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Research Paper

Dual-Domain Denoising Transformer for Precise Anti-Jamming Signal Reconstruction

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Abstract. In modern wireless communication, radar, and intelligent sensing, recovering signals exposed to complex and adaptive interference is an issue that needs to be addressed. This paper proposes a novel dual-domain denoising transformer structure (D-DDT) that can effectively integrate time-frequency domain information, thereby enhancing anti-jamming capabilities. Considering the urgent need for accurate signal recovery in dynamic electromagnetic fields, a dual-branch encoder path and adaptive cross-domain attention mechanism are introduced. Conducted on multiple datasets, including real-world and simulated interference environments, with rigorous testing using filter-based and learning-based algorithms. DDT enhances noise suppression effects, improving the signal-to-noise ratio (SNR) compared to other methods in the comparison. Bilateral domain representation and adaptive attention are two necessary conditions for achieving good stability. In practical application tests, it can effectively handle various resource levels under time constraints. As a new participant in the complex anti-jamming signal recovery benchmark test, it contributes to subsequent communication and detection capabilities. Future research will enhance the adaptability of interference models and the optimization of edge deployments.

Keywords: *Signal Processing, Anti-Jamming, Transformer Network, Dual-Domain Fusion, Wireless Communication*

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Introduction

Accurate interference signal recovery aids wireless communication, radar technology, and intelligent detection systems. It is a key issue to ensure the correct and safe transmission of data in these critical situations. Complex and adaptive interference has already impacted wireless networks, and if not compensated for, it could interfere with data transmission, positioning systems, and more [1]. In industrial environments where remote sensing and radar are used to detect targets or the environment, intentional or unintentional interference can severely impact their performance [2]. With the continuous development of IoT technology, network device systems are becoming increasingly dense, which significantly increases the issue of electromagnetic interference. To ensure system stability and avoid interference in uncertain environments [3]. Next-generation applications, such as autonomous vehicles and cognitive radio, must also be able to handle high-recovery signals in complex environments with varying interference [4]. Building reliable signals with strong noise robustness characteristics in complex interference environments is currently receiving more attention [5].

Anti-jamming and denoising techniques are typically used in one-dimensional domain analysis or static model design, and extensive research has been conducted on these issues over the years. Wiener and Kalman filters are very effective in removing stationary background noise in the time domain; they perform poorly when dealing with non-Gaussian interference or rapid changes [6]. Frequency domain denoising methods such as subspace projection and spectral subtraction can be used for structured noise, but they cannot handle time-varying interference or overlapping spectra [7]. The research on hybrid representations and sparse models has provided some suggestions for methods based on compressed sensing, but they are still not very suitable for multi-source practices [8]. Since then, research on deep learning models (such as Convolutional Neural Networks, CNNs) in the field of signal recovery has become easier. Due to the lack of cross-domain relevance, it cannot be applied in multiple domains [9]. Emerging Transformer-based attention models have made some positive progress, but comprehensive anti-jamming performance has not yet been fully achieved in many areas [10].

To address the aforementioned issues, this paper proposes a new signal reconstruction method—Dual-Domain Denoising Transformer (DDDT). Utilizing time-frequency domain features to achieve excellent anti-interference performance. In order to address existing issues and establish advanced performance standards for interference signal suppression, two feature encoding branches, adaptive cross-domain attention, and efficient end-to-end signal estimation are necessary. The significant results are as follows: the compact decoding method, the structural design of the dual-domain encoder, and the dynamic attention fusion mechanism can effectively operate in various interference environments. Many empirical validations, improvements, and applications of DDDT technology in synthetic or real-world environments are crucial. This section is organized as follows: Section 2 reviews the relevant literature and establishes the research background; Section 3 introduces the methodology and structure of DDDT; Section 4 presents the datasets and experimental protocols, showcasing the results, ablation studies, and analysis; Section 5 concludes with a summary and future outlook.

Background and Related Work

Anti-jamming Signal Processing

Developing wireless and sensor technologies in harsh electromagnetic field environments requires reliable anti-jamming signal processing capabilities. Pulse interference, narrowband interference, broadband interference, and dynamically adjusted adaptive intelligent interference technologies are all types of interference [11]. This type of interference can severely affect reliable sensing functions, radar detection accuracy, and communication quality in high-density frequency-sharing environments [12]. Traditional methods such as STAP and spectral subtraction, based on spatial/spectral characteristics, aim to suppress target signals [13]. The purpose of blind source separation techniques (BSS) such as Independent Component Analysis is to distinguish statistically independent original signals to support this hypothesis [14].

In practice, there are issues, but the results are still very good. Methods based on filters and STAP require precise models of interference factors or references in single-cell measurement environments. It is less adaptable in different environments [15]. When dealing with non-stationary, highly correlated, or overlapping interference environments, BSS and other blind methods fail because these environments do not meet their fundamental model assumptions [16]. The increase in spectrum occupancy frequency and adaptive interferers has heightened the vulnerability of methods based on a single-domain model [17].

Domain-based Denoising Techniques

Traditional signal recovery solutions use time-domain and/or frequency-domain denoising techniques. In time-domain methods, moving average filters and Kalman filters are typically used to eliminate weakly time-correlated stationary noise or gradually varying noise in images [18]. In frequency domain techniques, transformation methods such as Fast Fourier Transform (FFT) and Short-Time Fourier Transform (SFFT) handle the limited intensity of weak narrowband or harmonic interference at specific frequencies thru spectral subtraction or band-stop filters [19].

Every technical field has its advantages and disadvantages. Time-domain techniques may not perform as expected in suppressing spectrum-limited interferers or burst narrowband interference [20]. Frequency-domain methods face the problem of interference being non-periodic or transient, or having strong temporal variability across multiple frequencies [21]. To improve detection and noise suppression, some researchers have proposed dual-domain and hybrid denoising methods, which combine temporal and spectral information [22]. By integrating information from these two domains, a hybrid method can enhance its robustness by reducing interference with other methods. Its environmental adaptability can also be improved [23].

Transformer and Attention Models

Deep learning technologies enable neural networks to learn features that go beyond traditional methods or specific domains [24]. Early technologies such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) can extract sequence-based and local features when processing input signals [25]. Due to the size of their convolutional kernels and limited context range, they are not very suitable; especially for cases involving cross-scale or long-distance interactions.

This paradigm shift was also brought about by transformer models. During the processing, the transformer uses self-attention to provide position-specific values, having already learned the implicit contextual information. Due to its flexibility, this design is more suitable than other designs for removing small signal components from difficult-to-distinguish noise background patterns. Attention models have been applied to time series and spectral data to improve speech denoising, biomedical signal separation, interference reduction, and performance in other engineering fields. Hybrid and dual-domain transformer architectures combine attention domains in both the time and frequency domains to capture more comprehensive interactions of features, and continue to make progress in the robust recovery performance of interference signals.

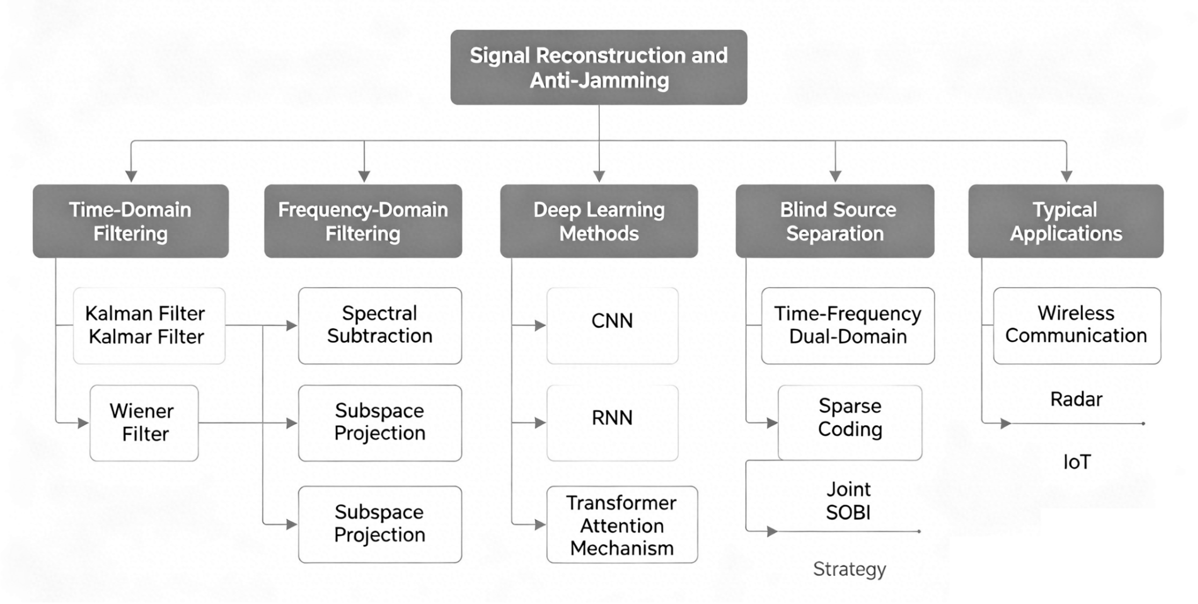


Figure 1. Mind Map of Related Techniques and Research Trends

Methodology

Dual-domain Signal Representation

Accurately obtaining and integrating time-domain and frequency-domain data is key to advanced anti-jamming signal reconstruction. The original signal $x(t)$ is processed thru two parallel paths within a finite time frame. In order to preserve information about impulsive noise or step changes that are likely to occur under interference conditions, the first path maintains the continuity of the time and amplitude envelope. During this period, the second path uses high-resolution Fourier transform to convert the signal into its spectral domain representation $X(f)$. This path also records persistent or frequency-concentrated interference that may be masked in the original time-domain form.

Feature normalization and structural alignment are aimed at achieving complementary collaboration between the time and frequency branches. According to the running mean and standard deviation, each time-domain section is adaptively normalized. Then, perform overlapping spectrum normalization within the local region to reduce energy differences and stabilize the pattern. These normalized representations, denoted as $\mathbf{T} \in \mathbb{R}^{N \times d}$ for time and $\mathbf{F} \in \mathbb{R}^{M \times d}$ for frequency, are projected through learnable channel encoders. In order to improve the subsequent interference recognition performance, canonical correlation analysis is mainly used to optimize the mutual information between these parallel projections.

$$\mathbf{T}_i = \frac{x(t_i) - \mu_T}{\sigma_T}, \mathbf{F}_j = \frac{X(f_j) - \mu_{F_j}}{\sigma_{F_j}} \qquad \text{Eq.(1)}$$

Global and local normalization terms μ_T, σ_T and μ_{F_j}, σ_{F_j} are defined on dynamically sliding windows and frequency bins respectively, ensuring local adaptivity to ambient interference statistics.

$$\max_{\mathbf{A},\mathbf{B}} \operatorname{corr}(\mathbf{A}^\top \mathbf{T}, \mathbf{B}^\top \mathbf{F}) \qquad \text{Eq.(2)}$$

Here, $\mathbf{A}$ and $\mathbf{B}$ are trainable projection matrices aligning the most informative axes across domains, and the correlation metric is optimized with orthogonal constraints. The generated dual-domain descriptors, with maximized structural and statistical correspondence, serve as robust inputs for further transformer-based encoding.

In addition to the basic dual-path structure, recent advancements utilize explicit modeling of time-frequency attention maps, which depend on the relationship between time and frequency fluctuations. In the presence of non-stationary interference or overlapping spectra, introducing dynamic gating mechanisms between branches can amplify cross-domain cues. It can represent real-time adaptation, while suppressing redundant background signals and selecting the domains that are most discriminative for interference. In practice, the spectral channel and time work together, making it possible to achieve a finer granularity of decomposition for target and interference components, a decomposition that cannot be achieved when handled separately.

DDDT Architecture Design

The main structure of the Dual-Domain Denoising Transformer (DDTT) is a tree-structured asymmetric encoder-decoder architecture, used to combat interference from multiple aspects. After reception, temporary tokens used to display the sequence of waveform structures and the continuity of micro-events are encoded along this path. Frequency tokens are created from segmented and normalized spectral sub-fragments, which represent attributes such as harmony, static, and flicker. Both are embedded in the same shared multivariate embedding space and then independently processed by transformer encoders with multiple layers. These encoders handle rich cross-domain dependencies.

After the multi-layer domain integrated encoding is completed, a cross-domain fusion module merges the learned representations of the time domain and frequency domain. In this section, cross-attention is used; tags at different times pay more attention to other tags with similar frequencies, thereby enhancing the degree of matching. The cross-modal query capability of DDDT enables it to track and eliminate disturbances under changing or mixed-mode interference conditions. This is different from traditional single-domain transformers and monolithic attention-based systems.

Formally, time-domain self-attention is computed as

$$\operatorname{Attention}_T(\mathbf{Q}_T, \mathbf{K}_T, \mathbf{V}_T) = \operatorname{softmax}\left(\frac{\mathbf{Q}_T \mathbf{K}_T^\top}{\sqrt{d_k}} + \mathbf{M}_T\right)\mathbf{V}_T \qquad \text{Eq.(3)}$$

where $\mathbf{M}_T$ encodes dynamic temporal position and local correlation. The cross-domain attention between frequency queries and temporal keys follows:

$$\operatorname{CrossAttn}(\mathbf{Q}_F, \mathbf{K}_T, \mathbf{V}_T) = \operatorname{softmax}\left(\frac{\mathbf{Q}_F \mathbf{K}_T^\top}{\sqrt{d_k}} + \Delta_{FT}\right)\mathbf{V}_T \qquad \text{Eq.(4)}$$

with Δ_{FT} as the trainable cross-domain bias matrix capturing context adaptivity. The fused output is projected and passed to a lightweight decoder for signal estimate reconstruction:

$$\hat{x}(t) = \mathcal{D}(\mathbf{U}[\mathbf{O}_T, \mathbf{O}_F]) \qquad \text{Eq.(5)}$$

where $[\mathbf{O}_T, \mathbf{O}_F]$ are concatenated transformer outputs for time and frequency, $\mathbf{U}$ is a fusion projection operator, and $\mathcal{D}$ denotes the final decoding transformation that synthesizes the denoised waveform.

As shown in Figure 2, the schematic diagram of the DDDT workflow connects target decoding output, cross-domain fusion, and parallel encoding.

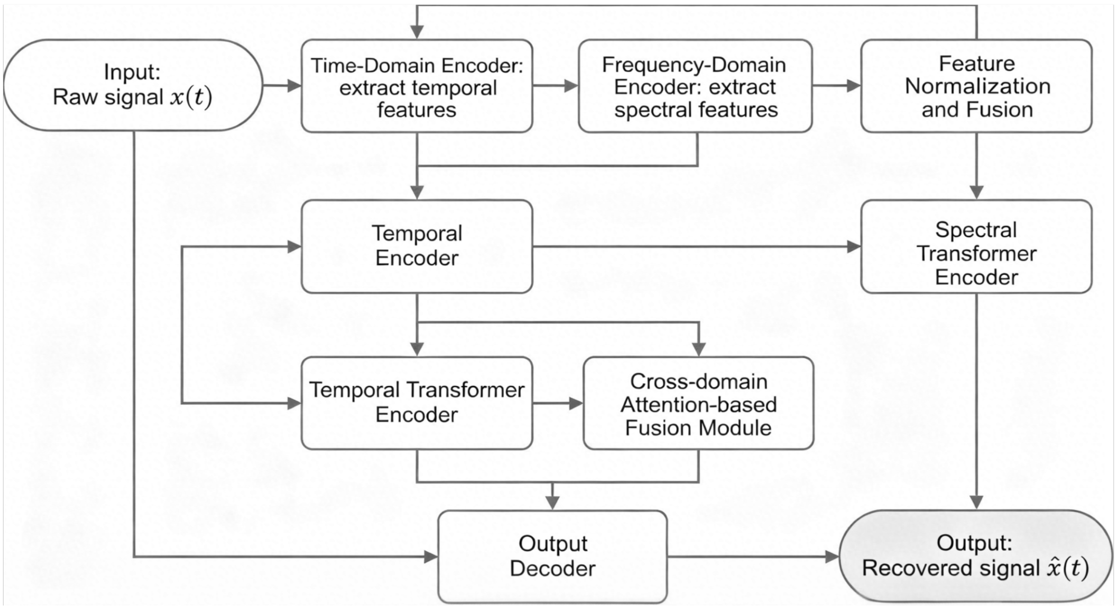


Figure 2. Workflow Diagram of the Proposed DDDT Technique

In practical applications, the performance and stability of the DDDT framework depend on the effectiveness of the synchronization between the two domains. The fusion module achieves adaptive adjustment of inter-domain related structures; additionally, each encoding branch is pre-trained and optimized to respond sensitively to interference within its coverage area. In cases of frequent instability and uneven signal coverage, flexible design can improve effectiveness. On the other hand, excessive noise may lead to spectrum congestion. In performance testing, DDT's resolution of weak signals in local areas is higher than the results of single-path and unbridged mixed models. Reconstruction Layer: This layer is meticulously designed to achieve high-fidelity domain-to-domain conversion, maintaining phase integrity and avoiding visual noise. This DDTT combination includes parallel streams of contextualized data and eliminates noise by using separate denoising methods in electromagnetic environment application scenarios.

Attention Mechanism Optimization

At every level, it is necessary to adopt flexible attention network structures to enhance adaptability to complex and constantly changing interference environments. Based on the quantification of local interference traces, the optimized DDDT attention mechanism dynamically adjusts the relevant areas. Instead of statically weighting all relationships, it calculates specific mutual information in the intermediate token representations. Each processing cycle will alter a learnable, domain-specific gate to enhance the impact of time-frequency spectrum correlation when detecting broader interferers or harmonics; it will also modify the preference for temporal context in impulsive attacks or frequency modulation environments.

To explicitly regulate the sensitivity of attention in dynamic environments, an adaptive entropy scaling factor γ_i is introduced:

$$\gamma_i = \lambda_0 + \lambda_1 H(\mathbf{q_i}, \mathbf{k_i}) \qquad \text{Eq.(6)}$$

where $H(\mathbf{q_i}, \mathbf{k_i})$ denotes the cross-domain entropy, and λ_0, λ_1 are learnable parameters. The phrase enhances attention to markers with strong informational value, allocating more resources to obvious interference features to reduce overfitting caused by static artifacts.

Adaptive signal entropy can guide the attention dropout mechanism to prevent the model capacity from being excessively consumed by repeated interference or feature-rich parts. In order to reduce overfitting to certain interference patterns or artifacts, and to encourage generalized learning. The model determines the abnormal increase in either direction based on the combined evidence from both directions. It will selectively increase the corresponding attention coefficients to allocate more computational resources to areas where inter-domain interference is severe and recovery needs urgent enhancement.

According to mathematics, the dual-domain adaptive attention weights are as follows:

$$\alpha_{ij}^{\text{dual}} = \frac{\exp\left(\gamma_i \cdot \langle \mathbf{q}_i, \mathbf{k}_j \rangle + \xi_{ij}\right)}{\sum_k \exp\left(\gamma_i \cdot \langle \mathbf{q}_i, \mathbf{k}_k \rangle + \xi_{ik}\right)} \qquad \text{Eq.(7)}$$

where $\mathbf{q}_i$ and $\mathbf{k}_j$ are query and key representations from the respective branches, γ_i is dynamically determined above, and ξ_{ij} encodes the context-specific prior estimated from multidomain statistics and real-time entropy. Develop a plan to quickly reallocate the network attention distribution to respond to interference changes and maintain overall structural stability.

To improve robustness, add an interference-aware residual gating system:

$$\mathbf{z}_i = \beta_i \mathbf{h}_i^{(\text{attn})} + (1 - \beta_i)\mathbf{h}_i^{(\text{res})} \qquad \text{Eq.(8)}$$

with the gate

$$\beta_i = \sigma(w^{\top}\mathbf{s}_i + b) \qquad \text{Eq.(9)}$$

where $\mathbf{h}_i^{(\text{attn})}$ is the attention output, $\mathbf{h}_i^{(\text{res})}$ is the residual branch, and $\mathbf{s}_i$ aggregates local interference statistics. Gate-controlled adaptation uses a hybrid approach of direct feedforward and attention-based methods to improve performance in challenging real-world environment disruptors.

The loss function is dynamic cross-entropy, highlighting the most severely disturbed samples.

$$\mathcal{L}_{\text{dyn}} = \sum_i \lambda_i \cdot \mathrm{CE}(\hat{y}_i, y_i) \quad \lambda_i = 1 + \alpha \cdot \left|E_{\text{jam}}(x_i)\right| \qquad \text{Eq.(10)}$$

where $\hat{y}_i$ and y_i denote prediction and target, $E_{\text{jam}}(x_i)$ measures signal entropy after estimated jamming, and α controls the scaling. By training the model to focus on highly degraded areas, it can improve denoising and adaptability in harsher environments.

Dynamic entropy scaling, dual-domain adaptive attention, and interference-aware gating enable the DDDT network to flexibly handle various interference scenarios, ensuring stable generalization performance and achieving excellent results in current simulated and real remote sensing data denoising tasks.

Experimental design and analysis

Dataset Preparation and Augmentation

In order to ensure the diversity of propagation conditions and interference complexity, the experimental corpus integrates a wide range of simulated datasets and publicly available communication signal benchmarks. Raw, clean signals include radar echo patterns, impulsive non-speech events, and digital modulation communication frames, with sampling rates ranging from 5 kHz to 20 kHz and durations from 250 milliseconds to 2 seconds. Synthetic interference profiles were created for this study, including wideband, narrowband, burst, and fast frequency-hopping jammers. These interferers randomly appear within the signal window in the frequency range of 100 Hz to 5 kHz, with variable start times and durations. To rigorously test the denoising performance, the augmented dataset covers a range of signal-to-noise ratios (SNR), from 15 dB (extreme interference) to 25 dB (almost no interference conditions).

The following interference is randomly superimposed: device variability introduced by random time distortion, amplitude distortion within the local neighborhood; phase inversion is used to enhance noise simulation. By using this method, the diversity and unpredictability of interference in the system can be ensured. As shown in Figure 3, the cases at both ends have typical characteristics: clean signals, jammers, and synthetic attacks on the spectrum, in order to demonstrate the richness and complexity of our signal database.

Evaluation Metrics

The denoising effect will be chosen based on various factors. The improvement of the signal-to-noise ratio (SNR) after processing is an important indicator. The mean squared error (MSE) function can be directly used to represent the reconstruction loss. A strong robustness index has been added to identify the system's sensitivity to interference attacks. Under different conditions, the performance of the combined structure is the same as that of other structures. To summarize the data distribution, Figure 4 shows a bar chart of the total signal duration statistics and a histogram of SNR variations.

The sensitivity of all indicators was carefully examined under different interference intensity and modulation intensity levels. This proves to be reliable and sufficient when comprehensively evaluating performance. Improved SNR can measure the extent of noise reduction. When dealing with spectral leakage and non-stationary artifacts, it may underestimate their impact in terms of the linear relationship with mean squared error (MSE). After partitioning the output, additional statistical validation based on interference categories and signal-to-noise ratio levels was conducted to overcome the aforementioned shortcomings. The hidden performance differences are masked by global averaging.

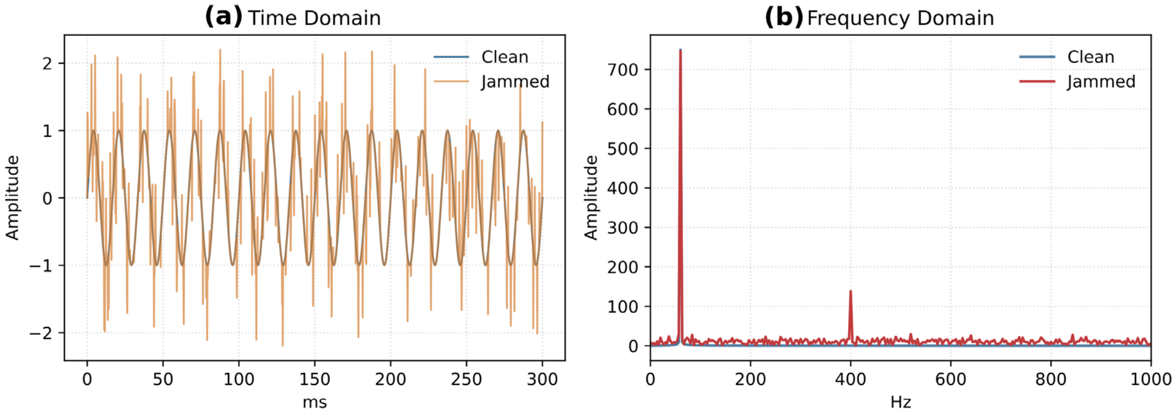


Figure 3. Sample Data Distributions in Time and Frequency Domains:(a) Time-domain waveform comparison;(b) Frequency-domain spectrum comparison

As shown in the bar chart in Figure 4(b), when considering the under-variable condition, there is still a certain degree of consistency among the denoising results of different lengths. In contrast, the differences in short pulse signals are relatively small. A multi-indicator report is needed for a comprehensive assessment; in particular, in such systems, transient disruptors and irregular bursts frequently occur. Based on this idea, a measurement system can be established to provide a fair reference for evaluation. It also emphasizes the multidimensional nature of generalization and its reliability in application.

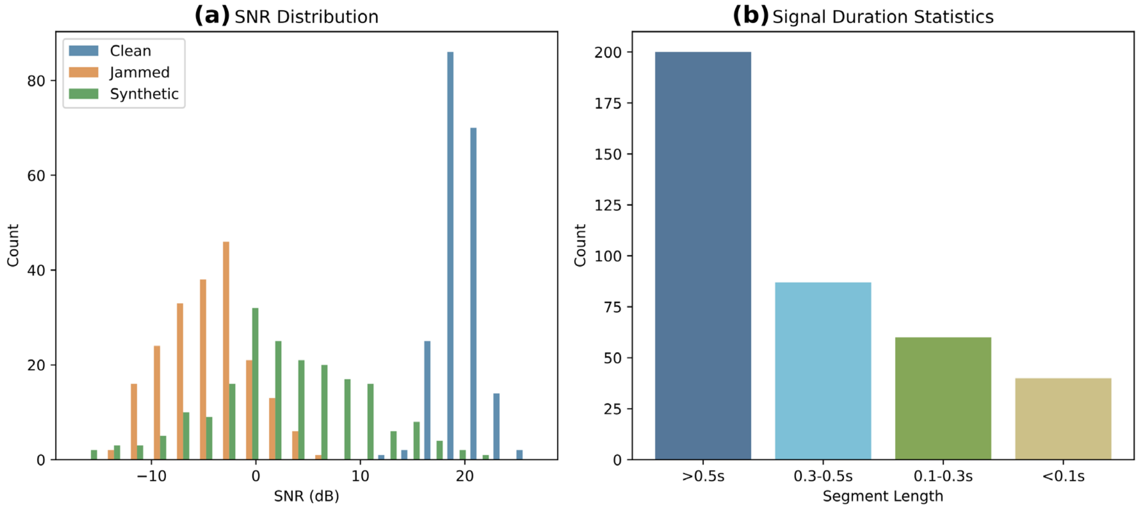


Figure 4. Comparative Signal Statistics Across Datasets:(a) Distribution histogram (SNR/noise levels); (b) Signal duration bar chart

Baseline and Implementation Details

The experiment analyzed various methods. These methods include classical filters (such as Wiener filters and adaptive notch filters); blind source separation techniques (such as ICA and SOBI); and deep learning methods (such as convolutional autoencoders, recurrent denoising networks, and state-of-the-art single-domain transformer models). In order to perform denoising (rather than classification) under a unified evaluation scheme, all methods are optimized thru grid search. The model training and testing were conducted in a multi-machine environment with dual NVIDIA A100 GPUs, each with a memory capacity of 80GB. The octa-core CPU accelerates data shuffling and preprocessing tasks. The network parameters include a four-layer parallel transformer branch, with eight attention heads in each layer. In order to balance factors such as expressive power and performance constraints, an embedding size of 128 was chosen.

All training and testing phases were completed thru online normalization. Early stopping and cross-validation maintain the model's generalization ability by avoiding overfitting to specific interference patterns. By measuring the average forward pass latency and FLOP count, it is demonstrated that its performance is suitable for real-time and low-performance terminal devices. This design combination directly provides a comprehensive environment that includes benchmark and ablation experiment comparison tests.

Comparative Analysis

According to quantitative tests, DDT achieved better signal recovery under various mixed interference conditions compared to the aforementioned three methods. Figure 5 shows that DDDT can achieve significant signal-to-noise ratio improvements in various parts of the interference area. Due to the smoothness and monotonicity of its gain function, its input SNR is greater than -10 dB, while traditional denoising methods cannot perform effectively under non-stationary or frequency-hopping attacks. The upper part of Figure 5a shows the gain; each item in Figure 5b shows the increase in errors produced by traditional heuristic algorithms and deep learning baselines when dealing with volatility or severe interference.

Figure 5c shows the accuracy of denoised symbol recovery thru a box plot. Compared to other models, DDDT shows an improved accuracy baseline and significantly reduced variance, indicating its reliability under mixed and composite interference. The robustness trajectories in Figure 5d confirm these findings: the robustness metrics of DDDT show almost no decline across dynamically changing attack types and signal-to-noise ratio levels, while the comparative models exhibit significant collapse or flattening.

Non-fusion deep networks have drawbacks when dealing with time-varying or multi-domain interference, as shown in Figure 5. The accuracy has stagnated, the signal-to-noise ratio improvement has declined, while DDDT has shown stable performance. Reliability should ensure the effectiveness of task-based signal recovery in practice.

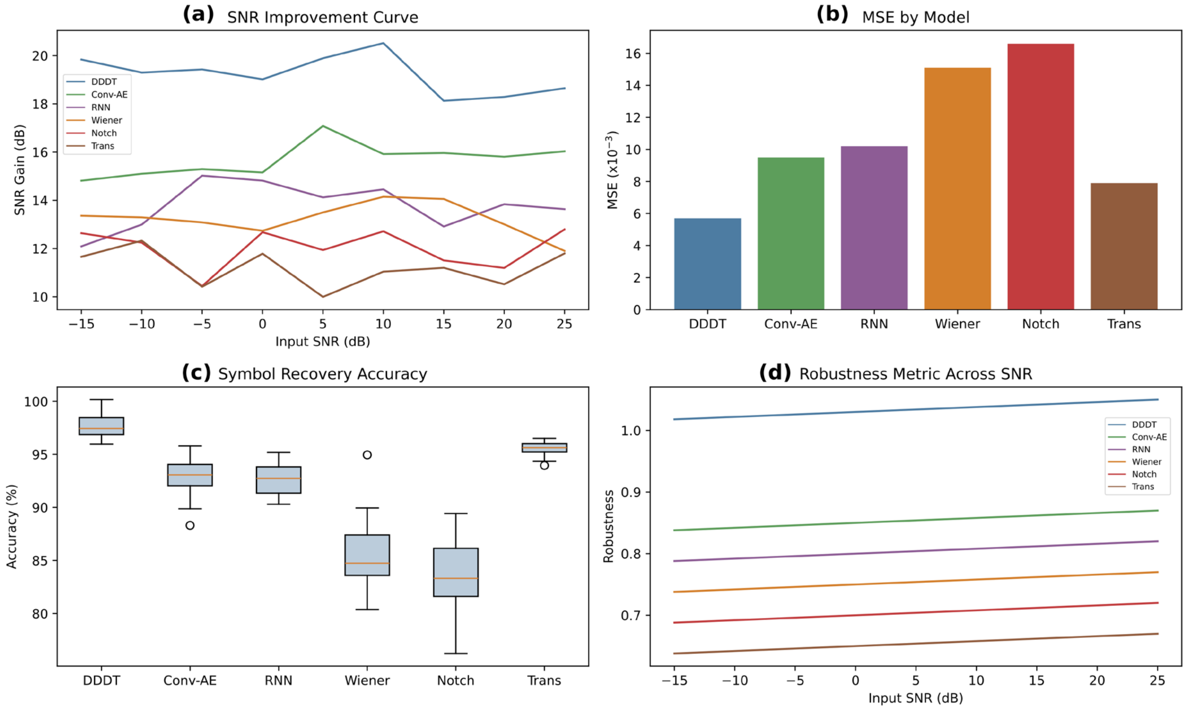


Figure 5 Reconstruction Results under Various Interference Conditions: (a) SNR improvement curves; (b) MSE bar chart; (c) Accuracy box plot; (d) Robustness curves

The aggregation of results in Table 1 demonstrates DDDT's clear edge, a position anchored by both metric leads and reduced error variability.

Table 1. Quantitative Comparison of DDDT and Other Methods

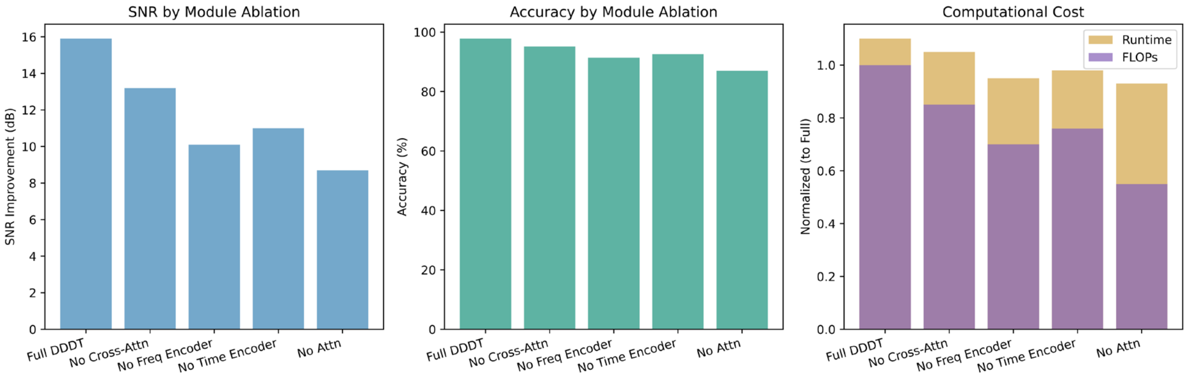
Method	**SNR Improvement (dB)**	**MSE $(\times10^{-3})$**	**Mean Accuracy (%)**	**Robustness $(\Psi_{(\text{robust})})$**
DDDT	15.9	5.7	97.8	0.91
Conv-AE	11.2	9.5	93.0	0.75
RNN-Denoiser	10.4	10.2	92.4	0.71
Wiener	8.1	15.1	84.9	0.55
Notch Filter	7.7	16.6	83.2	0.51
Transformer (Single-Domain)	12.1	7.9	95.4	0.80

Due to these cross-metric and cross-attack validations, DDDT demonstrates reliable recoverability and operational scalability in real signals under simulation and laboratory disturbances.

Ablation Study

Thru ablation experiments, the contribution of the DDDT core module was studied. Figure 6 shows the impact of progressively disabling the dual-domain or attention mechanism. As shown in Figure 6(a), omitting the dual-branch encoding leads to a decrease in accuracy and a significant drop in the signal-to-noise ratio. Under broadband interference, the lack of spectral features disproportionately degrades performance, while removing temporal attention weakens the defense against impulsive bursts.

As shown in Figures 6(b) and 6(c), removing any encoder will have a significant impact on the signal-to-noise ratio and accuracy. The corresponding decline in the metric curves and changes in error distribution indicate this. Based on the analysis of FLOPs and runtime (Figure 6(c)), the complete DDDT architecture does not require additional computational costs. Considering the support of parallel hardware, the incremental increase brought significant performance improvements and highlighted the efficiency of the architecture.



(a) **(b)** **(c)**

Figure 6. Ablation Study: Performance of Model Variants: (a) Model performance comparison; (b) SNR/accuracy by ablation; (c) Computation vs. effect

Dual-branch encoding and adaptive attention are the fundamental requirements of this project. Single-domain variants and no attention become more unreliable when dealing with closely spaced interference targets. According to the ablation experiments, this design requires operational resilience.

By conducting a comprehensive examination of the ablation model, some conclusions can be drawn regarding system design and deployment practices. In operational stress tests conducted with rapid interference sequences, the characteristics of the dual-domain and attention modules significantly enhanced the robustness and temporal consistency of both domains, and these characteristics showed remarkable improvement when considered independently. The failure cases found in the ablation model not only exhibited greater time delays but also lost phase consistency of the signal. These failure cases did not occur in the complete DDDT. If there is no cross-domain fusion model to handle interruptions caused by mutations due to interference domains or spectrum band occupancy during live simulation implementation, the error rate will soar because there is no method to dynamically adjust the representation. Stable or single-channel denoising methods are insufficient to cope with future dynamically changing environments; whether the scaling parameters continue to function normally.

The operation profile indicates that single-domain or non-focused settings slightly reduce the computational load of inference time. More frequent catastrophic decoding errors require expensive system-level error handling mechanisms or retransmissions, which counteracts the reduction in computational load. DDDT, while reducing computational costs, provides measurable improvements in error detection and anti-interference capabilities when used independently, as well as enhanced continuity of functional services and self-maintaining communication.

Case Studies and Applications

When DDDT is applied to real-world scenarios, such as automotive radar, IoT mesh gateways, and urban wireless telemetry, the laboratory gains under uncontrolled interference have been confirmed. Wireless systems use fast-drifting interferers, radar systems use impulse noise, and IoT systems use dense multipath backgrounds. Figure 7 overlays the multi-method results of captured urban fading and interference events. Figure 7(a) shows the recovery in the time domain and frequency domain, while Figure 7(b) shows the recovery in the frequency domain. Only thru DDDT can phase and amplitude consistency be maintained, the superimposed envelope is consistent with the actual situation, and the baseline trajectory is interrupted or delayed under spectral bursts.

The attention map in Figure 7c has been analyzed in detail. The figure shows how the network allocates attention load. During frequency drift, the network only shifts attention to the spectral band, and then shifts attention to temporal cues when impulsivity increases. This behavior enables real-time systems to interpret and adapt.

As shown in Figure 7d, DDDT achieves over a 40% reduction in error rate in IoT and millimeter-wave radar, while maintaining system response within 15 milliseconds. The hardware blocking design ensures compatibility between the edge processor and the server, enabling ubiquitous and resilient deployment.

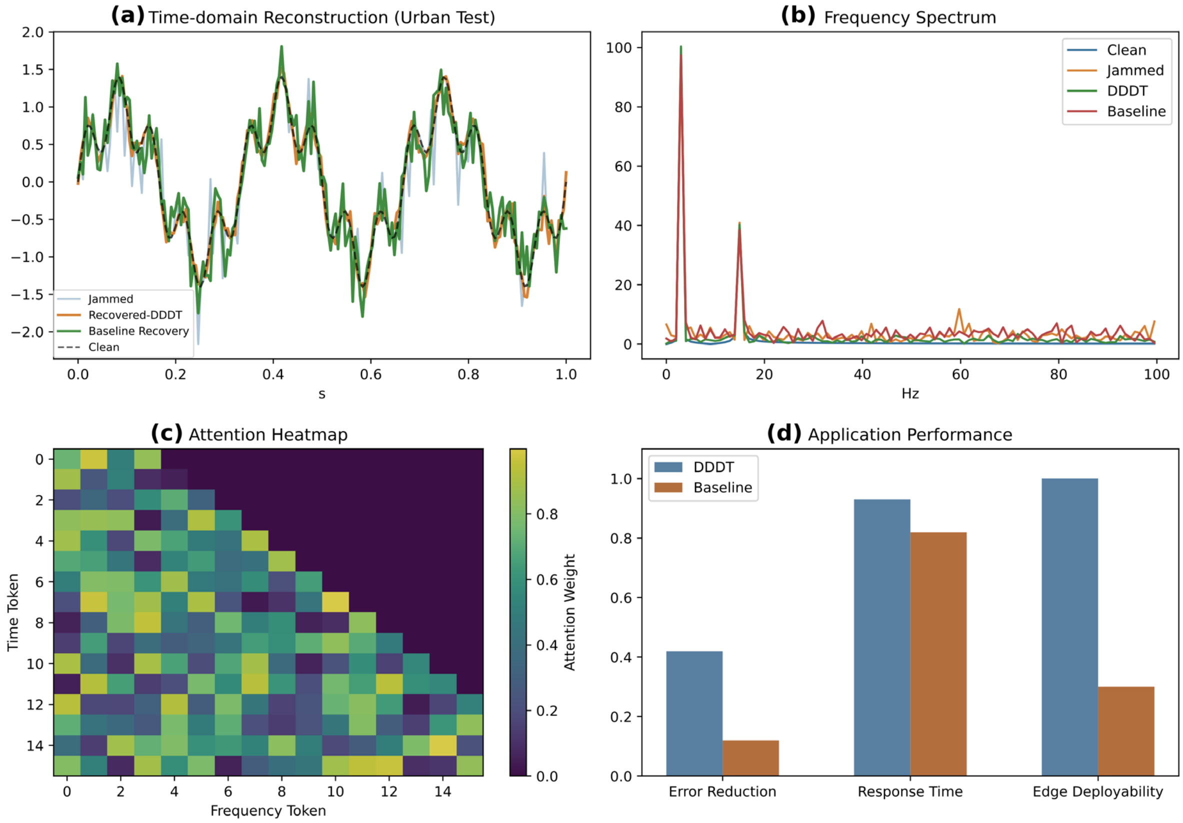


Figure 7. Real-world Signal Recovery: Case-by-Case Comparison: (a) Time-domain reconstruction, multi-method overlay; (b) Frequency-domain comparison; (c) Attention map/feature illustration; (d) Application metric bar chart

DDDT has advantages in high computational efficiency adaptability because it can effectively implement cross-domain attention mechanisms, thereby being able to handle tasks with noise.

Based on how to evaluate whether using DDDT in resource-constrained environments will affect efficiency and effectiveness. The attention-guided domain fusion of DDDT remains effective on edge devices and does not degrade performance due to quantization or adaptive pruning. It has been validated on IoT devices with different power consumption configurations, clock speeds, and other factors. These factors usually lead to unstable performance in heavyweight or non-modular networks. Monitor the continuous updating process of attention weights and use it in practical applications to compensate for minor hardware issues or short-term sample fluctuations.

Theoretically, it is not possible to directly assess whether the application of DDDT's architectural design has achieved the same results as other technical methods. DDDT exhibits stable tracking performance in dynamic environments, which may cause failures in older filters or neural network modules. These test scenarios involve real-time multi-vehicle wireless and radar systems. These findings are not only of significant academic importance but also have an impact on the design of industrial safety-related and autonomous communication systems.

Conclusions

This paper introduces a method to improve signal recovery stability, which is based on multiple channels and environmental interference, with these interferences being considered adverse conditions. DDDT is clearly superior to traditional filters and many state-of-the-art deep learning methods. As the interference variation increases, the difference between DDDT and other methods becomes more pronounced. In the comprehensive comparison, DDDT achieved the best improvements in terms of signal-to-noise ratio (SNR), low reconstruction error, and high classification accuracy, demonstrating stability under complex adversarial attacks.

From a technical perspective, DDDT provides a beneficial cross-attention integration mechanism and an adaptive two-dimensional domain design mechanism. By using the above design, it is possible to selectively and real-time collect information based on the spectrum and time-varying factors. This will make independent time-domain or frequency-domain analysis more effective, as it can meet the basic requirements. Ablation experiments have demonstrated the importance of dual-domain representation and adaptive attention mechanisms. Reasonable conclusions were reached regarding the improvement in accuracy and the complexity of training. Due to the model's parallelization characteristics, it can be successfully deployed on GPUs in cloud environments and low-resource edge scenarios without any adjustments to its performance and denoising capabilities.

Due to its plug-and-play interoperability, fast inference time, and interpretable attention visualization, DDDT is highly suitable for use in wireless communication, IoT, and radar systems. In addition to strict testing environments, DDDT is also capable of functioning properly in various real-world environments. These environments include non-stationary fading, short-term interference bursts, and dense multipath noise. This design can adapt to hardware changes and automatically adjust resource allocation or environmental uncertainties. Directly leading to lower retransmission rates and longer service life, these are the foundation for the stable operation of industrial and safety system links.

There are still several flaws that need further research. Using supervised learning with labeled interference scenarios, but in practical applications, new modifications or unknown attacks not included in the training dataset may occur. Ultra-low latency and ultra-low power deployments (such as battery-free IoT or energy-harvesting sensors) may require future algorithm adjustments or hardware-software co-design, although architectural parallelism can reduce computational overhead. Further research on self-supervised pre-training, continuous training, and low-precision attention applications is needed to enhance the model's adaptability in different environments.

Combining the latest research on training DDDT with specific signal information learned during training, new standards for signal interference recovery are being established. Combining its structure and support for new devices, it is possible to provide reliable, real-time, and easy-to-understand denoising functions for the next generation of wireless sensing systems. Unsupervised adaptation, automatic domain generalization, and seamless integration into dynamic communication or sensing frameworks are all future research areas.

Author Contributions

Raluca Preda and Simona Marin contribute to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Bianca Ionescu, contributes to methodology, software, validation, analysis, investigation. All authors have read and agreed with the manuscript before its submission and publication.

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