Advanced Signal Processing Techniques in Radar Imaging: A Survey

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Abstract

This survey paper explores the application of advanced signal processing techniques utilizing compressed sensing (CS) principles in radar imaging, focusing on the efficient estimation of Direction of Arrival (DOA), enhancement of Synthetic Aperture Radar (SAR) imaging, and optimization of Multiple-Input Multiple-Output (MIMO) radar systems. The paper addresses the pressing need for high-resolution radar outputs amidst constraints like limited bandwidth and interference, particularly in urban environments and automotive applications. It examines the benefits of CS in reducing data acquisition requirements while maintaining image quality, emphasizing innovations such as gridless techniques and structured waveforms. Key advancements include the integration of CS with MIMO radar for improved signal recovery and the development of robust sparse recovery methods for accurate target detection. The survey highlights the transformative impact of CS on radar technologies, offering insights into overcoming traditional limitations through innovative algorithms and optimization strategies. Future directions suggest enhancing algorithm adaptability and stability, improving real-time processing capabilities, and exploring applications in diverse radar scenarios. By synthesizing current challenges and advancements, this paper provides a comprehensive overview of the role of CS in advancing radar imaging, paving the way for more sophisticated and efficient radar systems.

1 Introduction

1.1 Motivation for the Survey

This survey is motivated by the urgent need for advanced radar imaging technologies that can deliver high-resolution outputs despite bandwidth limitations and interference challenges typical of conventional radar systems [1]. This necessity is particularly evident in automotive radar applications, where accurate target range estimation and angle detection are essential for autonomous driving [2]. The increasing density of radar systems in urban settings further complicates interference issues, highlighting the need for innovative signal processing solutions [3].

In Through-the-wall Radar Imaging (TWRI), the capability to detect and identify objects and individuals behind obstacles is critical, necessitating robust signal processing techniques to enhance electromagnetic wave penetration and resolution [4]. The demand for global situational awareness with a limited number of sensors emphasizes the importance of efficient signal processing methods [5].

The high computational and storage requirements associated with three-dimensional compressive sensing-based millimeter-wave imaging methods underscore the need for more efficient approaches [6]. In airborne radar systems, addressing range-ambiguous clutter suppression under high pulse repetition frequency conditions poses significant challenges [7]. Current interference mitigation techniques in Frequency Modulated Continuous Wave (FMCW) radar systems are inadequate, necessitating novel methodologies that operate without explicit interference detection [8].

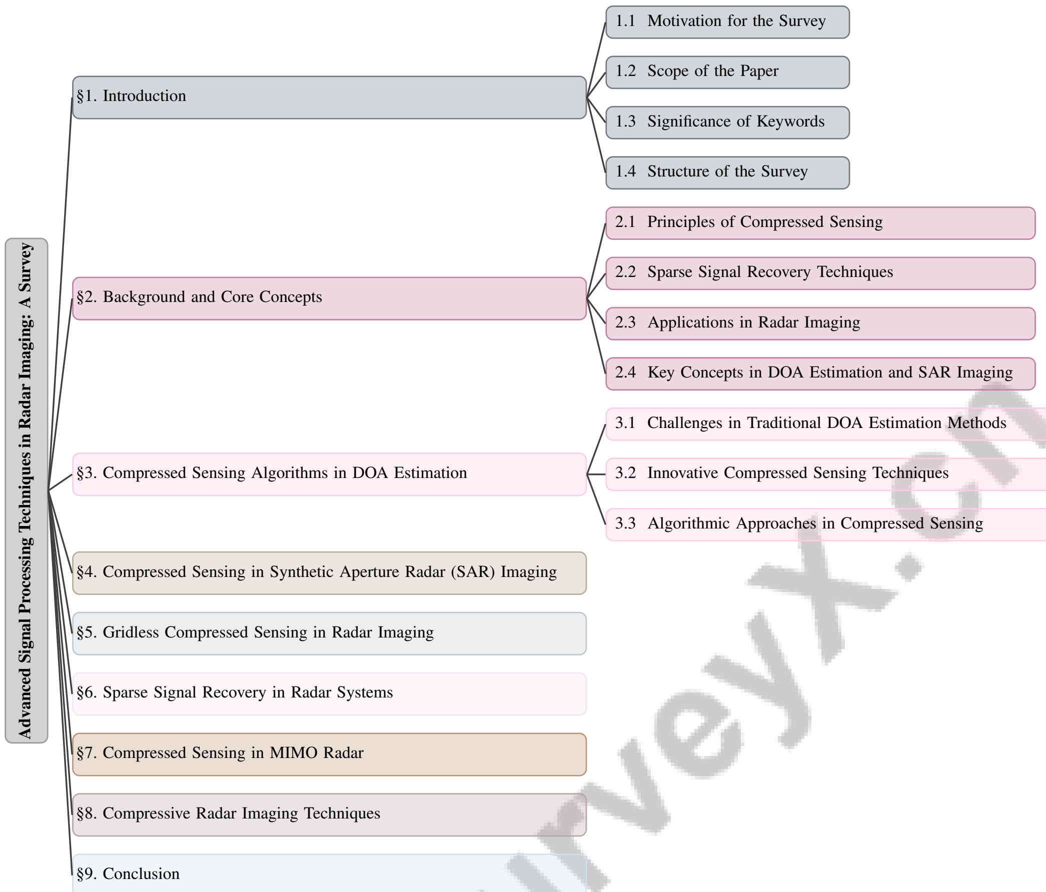

Figure 1: chapter structure

Moreover, enhancing radar imaging quality within existing hardware constraints, including improvements to traditional imaging methods such as back projection and Fast Fourier Transform, is a vital driver for this survey [9]. The challenges posed by massive connectivity in the Internet of Things (IoT) environment, which can be addressed through advanced compressed sensing techniques for efficient device activity detection, further illustrate the survey's relevance [10].

In high-density scenarios, such as UAV swarm localization, the demand for improved radar resolution and transmitting power is evident, necessitating advancements in signal processing techniques [11]. Additionally, the exploration of blind super-resolution and accurate recovery of high-frequency signals from low-frequency observations is crucial for overcoming the limitations of current radar imaging methods. Collectively, these motivations underscore the survey's significance in the field of radar imaging, aiming to provide a comprehensive overview of current challenges and advancements in signal processing techniques.

1.2 Scope of the Paper

This paper outlines the boundaries of advanced signal processing techniques in radar imaging, focusing specifically on methods leveraging compressed sensing principles. The survey investigates the dual-2D-CAMP approach applied to OFDM radar signals, emphasizing enhancements in radar signal processing [3]. It covers the reconstruction of sparse signals, categorizing various algorithms while intentionally omitting non-sparse signal reconstruction to maintain a clear focus on sparsity-based methodologies [12].

The survey extends to topics such as compressive sensing, massive MIMO, non-orthogonal multiple access (NOMA), and ultra-dense networks (UDN), explicitly excluding wireless communication techniques that do not utilize sparsity or sub-Nyquist sampling approaches [13]. It includes sparse scene reconstruction for automobile FMCW SAR, highlighting the advantages of FMCW radar,

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including reduced manufacturing costs and ease of implementation compared to conventional pulse radar systems [14].

Additionally, the paper explores the introduction of compressed domain signal processing (CSP) in MIMO radar, addressing challenges related to high sample complexity and computational demands [15]. It encompasses electromagnetic properties, antenna design, waveforms, and modeling techniques in TWRI, while excluding non-electromagnetic methods [4].

The limitations of previous linear theory-based methods are discussed, with a novel approach introduced using Voronoi tessellation and deep learning [5]. Furthermore, the survey defines specific topics and technologies, including a high-fidelity automotive MIMO radar sensing technique utilizing a sparse two-dimensional MIMO array [2].

The development of an interpolation-free holographic imaging algorithm as a sensing operator for compressive sensing in radar imaging is also explored [6]. Additionally, the integration of compressed sensing techniques with frequency diverse array (FDA) radar and MIMO technology for suppressing range-ambiguous clutter is included [7]. The scope further encompasses the design and operation of computational spectrometers, integrating nanophotonic structures and machine learning algorithms [16], as well as the development of a complex-valued CNN framework for radar imaging tasks [9]. The paper also discusses advancements in microwave photonic radar utilizing sparse stepped frequency chirp signals [1] and explores a grant-free random access scheme for IoT networks through compressed sensing techniques [10]. Lastly, the survey includes the development of a new method for blind super-resolution, aligning with sparse signal recovery techniques [17].

1.3 Significance of Keywords

The significance of keywords in this survey lies in their capacity to encapsulate core innovations and challenges within advanced radar imaging techniques. Compressed sensing, a pivotal concept, addresses the need for efficient data acquisition and processing by leveraging sparsity in signal representation, enabling high-resolution imaging with reduced data requirements. This principle is essential for overcoming the complexity of reconstructing spectral information from multiplexed data, a challenge exacerbated by the need for extensive calibration of filter response functions in computational spectrometry [16].

The survey focuses on enhancing target detection accuracy and imaging resolution through advanced techniques in Direction of Arrival (DOA) estimation and Synthetic Aperture Radar (SAR) imaging. DOA estimation is crucial in array signal processing, where precise identification of signal sources is vital for applications in communication, radar, and sonar. Recent advancements, including compressed sensing methods, address challenges such as antenna phase errors, thereby improving estimation performance. SAR imaging techniques are integral for applications like TWRI, enabling detection and tracking of objects behind obstacles by leveraging electromagnetic wave interactions. The integration of these technologies aims to provide more reliable and detailed information for various operational scenarios [18, 4, 19]. These concepts are vital for enhancing radar system performance, particularly in environments with limited bandwidth and high interference. Sparse signal recovery, another key term, emphasizes the importance of reconstructing signals from minimal measurements, facilitating advancements in radar imaging techniques.

Multiple-input multiple-output (MIMO) radar and compressive radar imaging are crucial for optimizing radar system capabilities, enhancing target detection and situational awareness. These techniques are essential for addressing high-density scenario challenges and improving radar imaging quality within existing hardware constraints. The integration of concepts from compressive sensing, convolutional neural networks, and frequency agile radar techniques establishes a robust framework for this survey, offering an in-depth exploration of recent advancements in signal processing methodologies tailored to enhance radar imaging capabilities. This comprehensive overview highlights the shift towards sparsity-driven approaches, the application of complex-valued neural networks for improved imaging quality, and the innovative use of structured sensing matrices in frequency agile radar systems, all of which contribute to overcoming traditional limitations in resolution and computational efficiency [9, 12, 20, 21].

1.4 Structure of the Survey

The organization of this survey is meticulously structured to provide a comprehensive examination of advanced signal processing techniques in radar imaging. The paper begins with an introduction that sets the stage by discussing the motivation behind the survey, the scope, and the significance of key terms. Following this, the second section delves into the background and core concepts, offering a detailed explanation of compressed sensing principles and their applications in radar systems. This section also covers sparse signal recovery techniques and their relevance to radar imaging, particularly in DOA estimation and SAR imaging.

The third section explores compressed sensing algorithms specifically in the context of DOA estimation, highlighting the challenges of traditional methods and the innovative techniques that enhance accuracy and efficiency. The fourth section examines the role of compressed sensing in enhancing SAR imaging, focusing on high-resolution imaging and data acquisition efficiency. This includes discussions on tomographic SAR imaging, gridless techniques, and signal reconstruction methods.

The fifth section shifts focus to gridless compressed sensing in radar imaging, detailing the limitations of grid-based methods and the advantages of gridless approaches. It also discusses advanced methods such as DeepInverse and their impact on radar imaging. The sixth section addresses the importance of sparse signal recovery in radar systems and explores advanced techniques and optimization strategies for performance enhancement.

In the seventh section, the application of compressed sensing in MIMO radar systems is analyzed, focusing on data acquisition and processing optimization. This section also examines the role of sparse signal recovery in target detection. The eighth section provides an overview of compressive radar imaging techniques, highlighting innovations in antenna design, measurement matrices, and methods like gridless MCI imaging and HoloCS.

Finally, the survey concludes with a summary of key findings, discussing the impact of compressed sensing algorithms on radar imaging and proposing future research directions. This structured approach facilitates a comprehensive investigation of radar imaging signal processing techniques, yielding significant insights into the latest advancements, such as the application of complex-valued convolutional neural networks (CNNs) for enhanced imaging quality and computational efficiency, as well as addressing challenges like limited resolution and high side-lobes associated with traditional methods. Furthermore, it explores innovative frameworks, including compressive sensing and frequency agile radar, which optimize sampling strategies and improve target detection capabilities in complex environments [9, 22, 20, 4, 21].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Principles of Compressed Sensing

Compressed sensing (CS) revolutionizes signal processing by reconstructing signals from limited measurements, exploiting signal sparsity. Key optimization techniques like Basis Pursuit and LASSO are pivotal for sparse signal recovery, significantly reducing data requirements while maintaining high resolution in radar imaging [23, 13]. CS simplifies complex estimation tasks in radar systems, transforming delay estimation into spectral challenges, as seen in Compressive Illumination and dual-2D-CAMP methods, which utilize sparsity to separate signals from interference [20, 3]. Advanced approaches like RAM-STAP enable gridless sparse recovery, estimating clutter covariance matrices without resolution constraints [24].

In line spectrum estimation, methods such as GDLS reformulate problems into efficient least squares estimations [25]. BSR techniques enhance recovery accuracy by exploiting block sparsity, reducing measurement needs [26]. Unlike traditional methods like MUSIC and ESPRIT, CS offers a robust framework that mitigates their limitations [27]. Scaled CS in automobile SAR assumes signal sparsity, advantageous for low-frequency signals [14]. CSP in MIMO radar reduces sample complexity by leveraging target echo sparsity [15]. SI-CS and HoloCS methods enhance localization accuracy and mitigate optimization complexity [28, 6].

Innovations in CS, such as RSRM, combine long-time integration with gridless sparse methods to improve radar resolution [11]. The SSFC radar employs microwave photonics to process sparse frequency chirp signals, enhancing detection resolution while minimizing interference [1]. RaSSteR

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enhances resolution in range and Doppler domains through random sparse frequency selection [29]. These advancements demonstrate CS's versatility in enhancing radar imaging capabilities with high accuracy and resolution from reduced data.

CS's theoretical foundations lie in convex optimization, with methods minimizing mismatch in observed signal intensities while ensuring non-negativity [30]. Analyzing sensing matrices in FAR systems highlights the importance of randomness in varying frequencies for understanding CS performance in dynamic environments [21]. The Sliding Frank-Wolfe algorithm, a modification of the classical method, exemplifies CS's mathematical foundations by solving the BLASSO problem over Radon measures [23].

2.2 Sparse Signal Recovery Techniques

Sparse signal recovery is crucial in radar systems for reconstructing signals from limited measurements with high accuracy. The inverse problem's ill-posed nature complicates recovery, as traditional methods struggle with noise and lack suitable optimization grids [23]. This survey categorizes sparse recovery algorithms into Convex and Relaxation, Greedy, and Bayesian approaches [31].

Convex and Relaxation methods, like Basis Pursuit, convert ℓ_0 minimization into ℓ_1 minimization, providing a robust framework for sparse recovery, albeit with reduced performance compared to ℓ_0 [31]. Greedy methods, such as OMP, iteratively select promising elements to approximate the signal, balancing efficiency with performance. Bayesian approaches enhance recovery accuracy by integrating probabilistic models and prior knowledge [32, 33, 34].

In high-dimensional contexts, traditional iterative algorithms face inefficiencies. Learning-based approaches, like CSEN, offer non-iterative solutions for support estimation, suitable for mobile and edge devices [9]. These methods employ deep learning to predict sparse signal support, circumventing iterative algorithms.

Accurate CSI is vital for effective beam selection in mmWave massive MIMO systems [35]. Techniques for recovering weak meteor signals highlight challenges posed by cross-interference in MIMO radar, necessitating robust methods. A proposed sparse sampling algorithm reconstructs lost samples, enhancing detection capabilities [36].

Jointly sparse signal recovery techniques, particularly in MMV models, are crucial for applications like channel estimation and device activity detection in MIMO-based grant-free random access systems. These techniques manage mMTC complexities in IoT, where only a subset of devices is active. By leveraging compressive sensing, optimization, and deep learning, these approaches enhance accuracy and efficiency, enabling faster detection of active devices with minimal computational overhead [10, 37, 12, 13, 38].

ADMM is an advanced algorithm for recovering unknown multidimensional frequencies from compressive measurements, addressing challenges like DOA estimation without grid-based constraints. It employs atomic norm minimization to integrate sparsity priors, demonstrating robustness in high-dimensional scenarios [39, 27, 40, 20, 12]. Integrating subspace methods and compressive sensing in DOA estimation enhances resolution in mixed signal scenarios, providing robust radar solutions.

The blind super-resolution problem, being ill-posed, relates closely to sparse signal recovery techniques, emphasizing innovative approaches to overcome these limitations [17]. Research has advanced in miniaturizing spectrometers for portable devices while maintaining high spectral resolution [16].

Various sparse signal recovery techniques in radar systems highlight innovative methodologies for signal reconstruction. These include matching components, constrained convex formulations, and Bayesian methods, each offering advantages in managing noise and sparsity. Compressive sensing capitalizes on radar signals' sparsity, enabling reconstruction from fewer measurements, enhancing performance in dynamic environments. Structured acquisition systems and advanced MIMO radar architectures optimize recovery guarantees while simplifying system design and calibration [12, 20, 22].

2.3 Applications in Radar Imaging

Compressed sensing (CS) is pivotal in advancing radar imaging technologies, particularly in DOA estimation and SAR imaging. By leveraging radar signals' sparsity, CS acquires high-resolution data with reduced measurements. In DOA estimation, CS enhances accuracy in challenging environments with low SNRs and limited snapshots [19]. Sparse signal recovery methods improve coherent source resolution, even with a single snapshot [19]. Integrating CS into massive MIMO radar systems optimizes signal source localization by exploiting spatial sparsity, enhancing radar performance in complex scenarios [2].

In SAR imaging, CS facilitates high-resolution image reconstruction from fewer measurements, addressing challenges like limited cross-track apertures and non-uniform antenna distributions [41]. The HoloCS method integrates CS with holographic imaging, enhancing computational efficiency and image quality [6]. Advanced methods like VGD-VHL and ScalGD-VHL enable blind super-resolution, crucial for recovering sparse scattering points in radar imaging [17].

CS's application in automotive radar systems is exemplified by a 4D MIMO radar imaging system, synthesizing large bandwidths and employing sparse arrays for high-resolution range-Doppler profiles and accurate angle estimation [2]. This is vital for driver assistance and autonomous driving, where radar interferences can degrade detection and lead to sensor blindness [36]. The RaSSteR method enhances detection and resolution in interference-prone scenarios with moving targets [29].

In airborne radar systems, CS techniques suppress range-ambiguous clutter, enhancing target detection in high-speed environments [7]. CS's ability to process interferences blindly and improve signal recovery accuracy underscores its advantages over traditional methods [8]. Microwave photonic radar with SSFC signals illustrates CS's potential in enhancing resolution and anti-interference capabilities, achieving precise target distinction [1].

CS's versatility in radar imaging is evident in UAV swarm localization, addressing high density and small radar cross-sections challenges [11]. Deep learning techniques, such as CV-CNN, demonstrate CS's role in enhancing image quality and computational efficiency [9]. Compressed sensing transforms radar imaging by improving resolution, reducing data requirements, and enhancing performance across modalities, including DOA estimation and SAR imaging, playing a crucial role in advancing radar technologies.

2.4 Key Concepts in DOA Estimation and SAR Imaging

DOA estimation and SAR imaging are fundamental to radar systems, enhancing situational awareness and signal processing. DOA estimation identifies signal arrival directions at sensor arrays, crucial for target tracking, localization, and navigation. Modern DOA estimation techniques manage high-dynamic-range signals while preserving original signal information, ensuring compatibility with existing methods [42]. Challenges like antenna phase inconsistencies necessitate robust solutions and advanced algorithms [18].

SAR imaging generates high-resolution images by simulating a large antenna aperture, invaluable for detailed ground mapping, surveillance, and reconnaissance. A core challenge is addressing phase errors that defocus images, often caused by uncertainties in observation positions [43]. Efficient SAR imaging requires minimizing the sensing matrix's mutual coherence, critical for optimizing sparse signal recovery [44].

Key concepts such as 'sparse scattering points' and 'gridless super-resolution' are integral to understanding CS applications in radar systems, particularly in enhancing ISAR imaging. The super-resolution problem involves recovering point source locations and intensities from noisy observations, crucial for radar imaging [30]. The Sliding Frank-Wolfe algorithm exploits the continuous nature of optimization problems, allowing precise spike localization and recovery [23].

Techniques like tensor compressive sensing with 2D cross-MIMO arrays enhance data acquisition speed and facilitate three-dimensional imaging, advancing radar capabilities [45]. Deep learning, exemplified by convolutional sparse support estimator networks, improves support estimation and enables advanced applications like anomaly detection and face recognition [46]. Utilizing prior statistical information about the beamspace channel, as demonstrated by the GM-LAMP network, boosts estimation accuracy in radar systems [35].

Integrating DOA estimation and SAR imaging is pivotal in evolving radar technologies, significantly enhancing resolution, accuracy, and efficiency across diverse applications, including remote sensing, through advanced methodologies such as CV-CNN and CS techniques. These innovations improve

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imaging quality and computational efficiency while addressing phase error challenges, broadening radar applications in fields like communication, security, and emergency response [9, 18, 4].

In recent years, the field of Direction of Arrival (DOA) estimation has seen significant advancements, particularly through the lens of compressed sensing algorithms. These developments not only address the limitations of traditional methods but also pave the way for innovative techniques that enhance signal recovery and estimation accuracy. Figure 2 illustrates the hierarchical structure of these compressed sensing algorithms, effectively highlighting the challenges associated with conventional approaches alongside the novel algorithmic strategies designed to overcome them. By examining this figure, one can appreciate the systematic progression from traditional methods to more sophisticated techniques, underscoring the importance of algorithmic optimization in achieving improved performance in DOA estimation.

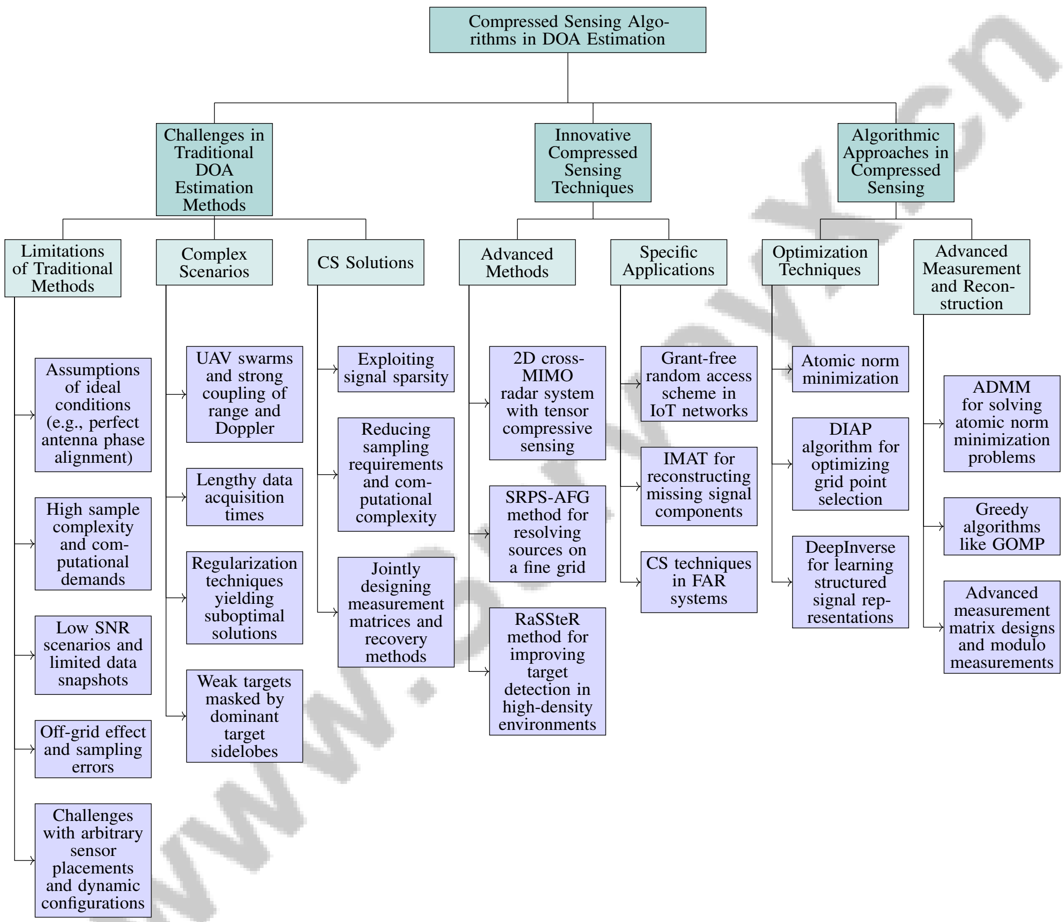

Figure 2: This figure illustrates the hierarchical structure of compressed sensing algorithms in DOA estimation, highlighting the challenges in traditional methods, the innovative techniques developed to address these challenges, and the algorithmic approaches that optimize signal recovery and estimation accuracy.

3 Compressed Sensing Algorithms in DOA Estimation

3.1 Challenges in Traditional DOA Estimation Methods

Traditional Direction of Arrival (DOA) estimation techniques, including MVDR and MUSIC, face significant challenges in modern radar applications due to their assumptions of ideal conditions, such as perfect antenna phase alignment and high angular resolution, which are rarely met in practice. These limitations lead to reduced accuracy, necessitating advanced techniques like compressed sensing (CS) and hardware-software co-design to enhance DOA estimation in complex environments

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[18, 42]. The high sample complexity and computational demands of processing data from numerous antennas further hinder traditional methods, particularly when large arrays are impractical due to spatial and cost constraints. Low SNR scenarios with limited data snapshots exacerbate issues like self-signal cancellation and inaccurate spatial covariance estimation, degrading performance [19]. The off-grid effect, where clutter does not align with predefined grid points, introduces sampling errors and inaccurate estimates [24]. Additionally, traditional methods struggle with arbitrary sensor placements and dynamic configurations, leading to inaccuracies [30].

Complex scenarios such as UAV swarms further complicate target detection due to the strong coupling of range and Doppler information. Lengthy data acquisition times for 2D synthetic apertures hinder real-time applications [45]. Regularization techniques often yield suboptimal solutions [17], while weak targets can be masked by dominant target sidelobes, limiting detection and feature extraction [21]. Removing interfered samples can introduce signal gaps, causing artifacts and reducing detection capability [36]. Methods like LASSO struggle to recover high-frequency details from noisy signals, highlighting the need for approaches that enhance resolution beyond the Rayleigh criterion [23].

Figure 3 illustrates the challenges faced by traditional DOA estimation methods, categorizing them into limitations, complex scenarios, and advanced techniques. It highlights not only the assumptions and computational demands of traditional methods but also the complexities of modern radar scenarios and the advanced techniques like compressed sensing that address these challenges. CS offers promising solutions by exploiting signal sparsity to reduce sampling requirements and computational complexity. CS techniques enable accurate recovery from fewer measurements, enhancing resolution and robustness in challenging scenarios. By addressing traditional methods' limitations, CS paves the way for more efficient radar imaging systems, as evidenced by approaches that jointly design measurement matrices and recovery methods to improve efficiency and accuracy [38].

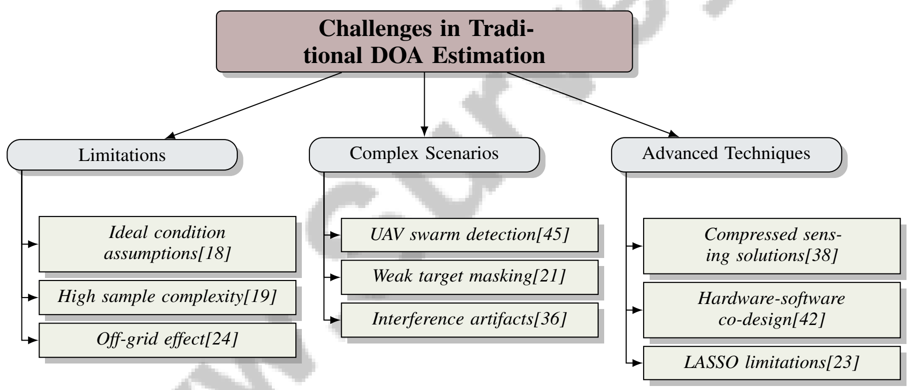


Figure 3: This figure illustrates the challenges faced by traditional DOA estimation methods, categorizing them into limitations, complex scenarios, and advanced techniques. It highlights the assumptions and computational demands of traditional methods, the complexities of modern radar scenarios, and the advanced techniques like compressed sensing that address these challenges.

3.2 Innovative Compressed Sensing Techniques

Innovative CS techniques have significantly advanced DOA estimation by overcoming the limitations of traditional methods and enhancing accuracy and efficiency. A key development is the use of a 2D cross-MIMO radar system with tensor compressive sensing, enabling rapid 3D imaging and displacement measurements, thus improving DOA estimation in complex environments [45]. This approach leverages radar signal sparsity to enhance resolution and reduce computational demands.

The SRPS-AFG method improves accuracy and stability in DOA estimation by resolving sources on a fine grid without extensive computations [30]. This method addresses the off-grid problem by using a Fourier series representation, enabling accurate DOA estimation without exhaustive grid searches [19].

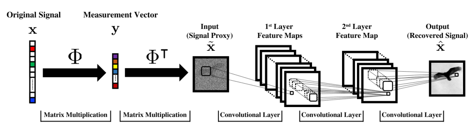
The RaSSteR method enhances performance against ECCM by randomizing carrier sequences and shuffling vacant bands, improving target detection in high-density environments where traditional methods struggle with interference and clutter [29].

In IoT networks, a grant-free random access scheme reduces access latency and improves device detection accuracy, allowing direct data transmission without waiting for permission, thus enhancing signal processing efficiency in DOA estimation [10].

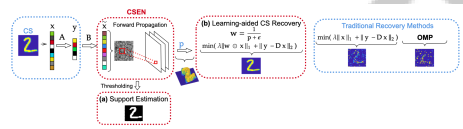
The IMAT reconstructs missing signal components by adaptively adjusting thresholds based on signal characteristics [36], making it particularly useful in automotive radar systems where signal integrity is crucial.

Employing CS techniques in FAR systems improves joint range-Doppler estimation, providing a theoretical guarantee of successful target recovery [21]. This approach enhances DOA estimation robustness in dynamic environments.

Collectively, these innovative CS techniques offer robust solutions to DOA estimation challenges, significantly enhancing radar systems' accuracy and efficiency. By addressing issues such as antenna phase errors and environmental noise, these methods facilitate advanced signal processing applications across various fields, including communication, radar, and sonar technologies [18, 27, 40, 47].



(a) Convolutional Neural Network (CNN) for Signal Recovery[33]



(b) Learning-Aided CS Recovery for Sparse Representation[46]

Figure 4: Examples of Innovative Compressed Sensing Techniques

As depicted in Figure 4, CS algorithms have emerged as pivotal innovations in DOA estimation, offering enhanced accuracy and efficiency. The first technique employs a CNN to reconstruct signals from a measurement vector, processing a signal proxy through multiple convolutional layers to approximate the original signal, highlighting deep learning's potential in refining signal recovery processes. The second technique focuses on learning-aided CS recovery for sparse representation, involving a two-step process: support estimation to identify non-zero element indices and subsequent learning-aided recovery to reconstruct sparse signals from limited measurements. These techniques exemplify innovative CS applications in DOA estimation, advancing traditional signal processing methodologies [33, 46].

3.3 Algorithmic Approaches in Compressed Sensing

Numerous algorithmic strategies have been developed in DOA estimation to exploit CS principles, enhancing precision and efficiency in signal recovery. A notable approach is atomic norm minimization, which employs a dual maximization strategy tailored for arbitrary array geometries to estimate DOA. This method is effective in scenarios with limited snapshots and low SNR, providing high-resolution estimates under challenging conditions [19].

The DIAP algorithm optimizes grid point selection probabilities for transmit and receive arrays, minimizing coherence and improving DOA estimation accuracy [48]. This approach is crucial for optimizing antenna configurations in radar systems, ensuring efficient signal acquisition.

Deep learning techniques, such as DeepInverse, have been integrated into CS frameworks to learn structured signal representations, significantly reducing signal reconstruction time [33]. By leveraging neural networks, DeepInverse addresses non-linearities and complexities in high-dimensional data, providing robust solutions for DOA estimation in complex environments.

The ADMM is a powerful optimization tool for solving atomic norm minimization problems, facilitating multi-dimensional line spectral estimation from multiple compressive measurements [39]. This method effectively handles computational challenges in large-scale DOA estimation, offering scalable solutions.

Greedy algorithms, such as GOMP, iteratively refine initial DOA estimates obtained from OMP through gradient-descent refinement, achieving high-resolution estimation [40]. These algorithms balance computational efficiency and recovery accuracy, making them suitable for real-time processing scenarios.

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Advanced measurement matrix designs reduce data size and computational complexity while enhancing robustness against noise, improving overall DOA estimation performance in noisy environments [47]. Modulo measurements allow for recovering DOA from high-amplitude signals without saturation issues common with traditional ADCs, enhancing the system's dynamic range [42].

Integrating clustering techniques, such as DBSCAN, with CS-based signal reconstruction facilitates identifying the most likely angles for DOA estimation [49]. This combination enhances the reliability of DOA estimates, particularly in environments with multiple signal sources.

The various algorithmic approaches highlighted in recent studies demonstrate the adaptability and efficacy of CS techniques in overcoming DOA estimation challenges. These methods optimize measurement matrices to minimize data size and environmental noise, particularly in massive MIMO radar systems, while enhancing computational efficiency and robustness in diverse operational conditions. By framing DOA estimation as a sparse reconstruction problem, they provide advanced solutions that significantly improve radar system performance, even amid antenna phase errors and other complexities [18, 47].

4 Compressed Sensing in Synthetic Aperture Radar (SAR) Imaging

4.1 Tomographic SAR Imaging and Gridless Techniques

Tomographic Synthetic Aperture Radar (SAR) imaging is pivotal for extracting three-dimensional information from multiple SAR images, enhancing radar imaging capabilities. Traditional grid-based methods often suffer from grid mismatch, which compromises spatial accuracy. Gridless techniques offer a solution by allowing continuous scene representation [50]. The gridless MCI imaging method, utilizing atomic norm minimization (ANM), resolves grid mismatch, enhancing SAR image fidelity and accuracy [50]. This method transcends predefined grids, offering flexibility and precision. The dual-2D-CAMP method advances SAR imaging by processing OFDM radar signals through a dual-2D approach, improving signal separation and image fidelity in the range-Doppler domain [3].

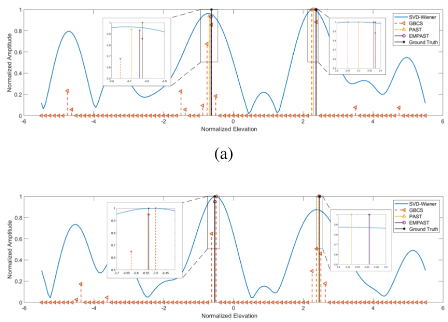
Compressive sensing (CS) techniques significantly contribute to efficient tomographic SAR imaging. Tohidi et al.'s method reduces measurement requirements while preserving high resolution, combining Capon beamforming for clutter suppression with hypothesis testing for target detection [15]. The SI-CS method employs coprime array technology to enhance localization accuracy, showcasing the potential of advanced configurations in SAR imaging performance [28].

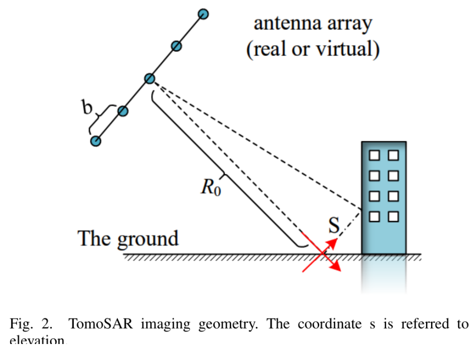
Correcting phase errors is crucial for maintaining image quality in SAR imaging. Li et al. present a two-step optimization framework to address these errors, enhancing image clarity [43]. Similarly, Shahbazi et al.'s 2D measurement matrix design (2D-MMDGD) optimizes data acquisition by reducing computational complexity while improving performance [44].

The integration of MIMO-OFDM systems in SAR imaging, as demonstrated by Liu et al., involves a two-stage approach for estimating scattered channels and extracting target location information, highlighting advanced signal processing techniques in SAR applications [51]. Furthermore, the joint design of sparse frequency and sparse array configurations proposed by Sun et al. achieves high-resolution imaging in four dimensions, underscoring the potential of innovative array designs to enhance SAR capabilities [2].

In airborne forward-looking radar systems, the MLC-FDA method combines main lobe correction and compressed sensing techniques to suppress range-ambiguous clutter, illustrating CS's efficacy in overcoming traditional imaging challenges [7]. The generation of wide bandwidth SSFC signals via recirculating frequency shifts enables precise target information extraction through microwave photonic dechirping, further enhancing SAR imaging precision [1].

These advanced SAR imaging techniques, including tomographic approaches and gridless methods, signify substantial progress in overcoming traditional grid-based limitations. By integrating compressive sensing advancements, innovative array designs, and sophisticated signal processing techniques, these methodologies improve SAR imaging's accuracy, efficiency, and resolution. This progress addresses challenges in achieving high resolution with limited sensor dynamic range and facilitates the practical implementation of radar systems utilizing structured waveforms and efficient measurement matrices, paving the way for advanced radar imaging systems in applications such as surveillance and remote sensing [9, 44, 20, 43, 52].





(a) Comparison of Different Elevation Estimation Methods[53]

(b) TomoSAR Imaging Geometry[25]

Figure 5: Examples of Tomographic SAR Imaging and Gridless Techniques

As shown in Figure 5, compressed sensing has emerged as a powerful technique in Synthetic Aperture Radar (SAR) imaging, particularly within Tomographic SAR (TomoSAR) and gridless methods. The first image provides a comparative analysis of various elevation estimation methods, such as SVD-Wiener, GBCS, PAST, and EMPAST, evaluated against ground truth over a range of normalized elevations. The second image illustrates TomoSAR imaging geometry, depicting an antenna array angled to the ground and a grid-patterned building as the target. This visualization highlights the intricate spatial relationships and precision required in TomoSAR imaging, emphasizing the antenna array's orientation and distance from the ground in capturing detailed three-dimensional information. Together, these images encapsulate advancements in SAR techniques, underscoring the integration of compressed sensing and gridless approaches to enhance image resolution and accuracy [53, 25].

4.2 Sparse Recovery and Signal Reconstruction Methods

Sparse recovery and signal reconstruction are crucial in Synthetic Aperture Radar (SAR) applications, enhancing image resolution and accuracy while minimizing data acquisition needs. Robust frameworks and methodologies have significantly improved SAR capabilities, effectively addressing challenges like noise interference and phase errors. Innovations such as gridless compressed sensing and deep learning approaches have been instrumental in enhancing image quality and computational efficiency, allowing precise three-dimensional reconstructions from UAV-borne platforms while tackling the "off-grid" effect and the limitations of traditional sparsity regularization methods. These developments facilitate rapid deployment and cost-effective solutions in urban mapping, enhancing noise immunity and overall imaging accuracy [9, 53, 41].

The integration of deep learning into sparse recovery processes, exemplified by the CV-CNN method, enhances imaging quality and processing speed compared to traditional methods [9]. This approach illustrates the transformative impact of machine learning in optimizing signal reconstruction for real-time applications.

In three-dimensional SAR imaging, the T-IAA method reconstructs sparse targets using a tensor compressive sensing framework, enabling efficient data processing and improved imaging results [45]. This method exemplifies advanced signal processing techniques' potential to overcome traditional grid-based limitations, providing robust solutions for high-resolution imaging in dynamic environments.

RaSSteR employs sparse recovery techniques to estimate high-resolution range and Doppler while consuming fewer spectral resources [29]. This method's optimization of spectral resource usage is particularly beneficial in bandwidth-limited scenarios, enhancing SAR imaging efficiency.

The Sliding Frank-Wolfe algorithm directly optimizes over the space of measures, improving recovery accuracy and robustness against noise [23]. This method's efficacy in complex signal environments makes it valuable for advanced SAR applications, especially where traditional methods struggle due to noise and interference.

As illustrated in Figure 6, the integration of advanced methods in sparse recovery and signal reconstruction for SAR applications has led to significant improvements in image quality, data efficiency, and computational performance. The figure highlights the hierarchical categorization of sparse recovery and signal reconstruction methods, focusing on gridless compressed sensing, deep learning integration, and advanced signal processing techniques, with references to key methodologies and innovations in each area. Notably, gridless compressed sensing techniques, addressing the "off-grid" effect and enhancing noise immunity, have proven effective in UAV-borne SAR tomography. This innovative approach leverages UAV platforms' advantages, such as single-flight 3D imaging capabilities and flexible trajectory planning, while utilizing multiple measurement vectors (MMV) models and atomic norm soft thresholding algorithms to optimize reconstruction accuracy and efficiency [12, 53].

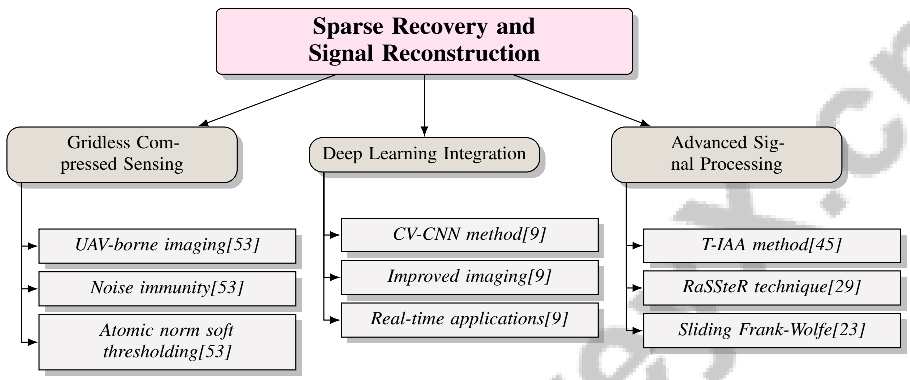


Figure 6: This figure illustrates the hierarchical categorization of sparse recovery and signal reconstruction methods, focusing on gridless compressed sensing, deep learning integration, and advanced signal processing techniques, with references to key methodologies and innovations in each area.

4.3 Compressive Sampling and Structured Waveforms

Compressive sampling and structured waveforms are vital for improving Synthetic Aperture Radar (SAR) imaging, optimizing the balance between data acquisition efficiency and image resolution. By leveraging compressive sensing principles, SAR systems achieve high-resolution imaging while significantly reducing required sampling rates, minimizing data volume collected. Integrating structured waveforms allows for efficient signal processing and enhances the system's ability to recover target parameters with fewer measurements, ultimately improving performance in various surveillance applications. Additionally, advancements in phase error correction methods for compressed sensing radar imaging further enhance image quality, effectively addressing phase discrepancies during data acquisition [43, 20]. Compressive sampling in SAR imaging utilizes radar signal sparsity to reconstruct high-resolution images from significantly fewer measurements, reducing the data acquisition burden while maintaining image quality, particularly advantageous in scenarios with limited bandwidth and high data throughput requirements.

Structured waveforms, designed through random interleaving patterns, play a crucial role in enhancing SAR systems' flexibility and robustness [54]. These waveforms maximize the information content of received signals, improving the system's ability to resolve fine details in the target scene. By employing compressive sensing techniques, the method efficiently reconstructs the signal, preserving SAR imaging's high-resolution capabilities even with reduced data input [54].

Structured waveforms also enable adaptive sensing strategies, allowing dynamic adjustments of waveform parameters based on the target environment and operational requirements. This adaptability is critical for optimizing SAR performance in diverse and challenging conditions, such as cluttered urban environments or complex terrain. Customizing waveform properties for specific imaging tasks significantly enhances radar systems' overall efficiency and effectiveness, facilitating improved target detection and characterization through advanced techniques like complex-valued convolutional neural networks (CV-CNN) and compressive sensing, resulting in better imaging quality, resolution, reduced side-lobes, and enhanced performance in challenging environments with interference [9, 20, 29].

Moreover, utilizing compressive sampling alongside structured waveforms supports developing advanced SAR imaging techniques, such as multi-channel and multi-static configurations, further enhancing spatial resolution and target discrimination capabilities. SAR systems' configurations leverage compressive sensing advantages, significantly reducing data acquisition requirements and enhancing processing efficiency. This advancement facilitates deploying SAR technology across various applications, including environmental monitoring, defense, and surveillance, enabling effective signal reconstruction from fewer measurements and faster target detection through improved algorithms and structured antenna placement [15, 20, 44, 48].

The synergy between compressive sampling and structured waveforms exemplifies the potential for innovation in SAR imaging, paving the way for more efficient, flexible, and high-performance radar systems. As research in Synthetic Aperture Radar technology progresses, integrating advanced techniques such as deep learning-based imaging methods and gridless compressed sensing is expected to yield substantial improvements in three-dimensional (3D) imaging capabilities, enhancing noise immunity, reducing computational burdens, and improving reconstruction accuracy, thus significantly expanding SAR technology's potential applications in urban mapping, through-the-wall imaging, and other critical areas [4, 53, 41].

5 Gridless Compressed Sensing in Radar Imaging

The inherent limitations of grid-based compressed sensing in radar imaging, such as discretization errors and the 'off-grid' effect, necessitate the evolution towards gridless methods. These advancements are crucial for improving reconstruction accuracy, as grid-based approaches often impair imaging quality and performance due to their reliance on predefined grids. This section explores the challenges of grid-based methods and highlights the need for gridless techniques to enhance radar imaging capabilities.

5.1 Challenges of Grid-Based Compressed Sensing

Grid-based compressed sensing methods face significant challenges, primarily due to discretization errors that lead to the 'off-grid' effect, particularly in the elevation dimension. This issue arises when grid discretization inaccurately represents continuous signal sources, thereby impairing reconstruction accuracy [53]. Techniques such as Microwave Coincidence Imaging (MCI) suffer from grid mismatch, which degrades imaging quality regardless of grid fineness [50]. In MIMO radar systems, these limitations manifest as misalignments with actual signal structures, affecting recovery performance [55]. The computational demands of grid-based methods further limit their applicability in real-time scenarios [41]. In high-density environments, such as UAV swarm localization, grid-based methods struggle to accurately localize targets due to their rigidity [11].

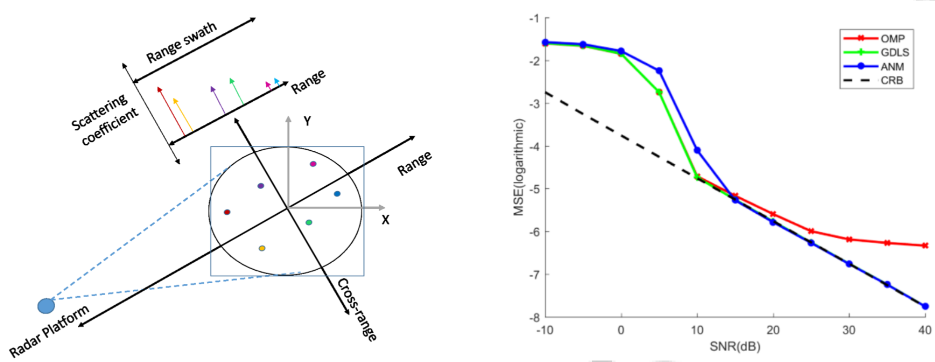
Gridless approaches provide a promising alternative by employing advanced optimization techniques that eliminate the need for predefined grids. The 2D-RWTM method enhances resolution and simplifies algorithms through precise scattering point localization [56]. These methods improve spike recovery accuracy and demonstrate robustness against noise, maintaining high imaging quality [41]. The CSP MIMO radar method exemplifies significant reductions in sample complexity, highlighting gridless techniques' efficiency in minimizing data requirements while preserving high-resolution capabilities [15]. Additionally, gridless methods streamline calibration processes and enable high-resolution imaging without complex receiver designs, showcasing their potential to overcome grid-based limitations [20].

5.2 Gridless Techniques in Radar Imaging

Gridless techniques mark a significant advancement in radar imaging, enhancing resolution and accuracy by bypassing the constraints of predefined grids. The Gridless Microwave Coincidence Imaging Method (G-MCI) utilizes a continuous compressed sensing framework to recover signal frequencies without grid reliance, improving imaging fidelity [50]. In three-dimensional imaging, particularly for UAV-borne Tomographic SAR (TomoSAR) applications, a gridless 3-D imaging framework employing multiple measurement vectors (MMV) significantly enhances reconstruction accuracy and super-resolution capabilities [53].

These techniques effectively eliminate discretization errors associated with traditional methods, mitigating the 'off-grid' effect that compromises image quality in UAV-borne synthetic aperture radar (SAR) tomography and space-time adaptive processing (STAP) [53, 24]. By facilitating continuous scene representation, gridless methods offer a more adaptable and precise approach to radar imaging, especially in dynamic and high-density environments where traditional methods falter.

The integration of gridless techniques underscores their transformative potential in radar imaging, providing advanced solutions that enhance resolution, accuracy, and efficiency. By addressing grid mismatch issues inherent in traditional methods, innovative techniques such as atomic norm minimization and reweighted trace minimization enable precise imaging of complex environments, crucial for applications like microwave coincidence imaging and synthetic aperture radar tomography [9, 53, 50, 56, 24]. As research advances, these techniques are poised to drive significant innovations in radar imaging, facilitating the development of sophisticated and high-performance radar systems.



(a) Scattering Coefficient and Range Swath in Radar Imaging[20]

(b) Comparison of MSE of Different Estimation Methods under Noise[25]

Figure 7: Examples of Gridless Techniques in Radar Imaging

As illustrated in Figure 7, gridless compressed sensing has emerged as a pivotal technique in radar imaging, enhancing precision and efficiency in signal processing. The first example highlights the relationship between the scattering coefficient and range swath, encapsulating the spatial dynamics captured by radar systems. The second example compares the mean squared error (MSE) of various signal estimation methods against signal-to-noise ratio (SNR), delineating the performance of methods such as Optimal Matching Pursuit (OMP), Gradient Descent Least Squares (GDLS), Alternating Non-negative Matrix (ANM), and the Cramér-Rao Bound (CRB). These examples collectively emphasize the transformative potential of gridless compressed sensing in refining radar imaging techniques [20, 25].

5.3 DeepInverse and Structured Representation

DeepInverse represents an advanced gridless method utilizing deep learning to enhance radar imaging by learning structured representations of signals, overcoming the limitations of traditional methods reliant on predefined grids prone to discretization errors. By employing neural networks, DeepInverse captures the underlying structure of radar signals, facilitating more accurate and efficient signal recovery [33].

Incorporating deep learning into radar imaging fosters adaptive algorithms capable of learning from data, thus improving resolution and robustness. In complex signal environments where traditional methods falter due to noise and interference, DeepInverse excels by enhancing radar systems' ability to resolve fine details and accurately localize targets [33].

Structured representation in radar imaging employs advanced optimization techniques to exploit the sparsity and structure inherent in radar signals, reducing dependence on predefined grids and improving image fidelity. By focusing on signals' intrinsic properties, structured representation methods offer a flexible and accurate framework for radar imaging, enhancing both resolution and computational efficiency [33].

The integration of DeepInverse and structured representation techniques, particularly through complex-valued convolutional neural networks (CV-CNN) and deep network-based methods, marks a significant advancement in radar imaging technology. As illustrated in Figure 8, this figure highlights the hierarchical structure of DeepInverse and structured representation in radar imaging, emphasizing key methodologies such as gridless methods, optimization techniques, and integration techniques like CV-CNN and deep network methods, which collectively enhance signal recovery and imaging quality. These innovations improve imaging quality by addressing limitations such as resolution and side-lobe reduction and enhance computational efficiency and robustness against noise and model errors, as demonstrated by extensive simulations and experiments [9, 41]. These methods provide robust solutions that enhance the accuracy, resolution, and efficiency of radar systems, paving the way for sophisticated and high-performance imaging capabilities. As research evolves, the fusion of deep learning and structured representation is expected to drive further innovations in radar imaging technology.

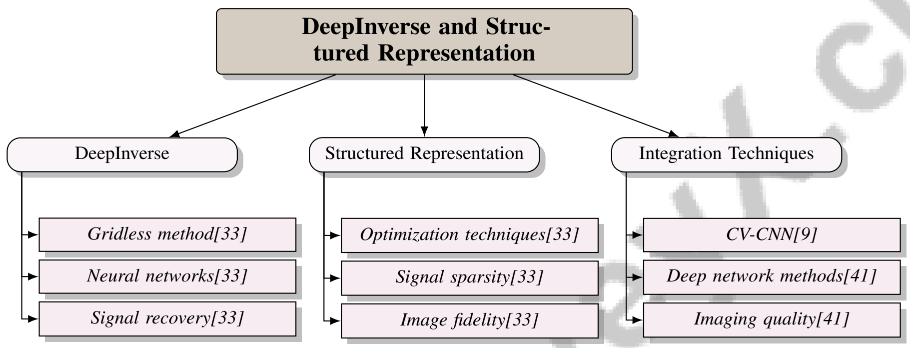


Figure 8: This figure illustrates the hierarchical structure of DeepInverse and structured representation in radar imaging, highlighting key methodologies such as gridless methods, optimization techniques, and integration techniques like CV-CNN and deep network methods, which enhance signal recovery and imaging quality.

6 Sparse Signal Recovery in Radar Systems

6.1 Importance of Sparse Signal Recovery in Radar Systems

Sparse signal recovery is pivotal in modern radar systems, enhancing performance in real-time processing and high-resolution imaging. The inherent sparsity of radar signals allows for efficient data acquisition and processing, critical in complex environments. The Iterative Method with Adaptive Thresholding (IMAT) exemplifies this by improving detection through reconstructing missing samples, thus enhancing radar accuracy and robustness [36]. In Frequency Agile Radar (FAR), tailored compressed sensing (CS) methods address traditional sidelobe issues, ensuring reliable target recovery and high-resolution detection in cluttered environments [21]. Sparse signal recovery also enables precise reconstruction of high-frequency signals from limited measurements, as demonstrated in UAV swarm localization where high radar resolution and localization accuracy are essential [11]. The Sparse Stepped Frequency Chirp (SSFC) radar highlights sparse recovery's role in boosting anti-jamming performance and ensuring robust operations without high-speed electronic components [1].

Advanced methodologies, such as 2D cross-MIMO radar systems, underscore sparse recovery's significance in achieving high-resolution imaging while minimizing data requirements [45]. These methods demonstrate computational efficiency and effectiveness in accurately estimating Directions of Arrival (DOAs) under challenging conditions, eliminating the need for fine grid searches [19]. The robustness of sparse recovery methods against noise and their adaptability to arbitrary source placements are crucial for reliable radar system performance [30]. Collectively, these techniques elevate radar capabilities, enhancing resolution, accuracy, and efficiency while addressing traditional system limitations.

6.2 Advanced Techniques for Sparse Signal Recovery

Advancing sparse signal recovery in radar requires innovative techniques addressing noise, measurement matrices, and computational complexity. Optimal measurement matrix selection is crucial, as exemplified by the 2D-MMDGD method, which uses gradient descent to iteratively optimize the measurement matrix, enhancing signal recovery efficiency [44]. Deep learning approaches, such as DeepCodec, outperform traditional methods like ℓ_1-minimization and DeepInverse, especially in challenging scenarios, by capturing complex signal structures and improving recovery accuracy [32].

Arjoune et al. classify sparse recovery algorithms into Greedy, Convex and Relaxation, and Bayesian approaches, each offering unique benefits. Greedy algorithms excel in speed for real-time applications, while Convex and Relaxation methods ensure lower recovery errors for high-precision tasks. Bayesian techniques balance recovery error and computational time, making them suitable for scenarios requiring both accuracy and efficiency [31]. The CS-MIMO approach exemplifies advancements in angular resolution, achieving significant improvements over standard MIMO configurations, enhancing resolution and target detection capabilities [52]. However, the coherence of the sensing matrix remains a challenge, necessitating ongoing research into optimizing matrix design for consistent performance across diverse conditions [57].

These advanced techniques reflect continuous innovations in sparse signal recovery, providing robust solutions that enhance radar capabilities by improving resolution, accuracy, and computational efficiency. The integration of deep learning techniques, particularly complex-valued convolutional neural networks (CV-CNNs), is expected to further enhance imaging quality and computational efficiency, addressing traditional methods' limitations by transforming imaging challenges into optimization problems and leveraging sparsity-driven approaches. This integration is crucial for advancing radar imaging systems and meeting modern application demands, including 3D Synthetic Aperture Radar (SAR) [9, 34, 41].

6.3 Optimization and Performance Enhancement

Benchmark	Size	Domain	Task Format	Metric

Table 1: This table presents a comprehensive overview of representative benchmarks used in optimizing sparse signal recovery methods. It details the size, domain, task format, and metric of each benchmark, providing a foundation for evaluating algorithmic performance in diverse radar system applications.

Optimizing sparse signal recovery methods in radar systems is vital for enhancing performance in complex and dynamic environments. Developing advanced algorithms capable of handling diverse measurement patterns without extensive retraining is a key strategy. The Learned Sparse Bayesian Learning (L-SBL) algorithm exemplifies this by adapting to arbitrary measurement patterns, maintaining high recovery accuracy across varying conditions [34]. Improving efficiency and accuracy in cognitive radio contexts is a research focus, driven by the need to optimize spectrum utilization and enhance signal detection in bandwidth-limited environments [31].

Optimizing measurement structures in MIMO radar systems is another avenue, with methods like Dorsch et al.'s achieving optimal recovery with fewer measurements, reducing computational burden and enhancing performance [22]. Integrating deep learning techniques into sparse recovery processes opens new optimization pathways. Neural networks capture complex signal structures, improving recovery accuracy where traditional methods struggle. The synergy between deep learning, particularly CV-CNNs, and sparse recovery algorithms is poised to catalyze significant advancements in radar imaging technology, enhancing imaging resolution and accuracy while improving computational efficiency. This integration addresses existing limitations, achieving superior imaging quality and faster processing times [9, 34].

The optimization of sparse signal recovery methods is a rapidly advancing field characterized by ongoing research aimed at enhancing algorithmic performance across diverse applications, including signal processing, cognitive radio, and imaging. Current efforts focus on developing innovative strategies addressing real-world data sparsity, computational efficiency, and deep learning integration, promising significant improvements in recovery speed and accuracy while accommodating various signal structures and measurement conditions [32, 34, 31, 33, 12]. As these techniques evolve, they will play a pivotal role in enhancing radar system capabilities, ensuring reliable and accurate signal processing in increasingly complex environments. Table 1 provides a detailed overview of representative benchmarks pertinent to the optimization of sparse signal recovery methods in radar systems.

7 Compressed Sensing in MIMO Radar

7.1 Integration of Compressive Sensing with MIMO Radar

Integrating compressive sensing (CS) with multiple-input multiple-output (MIMO) radar systems represents a significant advancement in radar technology, enhancing both signal recovery and system performance. By leveraging radar signal sparsity, CS minimizes data acquisition needs while maintaining high-resolution capabilities. For example, MIMO OFDM systems strategically allocate subcarriers to improve radar resolution and communication rates, demonstrating CS's dual benefits [58]. The random TDM/FDM-MIMO approach exemplifies this by enhancing waveform design flexibility and maintaining signal-to-noise ratio (SNR) and unambiguity, utilizing multidimensional CS techniques for superior signal reconstruction [54].

Urco et al. highlight the enhanced signal recovery achieved by integrating CS with MIMO radar architectures, addressing high-dimensional data processing challenges [55]. The CS-MIMO benchmark evaluates antenna designs, focusing on angular resolution and compression ratios, underscoring CS's advantages in radar capabilities [52]. The Dynamic Iterative Antenna Positioning (DIAP) algorithm further optimizes Direction of Arrival (DoA) estimation accuracy through optimal antenna placements, minimizing measurement matrix coherence [48].

Refined CS methods tailored to MIMO radar measurements optimize the measurement process, ensuring robust signal recovery with fewer measurements and reduced computational complexity [22]. Additionally, power allocation and antenna placement strategies minimize the number of transmit antennas while maintaining radar performance, highlighting CS's role in optimizing resource allocation [57]. Recent advancements in CS-MIMO integration demonstrate transformative impacts on radar technology, achieving significant improvements in angular resolution and efficiency, facilitating faster target detection and estimation [48, 44, 15, 57, 52].

7.2 Optimization Techniques for Data Acquisition and Processing

Optimizing data acquisition and processing in MIMO radar systems is essential for enhancing performance while minimizing resource utilization. Compressed sensing (CS) methods employing random structures effectively recover missing samples, crucial for restoring full processing gain and preserving Direction of Arrival (DoA) information [54]. A refined analysis of the restricted isometry property (RIP) for the measurement matrix ensures optimal recovery conditions, providing a robust framework for efficient signal reconstruction [22].

Effective optimization balances the trade-off between the number of antennas and the coherence of the sensing matrix, influencing detection performance and target resolution [57]. By optimizing antenna configurations and matrix coherence, radar systems achieve superior detection performance while reducing antenna requirements, lowering costs and complexity. These techniques highlight the transformative impact of advanced signal processing methods in MIMO radar systems, significantly enhancing data acquisition and processing efficiency. This improvement facilitates target parameter recovery at sub-Nyquist rates, supporting structured waveforms and optimized antenna placements that minimize mutual coherence [48, 20, 44, 47].

7.3 Sparse Signal Recovery and Target Detection

Sparse signal recovery is crucial for enhancing target detection capabilities within MIMO radar systems. By exploiting radar signal sparsity, these techniques enable accurate target reconstruction from limited measurements, improving detection accuracy and resolution. The effective recovery of sparse signals is vital for optimal detection performance, especially in complex environments with high-dimensional data. The stability and robustness of these methods depend significantly on the sensing matrix's adherence to the restricted isometry property (RIP). Joint power allocation and

AI-generated, for reference only.

antenna placement strategies further enhance sparse target estimation efficiency, reducing the number of antennas needed while maintaining high detection accuracy [57, 22].

Integrating sparse signal recovery methods with MIMO radar systems allows for a substantial reduction in transmit antennas without compromising detection capabilities, minimizing system complexity and cost while enhancing operational efficiency. Ajorloo et al. demonstrate this advantage through a method requiring fewer transmit antennas while achieving high detection performance [57]. Additionally, sparse recovery techniques facilitate precise target localization, even amidst noise and interference, by optimizing the measurement process and leveraging signal sparsity. This ensures reliable performance across diverse environments, advancing MIMO radar systems by enabling sophisticated compressed sensing techniques that improve detection resolution, accuracy, and efficiency [57, 22, 15, 44].

8 Compressive Radar Imaging Techniques

8.1 Advanced Antenna and Measurement Matrix Design

Innovations in antenna and measurement matrix design are pivotal for advancing compressive radar imaging, significantly boosting resolution and efficiency. By integrating compressive sensing (CS) with sophisticated antenna designs, radar systems achieve high-resolution imaging with reduced data acquisition demands. Strategic measurement matrix configurations optimize data acquisition and image resolution balance, ensuring robust signal recovery in challenging environments [22].

Antenna designs in compressive radar systems aim to maximize received signal information content, enhancing target scene detail resolution through structured waveforms that increase radar system flexibility and robustness [54]. CS techniques maintain high-resolution capabilities with reduced data input, streamlining signal processing and image reconstruction.

Adaptive sensing strategies dynamically adjust waveform parameters based on environmental and operational needs, optimizing radar performance in diverse conditions, such as cluttered urban settings or complex terrains [54]. Tailoring waveform properties to specific imaging tasks improves target detection and characterization, enhancing radar system efficiency and effectiveness.

The synergy between advanced antenna design and optimized measurement matrices exemplifies potential innovation in compressive radar imaging, offering pathways to more efficient, flexible, and high-performance radar systems. Ongoing research is expected to integrate novel techniques such as Through-the-Wall Radar Imaging (TWRI) and complex-valued convolutional neural networks (CV-CNN), improving imaging quality and operational capabilities. TWRI aids in detecting and tracking through materials, while sparsity-driven methods and frequency agile radar (FAR) enhance resolution and target estimation. Addressing electromagnetic wave interaction complexities with sophisticated algorithms is poised to expand radar technology applications significantly, enhancing accuracy and efficiency across various scenarios, from emergency response to military operations [9, 4, 21].

8.2 Gridless MCI Imaging Method

The Gridless Microwave Coincidence Imaging (G-MCI) method addresses the 'off-grid' problem inherent in traditional grid-based radar imaging methods. Utilizing atomic norm minimization, G-MCI achieves accurate recovery of scatterer positions and coefficients, circumventing limitations associated with predefined grid structures [50]. It eliminates discretization errors that degrade imaging quality, enhancing the fidelity and resolution of reconstructed images.

G-MCI's gridless nature allows for continuous and flexible imaging scene representation, resolving grid mismatch issues common in traditional microwave coincidence imaging (MCI) methods. This approach not only improves radar imaging precision but also preserves super-resolution capabilities essential for capturing details in complex environments [53, 50]. Accurate signal source representation ensures high-resolution imaging performance without the computational burden of fine grid searches.

Beyond enhancing image resolution, G-MCI demonstrates robustness against noise and interference, making it suitable for diverse radar applications. Atomic norm minimization provides a reliable signal recovery framework, ensuring performance even in challenging conditions. G-MCI integration into radar systems showcases its transformative potential by effectively addressing grid mismatch issues and enhancing resolution and imaging performance, particularly in complex environments, while maintaining super-resolution capabilities. Its efficiency and robustness signify a promising solution for advanced radar applications [9, 11, 50, 24].

8.3 HoloCS Method

The HoloCS method represents a significant advancement in radar imaging techniques, particularly within the context of compressive sensing (CS). By integrating holographic imaging principles with CS, HoloCS enhances radar system accuracy and efficiency, reducing the need for large sensing matrices and complex interpolation processes, thereby lowering computational complexity [6].

HoloCS exploits radar signal sparsity to achieve high-resolution imaging with fewer measurements, making it particularly effective in scenarios with limited bandwidth and high data throughput needs. The method efficiently reconstructs signals from a reduced dataset, maintaining image quality while minimizing data acquisition efforts. A holographic sensing operator captures essential target scene features, facilitating precise signal recovery and enhancing radar imaging capabilities [6].

HoloCS extends to various radar imaging contexts, including Synthetic Aperture Radar (SAR) and Inverse Synthetic Aperture Radar (ISAR), where high-resolution imaging is crucial. By combining compressive sensing with advanced holographic techniques, HoloCS significantly improves system ability to resolve intricate details and accurately localize targets, even in cluttered environments. This enhancement is achieved through an interpolation-free holographic imaging algorithm that serves as a sensing operator, circumventing computational burdens associated with traditional large-scale sensing matrices. Consequently, HoloCS accelerates computational speed and enhances image quality, making it particularly effective for high-resolution sensing and imaging applications [9, 16, 6]. This integration not only improves image fidelity but also enhances radar systems' robustness against noise and interference, ensuring reliable performance across diverse operational scenarios.

HoloCS exemplifies significant advancements achievable by merging holographic imaging techniques with compressive sensing principles, presenting a highly efficient and reliable framework that enhances radar imaging technologies. By employing an interpolation-free holographic algorithm as a sensing operator, this approach effectively mitigates computational challenges of large-scale sensing matrices, improving both image quality and processing speed. This innovative methodology facilitates high-resolution near-field millimeter-wave imaging and optimizes radar signal processing, making it a promising solution for various applications in surveillance and non-destructive testing [6, 20]. Continued research is expected to drive further innovations in radar systems, enhancing their resolution, accuracy, and computational efficiency.

9 Conclusion

9.1 Challenges and Future Directions

The integration of compressed sensing with radar imaging introduces both significant challenges and promising opportunities for future research. Key challenges include optimizing algorithmic performance in environments with closely spaced signal sources and developing adaptive dictionaries for Direction of Arrival estimation. These advancements are essential for enhancing radar system robustness across diverse operational contexts. Additionally, the variability of wall materials in Through-the-Wall Radar Imaging complicates real-time data processing, necessitating progress in material characterization and adaptive processing techniques to improve imaging quality.

In scenarios with high target density, enhancing the robustness of matrix completion techniques is crucial. Future research should aim to optimize these methods for better performance in complex environments. The design of sensing operators, such as those used in the HoloCS method, requires further exploration to expand their applicability and improve overall system performance. Real-time implementation and adaptability of algorithms to varying operational conditions are critical for advancing radar imaging capabilities, especially in airborne systems where range-ambiguous clutter suppression is vital.

Reducing computational complexity while maintaining performance in antenna placement optimization strategies presents another promising research avenue. Extending the GM-LAMP approach to channel estimation in terahertz communications holds significant potential, meriting exploration of unique channel characteristics in this domain. Optimizing regularization parameters and extending interference mitigation techniques to other signal processing domains can enhance radar imaging reliability and accuracy. The co-design of nanophotonic filters and deep learning algorithms offers an exciting research direction, with implications for developing new materials and fabrication techniques to bolster radar system performance.

Enhancing robustness against noise and exploring unsupervised learning techniques are additional crucial research directions. Future studies should also examine the field of view concerning CS MIMO antennas and explore configurations for improved performance. Refining the CV-CNN method for complex scattering models and investigating automatic focusing techniques could significantly enhance real-world application effectiveness. Addressing limitations in dynamic scenarios and improving the computational efficiency of sparse methods in localization frameworks remain critical. The application of proposed methods to related signal processing challenges indicates ongoing hurdles and potential avenues for future exploration.

Enhancing the bandwidth of the SSFC signal and investigating advanced algorithms for improved precision and robustness should be prioritized in future research. Additionally, extending methods to estimate both azimuth and elevation angles in noisy environments could yield valuable insights. Optimizing the computational aspects of RaSSteR and exploring its applications across various radar environments could lead to substantial benefits. Relaxing source separation constraints and applying these techniques to higher-dimensional signals, such as in 2D microscopy, represent promising research avenues. Extending algorithms to address more complex imaging scenarios and optimizing performance under varying noise levels are further areas ripe for investigation. Finally, optimizing algorithms for larger gaps and their applicability across different radar systems and interference scenarios could significantly enhance radar imaging capabilities.

These challenges and future directions highlight the dynamic nature of radar imaging research, with ongoing efforts poised to drive substantial technological advancements.

9.2 Stability and Accuracy in Compressive Radar Imaging

Stability and accuracy are pivotal in determining the effectiveness and reliability of compressive radar imaging systems. Compressive sensing techniques offer transformative potential for future wireless networks by enabling efficient signal reconstruction and resource utilization, thus enhancing the stability of radar imaging processes. Ensuring stability in CS-based imaging systems is crucial to maintain image fidelity across varying environmental conditions and noise levels.

Accuracy in compressive radar imaging is equally important, directly influencing the resolution and clarity of the images produced. Achieving high accuracy requires the development of sophisticated models and adaptive algorithms capable of accommodating environmental variability. This is particularly relevant in Through-the-Wall Radar Imaging, where emerging trends focus on creating models that account for the dynamic nature of wall materials and other environmental factors. Such advancements are essential for improving image quality and ensuring reliable detection and characterization of targets.

Ongoing research efforts aim to enhance stability and accuracy by optimizing sensing matrices and exploring novel signal processing techniques. These initiatives seek to reduce radar system sensitivity to noise and interference, thereby improving overall performance. Additionally, integrating adaptive algorithms capable of real-time adjustments to changing conditions represents a promising area for exploration, significantly enhancing the robustness of compressive radar imaging systems and ensuring consistent performance across diverse operational scenarios.

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