Adaptive Suppression Algorithm for Communication Signal Clutter Interference under Integrated Sensing and Communication System

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Abstract: Integrated sensing and communication (ISAC) systems integrate communication and sensing functionalities by sharing spectrum and hardware resources. Nevertheless, strong clutter components generated by ground object reflection of communication signals will submerge weak target echoes, severely degrading sensing performance. To address the failure of fixed-coefficient suppression methods in non-stationary clutter environments, this paper first analyzes the distribution discrepancies between clutter and target echoes in the range-Doppler domain, and then proposes an adaptive clutter suppression algorithm combining subspace projection and recursive least squares (RLS) estimation. Leveraging the structural property that clutter concentrates in the zero-Doppler region, the algorithm constructs a clutter subspace. It updates projection coefficients online via a variable forgetting factor to track environmental variations, and reduces iterative computational complexity to nearly quadratic order by exploiting the low-rank characteristic of the covariance matrix. Simulation results reveal that under an urban macro-cell non-stationary clutter scenario with a signal-to-clutter ratio (SCR) of -15 dB, the proposed algorithm improves the signal-to-interference-plus-noise ratio (SINR) by approximately 8 dB compared with classical cancellation methods. With a false alarm probability constraint of 10^{-6}, the target detection probability reaches 0.92, and the processing latency is less than 0.5 ms. The algorithm balances suppression performance and real-time requirements, providing a feasible scheme for the engineering implementation of the sensing link in ISAC systems.

Keywords: Integrated Sensing and Communication; Clutter Suppression; Subspace Projection; Recursive Least Squares; Interference Cancellation

1. Introduction

As a core enabling technology for the sixth-generation mobile communication (6G), integrated sensing and communication realizes deep integration of communication and sensing through shared spectrum and hardware resources, effectively alleviating spectrum scarcity and system energy consumption issues. However, when communication signals serve simultaneously as sensing probing waveforms, strong clutter components formed by reflections from stationary terrain, sea surfaces and building clusters tend to completely mask faint target echoes, drastically impairing system sensing performance. Traditional fixed-coefficient suppression schemes cannot adapt to complex time-varying environments, which creates an urgent demand for adaptive clutter suppression algorithms capable of environmental awareness. Centered on the clutter interference suppression of communication signals in ISAC systems, this paper analyzes the distribution differences between clutter and target echoes in the range-Doppler domain, establishes an adaptive filtering framework, develops an interference suppression method combining subspace projection and recursive least squares estimation, and verifies the robustness and effectiveness of the proposed algorithm in non-stationary clutter environments via simulations[1].

2. ISAC System Model and Analysis of Clutter Interference Characteristics

2.1 System Architecture and Signal Model

The ISAC system relies on dual-functional base stations to simultaneously perform communication data transmission and environmental sensing on a unified hardware platform. Distinct from the traditional separated radar and communication configuration, this architecture shares antenna arrays, radio frequency (RF) front-ends and signal processing resources, physically realizing spectrum reuse and energy consumption reduction. Orthogonal frequency division multiplexing (OFDM) waveforms transmitted by base stations support both information modulation and detection functions. After subcarrier mapping, communication symbols form a two-dimensional time-frequency resource grid. This framework maintains compatibility with existing communication standards while delivering range-Doppler resolution for sensing processing. The received signal at the receiving terminal consists of three superimposed components: target reflected echoes, environmental clutter, and receiver thermal noise. Among these, clutter originates from reflections of transmitted signals off stationary terrain, building clusters, sea surfaces and other scatterers, with power far exceeding that of target echoes, making it the most intractable interference source in the sensing receiving link. Notably, under the co-located transceiver configuration, transmitted signals directly leak into the receiving channel through antenna coupling and near-field scattering, generating severe self-interference that further limits the receiver's capacity to detect weak echoes. The above signal composition lays a foundation for subsequent clutter characteristic analysis and suppression algorithm design[2].

2.2 Statistical Properties and Range-Doppler Distribution of Clutter

The statistical features of clutter interference vary drastically across application scenarios, and such differences directly dictate the design orientation of suppression algorithms. In urban environments, exterior building walls and ground reflectors form dense scattering networks, leading to widely spatially distributed clutter with sharp amplitude fluctuations, which is generally characterized by Weibull or K-distributions. In marine scenarios, sea spikes induced by wave motion introduce obvious time-varying non-stationary clutter, where conventional fixed-parameter models perform poorly. From the perspective of the range-Doppler domain, stationary clutter clusters within a narrow band near zero Doppler, while echoes from moving targets appear as local peaks at the intersection of specific range and Doppler cells on this plane-these two components possess structurally separable spaces in the transform domain. However, the inherent high sidelobe property of OFDM communication signals causes clutter energy to spread across the range dimension. Sidelobes from adjacent strong clutter cells contaminate the range cells containing targets, submerging weak target echoes beneath the clutter sidelobe floor. This masking effect constitutes the primary bottleneck restricting improvements in sensing performance[3].

2.3 Mechanisms Underlying Clutter's Impacts on Communication and Sensing Performance

Clutter interference impairs ISAC systems along both communication and sensing links, with coupling effects existing between the two paths. For the communication link, superimposed strong clutter degrades the signal-to-noise ratio (SNR) for channel estimation. Clutter contamination on pilot symbols generates biases in frequency-domain channel response estimation, which propagate to all data symbol blocks through equalization and ultimately trigger a sharp rise in bit error rate (BER). For the sensing link, clutter masking exerts a more direct impact: when clutter power exceeds target echo power by more than 20 dB, target detection probability drops below 0.1 even after matched filtering, and the estimation accuracy of range and velocity parameters deteriorates drastically. A more subtle influence stems from the shared receiving channel for communication and sensing. Nonlinear processing modules introduced to guarantee communication demodulation performance, such as automatic gain control (AGC), compress the amplitude dynamic range of echo signals, resulting in further precision loss of faint target echoes during quantization. This indicates that clutter mitigation cannot rely solely on isolated optimization of the sensing receiver; joint performance constraints of communication and sensing must be considered at the system level[4].

3. Design of Adaptive Clutter Suppression Algorithm

3.1 Limitations of Conventional Clutter Suppression Approaches

Existing clutter suppression methods fall into three main categories: time-domain cancellation algorithms, transform-domain filtering thresholding methods, and subspace techniques based on eigendecomposition. Cancellation algorithms represented by echo cancellation algorithm (ECA) construct filter models by estimating cross-correlation functions between received and transmitted signals, achieving favorable cancellation performance under stationary clutter. Nevertheless, when clutter statistical properties fluctuate with environmental changes, the fixed filter structure fails to sustain optimal suppression performance, and frequent coefficient reconstruction introduces substantial computational overhead. Transform-domain filtering methods exploit the prior that clutter concentrates in the zero-Doppler region of the range-Doppler domain to design band-stop filters. Their critical flaw lies in the lack of adaptive threshold selection: excessively high thresholds leave residual clutter, while overly low thresholds eliminate valid target echoes. Subspace methods attempt to cancel clutter by projecting received signals onto the orthogonal complement of the clutter subspace via eigendecomposition. However, severe coupling between clutter and target echoes under low SCR conditions leads to aliasing of feature subspaces, substantially degrading suppression performance. A common deficiency across all above methods is the absence of online environmental awareness and adaptive coefficient updating for time-varying clutter, which forms the core motivation for the algorithm proposed in this paper[5].

3.2 Clutter Interference Suppression Framework Based on Subspace Projection

The proposed suppression framework centers on accurate clutter subspace estimation. It projects received signals onto the orthogonal complement of the clutter subspace to effectively eliminate clutter components while preserving target echoes. Specifically, based on the structural characteristic that clutter accumulates near zero Doppler in the range-Doppler domain, multiple target-free range cells are selected as reference data to estimate the clutter covariance matrix. Eigendecomposition is then performed, and the subspace spanned by dominant eigenvectors corresponding to large eigenvalues is defined as the clutter subspace. Since target echoes are approximately orthogonal to the clutter subspace, projection operations induce minor attenuation of target signals. Notably, clutter covariance matrices exhibit prominent low-rank properties in typical scenarios, where their effective rank is far smaller than system degrees of freedom. This characteristic not only provides a criterion for determining subspace dimensionality but also enables subsequent complexity optimization. Compared with conventional eigendecomposition methods that process all feature components indiscriminately, the proposed scheme leverages the physical sparsity of clutter to implement directional suppression, delivering stronger adaptability under non-uniform clutter environments. It is worth noting that projection inevitably introduces mild signal distortion. Quantitatively characterizing how such distortion affects downstream sensing processing represents a core issue requiring resolution during framework design[6].

3.3 Adaptive Least Squares Estimation and Coefficient Updating Strategy

Fixed-coefficient projection matrices cannot handle slow or abrupt variations in clutter statistical properties over time. Recursive least squares criteria are therefore adopted to realize online adaptive adjustment of suppression coefficients. Unlike classic least mean square (LMS) algorithms, RLS weights historical observation data via an exponential forgetting factor, enabling filter coefficients to track environmental shifts at a faster rate while eliminating the inherent drawback of gradient-based algorithms' sensitivity to step-size parameters[7]. The selection of the forgetting factor represents a trade-off between tracking speed and steady-state error: a smaller forgetting factor assigns higher weights to new data, enhancing environmental adaptability yet increasing steady-state misadjustment, whereas a larger forgetting factor yields the opposite effect. This paper adopts a variable forgetting factor strategy that dynamically adjusts the forgetting factor according to short-term clutter power estimates. The memory window is narrowed to accelerate response during rapid clutter fluctuations and widened to reduce steady-state error under relatively stable clutter conditions. The coefficient updating process is implemented recursively using the matrix inversion lemma, avoiding prohibitive computational costs associated with direct matrix inversion in each iteration. Furthermore, taking advantage of the natural synchronization between the communication signal frame structure and sensing processing cycles, coefficient updates are executed within the cyclic prefix interval of each OFDM symbol, minimizing interference of the adaptive process on data throughput.

3.4 Low-Complexity Implementation and Real-Time Optimization

From an engineering implementation perspective, computational overhead from subspace decomposition and recursive updates constitutes the primary barrier limiting practical deployment of the algorithm. The computational load of conventional eigendecomposition grows cubically with covariance matrix dimensionality, failing to meet real-time processing requirements of ISAC systems. Two structural optimizations are proposed in this paper: First, random numerical linear algebra methods are introduced to conduct approximate eigendecomposition by exploiting the low-rank property of clutter covariance matrices, reducing per-iteration computational complexity from $O(N^3)$ to nearly $O(N^2)$ with acceptable decomposition precision loss for engineering applications. Second, a block adaptive processing strategy is adopted: subspace estimation is executed a limited number of times within one coherent processing interval (CPI) rather than symbol-by-symbol real-time decomposition. This drastically cuts coefficient update frequency with performance degradation limited to less than 0.8 dB, freeing valuable computing resources for baseband processors. The above optimizations compress total algorithm processing latency to less than half the OFDM symbol period, satisfying real-time constraints of typical sensing scenarios. It should be clarified that complexity optimization must not compromise algorithm robustness[8]. The proposed dimensionality reduction retains dominant structural features of the clutter subspace, ensuring optimized algorithm performance closely matches that of full-dimensional processing under non-stationary clutter environments.

4. Simulation and Comparative Analysis of Algorithm Performance

4.1 Simulation Scenario and Parameter Configuration

A simulation platform replicating practical deployment environments is constructed to comprehensively evaluate the effectiveness of the proposed algorithm. System parameters are configured as follows: system bandwidth 100 MHz, carrier frequency 3.5 GHz, subcarrier spacing 30 kHz, transmit power 43 dBm, OFDM waveform, subframe duration 1 ms. The clutter scenario follows urban macro-cell propagation environments, incorporating 30 primary scatterers and multiple diffuse reflectors with low radar cross section (RCS). The SCR varies randomly from -20 dB to 0 dB to simulate temporal evolution of non-stationary clutter environments. Classical ECA time-domain cancellation and fixed-threshold transform-domain filtering are selected as benchmark algorithms. Evaluation metrics include SINR improvement, target detection probability, range and velocity estimation error, and single-frame processing runtime. The target is set as a small unmanned aerial vehicle (UAV) with radial velocity 15 m/s, RCS 0.01 m^2, located approximately 120 m from the base station. Under this parameter setup, target echo power is 15–20 dB lower than clutter power, accurately reproducing the challenge of weak target detection against strong clutter backgrounds. Monte Carlo simulations run independently for 500 trials to guarantee statistical reliability; positions and scattering coefficients of clutter scatterers are randomly regenerated for each simulation run[9].

4.2 Assessment of Interference Suppression Performance Under Non-Stationary Clutter Environments

Distinct performance hierarchies emerge across the three algorithms under non-stationary clutter with time-varying SCR. Classical ECA delivers acceptable performance under high SCR conditions through precise cancellation of transmitted signal replicas. However, when scatterer positions shift or scattering coefficients abruptly change in the environment, its fixed filter structure cannot respond promptly, leading to severe fluctuations in SINR improvement, with an average gain of merely 9.6 dB at SCR = -15 dB. Fixed-threshold transform-domain filtering achieves stable suppression under stationary clutter by leveraging energy aggregation in the range-Doppler domain, yet mismatches between thresholds and actual clutter power induce substantial performance fluctuations in time-varying scenarios. In contrast, the proposed algorithm tracks real-time clutter subspace variations via RLS coefficient updates. At SCR = -15 dB, it achieves an SINR improvement of 17.5 dB-an approximately 8 dB gain over ECA and a 5 dB gain over transform-domain filtering-with performance fluctuation controlled within 1.2 dB. In terms of target detection probability under a false alarm probability constraint of 10^{-6}, the proposed algorithm maintains a detection probability of 0.92 even at SCR = -18 dB, outperforming the two benchmark algorithms by 0.35 and 0.21 respectively, verifying its robust detection capability under complex non-stationary environments.

4.3 Analysis of Range and Velocity Estimation Accuracy

The ultimate objective of clutter suppression is to enhance target parameter estimation precision. This subsection further investigates residual clutter's impacts on range and velocity measurements post-suppression. Range estimation adopts matched filter peak detection, while velocity estimation is obtained via spectral peak interpolation within the same range cell. Simulation results indicate that without clutter suppression at SCR = -15 dB, the root mean square error (RMSE) of range estimation reaches 8.7 m and velocity estimation RMSE hits 2.3 m/s; under such conditions, targets are fully masked by clutter sidelobes and valid measurements cannot be generated. After processing via the proposed algorithm, range estimation RMSE drops below 0.6 m and velocity estimation RMSE falls to 0.18 m/s, nearly approaching theoretical bounds under clutter-free conditions, demonstrating that residual clutter interference on parameter estimation is suppressed to a negligible level. Notably, ECA achieves comparable estimation accuracy under high SCR, yet its estimation errors degrade rapidly when SCR decreases below -18 dB, exhibiting an obvious threshold effect. This phenomenon reveals fundamental differences in clutter suppression depth across strategies: ECA's cancellation capacity is constrained by correlation estimation precision between reference signals and clutter components, whereas subspace projection delivers more thorough residual clutter suppression. This partially explains the proposed algorithm's capacity to sustain stable precision within low SCR intervals.

4.4 Computational Efficiency and Real-Time Performance Analysis

Practical algorithm value depends not only on suppression performance but also on whether computational overhead meets real-time processing constraints. Single-frame processing duration and resource occupancy of each algorithm are compared on identical hardware platforms. Classical ECA requires only one correlation operation and filtering, with single-frame runtime of approximately 0.21 ms, making it the most computationally efficient among the three benchmarks. Fixed-threshold transform-domain filtering involves two-dimensional Fourier transforms, consuming roughly 0.38 ms per frame. The unoptimized version of the proposed algorithm takes 1.24 ms per frame-though superior in suppression performance, it nearly breaches the 1 ms subframe real-time processing limit. After optimization via low-rank approximation and block updating strategies, single-frame runtime is reduced to 0.46 ms, merely 21% longer than transform-domain filtering while delivering substantial performance gains. Further analysis of module runtime distribution reveals subspace updating accounts for nearly half of total processing time, indicating that future optimization priorities should target eigendecomposition acceleration. It should be noted that the above tests are conducted on general-purpose processors; real-time performance can be further improved if deployed on base station-specific vector processors or field-programmable gate arrays (FPGAs). Under the configuration of 100 MHz bandwidth and 1 ms subframe duration, the optimized algorithm achieves processing latency below 0.5 ms, retaining sufficient margin for cascaded data demodulation and sensing processing.

4.5 Parameter Sensitivity and Robustness Verification

Engineering deployment of adaptive algorithms inevitably faces parameter selection challenges. This subsection analyzes the influences of forgetting factor, block length and SCR variation rate on algorithm performance. When the forgetting factor varies between 0.95 and 0.99, SINR improvement fluctuates by no more than 1.5 dB, indicating low algorithm sensitivity to this parameter-engineers may adopt fixed values to achieve near-optimal performance for practical applications. Experiments on block length reveal a noteworthy trend: as block length increases from 16 to 64 symbols, SINR improvement first rises then slightly declines, peaking at 32 symbols. Excessively short blocks result in insufficient samples for subspace estimation and exacerbate ill-conditioned covariance matrices, while overly long blocks dilute temporal subspace resolution and weaken tracking capacity for non-stationary clutter. Moreover, when abrupt clutter fluctuations occur multiple times within a single CPI, performance degradation of the proposed algorithm is markedly milder than the two benchmark algorithms. Measured via the coefficient of variation of SINR improvement, the volatility of the proposed algorithm is only one quarter that of ECA. Overall, the algorithm maintains stable suppression performance within a reasonable parameter range, offering strong engineering adaptability and configurable flexibility.

5. Challenges and Future Outlook

5.1 Adaptability Bottlenecks under Complex Scenarios

Despite the favorable suppression performance of the proposed algorithm under non-stationary clutter environments, adaptability shortcomings persist in several extreme scenarios that require attention. When target radial velocity approaches zero, target echoes occupy nearly identical range-Doppler regions as stationary clutter. Subspace projection eliminates clutter while simultaneously attenuating target components, leading to sharp declines in detection probability-this issue is particularly prominent in urban slow pedestrian monitoring and suspended particle detection applications. Furthermore, the algorithm relies on the core assumption of approximate orthogonality between clutter and target subspaces, which breaks down under strong multipath propagation. Multipath transmission induces target echoes to enter the antenna array at multiple incident angles, with partial multipath components projecting onto directions coupled with clutter. This violates strict orthogonality conditions and elevates residual clutter power post-suppression. Estimation of clutter covariance matrices depends heavily on reference training samples, which introduces hidden risks: training samples contaminated by target-like signals pollute the clutter subspace and trigger erroneous elimination of valid target signals. This well-documented problem in traditional space-time adaptive processing (STAP) research also restricts practical deployment of the proposed algorithm. Developing automatic reference sample screening techniques without prior knowledge represents a promising direction for subsequent research.

5.2 Intelligent Clutter Suppression Driven by Combined Data and Model

Model-driven methods are inherently limited by reliance on precise mathematical modeling, while data-driven approaches provide a complementary technical pathway. Deep neural networks possess the capacity to directly learn nonlinear time-varying clutter patterns from extensive measured echo data, enabling end-to-end clutter suppression and target enhancement without accurate prior information. Recent studies have applied convolutional neural networks to sea clutter suppression and faint target detection, achieving performance superior to conventional model-driven methods. Nevertheless, poor interpretability of pure data-driven methods impedes their deployment in safety-critical scenarios-engineers struggle to identify error sources when network outputs contradict physical laws. A paradigm integrating physics-informed and data-driven modeling holds greater research promise: encoding the subspace projection structure from this paper as specialized neural network layers, and guiding network training via sparse constraints and physical structural priors. This approach retains the flexibility of data-driven learning while endowing models with physically interpretable characteristics. Deep unfolding networks serve as a concrete implementation of this concept, mapping each iteration of the proposed algorithm to a single network layer. Such architectures inherit convergence guarantees from model-driven algorithms while leveraging learned parameters to accelerate convergence beyond manually designed iterative formats. Multidimensional communication and sensing data native to ISAC systems naturally form training signals for multi-task learning, which can supply abundant supervision information for training intelligent suppression algorithms.

5.3 System-Level Cooperation and Standardization Promotion

Independent single-node suppression strategies face structural limitations within multi-base station networking scenarios. Transmitted signals from adjacent base stations introduce additional interference to local receivers, and interference characteristics dynamically shift with network topology and service load. Without inter-node coordination, suppression operations across stations may mutually degrade overall performance. Extending the proposed algorithm to a networked collaborative framework to realize joint clutter suppression and interference coordination using shared sensing data across multiple base stations represents an essential step to evolve sensing capacity from single-point to ubiquitous coverage. However, data forwarding overhead and synchronization precision requirements introduced by cooperation create new engineering constraints. In latency-sensitive scenarios, inter-node information interaction delay may exceed the time scale of clutter environmental variation, forcing trade-offs between suppression gain and communication overhead. On the other hand, ISAC technology standardization has entered a critical window, with unresolved issues including reference signal design, frame structure configuration and interference management mechanisms. As a core module of the sensing receiving link, clutter suppression algorithms require unified performance evaluation frameworks to achieve interoperability across equipment vendors, facilitating the transition of ISAC technology from laboratory verification to large-scale commercial deployment.

6. Conclusion

Aiming at severe strong clutter interference from communication signals in ISAC systems, this paper systematically analyzes range-Doppler distribution characteristics of clutter, constructs an echo signal interference model for ISAC systems, and proposes a clutter suppression algorithm integrating subspace projection and adaptive recursive least squares estimation. Simulation results verify that the algorithm significantly improves SINR and target detection probability under non-stationary clutter environments while reducing computational complexity, balancing sensing suppression performance and real-time processing requirements. It should be noted that the proposed method suffers performance degradation under extreme low SCR conditions. Future research will further explore dual data-model driven adaptive suppression architectures combining deep unfolding networks and physics-informed modeling, alongside distributed interference coordination mechanisms for multi-base station collaborative scenarios, to advance the practical deployment of integrated sensing and communication systems.

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