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GWO-optimized sparse Bayesian least squares regression for direction-of-arrival estimation in MIMO networks

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ABSTRACT

Accurate direction-of-arrival (DOA) estimation is a critical requirement for massive multiple-input multiple-output (MIMO) systems operating in fifth-generation (5G) and beyond (5G/B5G) wireless environments. Although sparse Bayesian learning (SBL)–based techniques have demonstrated improved robustness by exploiting signal sparsity, their performance is often limited by fixed hyperparameter selection, sensitivity to noise, and suboptimal residual error minimization. To address these challenges, this paper proposes an optimized sparse Bayesian least squares regression (SBLSR) framework in which grey wolf optimization (GWO) is employed to adaptively optimize Bayesian hyperparameters and regression coefficients. The proposed approach jointly enforces sparsity and minimizes estimation error, enabling robust DOA estimation under dynamic noise conditions and varying network density. Extensive simulations conducted in a massive MIMO environment demonstrate that the optimized SBLSR consistently outperforms conventional SBLSR and state-of-the-art benchmark techniques in terms of root mean square error (RMSE), closely approaching the Cramér–Rao lower bound (CRLB) across a wide range of signal-to-noise ratios, sensor configurations, and Monte Carlo trials. The findings validate that the suggested optimized SBLSR framework offers a noise-resilient solution for high-precision DOA estimation in practical massive MIMO and MIMO radar systems.

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1. INTRODUCTION

Future wireless communication systems need to support more applications, like smart cities, driverless cars, disaster monitoring, and large-scale internet of things (IoT) deployments. All above-mentioned technologies require accurate spatial sensing and low-latency signal processing [1]. Beyond fifth-generation (5G) networks meet these needs by using multiple-input multiple-output (MIMO) architectures, which enhance spectrum efficiency and spatial resolution by using a huge antenna array [2]. At the same time, mobile edge computing has become a key enabler for distributed intelligence and real-time processing, especially in mission-critical and unmanned aerial vehicle (UAV)-assisted sensing applications [3]. Present innovations in array design that include coprime and meta surface-assisted MIMO topologies have proved significant advancements in localization accuracy and angular resolution [4], [5]. Sparse antenna reconfiguration methods have been introduced to decrease hardware while maintaining good direction-of-arrival (DOA) estimation performance, which suits them for huge-scale MIMO setups [6].

Notwithstanding these inventions, the high computational complexity, susceptibility to noise, and decreased performance in low-signal-to-noise ratio (SNR) and correlated-signal conditions make DOA estimation difficult and challenging. Algorithms for DOA estimation, utilizing data driven and machine learning methodologies, have been explored to address these limitations, achieving enhanced accuracy in hybrid and massive MIMO infrastructures [5]. Still, their dependence on large amounts of training data and high processing costs makes them unsuitable for situations that change rapidly. Standard signal processing techniques, such as co-prime array-based DOA prediction methods, demonstrate reliable performance under certain conditions; however, they often lack robustness in real-time environments [7]. In practical situations, factors such as non-uniform noise, mutual coupling, and hardware issues make DOA estimation even less accurate. Suggested fast sensor array processing techniques aim to reduce computational overhead; however, their accuracy is compromised in noisy, snapshot-constrained environments [8].

Advanced radar architectures, such as frequency diversity array (FDA)-MIMO systems, have been developed to improve target localization by leveraging additional degrees of freedom, making reduced-dimension processing, and improving DOA estimation accuracy [9]. Proposed techniques for reduced complexity three-dimensional DOA estimate in auditory and electromagnetic sensors seek to optimize computing efficiency while keeping spatial resolution [7]. Nonetheless, these techniques frequently presuppose optimal noise scenarios and accurate array calibration. Noise-aware DOA estimation has attracted considerable demand in recent years. Spectrum-adaptive and colored-noise-resilient estimate methodologies have been devised to alleviate the effects of non-uniform noise conditions [10]. A lot of research has shown that many classical and modern DOA estimate methods don't work well in mixed-field and non-ideal situations, especially in large MIMO systems [11]. Researchers have used distributed MIMO setups and rotating array designs to improve accuracy in indoor and fading environments. However, these methods increase complexity [12]. Calibration-based techniques can make estimates more accurate, but they require precise hardware alignment and more power for processing [13].

Integrated sensing and communication (ISAC) systems have strengthened the connection between signal design and DOA estimation, highlighting the need for mixed optimization methods [14]. Changing antenna setups to estimate signal direction has made MIMO systems more flexible, especially in noisy settings. Sparse reconstruction methods use the fact that signals usually come from only a few directions, so they can estimate where signals come from with fewer measurements [11]. But traditional sparse solvers do not handle noise well and can give wrong results [15], automatically select the most important parts of a signal. This helps them perform better in noisy environments [16]. To make systems more robust, researchers have developed methods that focus on finding simpler solutions, such as ℓ_0-norm minimization and matrix completion. However, these methods often lead to optimization problems that are not convex [17].

Recent research has given importance to low complexity prediction techniques and tensor-based formulations to increase the accuracy of DOA prediction in massive MIMO and radar systems [18]. Techniques that can manage both coherent and uncorrelated sources demonstrate enhanced accuracy but encounter scaling challenges in extensive arrays [19]. Some techniques use the system's layout to find and track signal sources in ISAC systems, but they are less effective when there is a lot of noise [20]. Dividing the antenna array and steering signals together can improve accuracy, but this also slows down the system and makes it more complex [21]. Other methods, such as CUSE-TD, break down signal data in special ways and work well even in difficult situations, but they require a lot of computing power [22]. Machine learning-based MIMO receivers can improve signal direction and accuracy, but they also need significant computing resources [23]. Deep learning can help find signal sources in three dimensions, making the system more robust in moving vehicles and changing environments, but these methods are still hard to use in real time [24]. New signal processing methods for electromagnetic vector sensor (EMVS)-MIMO radar help the system handle noise better, but they require complex hardware. Beam space-based channel estimation methods work well for millimeter-wave systems, but they can be affected by noise and rounding errors [25]. Optimization methods like grey wolf optimization (GWO) are now more important for solving DOA estimation problems. Because of this, GWO is a strong option for adjusting hyperparameters when needed.

Even though there have been big improvements in finding where signals come from, current methods still have problems in large MIMO systems. Common algorithms like MUSIC and ESPRIT are easily affected by noise, can make mistakes, and do not work as well when signals are similar or when there is not much data. Methods that use sparse recovery, like orthogonal matching pursuit (OMP), are more accurate, but they do not work as well when there is a lot of noise or when things change quickly. Most recent sparse Bayesian learning (SBL) methods focus on making results sparse, but they often do not do enough to reduce errors or handle noise. In real 5G and future wireless networks, where speed, noise resistance, and accuracy matter, these issues limit their usefulness. Sparse Bayesian least square regression

(SBLSR) is a strong option for next-generation wireless systems that need scalable DOA estimation and noise handling. It performs well in noisy environments and can be used in tests of large MIMO radar systems with both unrelated and related signals. This improves the accuracy of DOA measurements in real-world situations.

The newness of this work lies in the integration of GWO with the SBLSR framework for adaptive DOA estimation. Unlike conventional SBL approaches that rely on fixed or heuristically selected hyperparameters, the proposed method employs GWO to dynamically optimize the Bayesian hyperparameters and regression coefficients, enabling joint sparsity enforcement and residual error minimization. This adaptive optimization enhances estimation accuracy, improves robustness under low-SNR and ensures stable convergence. Table 1 presents a comparison between the proposed approach and existing DOA estimation methods. In addition, the proposed framework maintains computational efficiency by avoiding expensive matrix decompositions, adapting to large-scale and real-time DOA estimation uses.

Table 1. Comparison of DOA estimation methods

Method	Core principle	Optimization strategy	Noise robustness	Computational complexity	Key limitation
MUSIC	Subspace-based	None	Low (sensitive to noise and correlation)	High ($O(M^3)$)	Requires eigen-decomposition
ESPRIT	Subspace-based	None	Moderate	High	Requires array structure constraints
OMP	Sparse recovery	Greedy selection	Moderate	Moderate	Sensitive to noise and sparsity level
SBLSR	Bayesian + regression	Fixed/heuristic parameters	High	Low ($O(KM^2)$)	No adaptive optimization
Proposed GWO-SBLSR	Bayesian + regression	Adaptive (GWO-based)	Very high	Moderate (controlled)	Slight optimization overhead

2. METHOD

The proposed method combines GWO and SBLSR to estimate the DOA accurately in challenging conditions. It starts by using a wide range of possible signal directions to simplify the received signals according to their angles. A Bayesian least squares regression model with Gaussian priors is used to estimate sparse source coefficients. Hyperparameters control the effects of sparsity and noise. GWO is used to adaptively tune these hyperparameters by minimizing the Bayesian reconstruction error. This makes convergence and estimation more accurate. After the optimized sparse coefficients are used to make a spatial spectrum, peak detection is used to find DOAs. This hybrid architecture is scalable for huge MIMO applications and offers strong performance in poor SNR and limited snapshots.

2.1. Massive multiple-input multiple-output system model

Consider M antenna elements in a uniform linear array (ULA) deployed at the base station of a massive MIMO system [5]. Let $K \ll M$ narrowband far-field sources arriving at antenna elements from unknown directions as given in (1).

$$\theta = [\theta_1, \theta_2, \dots, \theta_K] \tag{1}$$

The received signal at the antenna array for the t^{th} snapshot is modeled as given in (2).

$$\mathrm{y}(t) = \mathrm{A}(\theta)\mathrm{s}(t) + \mathrm{n}(t) \tag{2}$$

Where $\mathrm{y}(t) \in \mathbb{C}^{M\times 1}$ is the received signal vector, $\mathrm{A}(\theta) = [\mathrm{a}(\theta_1), \dots, \mathrm{a}(\theta_K)] \in \mathbb{C}^{M\times K}$ is the array manifold matrix, $\mathrm{s}(t) \in \mathbb{C}^{K\times 1}$ denotes source symbols, $\mathrm{n}(t) \sim \mathcal{CN}(0, \sigma_n^2\mathrm{I})$ is additive white Gaussian noise.

2.2. Sparse representation framework

The angular domain is discretized into a fine grid of G potential directions as in (3). This yields an overcomplete dictionary as in (4).

$$\Theta = \{\tilde{\theta}_1, \tilde{\theta}_2, \dots, \tilde{\theta}_G\}, G \gg K \tag{3}$$

$$\Phi = [\mathrm{a}(\tilde{\theta}_1), \mathrm{a}(\tilde{\theta}_2), \dots, \mathrm{a}(\tilde{\theta}_G)] \in \mathbb{C}^{M\times G} \tag{4}$$

The received signal is reformulated as in (5).

$$\mathrm{Y} = \Phi \mathrm{X} + \mathrm{N} \tag{5}$$

Where $\mathrm{Y} \in \mathbb{C}^{M\times T}$ is the measurement matrix and $\mathrm{X} \in \mathbb{C}^{G\times T}$ is the sparse signal matrix, $N \sim CN(0, \sigma_n^2\, I)$ represents noise. Only K rows of X are non-zero, corresponding to the true DOAs [4].

2.3. Sparse Bayesian least squares regression model

In the proposed SBLSR [17] framework, sparsity in the angular domain is enforced by modeling each row of the source coefficient matrix X with a zero-mean complex Gaussian prior, as expressed in (6). The variance hyperparameters γ_g control the activity of each potential direction, enabling automatic relevance determination by promoting sparsity in the solution. The statistical relationship between the observed measurements and the sparse coefficients is captured through the Gaussian likelihood function given in (7), which assumes additive white Gaussian noise with variance σ_n^2.

$$p(\mathrm{X} \mid \gamma) = \prod_{g=1}^{G} \mathcal{CN}\,(\mathrm{x}_g \mid 0, \gamma_g \mathrm{I}) \tag{6}$$

$$p(\mathrm{Y} \mid \mathrm{X}, \sigma_n^2) = \mathcal{CN}(\mathrm{Y} \mid \Phi\mathrm{X}, \sigma_n^2 \mathrm{I}) \tag{7}$$

By applying Bayes' theorem and minimizing the mean square error, the posterior mean of X is obtained as (8). By jointly exploiting the prior and likelihood models, the posterior distribution of X is derived, and the Bayesian least squares estimator in (9) yields the posterior mean of the sparse coefficients. The diagonal matrix Γ, formed by the hyperparameters γ_g, adaptively weights the contribution of each dictionary atom, leading to accurate and noise-resilient DOA estimation.

$$p(X \mid Y, \gamma, \sigma_n^2) \propto p(Y \mid X, \sigma_n^2)\, p(X \mid \gamma) \tag{8}$$

$$\widehat{\mathrm{X}} = \Gamma\Phi^H (\Phi\Gamma\Phi^H + \sigma_n^2 \mathrm{I})^{-1} \mathrm{Y} \tag{9}$$

Where $Y \in \mathbb{C}^{M\times N}$ denotes the received signal matrix, $\Phi \in \mathbb{C}^{M\times G}$ is the sensing (steering) matrix, $X \in \mathbb{C}^{G\times N}$ represents the sparse source coefficient matrix, and N denotes additive noise. The hyperparameter vector $\gamma = [\gamma_1, \gamma_2, \dots, \gamma_G]$ controls sparsity, and $\Gamma = \mathrm{diag}(\gamma)$. The noise variance is denoted by σ_n^2.

2.4. Grey wolf optimization -based hyperparameter optimization

To further improve sparsity enforcement and accelerate convergence, GWO is incorporated to optimize the Bayesian hyperparameter vector γ, as defined in (10). The optimization procedure is guided by a fitness function indicated in (11), that decreases the reconstruction error. The first part of the fitness function guarantees that the observed measurements and the reconstructed signals are exactly aligned.

The next part controls high hyperparameter values to impart sparsity regularization. GWO follows the social and predatory character of ey wolves, with the alpha, beta, and delta wolves leading the search process [13]. Using repeated position adjustments and encircling strategies, GWO adaptively optimizes the hyperparameters, facilitating effective sparsity regulation, enhanced estimation precision, and consistent convergence in DOA estimation. In contrast to conventional SBLSR, where hyperparameters are updated using fixed or heuristic rules, the proposed method employs GWO to iteratively update the hyperparameter vector γ. At each iteration, candidate solutions represent different hyperparameter configurations, and their fitness is evaluated using the objective function in (10). Based on the positions of the alpha, beta, and delta wolves, the hyperparameters are adaptively updated to minimize reconstruction error, leading to improved sparsity and estimation accuracy.

$$\gamma = [\gamma_1, \gamma_2, \dots, \gamma_G] \tag{10}$$

$$\mathcal{F}(\gamma) = \| \mathrm{Y} - \Phi\widehat{\mathrm{X}} \|_F^2 + \lambda \sum_{g=1}^{G} \gamma_g \tag{11}$$

The convergence behavior of the proposed approach is supported by the inherent properties of GWO, which balances exploration and exploitation through adaptive coefficient updates. This mechanism enables the algorithm to avoid local minima and converge toward a near-optimal solution. Combined with the Bayesian regression framework, which ensures stable estimation through prior modeling, the proposed GWO-SBLSR exhibits consistent convergence across different noise and snapshot conditions.

2.5. Direction-of-arrival estimation

Upon acquiring the optimized sparse coefficient estimates, the DOA information is derived by formulating a spatial power spectrum from the retrieved coefficients. As shown in (12), the squared ℓ_2-norm of each estimated coefficient vector linked to the discretized angular grid is used to make the spatial spectrum [14]. The peaks in this spectrum show that there are sources of signals. Then, as shown in (13), the DOAs are found by finding the angular grid points that are connected to the main spectral peaks. This peak-search-based estimation links the sparse reconstruction results directly to the real source directions, so there is no need to break down the eigenvalues.

$$P(\tilde{\theta}_g) = \| \hat{x}_g \|_2^2 \tag{12}$$

$$\hat{\theta} = \arg\max_{\tilde{\theta}_g} P(\tilde{\theta}_g) \tag{13}$$

2.6. Grey wolf optimization-optimized sparse Bayesian least squares regression

The GWO-optimized sparse least squares regression method initiates by creating an overcomplete steering dictionary using the discretized angular grid and setting the Bayesian hyperparameters and grey wolf population as described in Algorithm 1. During each iteration, sparse source coefficients are computed utilizing the SBLSR posterior mean formulation. A fitness function combining reconstruction error and sparsity regularization is then evaluated for all wolves, and the correct solutions are identified as α, β, and δ wolves. The hyperparameters are adaptively modified according to the grey wolf leadership hierarchy and encircling mechanism to direct the search towards the ideal solution. This iterative step lasts until the convergence criterion is achieved. A spatial power spectrum is obtained from the optimized coefficients, and the DOA are predicted by finding dominating spectral peaks, resulting in precise and reliable estimates.

Algorithm 1. GWO-optimized SBLSR

Input Number of antennas M, number of snapshots T, angular grid $\tilde{\Theta}$, received signal matrix Y, steering dictionary Φ, population size N_w, convergence threshold δ, maximum iterations $M^{\dagger}$

Output Estimated DOAs $\hat{\theta}$

Step 1 Start

Step 2 Construct the overcomplete steering dictionary Φ using the discretized angular grid $\tilde{\Theta}$

Step 3 Initialize Bayesian hyperparameters $\gamma^{(0)} = [\gamma_1^{(0)}, \gamma_2^{(0)}, \ldots, \gamma_G^{(0)}]$ and set iteration counter $l = 1$

Step 4 Initialize Grey Wolf population (α, β, δ, and ω wolves) with candidate hyperparameter vectors

Step 5 For loop (Repeat until convergence)

Step 6 Estimate sparse coefficients $\hat{X}^{(l)}$ using SBLSR: $\hat{X}^{(l)} = \Gamma^{(l)}\Phi^H\left(\Phi\Gamma^{(l)}\Phi^H + \sigma_n^2 I\right)^{-1} Y$

Step 7 Evaluate fitness function for each wolf: $\mathcal{F}(\gamma) = \| Y - \Phi\hat{X}^{(l)} \|_F^2 + \lambda \sum_{g=1}^{G} \gamma_g$

Step 8 Identify α, β, and δ wolves based on minimum fitness values

Step 9 Update hyperparameters $\gamma^{(l)}$ using GWO encircling and hunting mechanisms

Step 10 Check convergence: If $\| \gamma^{(l)} - \gamma^{(l-1)} \| < \delta$ or $l \geq M^{\dagger}$, then terminate

Step 11 Increment iteration counter $l = l + 1$ and repeat Step 5

Step 12 Construct spatial spectrum $P(\tilde{\theta}_g) = \| \hat{x}_g \|_2^2$

Step 13 Estimate DOAs by locating dominant peaks in the spatial spectrum

Step 14 Stop

3. RESULTS AND DISCUSSION

The settings are automatically adjusted using the grey wolf leadership structure and search algorithm to identify the optimal solution. The optimized parameters are subsequently used to construct a spatial power spectrum, from which the DOAs are determined by identifying the prominent peaks. The DOA error is estimated using (14).

$$RMSE = \sqrt{\frac{1}{M_S} \sum_{i=1}^{M_S} \left\| \hat{\theta} - \theta \right\|^2} \tag{14}$$

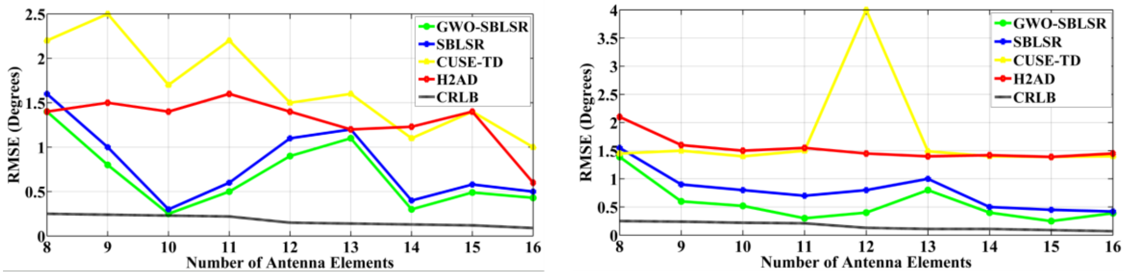
Where the parameter M_S refers to the number of Monte Carlo iterations, in this study, θ and $\hat{\theta}$ are the real and predicted results of the DOA measurement models, respectively. Table 2 shows the parameters that were employed in this simulation investigation. All root mean square error (RMSE) results are averaged over multiple Monte Carlo trials (1,000–5,000 runs) to ensure statistical reliability. The proposed method has also been evaluated under coherent signal conditions, where it maintains stable performance compared to benchmark techniques.

Table 2. Parameters for the simulation

Parameter	Specification
Tool used for simulation	MATLAB 2019
Proposed model	Proposed model
Benchmark models	Benchmark models
Antenna array configuration	ULA
Number of elements	8 to 16 elements
Spacing between elements	$\lambda/2$
Number of sources	2 to 4
SNR range	−10 dB to 10 dB
Number of snapshots	50 to 200
Noise model	Additive white Gaussian noise (AWGN)
Types of signals	Coherent and uncorrelated signals
Optimization technique	GWO
GWO population size	20 to 30 wolves
GWO iterations	50 to 100
M_c	1,000-5,000
Evaluation parameter	RMSE

3.1. Montecarlo iteration varied from 1,000 to 5,000

Figure 1 illustrates the RMSE performance as a parameter of the number of elements for different DOA estimation techniques, including the proposed GWO-SBLSR, conventional SBLSR, CUSE-TD [20], H2AD [23], and theoretical CRLB. Two simulation scenarios are considered: Monte Carlo (Mc) size of 1,000 as in Figure 1(a) and Monte Carlo (Mc) size of 5,000 as in Figure 1(b). In both cases, an overall reduction in RMSE is indicated as the sensor number increases, owing to the improved spatial resolution and enhanced array aperture. The consistent performance trends across different SNR levels, sensor configurations, and Monte Carlo trials.



(a) (b)

Figure 1. RMSE in relation to the number of antennas across different methods for: (a) Mc size of 1,000 (b) Mc size of 5,000

For Mc size of 1,000, the proposed GWO-SBLSR exhibits lower RMSE compared to the benchmark techniques across all sensor configurations, demonstrating improved robustness under limited statistical averaging. When the Mc size is raised to 5,000, all techniques yield more stable RMSE values due to increased statistical reliability. But the GWO-SBLSR still outperforms and is very close to the CRLB. The smaller RMSE gap in the higher Mc scenario shows how stable and efficient the optimized SBLSR framework is at converging. These findings indicate that the proposed technique works better for predicting DOA and can handle more sensors, even when the Monto Carlo conditions vary.

3.2. Variation in signal-to-noise ratio values

For alternative DOA estimation algorithms, Figure 2 shows the RMSE at different SNR values between 10 dB and -10 dB. The RMSE corresponding to each SNR level is presented in Figures 2(a) to 2(e). Improved signal quality and higher spatial resolution with more sensors result in lower RMSE for all approaches at higher SNR levels (10 dB and 5 dB). Notwithstanding, the proposed GWO-SBLSR exhibits nearly flawless estimation performance, consistently obtaining the lowest RMSE across all sensor combinations and maintaining a close proximity to the CRLB. However, the RMSE of standard SBLSR is higher, and the performance of CUSE-TD [20] and H2AD [23]differs substantially, particularly for smaller sensor arrays. As the SNR decreases to 0 dB, -5 dB, and -10 dB, noise becomes more noticeable, which raises the RMSE for all methods. In these hard-to-hear situations, the performance difference between the suggested GWO-SBLSR and benchmark techniques is quite noticeable. The improved SBLSR effectively manages noise, maintaining low and stable RMSE values across different sensor counts. GWO-based tuning enables robust performance even in challenging signal transmission environments.

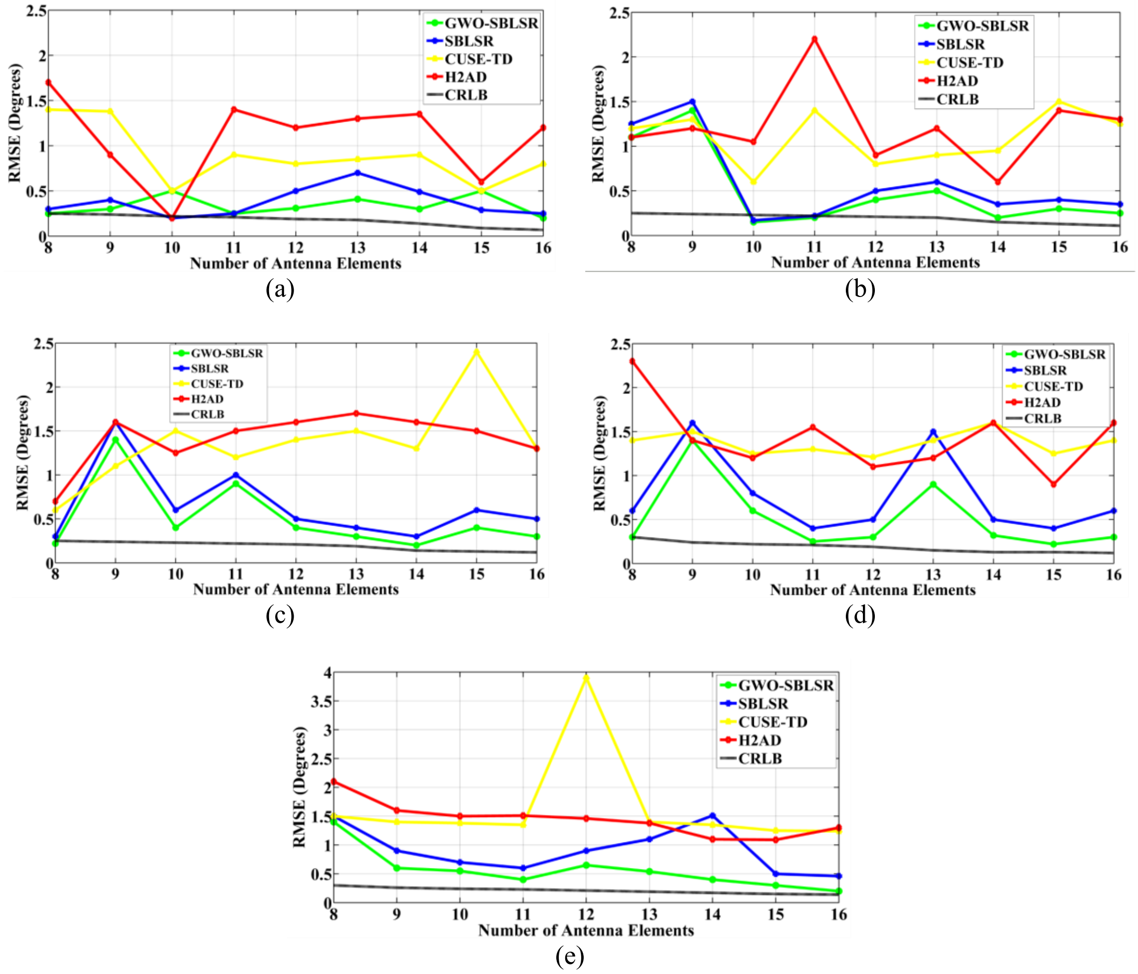


Figure 2. RMSE in relation to the number of sensors across different techniques at: (a) SNR=10 dB, (b) SNR=5 dB, (c) SNR=0 dB, (d) SNR=-5 dB, and (e) SNR=-10 dB

3.3. Discussion

Table 3 compares the RMSE values of the proposed GWO-SBLSR with existing techniques CUSE-TD [20], H2AD [23], and the SBLSR [17] SNR values varied from -10 dB to 10 dB. As SNR increased from -10 dB to 10 dB, all methods show a considerable reduction in RMSE, reflecting improved prediction in favorable noise conditions. The observed RMSE values exhibit low variation across trials, indicating stable convergence behavior.

At low SNR values -10 dB and -5 dB, where the noise power is severely dominating signal power, the proposed technique indicates clear RMSE reduction compared to existing methods. This shows that GWO-based hyperparameter optimization is effective at reducing errors caused by noise, as shown in Figure 3. The optimized SBLSR keeps beating other methods at moderate and high SNR levels and comes very close to the theoretical performance limits. The RMSE comparison graph that goes with this shows the same trend and clearly shows that the suggested GWO-SBLSR works better over the whole SNR range. These results confirm that the updated SBLSR framework provides a dependable and noise-resistant way to estimate DOA for large MIMO applications.

Table 3. Comparing RMSE with current methods

SNR (in dB)	RMSE in CUSE-TD [20] (in deg)	RMSE in H2AD [23] (in deg)	RMSE in SBLSR [17] (in deg)	RMSE in GWO SBLSR [Proposed] (in deg)
-10	2.01	1.77	1.47	1.4
-5	1.86	1.72	1.22	1.02
0	1.52	1.34	0.82	0.72
5	1.33	1.21	0.65	0.62
10	0.76	0.86	0.57	0.42

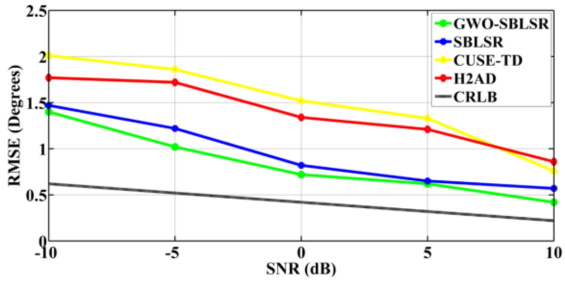


Figure 3. RMSE versus SNR performance comparison

4. CONCLUSION

This study presents an improved SBLSR framework for DOA estimation in extensive MIMO systems. The proposed approach employs GWO to dynamically optimize Bayesian hyperparameters and regression coefficients within the SBLSR model. This makes it possible to effectively enforce sparsity and reduce residual error even when the level of noise changes. This integration makes the estimates more stable and accurate while still keeping the structure easy to compute. Simulation results show that the proposed GWO-SBLSR always has a lower RMSE than traditional SBLSR and other DOA estimating algorithms, no matter what SNR level, sensor setup, or Monte Carlo trial is used. When it comes to both coherent and uncorrelated signals, the method works very well and gets results that are close to the Cramér–Rao lower bound (CRLB). The study of computational complexity indicates that enhanced estimation performance is associated with a minimal increase in runtime. These results show that the proposed improved SBLSR framework is a viable and scalable solution for practical applications of massive MIMO and MIMO radar. Future efforts may expand the framework to include wideband signal models and ISAC systems. The practical applicability of the proposed GWO-SBLSR framework extends to real-world massive MIMO systems in 5G and beyond (B5G) wireless communications, where accurate DOA estimation is essential for beamforming and user localization. The computational structure of the proposed method, which avoids expensive matrix decomposition operations, makes it suitable for scalable implementation in systems with a large number of antenna elements. In addition, the robustness of the method under low-SNR and snapshot-limited conditions enhance its suitability for dynamic wireless environments. Furthermore, the proposed framework can be effectively integrated into emerging ISAC systems, where joint radar sensing and communication functionalities require reliable direction estimation. The adaptive hyperparameter optimization enabled by GWO supports real-time operation and improves estimation stability, making the approach promising for practical deployment in next-generation wireless and radar platforms.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

INFORMED CONSENT

This study does not involve human participants or personal data; hence, informed consent is not applicable.

DATA AVAILABILITY

The data and code used for the implementation are available from the corresponding author, [AGAB], upon reasonable request to facilitate the reproduction of the results presented in this manuscript.

REFERENCES

[1] S. Zhou, W. Jadoon, and I. A. Khan, "Computing offloading strategy in mobile edge computing environment: a comparison between adopted frameworks, challenges, and future directions," *Electronics*, vol. 12, no. 11, May 2023, doi: 10.3390/electronics12112452.

[2] D. Meng, W. An, F. Wen, and J. Shi, "DOA estimation via a novel sparse sampling method in the presence of unknown mutual coupling," *Signal Processing*, vol. 244, Jul. 2026, doi: 10.1016/j.sigpro.2026.110534.

[3] S. Liu, J. Zhao, and D. Wu, "A 2D DOA estimation algorithm based on a large-spacing non-uniform L-shaped array," *Journal on Advances in Signal Processing*, vol. 2026, no. 1, Mar. 2026, doi: 10.1186/s13634-026-01320-4.

[4] Q. Wang, H. Yu, J. Li, F. Ji, and F. Chen, "Adaptive grid refinement method for DOA estimation via sparse Bayesian learning," *IEEE Journal of Oceanic Engineering*, vol. 48, no. 3, pp. 806–819, Jul. 2023, doi: 10.1109/JOE.2023.3235055.

[5] H. Al Kassir *et al.*, "Improving DOA estimation via an optimal deep residual neural network classifier on uniform linear arrays," *IEEE Open Journal of Antennas and Propagation*, vol. 5, no. 2, pp. 460–473, 2024, doi: 10.1109/OJAP.2024.3362061.

[6] H. Masoumi *et al.*, "In-sector direction-of-arrival estimation using a switched receive array," *IEEE Sensors Letters*, vol. 10, no. 5, pp. 1–4, May 2026, doi: 10.1109/LSENS.2026.3680296.

[7] M. E. R.-Ángeles and I. Y. O.-Flores, "Recent advances in applications and performance improvement schemes in wireless communication," *Telecom*, vol. 7, no. 1, Jan. 2026, doi: 10.3390/telecom7010012.

[8] D. Veerendra, B. N. Umesh, M. Nagabushanam, and B. R. Babu, "Enhanced direction of arrival estimation via fast sensor array processing," *IEEE Sensors Letters*, vol. 7, no. 6, pp. 1–4, 2023, doi: 10.1109/LSENS.2023.3278309.

[9] A. Dogra, R. K. Jha, and S. Jain, "A survey on beyond 5G network with the advent of 6G: architecture and emerging technologies," *IEEE Access*, vol. 9, pp. 67512–67547, 2021, doi: 10.1109/ACCESS.2020.3031234.

[10] W. Xu, M. Liu, and S. Yi, "Spectrum attention mechanism-based acoustic vector DOA estimation method in the presence of colored noise," *Applied Sciences*, vol. 15, no. 3, Jan. 2025, doi: 10.3390/app15031473.

[11] M. Iqbal, T. Ashraf, M. Zubair, S. M. Jameel, M. Jazib, and J.-Y. Pan, "A comprehensive survey on reconfigurable intelligent surfaces (RIS) and STAR-RIS for next-generation wireless networks," *Discover Applied Sciences*, vol. 7, no. 11, Oct. 2025, doi: 10.1007/s42452-025-07684-w.

[12] M. N. Khan, R. A. Khan, S. Bourouis, G. I. Kiani, M. U. Ali, and J. Iqbal, "Design and implementation of a circularly polarized wideband MIMO antenna array employing polarization diversity and dash-decoupling structures for enhanced isolation in satellite and X-band communication systems," *Measurement*, vol. 277, Jun. 2026, doi: 10.1016/j.measurement.2026.121423.

[13] I. Dagal *et al.*, "Prioritized multi-step decision-making gray wolf optimization algorithm for engineering applications," *Engineering Reports*, vol. 7, no. 5, May 2025, doi: 10.1002/eng2.70154.

[14] A. B. A. Gowda, N. V. Babu, N. Anughna, and J. J. Jijesh, "A comprehensive survey on subspace-based direction of arrival estimation algorithms: performance, accuracy and complexity analysis," in *2025 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*, Apr. 2025, pp. 1–7, doi: 10.1109/ICKECS65700.2025.11035231.

[15] A. Lawal, K. N. Aliyu, A. Zerguine, and A. Muqaibel, "Direction of arrival estimation using hybrid CNN-GRU," in *2025 IEEE 22nd International Multi-Conference on Systems, Signals & Devices (SSD)*, 2025, pp. 574–577, doi: 10.1109/SSD64182.2025.10989880.
[16] Y. Yang, M. Mao, J. Xu, H. Liu, J. Wang, and K. Song, "Millimeter-wave antennas for 5G wireless communications: technologies, challenges, and future trends," *Sensors*, vol. 25, no. 17, Sep. 2025, doi: 10.3390/s25175424.
[17] A. G. A. Byregowda, B. N. Venkateshappa, and P. Cheluvegowda, "Sparse Bayesian least squares regression model for direction of arrival estimation in massive MIMO networks," *Mathematical Modelling of Engineering Problems*, vol. 12, no. 7, pp. 2341–2350, 2025, doi: 10.18280/mmep.120714.
[18] Y. Jiarun and W. Yafeng, "MDTCNet: multi-task classifications network and TCNN for direction of arrival estimation," *China Communications*, vol. 21, no. 10, pp. 148–166, 2024, doi: 10.23919/JCC.fa.2022-0619.202410.
[19] X. Tong, Y. Hu, Z. Deng, and E. Hu, "Accelerating broadband DOA estimation: a real-valued and coherent sparse Bayesian approach for 5G sensing," *Electronics*, vol. 14, no. 16, Aug. 2025, doi: 10.3390/electronics14163174.
[20] R. Dakulagi, R. Raushan, S. Dutta, M. T. Alosaimi, and M. V. -Galindo, "CUSE-TD algorithm for precision detection of coherent and uncorrelated signals," *IEEE Access*, vol. 13, pp. 11307–11319, 2025, doi: 10.1109/ACCESS.2024.3525360.
[21] D. Li, G. Sun, and Y. Ji, "DOA estimation via distributionally robust optimization with gain-phase errors," *IEEE Signal Processing Letters*, vol. 33, pp. 1101–1105, 2026, doi: 10.1109/LSP.2026.3667071.
[22] J. Zhang, X. Xu, and Z. Ye, "Robust DOA estimation based on the star-transformer," in *2025 IEEE 25th International Conference on Communication Technology (ICCT)*, Oct. 2025, pp. 763–767, doi: 10.1109/ICCT67417.2025.11374086.
[23] F. Shu *et al.*, "A new heterogeneous hybrid massive MIMO receiver with an intrinsic ability of removing phase ambiguity of DOA estimation via machine learning," *IEEE Transactions on Machine Learning in Communications and Networking*, vol. 3, pp. 17–29, 2025, doi: 10.1109/TMLCN.2024.3506874.
[24] I. Anafo, R. Ganguli, and N. Sarantsatsral, "BoxRF: a new machine learning algorithm for grade estimation," *Applied Sciences*, vol. 15, no. 8, Apr. 2025, doi: 10.3390/app15084416.
[25] D. Zhu, B. Chen, and X. Cheng, "DOA and polarization estimation for compressed EMVS array with arbitrary sensor geometry," *Digital Signal Processing*, vol. 131, Nov. 2022, doi: 10.1016/j.dsp.2022.103778.

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