IJETIR
ISSN (Online) 2583-0554
IJETIR
Impact Factor: 5.731
International Journal of Emerging Technologies and Innovative Research (IJETIR)
Volume 5, Issue 12, December 2025

Comprehensive Survey on Advancements and Challenges in Direction-of-Arrival Estimation for MIMO Systems

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Abstract: *The pursuit of enhanced wireless communication through multiple-input multiple-output (MIMO) technology has revolutionized array signal processing, particularly in the realm of direction-of-arrival (DoA) estimation. MIMO systems, leveraging multiple antennas for both transmission and reception, exploit spatial diversity to significantly improve data rates and overall system performance. The integration of smart antennas, capable of dynamically adjusting their radiation patterns based on estimated DoAs, further enhances signal reception and reduces degradation caused by multipath propagation. Despite substantial progress, several challenges persist in achieving ultra-high precision DoA estimation, particularly in massive MIMO systems, which demand advanced algorithms to cope with narrower beam widths, higher circuit costs, and increased energy consumption. Furthermore, hardware impairments, such as antenna element failures, continue to degrade estimation accuracy in large-scale array systems. This survey comprehensively reviews the current state of DoA estimation methods in MIMO systems, highlighting their advantages and limitations, and identifies critical research gaps that need to be addressed to advance the field. By synthesizing recent developments and proposing future research directions, this paper aims to guide the development of robust, efficient, and adaptive DoA estimation techniques suitable for modern wireless communication systems.*

Keywords*:* Multiple-input Multiple-output(MIMO), Direction-of-arrival (DoA), Wireless Communication, Higher Circuit Costs, Sparse Representation

I. INTRODUCTION

Delay-of-arrival (DoA) estimation has been a major area of study in the field of array signal processing for a considerable length of time. The application of multiple-input multiple-output (MIMO) antennas is widely acknowledged as a significant technical advancement in the field of wireless communication. Using many antennas for both transmission and reception is known as spatial diversity, and it is a central division of MIMO (multiple-input multiple-output) systems. MIMO (Multiple-Input Multiple-Output) technology development has evolved significantly with the use of smart antennas. Incoming signals' predicted Direction of Arrival (DoA) can be exploited by the antennas to alter their emission patterns [1]. The main goal of smart antenna design is to enhance signal reception while mitigating the negative effects of multipath propagation and signal fading, which can lead to a decline in signal quality. The objective is achieved by pointing the major lobes of the antennas in the direction of the targeted users and successfully reducing interference from other directions. Accurate signal direction of arrival (DoA) prediction is made possible by the next characteristic. Researchers are currently focusing on creating innovative techniques like electromagnetic skins to enhance communications. Electromagnetic skins are a series of specialized structures designed to be integrated into antenna systems. They possess the ability to regulate and alter the properties of radiation and scattering [2]. With smart antennas in Multiple-Input Multiple-Output (MIMO) systems, accurate DoA prediction is a necessary precondition for beamforming, spatial signal processing, and ensuring stable link performance. Enhancing the accuracy of Dead-on-

Arrival (DoA) estimates through research in this particular area might lead to significant improvements in the functioning of several applications, including vehicle communications [3].

Massive multiple-input multiple-output, or MIMO, has attracted a lot of attention recently due to its remarkable ability to increase energy efficiency and attainable rate by a factor of 10. In [4], the beam width of the primary lobe steadily decreases as the number of antennas increases. For huge MIMO systems with multiple antennas to function properly, the Direction of Arrival (DOA) must be accurately determined. The growing expense of circuits and energy consumption is impeding the widespread application of massive MIMO technology. Innovative array topologies have been proposed in different ways to tackle this issue in large-scale MIMO systems. New techniques need to be created to recognize (DOA) scenarios, and it's crucial to assess how well these algorithms work in various settings. Significant progress has been achieved in the field of Direction of Arrival (DOA) estimations in large-scale Multiple-Input Multiple-Output (MIMO) systems. These innovations have been driven by the growing demands in wireless communications and related industries. MIMO radars may be categorized into two groups: statistical MIMO radars and collocated MIMO radars, depending on their antenna layouts. Statistical multiple-input multiple-output (MIMO) radars can achieve high-resolution target localization and spatial diversity gain by concurrently observing numerous spatial features of targets. This is made easier by the deployment of widely dispersed broadcast and receive antennas [5]. Like monostatic and bistatic MIMO radars, colocated Multiple-Input Multiple-Output (MIMO) radars make use of closely spaced antennas to efficiently enhance the virtual array aperture's size. When employing a larger aperture, it is required to use many waveforms to increase the spatial resolution. Investigating the problem of angle estimation in bistatic Multiple-Input Multiple-Output (MIMO) radars when an array component fails is the primary objective of our research team. Recently, there has been a lot of interest in the ability of bistatic multiple-input multiple-output (MIMO) radars to correctly anticipate the directions of arrival (DOAs) and directions of departure (DODs) of targets.

In recent years, several techniques for determining the Direction of Arrival (DOA) and Direction of Departure (DOD) have been developed. In this particular context, algorithms based on sparsity ESPRIT, Capon, and MUSIC are employed. , as well as tensor breakdown [6]. There are several transmit and receive antenna components in an array radar system. For power supply, each component has a separate transmit/receive module. The three primary components of the module are an up/down converter, a power amplifier, and an antenna-feeder system. Realistic array systems, especially those with a large number of transmit/receive modules, have been seen to experience hardware degradation when operated continuously over extended periods. It is not unusual for one or more antenna components to fail in large-scale array systems. The presence of defective parts weakens the MIMO radar array's structural integrity, lowering the total number of virtual elements in the virtual array. Due to these errors, the estimations for the angle estimation methods [7] become much less accurate.

To determine the Direction of Arrival (DOA) in a Uniform Linear Array (ULA) with failed elements, missing data is retrieved using a Minimal Resource Allocation Neural Net (MRAN). The inherent limitation of this approach is that it cannot train the network in conditions of failure or noise. The techniques for figuring out the Direction of Arrival (DOA) are shown in the paper [8], this technique targets to be robust and dependable. The technique is based on the basic architecture of a deep neural network. The purpose of denoising autoencoders (DAEs) is to return broken array signals to their original, uncorrupted state. The primary disadvantage of this approach is that it needs a lot of labeled data to train well. The issue of computing angles when an element fails has been addressed in several ways.

The authors in [9] present a method for estimating DOA that utilizes the Toeplitz structure of the covariance matrix. The matrix completion (MC) theory is used to reconstruct the missing data from the failed elements. A structured Hankel matrix is created by dividing the covariance matrix into four quadrants. Ensuring that neither a column nor a row is empty is the aim of this transformation. The angle estimate performs better when the full covariance matrix is rebuilt using the Monte Carlo (MC) method. A method has been developed to deal with the issue of array element failure in bistatic MIMO radar systems. The data gets larger as a result of the Hankelization process, greatly increasing the computing complexity. Direction-of-arrival (DOA) and direction-of-departure (DOD) estimation is an essential component in the field of MIMO radar signal processing. Multiple-input multiple-output (MIMO) radar has received a lot of interest in the field of array signal processing due to its numerous potential advantages over traditional phased-array radar systems. The two primary benefits of the technology are higher resolution and more degrees of freedom [10]. The Direction of Arrival (DOA) and

Direction of Departure (DOD) estimation methods that are often seen in the literature frequently employ conventional subspace-type techniques.

Degrees of freedom and antenna array

The Coarray MUSIC method makes use of the Toeplitz structure of the array covariance matrix. To obtain an accurate estimate, it is necessary to have a substantial number of temporal snapshots for this approach. The computational burden of coarray MUSIC is high due to the requirement of performing eigenvalue decomposition (EVD) on the coarray covariance matrix. Various methodologies can be employed to estimate U-DOA. The tactics employed in this study encompass sparse recovery-based techniques [11], joint sparse support recovery (JSSR)-based techniques, and sparse Bayesian learning (SBL)-based techniques. The computational cost of these methods is significant due to the need to solve a constrained 1-norm minimization problem or employ an iterative approach to estimate the hyperpa rameters of the signal model. The execution of a comprehensive grid search is required to obtain estimates of the Direction of Arrivals (DOAs) using these methods. The entire set of potential Directions of Arrival (DOAs) needs to be partitioned into a dense grid. To address off-grid circumstances, several techniques have been devised to estimate the Uniform Direction of Arrival (U-DOA). The research employs various techniques, such as off-grid versions of sparse recovery, coarray root-MUSIC, maximum likelihood estimation (MLE) [12], JSSR, and SBL. Off-grid techniques often involve tackling computationally intensive problems such as atomic norm minimization (ANM) or convex semi-definite programming (SDP).

In recent years, there has been a notable rise in the level of interest surrounding the FDA (Frequency Diverse Array) radar [13]. The FDA (Frequency Domain Analysis) approach is employed to generate a frequency increase across the transmitters. The outcome is the generation of a beam pattern that is contingent upon the time, angle, and range. The statement highlights the distinctions between conventional Power Amplifier (PA) systems and systems that produce angle-dependent beampatterns. The increase in injected frequency is typically significantly smaller than the reference carrier frequency and generally exhibits a linear pattern. The relationship between the joint range-angle domain and the beampattern is established through the utilization of the traditional Frequency Diverse Array (FDA). The presence of uncertainty introduces a challenge in accurately determining the angle and range of the target. The receivers utilize Multiple-input multiple-output (FDA-MIMO) technology to effectively segregate the broadcast waveform.

The classification of robust adaptive beamforming methods can be divided into three main categories: diagonal loading methods, eigenspace-based approaches, and covariance matrix reconstruction. The application of the diagonal loading approach enhances the resilience of the beamformer. The proposed approach entails enhancing the sample covariance matrix by incorporating a scaled identity matrix [14]. Nevertheless, despite the availability of various suggested approaches, determining the optimal diagonal loading factor can pose a challenge. The estimation of singular values (SVs) and covariance matrix is performed using eigenspace-based techniques, which leverage orthogonality.

In the last decade, several techniques have been developed and published for determining the Direction of Arrival (DOA) for sparse arrays. The estimation of the Direction of Arrival (DOA) is achieved by modeling an enhanced second-order virtual array signal with an increased number of virtual sensors. The utilization of sparse array-based Direction of Arrival (DOA) estimates approaches in practical scenarios can give rise to various challenges. The reason for this is that the creation of these approaches was based on the fundamental assumptions of perfect array systems and stationary Gaussian noise. The accuracy of the modeled increased second-order virtual array signal may be compromised if the RF chains exhibit gain-phase issues. Furthermore, empirical research has substantiated the prevalence of impulsive noise in various applications, including communication channels, radar, sonar, and image processing [15]. The term outliers is commonly employed to refer to measurements that have been influenced by spurious noise. The presence of outliers significantly affects the performance of Direction of Arrival (DOA) estimators that only consider stationary noise. The enhanced second-order virtual array signal can be differentiated from the one obtained from stationary Gaussian processes by utilizing the heavy-tail probability density function (PDF).

Problem statement

The increasing demand for high-precision and efficient wireless communication systems has highlighted several challenges in the field of multiple-input multiple-output (MIMO) technology, particularly in direction-of-arrival (DoA) estimation. Massive MIMO systems require ultra-high precision DoA estimation to leverage their potential, yet achieving this is hampered by narrower beam widths, higher costs, and increased energy consumption. Additionally, hardware impairments such as antenna element failure in MIMO radars significantly degrade estimation accuracy. Traditional subspace-based methods like MUSIC and ESPRIT, while effective, are computationally intensive, making real-time processing challenging. Sparse array-based algorithms struggle with gain-phase errors and outliers in practical scenarios, and deep learning-based methods lack generalization and interpretability. Furthermore, iterative algorithms for sparse representation are computationally burdensome, and reconfigurable antenna systems face issues with electromagnetic compatibility and system complexity. Addressing these gaps is crucial for developing robust, efficient, and adaptive DoA estimation techniques that meet the evolving needs of modern wireless communication systems.

II. RELATED WORK

Recently, the idea of sparse signal reconstruction has been applied to estimate the direction of arrival (DOA) in arrays even when defects and outliers are present. Sparse signal reconstruction-based techniques perform better than subspace-based and machine learning-based algorithms when dealing with low signal-to-noise ratios and a small number of pictures. Furthermore, these methods are made to function even in the absence of any prior knowledge about the quantity of sources. To reduce gain-phase errors, a sparse Bayesian learning framework is included in the direction of arrival (DOA) estimate procedure [16]. Methods for outlier-resistant DOA estimation based on Sparse Bayesian approaches. The outliers are represented as sparse unknown vectors in these approaches. However, the solution space of these techniques becomes much larger when outliers are taken into account as the unknown signals of interest, leading to an increase in computing cost. The article "Gain-Phase Errors in Sparse Bayesian-Based Direction of Arrival (DOA) Estimation for Coprime Arrays" describes how to estimate the direction of arrival (DOA) using coprime arrays and assess the effects of gain-phase errors through the use of a sparse Bayesian approach. The inquiry is predicated on the studies documented in reference [17]. The generation of inconsistent models in the presence of outliers may result from the authors' failure to take outliers into account at the same time. Examining Direction of Arrival (DOA) estimations with a sparse array in the presence of outliers and gain-phase errors is one major problem.

The residual neural network is suggested as a technique to improve the direction of arrival (DOA) estimation accuracy. The technology is capable of offering controlled instruction, a deep convolution network was suggested as the learning method for the transition from array output to DOA spectrum. The networks outlined above are intended to examine the recovered spatial spectrum's peaks to ascertain the Direction of Arrival (DOA). One way to think about the process is as a classification issue. This approach involves mapping the incoming sources to the Direction of Arrival (DOA) using a supervised deep neural network. It is necessary to be aware of the quantity of sources beforehand, though. To decrease computational complexity, the deep neural network has been built to learn the nonlinear connection between the output of an array and the related direction of arrival (DOA). Under [18], it is shown how to build a deep neural network for MIMO radar DOA estimation under nonideal circumstances. An autoencoder and a feedforward network are the foundation of this network. Furthermore, a deep learning classifier for the Direction of Arrival (DOA) estimate in MIMO radar systems is presented in a paper by [19]. The classifier integrates spatial filtering prerotation and uses a single-image methodology. The classifier is capable of estimating the Direction of Arrival (DOA) in both ON-grid and OFF-grid circumstances.

The aforementioned networks have a comparatively reduced ability to generalize in contrast to model-based methods, which do not allow for parameter interpretation of the network. Iterative methods like the Alternate Direction Method of Multipliers (ADMM), and the FOCal Underdetermined System Solver (FOCUS) [20] can be used to solve the sparse representation problem. The iterative stages of a technique are transformed into layers of a network according to the well-known notion of deep unfolded networks. The network's parameters are updated using gradient descent in this technique. The study's conclusions suggest that applying model- and data-based methods can benefit deeply unfolded networks. The sparse linear inverse issue is defined and optimized using three different approaches. These methods include the ADMM network (ADMM-Net), the learned iterative shrinkage thresholding algorithm (LISTA), and the learned vector approximation message forwarding algorithm. These algorithms' use of interpretable parameters improves their generalization capacity and accelerates the rate of convergence. Convolutional layers are included in the LISTA-Toeplit network [21] to improve the convergence rate over the original LISTA approach. Unfortunately, the networks indicated above are not appropriate to be directly used in OFF-grid Direction of Arrival (DOA) estimates using multilayer arrays.

A method for determining the direction and the antenna's hardware layout make up the antenna array direction-finding system. In a conventional antenna array system, the system's optimal operation depends on every antenna being active at the same time [22]. On the other hand, a particular set of antennas can accurately and efficiently establish the direction of arrival (DOA) in situations when there are few incident sources. Furthermore, if several antennas are used simultaneously, the system might experience ongoing issues with electromagnetic compatibility. Signal distortion and crosstalk are two problems that can significantly reduce the system's overall communication quality.

There has been a lot of research done on reconfigurable antenna systems' capacity to dynamically modify an antenna's operating state in response to environmental demands In situations where there are few target signals, the system might disable some antennas. This study's method seeks to reduce electromagnetic compatibility between antennas while using the fewest resources possible. In engineering applications, moveable components including graphene, liquid metal complexes, microwave switches, and variable capacitors are frequently used to load the antenna surface. These devices provide control over the current distribution on the antenna surface, hence enabling the reconfiguration of the antenna state [23].

In traditional antenna array direction-finding technologies, phase or amplitude plays the primary role in determining the direction of arrival. Unfortunately, noise can affect the procedure, leading to low accuracy. The development of technology has led to a great deal of interest in subspace-based tactics. Among the techniques used for signal analysis are subspace fitting, maximum-likelihood, multiple signal classification (MUSIC), and estimate of signal parameters via rotational invariance approaches (ESPRIT). A technique for creating a Variable Area Amplifier (VAA) almost twice the size of a Rectangular Area Amplifier (RAA) was examined. Real-world scenarios have not been used using the existing technique. The technique is based on using received signals as statistical cumulants where the order is greater than two. It is well known that these cumulants have a limited tolerance to measurement mistakes in the parameters of the received signals.

Using the method suggested [24], the interpolation problem between RAA and VAA is expressed as a minimization problem with various constraints in the form of inequalities. Multiple spatial filters are used inside the defined space as part of the approach used to minimize interpolation error in the sector. When processing signals coming from sources beyond the interpolation sector, a consistent response can be achieved.

[13] Introduced Variable Axisymmetric Apodization (VAA), an interpolation method. The Radial Apodization Algorithm (RAA) is copied and shifted in this manner. This makes it simpler to select the array orientation, interelement spacing, or VAA element count. The ESPRIT method makes use of the shift's generated invariance. The use of this strategy necessitates carrying out the steps sector by sector.

A transformation matrix may be obtained by implementing the recommendation, which tries to lessen bias in the direction of arrival (DOA) estimation. The second-order parts of the MUSIC technique's output function extension were expressed as a Taylor series to construct the DOA error formula. The formula was used to develop the transformation algorithm, which included the least squares approach to reduce error. Signals found outside of the transformation sector were ignored using the Friedlander approach [25]. Hyberg's method was extended to account for the short duration of the observations.

Table 1 survey table

Reference	Method	Advantages	Disadvantages	Research Gap
[12]	MRAN for DOA estimation in ULA	Recover missing data effectively	Requires training under no failure and no noise cases	Need for methods that handle failures and noise robustly
[16]	DAE-based DOA estimation	Recover damaged array signals	Requires a large amount of labeled data for training	Need for data-efficient methods with less dependency on labeled data

[9]	Capon algorithm	High-resolution target location	Performance deteriorates with hardware impairments	Development of algorithms that maintain accuracy despite hardware failures
[10]	MUSIC algorithm	High accuracy in angle estimation	High computational complexity	Need for low-complexity algorithms that retain high accuracy
[11]	ESPRIT algorithm	Faster computing speed than other beamformers	Requires shift-invariant array geometry	Algorithms that are independent of specific array geometries
[7]	Weighted average algorithm	Simple implementation	Limited robustness to gain-phase errors and outliers	Enhanced robustness to gain-phase errors and outliers
[18]	Particle swarm optimization	Effective in solving optimization problems	High computational burden	More computationally efficient optimization techniques
[20]	Covariance matrix reconstruction	Utilizes virtual antenna elements to compensate for faulty elements	High complexity during Hankelization operation	Reducing computational complexity in covariance matrix reconstruction
[11]	Toeplitz structure and MC theory	Improved angle estimation performance	Increased computational complexity due to size expansion during Hankelization	Efficient handling of computational complexity in Toeplitz-based methods
[21]	Residual neural network for DOA	Improved accuracy	Limited generalization ability	Development of deep learning models with better generalization capabilities
[22]	Deep convolution network	Learns transformation from array output to DOA spectrum	Requires knowledge of the number of sources in advance	Algorithms that do not require prior knowledge of the number of sources
[23]	FOCUSS iterative algorithm	Solves sparse representation problems	Computationally intensive	Efficient sparse representation techniques with reduced computational demands
[24]	Deep unfolded networks	Combines advantages of data-based and model-based methods	High complexity and training requirements	Simplifying and optimizing deep unfolded network structures
[7]	Reconfigurable antenna array system	Dynamically controls antenna working state to reduce resource consumption	Electromagnetic compatibility issues and system complexity	Enhanced adaptability and efficiency in reconfigurable antenna systems
[9]	RD-MUSIC algorithm	Avoids the high computational cost of multidimensional search	Reduced accuracy of parameter estimation	Maintaining high accuracy while reducing computational costs
[8]	Deep learning DOA classifier	Achieves DOA estimation with a single snapshot	Poor generalization compared to model-based methods	Combining interpretability and generalization in deep

				learning-based DOA estimation methods
[25]	LISTA-Toeplit network	Accelerates convergence rate	Not directly applicable for OFF-grid DOA estimation	Adapting LISTA-Toeplit networks for OFF-grid scenarios

III. RESEARCH GAP

Ultra-High Precision in Massive MIMO Systems:

Challenge: The increasing number of antennas in massive MIMO systems requires ultra-high precision in DoA estimation. However, achieving this precision remains challenging due to narrower main lobes and increased circuit cost and energy consumption.

Gap: There is a need for novel DoA estimation algorithms that can handle the precision requirements and mitigate the high costs and energy demands associated with massive MIMO systems.

Handling Array Element Failure in MIMO Radars:

Challenge: In large-scale array systems, hardware impairments such as antenna element failure can significantly degrade DoA estimation accuracy.

Gap: Existing methods, such as MRAN and DAE-based approaches, either require extensive labeled data or lack robustness under noise conditions. There is a need for more resilient methods that can accurately estimate DoA in the presence of hardware impairments.

Computational Complexity in Subspace-Based Method:

Challenge: Conventional subspace-based methods like MUSIC and ESPRIT are computationally expensive, especially for real-time processing.

Gap: There is a need for developing low-complexity DoA estimation algorithms that can provide high accuracy without the computational burden of extensive spectral searches or iterative processes.

Robustness to Gain-Phase Errors and Outliers:

Challenge: Sparse array-based DoA estimation algorithms often assume ideal array systems and stationary Gaussian noise, which is not always the case in real-world scenarios.

Gap: Research is needed to develop DoA estimation techniques that can effectively handle gain-phase errors and outliers, improving robustness and accuracy in practical environments.

Generalization Ability of Deep Learning-Based Methods:

Challenge: While deep learning approaches have shown promise, their generalization ability is often poor compared to model-based methods, and their parameters are not easily interpretable.

Gap: Developing deep learning models with better generalization capabilities and interpretable parameters for DoA estimation in various scenarios remains an open research area.

Sparse Representation and Computational Efficiency:

Challenge: Iterative algorithms like FOCUSS and ADMM can solve sparse representation problems but are computationally intensive.

Gap: There is a need for efficient algorithms that can leverage sparse representation without incurring high computational costs, possibly through advanced network structures like deep unfolded networks.

Adaptability of Reconfigurable Antenna Systems:

Challenge: Reconfigurable antenna systems dynamically control the working state of antennas but face issues with electromagnetic compatibility and system complexity.

Gap: Research is needed to enhance the adaptability and efficiency of reconfigurable antenna systems, ensuring reduced resource consumption and improved electromagnetic compatibility in diverse operational environments.

IV. CONCLUSION

This survey has examined the advancements and challenges in direction-of-arrival (DoA) estimation for multiple-input multiple-output (MIMO) systems. MIMO technology, along with smart antennas, has notably enhanced wireless communication by leveraging spatial diversity. However, achieving ultra-high precision DoA estimation in massive MIMO systems remains complex due to narrower beam widths, higher costs, and increased energy consumption. Hardware impairments, such as antenna element failures, further complicate accurate estimation, highlighting the need for resilient and adaptive algorithms. Traditional methods like MUSIC and ESPRIT are effective but computationally intensive, necessitating more efficient solutions. Emerging deep-learning approaches and sparse representation techniques show promise but require improvements in generalization, interpretability, and computational efficiency. Reconfigurable antenna systems also face challenges related to electromagnetic compatibility. Identifying these research gaps underscores the necessity for continued innovation in DoA estimation methods. Future research should focus on developing robust, efficient, and scalable techniques to meet the demands of modern wireless communication systems, ultimately advancing the field of MIMO technology.

ACKNOWLEDGEMENT

I would like to express our sincere gratitude to all those who have supported and contributed to this research project. Primarily, I extend our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process. No funding is raised for this research.

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