretizes these features, which are then processed by the GCSAO-LSSVM classifier to output preliminary jamming effect levels. When pre-evaluation levels are identical, the second stage (quantitative evaluation) activates by applying IEWM for weighted analysis and ITOPSIS for refined scoring.

The main innovations and contributions of this paper are as follows:

(1) This paper proposes a discretization algorithm based on an improved K-means clustering in order to reduce the influence of deviation value on LSSVM classification. To avoid the clustering center falling into local optimum, the algorithm replaces random initialization with probabilistic distance weighted initialization. By optimizing the number of bins through information entropy, the optimal number of bins can be automatically selected to balance the amount of information and complexity. Through K-means clustering and IQR, boundary adjustment is carried out to enhance the inclusion of noise values and avoid boundary sensitive problems. Finally, the adaptive discretization of PDW parameters is realized.

(2) This paper proposes a method based on GCSAO to optimize the parameters of LSSVM from the perspective of improving the accuracy of pre-assessment of interference effects. The optimal initial value set and periodic oscillation mutation operator are used to prevent the parameters from entering the local optimum, so as to find the optimal parameters and improve the accuracy of pre-assessment of interference effects.

(3) IEWM is presented for subjective and objective weighting when the pre-evaluation level of jamming effect is the same. The non-normal distribution data is processed by the kernel density estimation of adaptive bandwidth, which improves the stability of weight and reduces the influence of deviation data. Tsallis entropy is used to calculate the objective weight and enhance the adaptability to complex data. Through the combination of game theory,

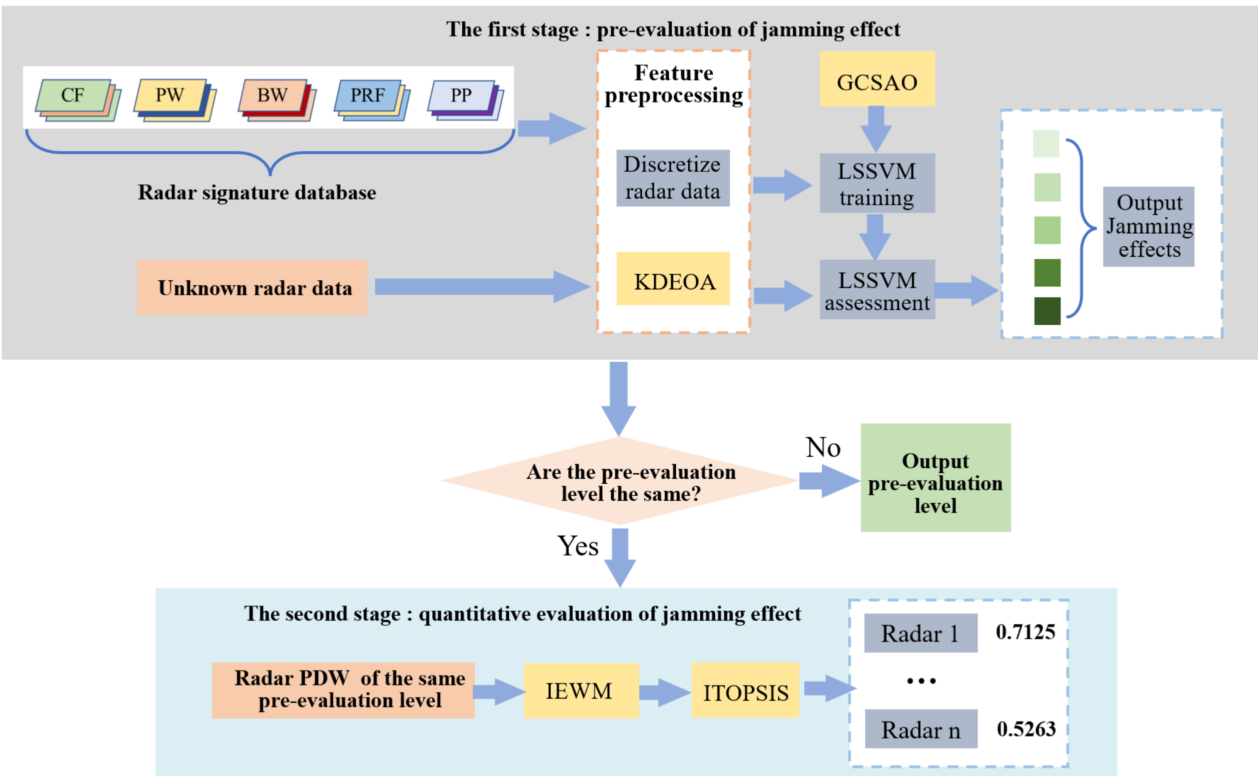

Fig. 1. The framework of two-stage optimization framework for radar jamming effectiveness evaluation.

the difference between subjective and objective weights is minimized, and the Nash equilibrium solution is obtained to avoid the one-sidedness of single weighting, so that the combined weights are in line with the data law.

(4) An ITOPSIS method is proposed on the basis of obtaining the weights after subjective and objective weighting. The influence of deviation value on standardization results is reduced and the robustness is improved through IQR standardization. The optimal clustering number is selected by the contour coefficient to avoid artificial setting deviation and improve the rationality of data grouping. By balancing the global and local ideal solutions through dynamic coefficients, the adaptability to complex interference scenarios is enhanced, and the interference effect is further quantitatively evaluated.

2. Jamming Effect Pre-evaluation

From the jammer's perspective, this section evaluates jamming effectiveness by monitoring operational status changes of the target radar. It can be seen from Fig. 1 that potential deviated pulse information is extracted as feature attributes to establish a radar knowledge base. The radar PDW data undergo KDEOA-based discretization for model training. During operation, intercepted radar signals are similarly discretized and processed by the trained model for preliminary jamming effectiveness assessment.

2.1 K-means Discretization Algorithm Based on Entropy Optimization (KDEOA)

The pre-evaluation of jamming effects in this study involves the determination of the radar's operational state by using predefined evaluation metrics from an established radar knowledge base, which is then followed by assessing jamming effectiveness through comparative analysis of pre- and post-jamming state variations. During radar database construction, we have considered both the acquisition difficulty of feature attributes and their correlation with radar operational state changes, so five key characteristic attributes were selected as evaluation metrics for the radar knowledge base: carrier frequency (CF), bandwidth (BW), pulse width (PW), pulse repetition frequency (PRF), and peak power (PP) [27].

Jamming-induced perturbations in radar operating parameters serve as critical indicators of jamming effectiveness. Carrier frequency (CF) instability reflects frequency-domain jamming techniques, while pulse width (PW) distortion demonstrates the time-domain interference impacts on range resolution. Bandwidth (BW) abnormalities reveal signal processing degradation, and pulse repetition frequency (PRF) anomalies indicate compromised Doppler and ranging capabilities. Peak power (PP) adjustments under jamming conditions expose the radar's countermeasure strategies while simultaneously highlighting its vulnerability to detection or saturation. These five parameters collectively capture the multidimensional effects of electronic warfare on radar performance, spanning time, frequency, and power domains. Collectively, these components afford a comprehensive analytical framework for examining the manner in which electronic attacks attenuate detection probability, resolution, tracking accuracy, and operational stealth.

Under complex electromagnetic environments, pulse descriptor word (PDW) data acquired by jamming systems frequently exhibit significant deviations caused by radar mode switching, electromagnetic interference, and receiver noise. To address this challenge, we develop an improved K-means clustering-based [28] discretization algorithm that transforms continuous PDW parameters into discrete states via optimal partitioning. The proposed methodology operates through the following key processes:

(1) Using probabilistic distance weighted initialization instead of random initialization:

$$P(x_i = c_k) = \frac{D(x_i)^2}{\sum_{j=1}^{N} D(x_j)^2} \tag{1}$$

where x_i is the i-th data point, c_k is the k clustering center, $D(x_i)$ represents the minimum distance to the existing center, and N is the total number of samples in the data set.

(2) For each feature vector, calculate the information entropy [29] under different box numbers $K \in [K_{\min}, K_{\max}]$:

$$H(K) = -\sum_{k=1}^{K} p_k \log_2 p_k, \quad p_k = \frac{n_k}{N} \tag{2}$$

where p_k is the proportion of samples in the k box, n_k is the number of samples in the box k, and the optimal number of boxes K^* satisfies:

$$K^* = \arg\max_K \left[H(K) - \lambda \cdot K \right] \tag{3}$$

where λ is the complexity penalty factor.

(3) For a PDW dataset $X \in \mathbb{R}^{N \times M}$ comprising N pulses with M parameters, the K-means clustering is used to calculate the clustering center of each bin, and the discretization process of the i-th characteristic x_i in the parameter m is defined as follows:

$$\{c_1, \ldots, c_k\} = \arg\min_C \sum_{k=1}^{K} \sum_{x_i \in S_k} \| x_i - c_k \|^2 \tag{4}$$

where C represents the cluster center.

(4) Adjust the boundaries $\{e_0, \ldots, e_K\}$ based on the IQR introduced by the clustering center.

$$e_k = \begin{cases} c_1 - 1.5 \cdot \mathrm{IQR}, & k = 0 \\ \dfrac{c_{k-1} + c_k}{2}, & 1 < k \le K \\ c_k + 1.5 \cdot \mathrm{IQR}, & k = K + 1 \end{cases} \tag{5}$$

(5) Discretize mapping based on box partitioning.

$$y_i = \{k| \ e_k \le x_i < e_{k+1}\} \ . \tag{6}$$

The KDEOA replaces random initialization by probabilistic distance weighted initialization to avoid the cluster center falling into local optimum. By optimizing the number of binning through information entropy, the optimal number of binning can be automatically selected to balance the amount of information and complexity. The boundary adjustment is performed by K-means clustering and IQR to enhance the tolerance of noise values and avoid boundary sensitivity problems. Finally, the adaptive discretization of PDW parameters is achieved with robustness, adaptability and physical interpretability, and is suitable for complex signal processing scenarios such as electronic warfare.

2.2 Pre-evaluation Model for Jamming Effect Based on GCSAO-LSSVM

The limited number of intercepted signals makes the pre-evaluation of jamming effectiveness a small-sample classification problem, for which SVM has demonstrated superior accuracy [30]. This work employs LSSVM for multifunctional radar status identification. As an SVM variant optimized for classification and regression tasks, LSSVM replaces traditional inequality constraints with equality constraints and adopts a squared error loss function. This formulation converts the optimization problem into solving linear equations, significantly reducing computational complexity compared to quadratic programming while maintaining solution speed.

The LSSVM implementation involves a penalty coefficient r that balances classification margin and accuracy. Excessively high r values may lead to overfitting by prohibiting classification errors, thereby restricting the classifier's applicability to linearly separable samples. Conversely, excessively low r values will result in excessively large classification margins that compromise accuracy. For linearly inseparable problems, the kernel parameter g governs the influence range of individual samples.

Parameter selection critically influences SVM classification performance: both g and r significantly affect the final classification accuracy. To optimize radar threat level classification performance and enhance LSSVM recognition accuracy, we utilize the GCSAO algorithm, which identifies optimal parameter combinations to enhance SVM recognition accuracy.

The SAO algorithm is biologically inspired by the physical processes of snow sublimation and melting phenomena [31]. This metaheuristic algorithm addresses the common limitations of population-based optimization methods by effectively balancing exploration and exploitation. The SAO framework comprises four distinct phases: (1) initialization, (2) exploration, (3) exploitation, and (4) a dual-population mechanism. In the present study, we propose several modifications to enhance the original SAO algorithm.

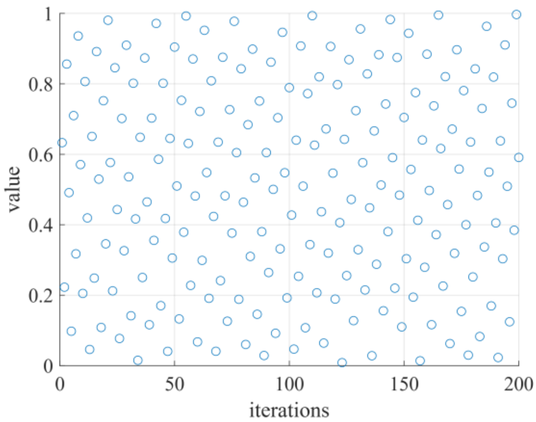

Fig. 2. Spatial distribution mapping of optimal point set initialization

During the initialization phase, the SAO algorithm conventionally employs randomly generated population positions. In this study, we implement optimal point set method for population initialization, which achieves more uniform spatial distribution of candidate solutions and expands the effective search space. This initialization strategy enhances initial solution quality, mitigates the limitations of random initialization, and facilitates escape from local optima attraction. The spatial distribution mapping after 200 iterations is illustrated in Fig. 2.

This study introduces a periodic oscillatory mutation strategy to optimize both the exploration and exploitation phases of the SAO algorithm. Inspired by cyclical patterns in biological evolution, this strategy dynamically adjusts mutation rates during iterations to maintain an optimal balance between exploration and exploitation. The approach improves population diversity, facilitating escape from local optima while promoting broader search-space exploration. The overall process of GCSAO-LSSVM algorithm is as follows:

Algorithm 1: **GCSAO-LSSVM**

```
Initialize the key parameters (g, r) are via the optimal point set
approach.
Recognition and classification were performed using LSSVM.
Record the current best individual G(t)
while (t < t_max) do
   Calculate the snowmelt rate M
   Randomly divide the whole population P into two
   subpopulations Pa and Pb
   for each individual do
      Update each individual's position through periodic
      oscillatory mutation strategy
   end for
   Fitness evaluation
   Update G(t)
   t = t + 1
end while
Return G(t)
```

2.3 Complexity Analysis of Pre-evaluation Stage

The computational complexity of the KDEOA discretization process is mainly governed by its probabilistic distance-based initialization and iterative K-means clustering stages. The overall time complexity is $O(n^2 + n \cdot M \cdot k \cdot t)$, where n is the number of pulses, M is the number of parameters, k is the number of clusters, and t represents iterations. The quadratic term originates from the pairwise distance computations during center initialization, while the clustering operation scales linearly with respect to the dimensions and clusters. The space complexity is $O(n \cdot M)$, which is required for storing the raw and discretized pulse data.

The GCSAO-LSSVM model exhibits significant computational demand during the offline training phase, primarily due to the $O(n^3)$ complexity associated with solving the linear system in LSSVM training, coupled with the hyperparameter optimization performed by the GCSAO algorithm. The latter requires $O(G \cdot P \cdot n^3)$ operations, where G is the number of generations and P is the population size. In contrast, the online prediction step is computationally efficient, with a complexity of $O(n_{\mathrm{sv}} \cdot M)$, where n_{sv} is the number of support vectors, making it suitable for real-time jamming effect assessment.

3. Quantitative Evaluation of Jamming Effects

Effective jamming impedes radar target confirmation and tracking capabilities, thereby maintaining the system in a low-threat state. In contrast, ineffective jamming fails to alter radar performance, permitting gradual transition to a high-threat operational mode. Jamming efficacy can be assessed through observed radar state transitions. Nevertheless, in adversarial scenarios, the radar may sustain a static operational state for extended durations. In such cases, quantitative analysis of parameter variations becomes necessary to evaluate jamming effectiveness definitively.

3.1 Improved Entropy-based Weighting Method (IEWM)

Excessive incorporation of evaluators' subjective judgments compromises objectivity in assessment, while biased data further degrades quantitative evaluation accuracy. To address these limitations, this study employs IEWM for objective weighting. The methodology involves: (i) standardizing the kernel density [32] of raw data, (ii) computing Tsallis entropy [33] weights, and (iii) integrating subjective and objective weights through game-theoretic synthesis [34]. This approach establishes weighting coefficients solely based on inter-parameter correlations, completely avoiding decision-maker subjectivity. The mathematically rigorous framework provides robust theoretical foundations while effectively mitigating biased-induced distortions. The implementation procedure comprises the following key steps:

1) The decision matrix $\mathbf{A} = (a_{ij})_{N \times M}$ is constructed from N samples with M evaluation indicators, followed by computation of the sample data's skewness coefficient v_i:

$$v_i = \frac{\frac{1}{N}\sum_{i=1}^{N}\left(a_{ij} - \bar{a}_j\right)^3}{\left(\frac{1}{N}\sum_{i=1}^{N}\left(a_{ij} - \bar{a}_j\right)^2\right)^{3/2}}. \tag{7}$$

2) The Shapiro-Wilk test statistic p is computed to evaluate data normality, while an adaptive approach is employed to determine the optimal kernel density bandwidth h_j:

$$h_j = \begin{cases} 1.06 \cdot \hat{a}_j \cdot N^{-1/5}, & \text{if } v_i > 1 \,\&\, p >= 0.05 \\ 3.5 \cdot \hat{a}_j \cdot N^{-1/3}, & \text{if } v_i > 1 \,\&\, p < 0.05 \end{cases} \tag{8}$$

3) Calculate kernel density estimation z_{ij} of data.

$$z_{ij} = \frac{1}{N \cdot h_j}\sum_{i=1}^{N} K_{\mathrm{Gau}}\left(\frac{a_j - a_{ij}}{h_j}\right) \tag{9}$$

where K_{Gau} is a Gaussian kernel function.

4) Calculate probability matrix p_{ij}:

$$p_{ij} = \frac{z_{ij}}{\sum_{i=1}^{N} z_{ij}}. \tag{10}$$

5) The sensitivity of entropy to probability distribution is controlled by parameter q. And then calculate Tsallis entropy H_{j}:

$$H_j = \frac{1 - \sum_{i=1}^{N}(p_{ij})^q}{q-1}. \tag{11}$$

6) Calculate entropy weight w_j^{entropy}:

$$w_j^{\mathrm{entropy}} = \frac{1 - H_j}{\sum_{j=1}^{M}(1 - H_j)}. \tag{12}$$

7) Research findings demonstrate that frequency-domain anti-jamming measures exhibit superior effectiveness compared to time-domain approaches. Significant variations in carrier frequency and pulse repetition frequency indicate a strong radar jamming, which suggests that frequency-domain countermeasures yield more pronounced jamming effects. While peak power primarily influences radar detection probability, signal bandwidth and

Indicator	CF	PW	BW	PRF	PP
score	0.3	0.1	0.1	0.3	0.2

Tab. 1. Subjective rating of indicators.

pulse width predominantly affect measurement accuracy and resolution, indicating comparable anti-jamming efficacy levels. The corresponding subjective weight assignments are presented in Tab. 1.

The Tsallis entropy weight and subjective weight are combined by game theory to obtain the final subjective and objective combination weight w.

The IEWM method employs adaptive bandwidth kernel density estimation to handle non-normal distribution data, enhancing weight stability while mitigating the impact of deviated data. Tsallis entropy is utilized to compute objective weights to improve adaptability to complex datasets. By integrating game theory, the method minimizes discrepancies between subjective and objective weights, achieving a Nash equilibrium solution to avoid bias from single-weighting approaches. The resulting combined weight not only adheres to data-driven principles but also preserves domain knowledge, providing a robust foundation for interference effect evaluation.

3.2 Improved TOPSIS (ITOPSIS)

On the basis of obtaining the combined weight, in order to further reduce the influence of the deviation value, the improved TOPSIS method is used for quantitative evaluation. Firstly, the original data is standardized by IQR, and the K-means clustering method is used to select the optimal clustering cluster and improve the calculation of the ideal solution. The basic process is as follows:

1) Calculate the median $a_{i,\,\mathrm{median}}$ of the data and the difference $a_{i,\,\mathrm{iqr}}$ between the two quartiles, and standardize the data using IQR to obtain $\mathbf{B} = (b_{ij})_{m\times n}$:

$$b_{ij} = \frac{a_{ij} - a_{i,\mathrm{median}}}{a_{i,\mathrm{iqr}}}. \tag{13}$$

2) Normalize the original matrix in order to streamline the analysis and mitigate dimensional and magnitude effects on computations. The standardized matrix $\mathbf{C} = (c_{ij})_{m\times n}$ is obtained through the following procedure. If the evaluation index is the maximum value index, then:

$$c_{ij} = \frac{b_{ij} - \min(b_{ij},...,b_{in})}{\max(b_{ij},...,b_{in}) - \min(b_{ij},...,b_{in})}. \tag{14}$$

If the evaluation index is the minimum value index, then:

$$c_{ij} = \frac{\max(b_{ij},...,b_{in}) - b_{ij}}{\max(b_{ij},...,b_{in}) - \min(b_{ij},...,b_{in})}. \tag{15}$$

3) Calculate the weighted matrix:

$$\mathbf{V} = C\cdot \mathrm{diag}(\mathbf{w}). \tag{16}$$

4) Determine the optimal cluster number l for K-means clustering by employing the silhouette coefficient method [35]. The silhouette coefficient quantifies clustering quality by evaluating both intra-cluster cohesion and inter-cluster separation. For each sample i, this metric $s(i)$ is computed based on its dissimilarity $F(i)$ within the cluster and its dissimilarity $E(i)$ to the nearest neighboring cluster, defined as:

$$s(i) = \frac{E(i) - F(i)}{\max\{E(i), F(i)\}}. \tag{17}$$

5) Identify the positive Z_j^+ and negative Z_j^- ideal solutions of the weighted matrix, with the cluster exhibiting minimum distance to A designated as optimal. Local ideal solutions (L_j^+, L_j^-) are then derived from this optimal cluster. Subsequent calculation of the optimal cluster's population proportion yields a dynamic fusion coefficient α, enabling computation of the fused positive D_i^+ and negative D_i^- ideal solutions.

$$\begin{cases} D_i^+ = \sqrt{\sum\limits_{j=1}^{n}\left(V_{ij} - \alpha\cdot L_j^+ - (1-\alpha)\cdot Z_j^+\right)^2} \\ D_i^- = \sqrt{\sum\limits_{j=1}^{n}\left(V_{ij} - \alpha\cdot L_j^- - (1-\alpha)\cdot Z_j^-\right)^2} \end{cases}. \tag{18}$$

6) Compute the closeness coefficient S_i between each candidate solution and the optimal solution, where higher values indicate superior jamming efficacy and lower values correspond to diminished jamming effectiveness, thereby enabling performance ranking:

$$S_i = \frac{D_i^-}{D_i^- + D_i^+}, i = 1, 2, \cdots, m. \tag{19}$$

The ITOPSIS method employs IQR standardization to mitigate the impact of outliers on normalization results, thereby improving robustness. The silhouette coefficient is utilized to automatically determine the optimal cluster number, eliminating subjective bias in data grouping and enhancing partitioning rationality. By dynamically balancing global and local ideal solutions through adaptive coefficients, the method achieves improved adaptability to complex interference environments. The resulting scoring output provides a direct quantitative measure of interference effectiveness, facilitating rapid decision-making in electronic warfare applications.

3.3 Complexity Analysis of Quantitative Evaluation Stage

In addition to empirical runtime measurements, we provide a theoretical analysis of the computational complexity for each component of the proposed methodology.

For the IEWM, the computational cost mainly arises from kernel density estimation (KDE) and entropy calculation. Let n be the number of samples and d the number of indicators. The adaptive KDE step has a time complexity of $O(n^2d)$ due to pairwise distance computations. The Tsallis entropy calculation requires $O(nd)$ operations. The game-theoretic integration of subjective and objective weights is $O(d^2)$. Therefore, the overall complexity of IEWM is dominated by KDE, and then yields $O(n^2d)$.

For the ITOPSIS method, the IQR standardization step is $O(nd)$. The K-means clustering, applied to determine the ideal solutions, has a time complexity of $O(ndkt)$, where k is the number of clusters and t the number of iterations. The silhouette coefficient calculation used to choose the optimal k requires $O(n^2d)$ per candidate k. The dynamic ideal solution fusion and distance computations are both $O(nd)$. Hence, the overall complexity of ITOPSIS is $O(n^2d + ndkt)$.

The space complexity of the IEWM algorithm is predominantly dictated by the storage requirements for kernel density estimates and weight vectors, which collectively entail a space complexity of $O(nd)$. Meanwhile, the ITOPSIS algorithm necessitates the storage of clustering outcomes, distance matrices, and ideal solutions. These storage demands also culminate in a space complexity of $O(nd)$.

4. Experiment

4.1 Data Preparation

This simulation adopts the "Mercury" multifunction radar (MFR) case study published by Dr. Fred A [32]. To ensure realistic parameterization, all radar parameters are constrained by established pulse compression ratios and duty cycle requirements. The Mercury MFR operates in five distinct modes with escalating threat levels: search, acquisition, non-adaptive tracking, range resolution, and track-while-scan. Radar linear frequency modulation (LFM) pulse signals were generated for each operational state, with independent additive noise levels of 10%, 30%, and 50% applied to each condition. The complete dataset consists of 200 samples per noise level, yielding a total of 4000 distinct signal realizations for comprehensive performance evaluation. The computer hardware parameters used for simulation were Intel i9-14900K CPU, 64 GB RAM, NVIDIA RTX 4090 GPU, and Matlab version 2024.

To simulate jammer-based analysis and processing of intercepted radar signals, parameter estimation techniques are employed to extract pulse descriptor words (PDWs). The carrier frequency is determined through instantaneous frequency analysis, while pulse width estimation utilizes an adaptive pulse detection approach. Signal bandwidth is derived from the –3dB spectral bandwidth calculation. For pulse repetition interval (PRI) estimation, significant peaks in the time-domain auto-correlation function are identified to compute the average PRI, from which the pulse repetition frequency (PRF) is subsequently determined. Peak power estimation is achieved by calculating the average power within the pulse region. The error between the estimated value and the actual value is shown in Fig. 3. It can be seen that the CF error is only 1.3%, the PP error is 5.7%, and the overall estimation error is small, which meets the requirements of subsequent experiments.

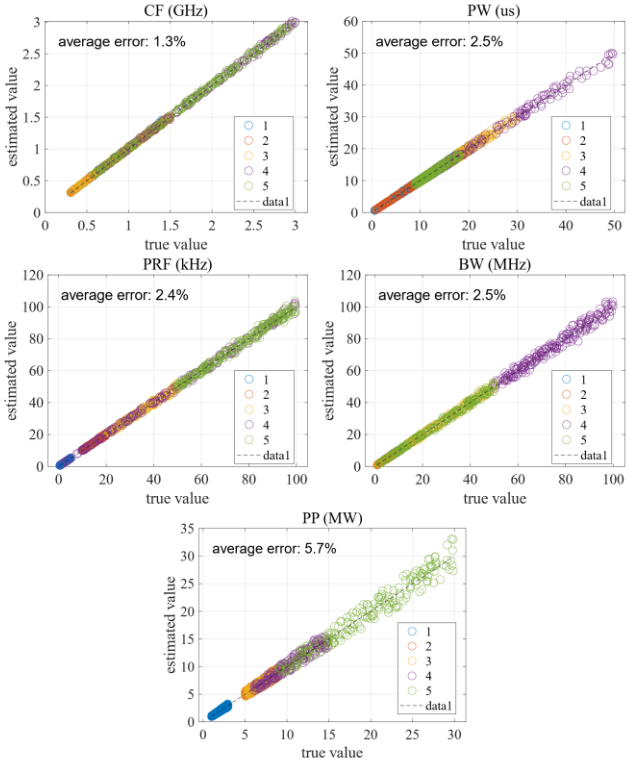

Fig. 3. The error between the estimated value and the actual value.

The complete dataset consists of 200 samples per noise level per operational mode, yielding a total of 4000 distinct signal realizations (5 modes × 4 noise levels × 200 samples) for model training and parameter optimization. To ensure a rigorous and unbiased evaluation and to prevent any data leakage, an additional independent test set was generated using the same signal generation protocol. This test set comprised 1000 completely novel signal realizations (5 modes × 4 noise levels × 50 samples) that were never used during any stage of model development. The hyperparameter tuning process for algorithms like GCSAO was conducted via cross-validation on the 4000-sample training set. This approach guarantees that the final performance evaluation on the 1000-sample test set is entirely objective and reflects the model's true generalization capability to unseen data.

4.2 Experiment of KDEOA

To validate the effectiveness of the proposed discretization method, we conducted simulation experiments using a dataset comprising 4000 radar PDW samples (Sec. 4.1), each being characterized by five features. The experimental procedure involved data normalization followed by processing with our improved discretization method. After

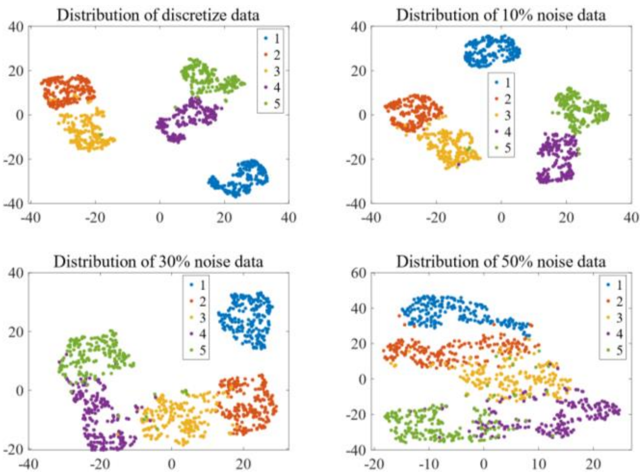

Fig. 4. The t-SNE visualization of discretized data across various noise levels.

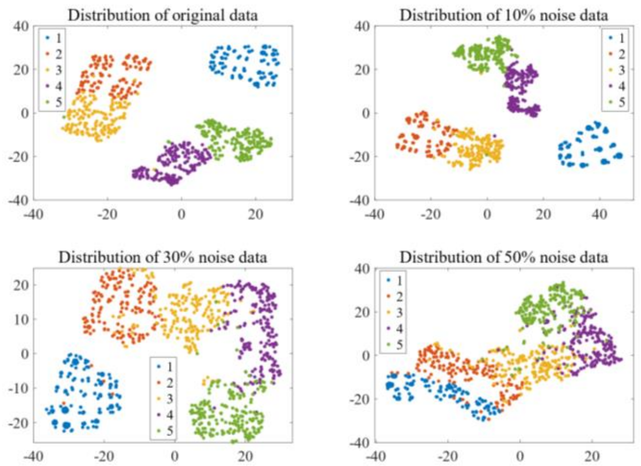

Fig. 5. The t-SNE visualization of original data across various noise levels.

cross-validation, the value of the complexity penalty factor λ is selected to be 0.1.

Figure 4 presents the t-SNE visualization of discretized data across various noise levels, while Figure 5 shows the original data distribution. Comparative analysis reveals that increasing noise levels cause gradual dispersion of data points and blurring of category boundaries in the original data. In contrast, the KDEOA-processed discrete data consistently preserves the original distribution characteristics across all noise conditions. Notably, even under high noise levels (50%), the discretized data maintains distinct class boundaries, demonstrating its superiority in noise robustness.

4.3 Experiment of GCSAO-LSSVM

In order to verify the effectiveness of the GCSAO-LSSVM algorithm, the 4000-sample training set was used for model training and hyperparameter optimization. The upper and lower limits of r and g were set to [0.0001, 300] and [0.0001, 100], respectively. The population size was set to 50, and the maximum number of iterations was set to 100.

Four optimization algorithms namely genetic algorithm (GA), particle swarm optimization (PSO), SAO, and the proposed GCSAO. were employed for support vector machine parameter optimization. The GA parameters were configured as a crossover probability of 0.4 and a mutation probability of 0.01. In the case of PSO, the velocity vector was restricted to the interval [–0.2, 0.8], with an inertia factor ranging from [0, 2] and learning factors set to 1.6 and 1.7, respectively. To prevent premature convergence, the inertia factor decreased linearly during the iterative process. To assess the statistical reliability of the experimental outcomes, 30 independent repeated trials were conducted under the aforementioned conditions. The penalty coefficient r, optimal parameters g, and classification accuracy (Acc) obtained from each trial were recorded. The mean values and variances of these results are summarized in Tab. 2.

As shown in the experimental results, the proposed GCSAO algorithm achieves an average accuracy of 0.9868, outperforming GA (0.9759), PSO (0.9824), and SAO (0.9867). Notably, the standard deviation of accuracy is zero, indicating excellent stability in performance. For the parameter g, the mean value is 0.0176 with a standard deviation of 0.0096, demonstrating satisfactory consistency. Although the mean value of the parameter r is higher, its standard deviation remains considerably lower (31.6968) compared to other algorithms. These results collectively confirm that the GCSAO-LSSVM algorithm exhibits high accuracy and strong stability, validating its effectiveness.

The optimal group of 30 groups was selected for analysis. Figure 6 is the optimization process of GCSAO on parameter g and penalty coefficient r. Due to the periodic oscillation strategy, it can be clearly seen that the r value jumps out of the local optimal solution after the 21th iteration. Finally, the penalty coefficient r value is determined to be 265.6273, and the optimal parameter g value is 0.0179.

The accuracy optimization curves of each algorithm are shown in Fig. 7. As shown in Fig. 7, comparative analysis revealed that GCSAO-LSSVM outperformed competing methods in terms of both convergence speed and recognition accuracy, achieving significantly higher values for the latter.

value	GA	PSO	SAO	GCSAO
Mean r	192.3358	170.2072	239.5829	278.7789
Std r	102.8905	69.3068	88.7055	31.6968
Mean g	0.1261	0.0069	0.0168	0.0176
Std g	0.08231	0.0117	0.0103	0.0096
Mean Acc	0.9759	0.9824	0.9867	0.9868
Std Acc	0.0066	0.0023	0	0

Tab. 2. The final value of parameters g and r under different methods.

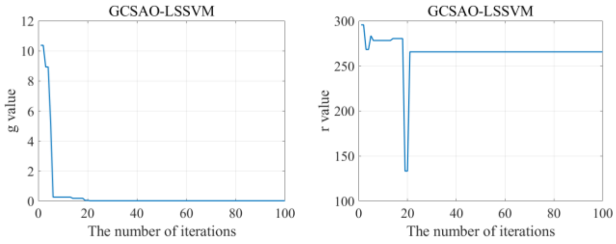

Fig. 6. Optimization process of parameters g and r.

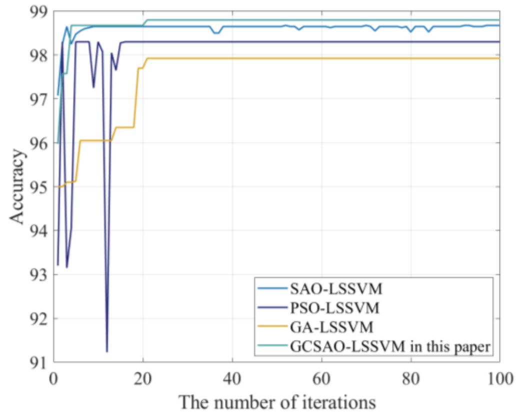

Fig. 7. The accuracy optimization curves of the comparison algorithm.

Figure 8 compares the classification accuracy of the LSSVM models under various noise conditions and discretization strategies. The results indicate a consistent decline in accuracy among all methods as the noise ratio increases. Notably, the K-means-based discretization approach consistently surpasses the performance of non-discretized data in noisy scenarios, underscoring the role of discretization in enhancing model robustness through an effective feature grouping. The proposed KDEOA method achieves the highest accuracy among all compared techniques at every noise level, demonstrating its superior capability in handling biased data. This performance gain

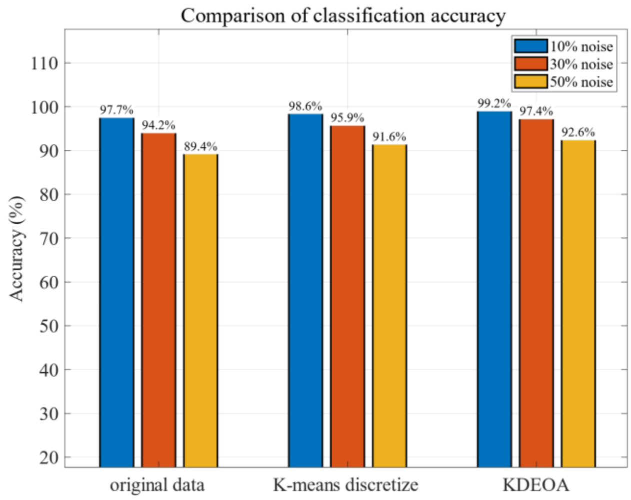

Fig. 8. Comparison of the classification accuracy of LSSVM under different noise conditions and different discretization methods.

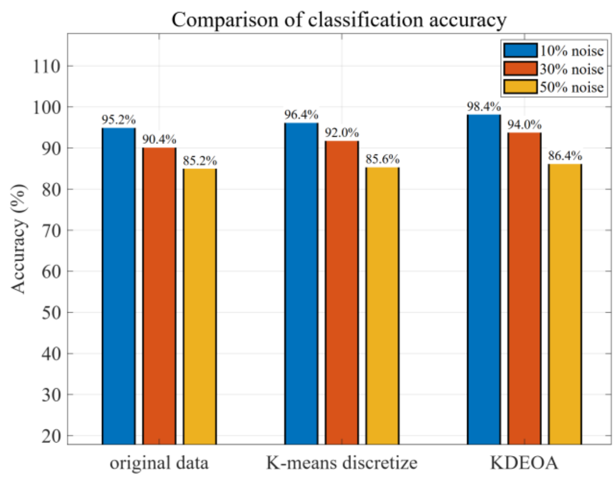

Fig. 9. Comparison of classification accuracy of LSSVM on newly generated data.

suggests that our discretization strategy facilitates more discriminative feature partitioning, thereby strengthening the model's resilience against signal contamination.

To evaluate the model's generalization capability, an additional 1,000 data samples were generated for testing. The results, summarized in Fig. 9, indicate that although the accuracy of all methods declined to some extent under different noise conditions on the newly generated dataset, the proposed KDEOA consistently outperformed both the original data and the K-means method across all scenarios. This demonstrates that KDEOA not only achieves effective classification on the training set but also exhibits strong generalization ability, maintaining high classification accuracy on unseen data.

4.4 Experimental of IEWM

To validate the effectiveness of the proposed IEWM for subjective-objective weighting, comparative analyses were conducted with four alternative approaches: conventional EWM, EWM with game theory, EWM with Tsallis entropy, and EWM with kernel density standardization. Through cross validation, the sensitivity coefficient q of entropy to probability distribution is determined to be 0.8.

The stability of each weighting method against noise was quantified by using the weight variation rates (WVR). This metric measures the average relative change in the calculated weights when noise is introduced to the dataset, compared to the weights derived from the clean data. For each method, the WVR at a specific noise level is defined as:

$$\mathrm{WVR} = \left(\frac{1}{M} \sum_{j=1}^{M} \frac{\left| w_{j,\text{noise}}^{\text{entropy}} - w_{j,\text{clean}}^{\text{entropy}} \right|}{w_{j,\text{clean}}^{\text{entropy}}} \right) \times 100\% \qquad (20)$$

where M is the number of evaluation indicators, $w_{j,\text{clean}}^{\text{entropy}}$ is the weight of the j-th indicator calculated from the original and clean dataset, $w_{j,\text{noise}}^{\text{entropy}}$ is the weight of the j-th indicator calculated from the noisy dataset.

Table 3 presents the comparative results of weight variation rates between contaminated samples and original data. As evidenced in Tab. 3, the proposed IEWM achieves remarkable improvements in weight stability, reducing variation rates to just 0.11–0.23% across noise levels - a 20× improvement over standard EWM (6.30% at 50% noise), and demonstrates superior performance in weight variation rate compared to alternative approaches. This advantage stems from two key considerations: (1) comprehensive incorporation of characteristic attributes from the complete radar dataset, and (2) explicit inconsistencies between biased samples and original data. The results confirm that the IEWM algorithm effectively mitigates the adverse impacts of biased data.

4.5 Experimental of ITOPSIS

To validate the efficacy of the proposed ITOPSIS method, through utilizing radar data from prior IEWM experiments, comparative analyses were performed against conventional TOPSIS, TOPSIS with mixed ideal solutions, and TOPSIS with IQR standardization.

For each noise level, the quantitative jamming effect score was calculated for every sample in the test set using each TOPSIS variant. The "ground truth" reference score for each sample was defined as its score computed by the standard TOPSIS method on the clean and uncontaminated data. The effectiveness of each method was then evaluated by measuring how well its scores under noise correlated with these reference scores. This was quantified using the Pearson correlation coefficient between the method's output scores and the reference scores across all test samples. A higher correlation coefficient indicates that the method's evaluation results are more consistent with the baseline, which demonstrates better robustness to noise.

Table 4 presents the correlation coefficients between evaluation results and reference sample data under varying biased contamination levels. The results demonstrate that all four methods exhibit declining correlation values with increasing biased proportions. Notably, the proposed ITOPSIS demonstrates significant improvements over existing .methods, achieving a .49.5% .higher correlation

Method	Random Noise		
	10%	30%	50%
EWM	5.63%	6.18%	6.30%
EWM with Tsallis entropy	3.37%	4.76%	5.35%
EWM with game theory	2.12%	2.25%	2.35%
EWM with kernel density standardization	0.16%	0.27%	0.31%
IEWM	**0.11%**	**0.22%**	**0.23%**

Tab. 3. Comparison of weight variation rates under different method.

Method	Random Noise		
	10%	30%	50%
TOPSIS	0.5609	0.5061	0.3645
TOPSIS with mixed ideal solutions	0.5642	0.5275	0.3700
TOPSIS with IQR standardization	0.8277	0.7740	0.6945
ITOPSIS	0.8382	0.7806	0.7290

Tab. 4. Comparison of correlation coefficient between different methods.

(0.7290 vs 0.3645) than conventional TOPSIS under 50% noise conditions, and maintains superior robustness against biased perturbations, effectively mitigating their adverse effects on evaluation accuracy.

4.6 Computational Complexity Analysis

To evaluate the computational efficiency of the proposed algorithm and ensure statistical significance, a total of 4000 samples were included in the tests. The runtime of different algorithmic components under various ablation settings is illustrated in Fig. 10. All pre-evaluation procedures were kept consistent across experiments. A comparison was conducted among seven distinct method combinations from Sec. 4.4 and 4.5, which were numbered from 1 to 7, specifically: IEWM + ITOPSIS, EWM with Tsallis entropy + ITOPSIS, EWM with game theory + ITOPSIS, EWM with kernel density standardization + ITOPSIS, IEWM + TOPSIS with IQR standardization, IEWM + TOPSIS with mixed ideal solutions, and standard EWM + TOPSIS.

As shown in Fig. 10, the computational time varies across different stages of each algorithm. The discretization stage consumes relatively little time, ranging between 0.0121 and 0.0133 seconds. In contrast, the pre-evaluation stage is the most time-consuming, accounting for 81.6% to 87.3% of the total runtime. The proposed IEWM shows comparable time consumption to standard EWM, while

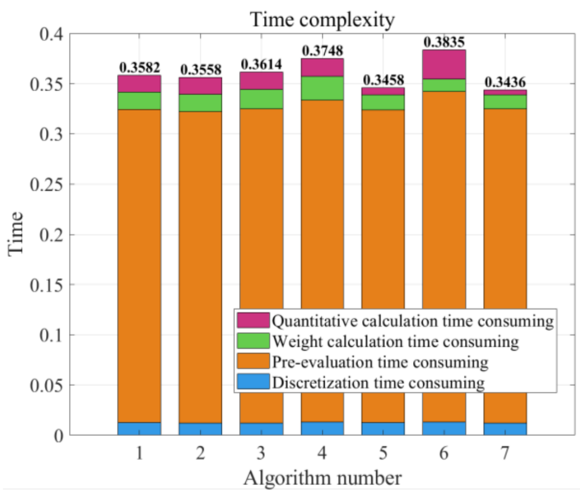

Fig. 10. The time comparison with different ablation experiments.

ITOPSIS requires approximately four times longer than conventional TOPSIS. This increase is mainly attributable to the fact that TOPSIS computes ideal solutions using simple global maxima and minima, whereas ITOPSIS incorporates more computationally intensive techniques such as silhouette coefficient analysis, K-means clustering, and dynamic fusion of ideal solutions. Despite the increased time cost of ITOPSIS, its impact on the overall computational time remains limited. The fact that the entire proposed algorithm processes 4000 samples in only 0.3582 seconds demonstrates high efficiency and meeting real-time processing requirements.

For the space complexity, after testing, the peak running memory space occupied by the LSSVM model in the pre-evaluation stage is 36.7 M, the model parameter size is 0.87 M, and the space complexity of the remaining calculation parts is negligible.

In summary, the proposed algorithm requires only 0.3582 seconds to process 4000 samples, with reasonable memory consumption, which fully satisfies real-time application demands. These results confirm the computational efficiency and practical viability of the method.

5. Conclusion and Discussion

This study presents a two-stage optimization framework for evaluating radar jamming effectiveness under non-cooperative and adversarial conditions. The proposed methodology addresses key challenges from data deviations caused by radar mode switching, electromagnetic interference, and receiver noise.

In the first stage, we introduced the KDEOA algorithm to discretize continuous PDW parameters, ensuring robustness against biased data. The GCSAO-optimized LSSVM further enhanced pre-evaluation accuracy by dynamically balancing exploration and exploitation during parameter optimization.

In the second stage, the IEWM method integrated kernel density estimation and game-theoretic weighting to minimize subjective biases, while the ITOPSIS approach leveraged IQR standardization and adaptive clustering to refine quantitative evaluation under biased conditions. Experimental results demonstrated the framework's superiority in maintaining high accuracy across noise levels (up to 50% contamination), with IEWM achieving the lowest weight variation rate and ITOPSIS exhibiting the strongest correlation.

While the proposed framework demonstrates robust performance in jamming evaluation, certain limitations should be noted as well. Firstly, the method assumes relatively stable radar behavior patterns, which may not hold for advanced cognitive radars with which employs adaptive countermeasures. Secondly, the evaluation accuracy depends heavily on the quality of extracted PDW parameters, which means that severe signal distortions in highly cluttered environments could degrade performance. Thirdly, the current implementation focuses more on single-jammer scenarios and does not account for coordinated jamming strategies or multi-radar networks, potentially limiting its applicability in complex electronic warfare scenarios.

Future research will focus on three key directions: (i) developing real-time adaptive learning mechanisms by using reinforcement learning to handle dynamic radar countermeasures, (ii) extending the framework to multi-jammer scenarios by modeling cooperative jamming effects and radar network interactions, and (iii) validating the approach through hardware-in-the-loop testing with field-collected data to assess practical deployment feasibility.

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