Three-Dimensional SAR Imaging and Advanced Reconstruction Techniques: A Survey

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Abstract

Three-dimensional Synthetic Aperture Radar (3D SAR) imaging represents a significant advancement in radar technology, offering enhanced spatial resolution and comprehensive target characterization over traditional two-dimensional methods. This survey explores the integration of advanced reconstruction techniques, such as sparse reconstruction and compressed sensing, which leverage signal sparsity to efficiently process high-dimensional data, thereby improving image resolution and robustness. The incorporation of deep learning and neural networks further augments these capabilities, facilitating superior image reconstruction quality and computational efficiency. Key innovations include frameworks like AETomo-Net and the QXS-SAROPT dataset, which enhance SAR-optical data fusion and reduce computational demands. Despite these advancements, challenges remain, particularly in adapting to diverse imaging conditions and managing computational complexity. Future research is poised to address these challenges by refining reconstruction techniques, expanding datasets, and integrating novel machine learning methodologies. These efforts promise to unlock new applications and improve the robustness, efficiency, and adaptability of SAR systems across various domains, reinforcing their role as vital tools in modern imaging and analysis.

1 Introduction

1.1 Significance of Three-Dimensional SAR Imaging

Three-dimensional (3D) Synthetic Aperture Radar (SAR) imaging marks a significant advancement over traditional two-dimensional (2D) techniques by mapping target scattering centers into a 3D spatial domain, producing point cloud representations [1]. This capability addresses limitations of 2D imaging, such as cross-range scaling and unknown projection planes, providing a comprehensive view of target spatial characteristics. The applications of 3D SAR imaging are extensive, encompassing urban mapping for monitoring land cover changes and urban development [2], as well as non-destructive inspection techniques, such as millimeter-wave imaging for through-the-wall imaging and concealed weapon detection [3].

In Automatic Target Recognition (ATR), 3D SAR imaging significantly enhances recognition accuracy by utilizing the spatial information afforded by the third dimension [4]. In TomoSAR imaging, integrating multi-dimensional features is critical for improving imaging performance and quality, essential for accurate image interpretation [5]. Furthermore, 3D SAR imaging is gaining traction in communication technologies, particularly in RIS-aided systems, suggesting promising applications in future communication infrastructures [6].

3D SAR imaging also addresses challenges like speckle noise contamination, which complicates SAR image processing [7]. By delivering detailed scene representations, 3D imaging enhances data fusion and interpretation, as demonstrated by datasets like SEN1-2, which foster deep learning in SAR-optical data fusion [8]. Additionally, RF tomographic imaging benefits from the enhanced spatial resolution of 3D SAR, proving vital for applications in smart buildings and emergency response [9].

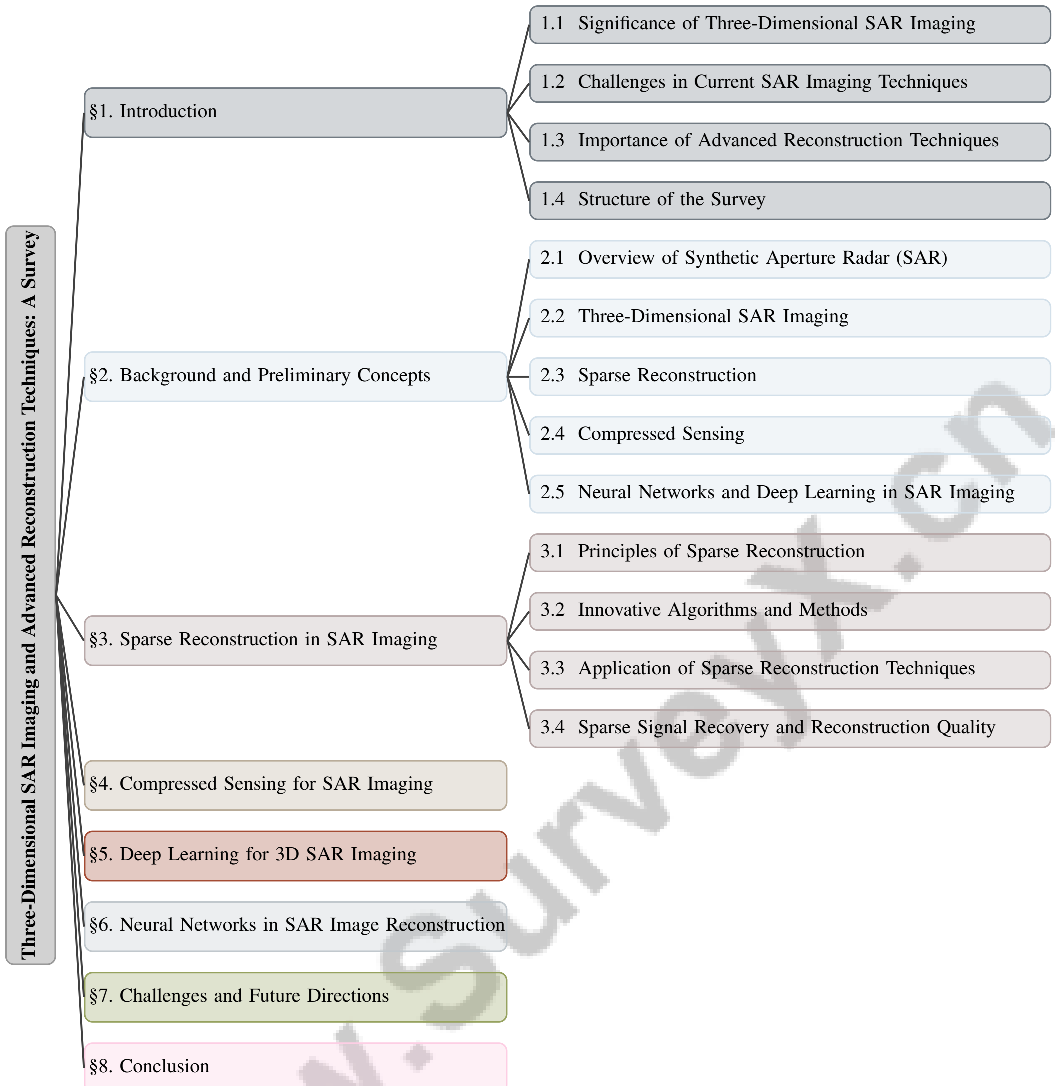

Figure 1: chapter structure

These diverse applications highlight the transformative impact of 3D SAR imaging across various fields, underscoring its significance in advancing scientific research and practical implementations.

1.2 Challenges in Current SAR Imaging Techniques

Current synthetic aperture radar (SAR) imaging techniques face numerous challenges that impede image reconstruction quality and efficiency. A primary issue is the computational complexity of existing tensor-based methods, which restrict scalability and effectiveness in realistic scenarios [9]. The high-dimensional nature of SAR data exacerbates traditional methods' inefficiencies, especially in high-dimensional wireless channel estimation, where significant pilot overhead and complex optimization problems present substantial hurdles [10].

Missing data further complicates sparse signal recovery, as methods like LASSO and IHT often fail to reconstruct the underlying information effectively [11]. The ill-posed nature of tensor approximations and NP-hardness of related computational problems hinder existing methods from adequately addressing tensor decomposition uniqueness [12]. These issues are compounded by limitations in current SAR techniques, which struggle to enhance image quality due to discrepancies in range- and cross-range resolutions and nonuniform radar returns based on aspect angles [13].

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In compressed sensing, substantial computational and memory burdens render current methods impractical for real-time high-resolution imaging [6]. The inefficiency of pure random sensing matrices in terms of memory usage and computational cost complicates signal reconstruction [14]. Moreover, traditional methods encounter difficulties in blind signal separation due to the underdetermined nature of recovering separate underlying signals from mixed observations [15].

Existing SAR systems also struggle with simultaneous optimization across multiple domains, leading to increased training complexity and parameter counts [16]. The challenge of effectively detecting and classifying UAVs is pronounced, as current radar systems grapple with resolution and accuracy issues due to clutter and limited processing capabilities [17]. These multifaceted challenges highlight the urgent need for advancements in SAR imaging techniques to enhance image reconstruction quality and computational efficiency, enabling more robust SAR systems.

1.3 Importance of Advanced Reconstruction Techniques

Advanced reconstruction techniques are pivotal for improving Synthetic Aperture Radar (SAR) imaging quality by overcoming traditional methods' limitations. Sparse reconstruction and compressed sensing have proven instrumental in enhancing image resolution and noise robustness. These methodologies enable the recovery of fine details from sparse data, as evidenced in Direction of Arrival (DoA) estimation applications, where compressed sensing exploits sparsity for improved accuracy [18]. The integration of deep learning models further enhances these capabilities by leveraging redundancy in sub-sampled RF data to improve image quality, as demonstrated in efficient B-mode ultrasound image reconstruction [19].

Developments in memory-efficient model-based deep learning algorithms provide theoretical guarantees similar to compressed sensing methods, optimizing computational resources while maintaining high reconstruction quality [20]. Innovations like the Fourier domain Range-Doppler method facilitate efficient sub-Nyquist sampling, reducing data acquisition requirements by eliminating the need for oversampling [21].

In moving target imaging, parametric sparse representation techniques effectively manage phase compensation, enhancing reconstruction accuracy and speed [22]. The combination of compressed sensing and modern deep learning approaches, particularly autoencoders, shows promise in addressing challenges such as blind signal separation, broadening the applicability of advanced reconstruction techniques [15].

These advanced methodologies extend to the semantic segmentation of Polarimetric SAR (PolSAR) data, where deep learning models enhance land use and land cover classification [2]. Furthermore, innovative frameworks combining compressed sensing, iterative adaptive approaches, and principal component analysis improve UAV detection capabilities, reducing required pulses and enhancing micro-Doppler feature extraction [17].

Advanced reconstruction techniques, including deep learning-based methods like the analytic learned ISTA (ALISTA) and innovative compressed sensing approaches, significantly elevate the quality and efficiency of SAR imaging. These advancements facilitate high-resolution three-dimensional reconstructions from limited observations and enable progressive image acquisition and reconstruction in various applications, such as flatbed scanners and remote sensing systems. By enhancing the reliability of image interpretation and analysis, these techniques expand SAR's applicability across diverse fields, including ATR, where specialized convolutional neural networks (CNNs) tackle challenges related to limited data and complex imaging scenarios [23, 24, 4].

1.4 Structure of the Survey

This survey systematically explores three-dimensional Synthetic Aperture Radar (SAR) imaging and the advanced reconstruction techniques that enhance its capabilities. The introduction highlights the significance of 3D SAR imaging and its applications, followed by a discussion on the challenges faced by current SAR imaging techniques. It emphasizes the critical role of advanced reconstruction techniques, such as iterative algorithms and deep learning methods, in effectively addressing image reconstruction challenges from limited data, as demonstrated through applications in compressed sensing, progressive image scanning, and macro-level feature detection [25, 26, 24, 27]. The introduction concludes with an outline of the survey's structure.

The second section delves into background and preliminary concepts, providing an overview of SAR technology and its role in imaging. This section covers key concepts such as three-dimensional SAR imaging, sparse reconstruction, compressed sensing, and neural networks' roles in SAR imaging.

The third section focuses on sparse reconstruction in SAR imaging, detailing principles, innovative algorithms, and applications, while discussing image reconstruction quality and signal recovery using sparse techniques.

Section four examines compressed sensing in SAR imaging, providing a comprehensive overview of its principles and benefits. It highlights advancements in sensing matrices that enhance data acquisition and sampling strategies, discussing the significance of compressed sensing in reconstructing high-dimensional sparse signals from limited linear measurements and emphasizing the evolution of algorithms like Regularized Orthogonal Matching Pursuit (ROMP) and Compressive Sampling Matching Pursuit (CoSaMP), which have improved recovery guarantees and computational speed [28, 29].

The fifth section investigates deep learning techniques' integration in three-dimensional SAR imaging, discussing how neural networks improve image reconstruction quality and computational efficiency.

In section six, we evaluate various neural network architectures' impacts on SAR image reconstruction quality, covering evaluation and benchmarking methods, interpretability, robustness, and computational complexity.

The seventh section identifies current challenges in three-dimensional SAR imaging and reconstruction techniques, discussing potential future research directions and technological advancements.

The survey concludes by synthesizing main findings and emphasizing advanced reconstruction techniques' critical role, such as compressed sensing and deep learning, in enhancing SAR imaging capabilities. It underscores the significant potential for future research to address challenges such as noise resistance, computational efficiency, and developing specialized CNNs for ATR, ultimately paving the way for improved performance and real-time applications in the field [23, 24, 4].The following sections are organized as shown in Figure 1.

2 Background and Preliminary Concepts

2.1 Overview of Synthetic Aperture Radar (SAR)

Synthetic Aperture Radar (SAR) is an advanced imaging technology that generates high-resolution images by exploiting the movement of the radar platform to create a large synthetic aperture. This enables resolutions finer than the physical antenna size, essential for applications such as earth observation, military reconnaissance, and environmental monitoring. SAR's capability to acquire data in adverse weather conditions and integrate deep learning for data fusion and analysis enhances its utility across various fields [30, 8, 24, 27]. SAR operates by transmitting radar pulses and processing the reflected signals' phase and amplitude to construct images, leveraging the Doppler effect for high-resolution imaging [13].

Challenges in image quality, especially in Spot-SAR mode, arise from irregular grid structures and nonuniform reflectivity patterns [13]. Advanced signal processing techniques, such as compressed sensing, optimize data acquisition by enabling efficient image reconstruction from fewer samples, reducing acquisition time and computational load. This method exploits scene sparsity, allowing SAR systems to maintain high image quality even in resource-constrained environments.

SAR systems are versatile, functioning effectively in diverse conditions, including day and night and through cloud cover, vital for continuous monitoring and surveillance. Recent advancements in deep learning have bolstered SAR's Automatic Target Recognition (ATR) capabilities, achieving high recognition rates even under challenging conditions, solidifying SAR's importance in military and civilian applications [31, 32, 4, 8]. Ongoing developments in SAR technology, including novel algorithms and deep learning integration, continue to broaden its applications and capabilities.

2.2 Three-Dimensional SAR Imaging

Three-dimensional (3D) Synthetic Aperture Radar (SAR) imaging represents a significant advancement in remote sensing, enabling comprehensive volumetric reconstructions of target scenes and addressing the limitations of two-dimensional imaging. This capability is essential for applications ranging from environmental monitoring to urban planning. The MV3D InISAR method exemplifies this progress by integrating multiple 3D reconstructions from various perspectives, producing detailed images that enhance situational awareness [1].

3D SAR imaging is particularly valuable in polarimetric SAR (PolSAR) image segmentation, crucial for detailed surface property analysis [33]. The additional spatial information provided by 3D imaging enhances segmentation accuracy, facilitating a deeper understanding of target scene scattering mechanisms.

In millimeter-wave systems, 3D SAR imaging delivers comprehensive models from a single viewpoint, crucial for applications such as through-the-wall imaging and concealed object detection [3]. TomoSAR imaging employs multi-dimensional approaches to improve imaging performance and interpretation [5]. In RF tomographic imaging, 3D SAR is framed as a tensor sensing problem, enhancing spatial resolution and enabling effective data fusion for applications like smart building monitoring [9].

Innovative techniques, such as the two-stage wavenumber domain imaging method, optimize phase shifts and employ Fourier transform methods to improve 3D SAR reconstruction accuracy and efficiency [6]. 3D SAR imaging provides unprecedented detail and accuracy, with compressed sensing techniques revolutionizing scientific research and practical applications through efficient signal acquisition and reconstruction, enhancing privacy while maintaining high classification accuracy. Novel algorithms for progressive image scanning and reconstruction improve image quality from limited projections, applicable to systems like flatbed scanners and remote sensing imagers [24, 27].

2.3 Sparse Reconstruction

Sparse reconstruction is a vital technique in synthetic aperture radar (SAR) imaging, enhancing image quality by leveraging radar data's inherent sparsity. Many natural scenes can be represented by a limited number of significant components, facilitating efficient data processing and accurate image recovery from reduced measurements. This is particularly beneficial in SAR imaging, where high-resolution reconstruction is often challenged by large data volumes. Compressed sensing techniques, such as the analytic learned iterative soft-thresholding algorithm (ALISTA), enable efficient three-dimensional reconstruction from limited observations, addressing computational complexity and noise resistance. Deep learning for parameter optimization further enhances reconstruction quality, achieving high-resolution results even with fewer data samples [23, 31, 24, 27].

Sparse reconstruction principles are implemented through optimization problems that impose sparsity in image representation. Techniques like Lasso and Continuous Basis-Pursuit (C-BP) estimate unknown measures from low-resolution, noisy observations, as demonstrated by Duval et al. in their focus on sparse regularization methods for deconvolution tasks [34]. These methods enhance image resolution and robustness against noise in SAR applications.

Innovative algorithms, such as the Generalized Approximate Message Passing (GAMP), provide a Bayesian framework accommodating various analysis operators and regularizers, enhancing flexibility and performance in sparse reconstruction. The Sparse Reconstruction with Multiple Walsh Matrices (SRMWM) exemplifies the versatility of sparse techniques by employing a unique matrix structure to enhance reconstruction efficiency, aligning with compressed sensing principles crucial for recovering sparse signals from lower-dimensional projections. Furthermore, SRMWM utilizes the restricted isometry property to ensure effective reconstruction [35, 36, 37].

Integrating sparse reconstruction with compressed sensing principles boosts signal recovery accuracy and computational efficiency by exploiting data sparsity, allowing for high-quality image reconstruction from fewer samples. In SAR imaging, tensor decompositions combined with compressed sensing techniques enhance signal modeling and recovery from multiple sensor arrays, effectively addressing high-dimensional data challenges. Recent advancements allow for the reconstruction of sparse scenes below the Nyquist rate while significantly reducing speckle noise, improving image quality and efficiency in complex data processing [29, 38, 12, 39].

Methods like the Graph Fused Lasso with Extended Neighbourhood Total Variation (GFLENTV) integrate graph signal processing with innovative neighborhood definitions to improve denoising and resolution in SAR imaging. The combination of Fourier Transform and Compressed Sensing techniques alleviates computational burdens while preserving high image quality, showcasing the evolution of sparse reconstruction methodologies. Adaptive sampling-reconstruction frameworks optimize sampling mask selection and reconstruction networks based on input data characteristics, enabling efficient recovery of high-dimensional signals from minimal measurements, enhancing performance in imaging and remote sensing applications [29, 27, 28, 40, 24].

Sparse reconstruction techniques are vital for reducing data acquisition requirements while maintaining high-resolution outputs in SAR imaging. The advancement of sophisticated algorithms, particularly in compressed sensing and deep learning, significantly enhances SAR imaging capabilities and applications. These innovations enable precise and efficient image reconstruction under challenging conditions, such as sub-Nyquist sampling and severe speckle noise, expanding SAR's utility across diverse domains, including remote sensing and environmental monitoring. Techniques allowing effective multilook processing during reconstruction improve image quality while managing computational complexity, and deep learning approaches effectively remove noise from SAR images, facilitating better downstream analysis [30, 41, 24, 39].

2.4 Compressed Sensing

Compressed sensing (CS) is a transformative approach in synthetic aperture radar (SAR) imaging, enhancing the efficient acquisition and reconstruction of high-resolution images from a reduced set of measurements. The foundational principle of CS exploits signal sparsity, allowing for accurate signal recovery with fewer samples than traditionally required by the Nyquist-Shannon sampling theorem. This is particularly beneficial in SAR imaging, where bandwidth constraints and rapid data acquisition are common [42].

In SAR systems, compressed sensing reduces data acquisition requirements while preserving image quality, enhancing imaging efficiency in resource-limited scenarios. CS's application is exemplified by its ability to improve resolution and accuracy in unmanned aerial vehicle (UAV) detections, leveraging radar signal sparsity for superior imaging outcomes [17].

However, standard CS techniques face challenges when imaging off-grid targets, as significant gridding errors can hinder accurate target recovery. Addressing these limitations necessitates the development of advanced methods to enhance reconstructed image fidelity [43]. Innovative frameworks, such as the divide-and-conquer approach, enable accurate reconstruction with fewer measurements by effectively managing non-uniform energy distribution within the Fourier measurement domain [44].

The integration of compressed sensing with deep learning methodologies further augments SAR imaging capabilities. Hybrid methods enhance image reconstruction efficiency and quality, demonstrating CS techniques' potential to maintain image fidelity even in challenging conditions [15].

Compressed sensing offers a powerful framework for addressing large-scale optimization challenges and improving imaging quality in SAR systems. Advanced algorithms that integrate robust statistics and CS techniques have been developed to recover images from compressed data, even amidst impulsive noise. This approach reduces the required raw data samples without compromising resolution and improves signal-to-noise ratios, facilitating more accurate and efficient image reconstruction. Innovations such as the Regularized Orthogonal Matching Pursuit (ROMP) and Compressive Sampling Matching Pursuit (CoSaMP) bridge the gap between speed and reliability in sparse recovery, making CS increasingly applicable in various SAR imaging tasks [38, 45, 29]. Continuous algorithmic advancements expand CS techniques' capabilities and applications, enabling more efficient and accurate image reconstruction across diverse domains.

2.5 Neural Networks and Deep Learning in SAR Imaging

Neural networks, particularly convolutional neural networks (CNNs), have significantly enhanced synthetic aperture radar (SAR) imaging by improving image reconstruction quality and computational efficiency. This transformation is largely due to their powerful feature-extraction capabilities and end-to-end operational potential, which facilitate automatic target recognition (ATR) and effectively tackle challenges such as speckle noise reduction. Recent deep learning techniques, including data augmentation and generative adversarial networks (GANs), have further improved the robustness and accuracy of SAR image processing, enabling better performance in applications like real-time recognition and complex data analysis [7, 30, 4]. These methodologies leverage neural networks to address unique SAR data challenges, such as speckle noise, complex scene structures, and the need for high-resolution imaging.

A critical application of neural networks in SAR imaging is in ATR, where specialized CNNs have been developed to enhance recognition rates. The integration of Sparse Coding (SC) with CNNs has led to significant improvements in target recognition, highlighting deep learning's potential in refining SAR ATR systems [46]. The shift towards deep learning in SAR ATR is further emphasized by categorizing existing research into traditional and deep learning methods, underscoring the transformative impact of these technologies [4].

The integration of deep learning with SAR imaging is also evident in frameworks like AETomo-Net, which employs a U-Net-like structure for feature extraction and fusion. This approach highlights neural networks' role in enhancing SAR imaging through multi-dimensional feature extraction and integration [5]. The QXS benchmark promotes the advancement of deep learning-based SAR-optical fusion approaches, providing a dataset for comparing and testing different models in this domain [32].

Innovative deep learning methodologies, such as the Generative Channel Estimator (GCE), utilize GANs to improve channel estimation from compressed pilot measurements, showcasing deep learning's role in optimizing SAR imaging processes [10]. The Joint Deep Probabilistic Subsampling (JDPS) method integrates a specialized measurement model with a Complex Learned FISTA (CL-FISTA) network to optimize selection matrices, demonstrating deep learning's potential in refining SAR data acquisition and processing [16].

Deep learning models also contribute to SAR imaging by incorporating model-aware regularization techniques that enhance generalization performance in solving inverse problems. The Model-Aware Regularization (MAR) approach exemplifies this by integrating knowledge of the forward operator into neural network training, improving robustness and accuracy in SAR image reconstruction [47].

Neural networks and deep learning are pivotal in advancing SAR imaging, offering innovative solutions that improve image quality, enhance computational efficiency, and expand SAR systems' applicability across diverse domains. The ongoing advancement of deep learning techniques is poised to significantly enhance Synthetic Aperture Radar (SAR) imaging capabilities, facilitating improved image despeckling, automatic target recognition, and multi-sensor data fusion. This progress promises to advance scientific research and drive practical applications across various fields, including military and civilian uses, by enabling more accurate interpretation and analysis of SAR data in diverse conditions [30, 4, 8, 7, 31].

3 Sparse Reconstruction in SAR Imaging

Category	Feature	Method
Principles of Sparse Reconstruction	Sampling and Recovery Techniques Guided Recovery Methods Advanced Integration Approaches	CA-NLS[48] SCOMP[43] JDPS[16], MJSR[49]
Innovative Algorithms and Methods	Regularization Techniques Sparse Reconstruction Methods Fusion Strategies	GAP[50], MAR[47] DDS-BCS[51], SRMWM[35], q-ISTA[52] CCNN[46]
Application of Sparse Reconstruction Techniques	Efficiency and Tradeoff Strategies Optimization Techniques Feature Integration and Enhancement Phase and Coefficient Management	DCS[53] SARA[54], CJS[55] AETomo-Net[5], L-FISTA-ResNet[56] PSR[22], FDRDA[21]
Sparse Signal Recovery and Reconstruction Quality	Feature Enhancement Strategies Iterative Refinement Techniques Robust Optimization Approaches Precision in Reconstruction	ATP-Net[57] GOMP[18], SARA[58], GCE[10] RCS[45] SSD[34]

Table 1: This table presents a comprehensive overview of various methods employed in sparse reconstruction for synthetic aperture radar (SAR) imaging. It categorizes these methods into four main areas: principles of sparse reconstruction, innovative algorithms and methods, applications of sparse reconstruction techniques, and sparse signal recovery and reconstruction quality. Each category further details specific features and corresponding methods, highlighting the diverse approaches and advancements in enhancing SAR imaging performance.

Sparse reconstruction techniques are pivotal in advancing synthetic aperture radar (SAR) imaging by addressing challenges in data acquisition and processing. This section explores the core principles and innovative algorithms that underpin sparse reconstruction, enhancing image quality and computational efficiency. By leveraging the sparsity inherent in natural scenes, sparse reconstruction reduces data requirements and facilitates effective signal recovery, thereby improving imaging performance across various applications. Table 1 provides a detailed categorization of methods and features pertinent to sparse reconstruction in SAR imaging, illustrating the breadth of approaches and innovations in this field. Additionally, Table 5 offers a detailed categorization of methods and features pertinent to sparse reconstruction in SAR imaging, illustrating the breadth of approaches and innovations in this field.

?? illustrates the hierarchical structure of sparse reconstruction in SAR imaging, detailing the principles, innovative algorithms, and applications. The principles section covers core concepts such as sparsity and compressed sensing, alongside mathematical foundations like 1-minimization and innovative designs including Bayesian inference methods. The algorithms section presents enhancements such as model-aware regularization and deep learning integration, featuring methods like CRN and QISTA-Net. Additionally, the applications section highlights improvements in imaging, frameworks such as AETomo-Net, and algorithmic advancements, showcasing the transformative impact of sparse reconstruction on SAR imaging.

3.1 Principles of Sparse Reconstruction

Method Name	Signal Representation	Algorithmic Approaches	Application Domains
ATP-Net[57]	Ternary Sampling Matrix	Deep Reconstruction Network	Image Reconstruction
CA-NLS[48]	Compressed Sensing	Basis Pursuit	Sar Imaging
JDPS[16]	Fourier Coefficients	Cl-FISTA Network	Ultrasonic Imaging
MJSR[49]	Compressed Sensing	Parallel-coordinate Descent	Channel Estimation
SCOMP[43]	Greedy Pursuit Algorithm	Basis Pursuit	Sar Imaging
SSD[34]	Sparse Regularization Methods	Basis-Pursuit C-BP	Imaging And Signal

Table 2: Summary of Sparse Reconstruction Methods: Signal Representations, Algorithmic Approaches, and Application Domains. This table provides a comprehensive overview of various methods employed in sparse reconstruction, highlighting their unique signal representation techniques, underlying algorithmic approaches, and specific application domains. The information is essential for understanding the diverse strategies used in enhancing SAR imaging and related fields.

Sparse reconstruction in SAR imaging capitalizes on the sparsity of natural scenes to reduce data acquisition needs while maintaining high image quality. This technique represents signals with minimal non-zero coefficients, utilizing compressed sensing to simultaneously acquire and compress data. Advanced algorithms, such as Basis Pursuit and Matching Pursuit, ensure accurate image recovery even in noisy conditions. By selecting measurements above a threshold, essential features are captured, enhancing applications like print error detection and MRI [59, 60, 37, 27].

The foundation of sparse reconstruction is ℓ_1-minimization, which promotes sparsity by focusing on solutions with fewer non-zero coefficients, reducing dimensionality and computational costs [61]. The restricted isometry property (RIP) ensures unique reconstruction of sparse vectors under projection constraints.

In non-Cartesian settings, anisotropic compressed sensing techniques address coherence issues in the sensing matrix, enhancing sparse signal recovery. Innovative designs, like the ternary sampling matrix with attention mechanisms, improve sampling and reconstruction [57].

Bayesian inference methods, such as those using the G-STG prior, offer flexible sparse reconstruction by adaptively modeling sparsity, leading to efficient and accurate recovery. The Correlation-Aided Nonlinear Least Squares (CA-NLS) method exemplifies the use of correlation information to guide sparse recovery [48].

The integration of deep learning with sparse reconstruction, as seen in the Joint Deep Probabilistic Subsampling (JDPS) method, optimizes selection matrices and enhances reconstruction techniques [16]. Structured approaches like CJS, combining total variation and joint sparsity recovery, further improve accuracy [49].

Innovative algorithms, such as Support-Constrained Orthogonal Matching Pursuit (SCOMP), leverage support constraints to improve off-grid target recovery [43]. Sparse Spikes Deconvolution (SSD) refines spike localization, addressing instability in traditional methods [34].

These principles are instrumental in advancing SAR imaging, offering robust solutions that enhance image quality and efficiency. Table 2 presents a detailed comparison of different sparse reconstruction methods, emphasizing their signal representation techniques, algorithmic approaches, and application domains, which are crucial for advancing SAR imaging technologies. The ongoing development of sophisticated algorithms, including compressed sensing and structured low-rank matrix completion, promises further enhancements in SAR imaging capabilities [29, 27, 54, 24, 59].

3.2 Innovative Algorithms and Methods

In SAR imaging, innovative algorithms have been developed to enhance sparse reconstruction. Model-aware regularization strategies improve generalization by embedding domain-specific knowledge into neural networks, enhancing robustness and accuracy [47]. The Gradually Atom Pruning (GAP) method dynamically adjusts regularization based on signal characteristics, improving reconstruction quality [50].

The Divide-and-Conquer approach optimizes performance by learning correlations across blocks, reducing processing time and improving efficiency [51]. Structured random matrices, fulfilling the Restricted Isometry Property (RIP), enhance signal recovery from compressed measurements [35].

Deep learning architectures, like the Cascaded Reconstruction Network (CRN), improve image reconstruction from compressed sensing measurements [62]. The l1-2-CCNN method demonstrates the effectiveness of combining Sparse Coding and CNN outputs for enhanced SAR imaging [46]. The QISTA-Net method addresses the non-convex ℓ_q-norm problem, crucial for precise sparse reconstruction [52].

Sparse Spikes Deconvolution (SSD) enhances spike localization by merging principles from Lasso and Continuous Basis-Pursuit, addressing instability in traditional methods [34].

Collectively, these innovative algorithms significantly advance sparse reconstruction in SAR imaging, offering robust solutions that enhance image quality and computational efficiency. As depicted in Figure 2, this figure illustrates the classification of innovative algorithms and methods in SAR imaging, focusing on model-aware strategies, deep learning techniques, and signal recovery methods, each contributing to enhanced image reconstruction and computational efficiency. The continuous development of methodologies, particularly through compressed sensing, multilook processing, and deep learning, promises to enhance SAR systems' performance and versatility, improving target recognition and imaging of moving objects [41, 4, 39, 31, 24].

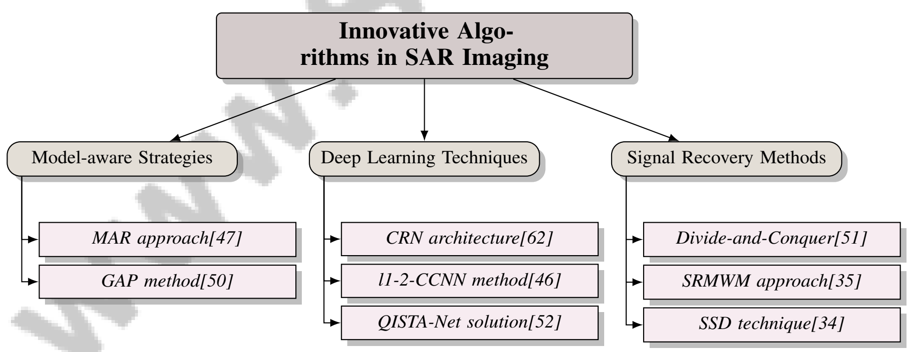


Figure 2: This figure illustrates the classification of innovative algorithms and methods in SAR imaging, focusing on model-aware strategies, deep learning techniques, and signal recovery methods, each contributing to enhanced image reconstruction and computational efficiency.

3.3 Application of Sparse Reconstruction Techniques

Sparse reconstruction techniques enhance SAR imaging by improving image quality and resolution through efficient data processing. In moving target refocusing, parametric sparse representation methods effectively manage phase compensation, as demonstrated in experiments with GF-3 satellite data [22]. The Sub-Nyquist SAR method employs Fourier series coefficients for effective image reconstruction, optimizing data acquisition [21].

Structured sparse matrices, such as T-orthogonal and row-orthogonal ensembles, outperform standard Gaussian ensembles in high noise scenarios [61]. The AETomo-Net framework leverages multi-

Method Name	Image Quality Enhancement	Data Processing Efficiency	Versatility in Applications
PSR[22]	Improved Image Quality	Reduces Computational Burden	Moving Target Refocus
FDRDA[21]	High Spatial Resolution	Sub-Nyquist Sampling	Cognitive Radar Applications
AETomo-Net[5]	Enhanced Imaging Quality	Reduced Computational Time	Different Imaging Scenarios
L-FISTA-ResNet[56]	Residual Network	Computational Efficiency	Real-time Applications
SARA[54]	Improved Reconstruction Quality	Compressive Imaging	Image Reconstruction
DCS[53]	-	Sampling-complexity Tradeoffs	Neural Signal Processing
CJS[55]	-	-	Inverse Scattering Applications

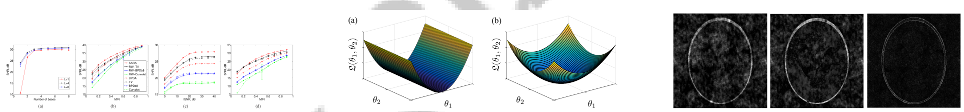
Table 3: Summary of sparse reconstruction techniques applied in SAR imaging, highlighting their impact on image quality enhancement, data processing efficiency, and versatility across various applications. The table compares different methods, including PSR, FDRDA, AETomo-Net, L-FISTA-ResNet, SARA, DCS, and CJS, based on these key performance metrics.

dimensional features to enhance imaging quality, resulting in more continuous images with fewer outliers [5].

The QXS dataset supports tasks like image matching and ship detection, demonstrating sparse reconstruction's utility in data fusion and detection [32]. In physics-assisted deep learning, the L-FISTA-ResNet method achieves superior FMCW radar quantitative imaging, showcasing advanced imaging solutions [56].

These applications highlight the wide-ranging impact of sparse reconstruction techniques in SAR imaging, improving image quality, resolution, and computational efficiency. Recent advancements in compressed sensing have enabled effective multilook processing, reducing speckle noise while operating below the Nyquist rate. Algorithms like Regularized Orthogonal Matching Pursuit (ROMP) and Compressive Sampling Matching Pursuit (CoSaMP) enhance sparse recovery reliability. The Low-rank and Adaptive Sparse Signal (LASSI) model further illustrates the versatility of these techniques in SAR imaging and beyond [29, 63, 54, 39, 23].

Table 3 summarizes various sparse reconstruction techniques employed in SAR imaging, emphasizing their contributions to enhancing image quality, optimizing data processing, and their adaptability to diverse applications.



(a) Comparison of Different Image Restoration Methods in Different Conditions[54]

(b) Optimization landscape for two-dimensional variables[53]

(c) Oval Shape Detection and Analysis[55]

Figure 3: Examples of Application of Sparse Reconstruction Techniques

As shown in Figure 3, sparse reconstruction techniques enhance image quality and extract meaningful information from complex datasets in SAR imaging. The first example compares various image restoration methods, highlighting sparse reconstruction's capability to optimize image clarity under diverse conditions. The second example visualizes optimization landscapes for two-dimensional variables, demonstrating sparse reconstruction's ability to navigate complex terrains for optimal solutions. Lastly, the "Oval Shape Detection and Analysis" example illustrates sparse reconstruction's robustness and adaptability in detecting and analyzing shapes in images with varying detail and noise levels. These examples underscore the transformative impact of sparse reconstruction techniques in advancing SAR imaging applications [54, 53, 55].

3.4 Sparse Signal Recovery and Reconstruction Quality

Sparse signal recovery is crucial in SAR imaging, significantly impacting reconstruction quality. Techniques like Generalized Orthogonal Matching Pursuit (GOMP) offer high-resolution estimation, reducing sampling errors and enhancing image reliability [18]. The GCE method improves sparse signal recovery in low SNR conditions, outperforming conventional methods [10].

Structured sensing matrices simplify hardware implementation and enhance recovery performance across imaging and communications applications [14]. The ATP-Net framework achieves higher

Method Name	Reconstruction Techniques	Performance Metrics	Application Scenarios
GOMP[18]	Gradient Omp	Mean-squared Error	Radar Communications
GCE[10]	Gce	Nmse	Wireless Channel Estimation
ATP-Net[57]	Ternary Sampling Matrix	Peak Signal-to-noise	Image Reconstruction Scenarios
RCS[45]	Fista, Admm	Convergence Speed	Complex Signal Structures
SARA[58]	Reweighted Approach	Snr	Radio-interferometric Imaging
SSD[34]	Sparse Spikes Deconvolution	Spike Recovery Accuracy	Imaging And Signal

Table 4: Overview of various sparse signal recovery methods, detailing their reconstruction techniques, performance metrics, and application scenarios. The table highlights the specific methodologies employed by each method and their effectiveness in improving signal recovery and reconstruction quality in different contexts.

PSNR values and improved visual quality, essential for maintaining high-quality SAR images at lower sampling rates [57].

Robust Compressive Sensing (RCS) methods optimize the robust CS objective function, minimizing computational overhead while ensuring accurate signal recovery [45]. The SARA algorithm outperforms existing methods in SNR and visual artifact reduction, demonstrating its effectiveness in radio interferometric imaging [58].

Anisotropic compressed sensing techniques address coherence issues in non-Cartesian settings, improving sparse signal recovery accuracy [64]. The Sparse Spikes Deconvolution (SSD) method enhances spike recovery accuracy in low noise scenarios, improving SAR image reconstruction reliability [34].

As illustrated in Figure 4, various sparse signal recovery techniques are categorized into high-resolution methods, robust recovery methods, and structured sensing matrices, highlighting key methodologies and their contributions to improving SAR imaging quality. Table 4 provides a comprehensive summary of sparse signal recovery methods, illustrating their reconstruction techniques, performance metrics, and application scenarios, which are crucial for enhancing SAR imaging quality. Advancements in sparse signal recovery techniques are pivotal in enhancing SAR imaging, offering robust solutions that improve image quality and computational efficiency. The ongoing development of methodologies, such as multi-static imaging, compressed sensing, and deep learning applications, promises to enhance SAR technology's analytical capabilities and practical applications across various fields, enabling more accurate imaging of moving targets, improved speckle reduction, and better target recognition [31, 41, 24, 39].

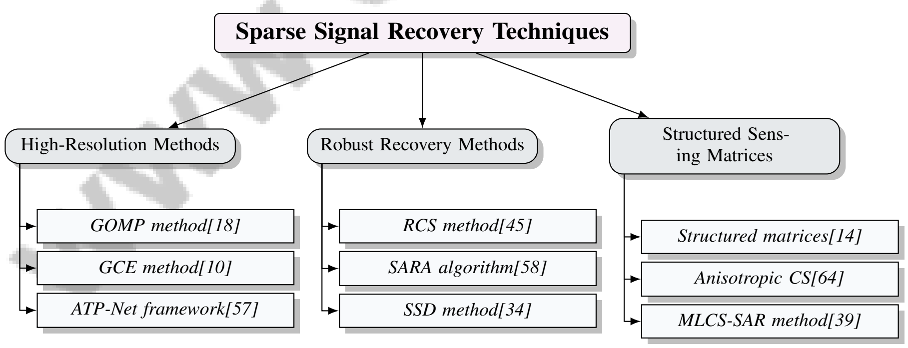


Figure 4: This figure illustrates various sparse signal recovery techniques categorized into high-resolution methods, robust recovery methods, and structured sensing matrices, highlighting key methodologies and their contributions to improving SAR imaging quality.

4 Compressed Sensing for SAR Imaging

4.1 Concept and Advantages of Compressed Sensing

Compressed Sensing (CS) transforms signal processing by enabling the recovery of sparse signals from fewer measurements than traditionally required by the Nyquist-Shannon sampling theorem [65]. By exploiting the inherent sparsity of natural signals, CS facilitates efficient data acquisition and

Feature	Principles of Sparse Reconstruction	Innovative Algorithms and Methods	Application of Sparse Reconstruction Techniques
Signal Representation	Minimal Non-zero Coefficients	Model-aware Regularization	Parametric Sparse Representation
Algorithmic Approach	1-minimization	Deep Learning Integration	Phase Compensation
Application Domain	Mri, Error Detection	Signal Recovery	Moving Target Refocusing

Table 5: This table provides a comprehensive comparison of various methods in sparse reconstruction, focusing on their key features in signal representation, algorithmic approaches, and application domains. It highlights the diversity of techniques employed in sparse reconstruction, showcasing the integration of minimal non-zero coefficients, deep learning, and parametric sparse representation to enhance synthetic aperture radar (SAR) imaging.

processing, significantly benefiting synthetic aperture radar (SAR) imaging. This technique allows for high-resolution image reconstruction from compressed measurements, reducing data rates, storage needs, and computational demands [27].

In SAR imaging, CS optimizes data acquisition efficiency while maintaining image quality, particularly under bandwidth constraints and rapid data collection needs. Techniques like the Iterative Method with Adaptive Thresholding (IMAT) enhance sparse signal recovery through adaptive thresholding, even with missing data [11]. Moreover, approaches such as QISTA-Net address the ℓ_q-norm minimization problem effectively, offering superior reconstruction performance and faster processing [52].

Neural network architectures further enhance CS, as demonstrated by the Compressed Sensing Recurrent Network (CSRN), which uses a hierarchical structure and recurrent learning for high-quality reconstructions with fewer parameters, reducing computational costs and energy consumption [43]. Perturbation techniques like SCOMP modify the CS framework for more accurate target recovery in off-grid scenarios [43].

CS provides a robust framework for SAR imaging by significantly reducing data acquisition needs while improving computational efficiency and image quality. Recent advancements, such as robust CS, address challenges like impulsive noise by integrating robust statistics for outlier suppression during image recovery. Innovations in multilook processing enhance speckle reduction while reconstructing sparse scenes below the Nyquist rate. Deep learning approaches, such as the analytic learned ISTA (ALISTA), streamline parameter tuning in TomoSAR imaging, leading to improved three-dimensional reconstructions even with limited samples. These developments underscore CS's transformative potential in SAR applications [23, 45, 39]. Ongoing advancements in CS methodologies continue to expand its applicability, driving scientific research and practical implementations in SAR imaging.

4.2 Innovations in Sensing Matrices

Advancements in sensing matrices have significantly enhanced compressed sensing (CS) capabilities in synthetic aperture radar (SAR) imaging, addressing challenges in signal recovery and computational efficiency. The Sparsity Averaging Reweighted Analysis (SARA) improves image reconstruction quality by exploiting data coherence using a dictionary of multiple coherent frames [58].

Statistical frameworks like the CROD method integrate advanced statistical techniques with CS to improve detection accuracy and reliability in SAR imaging by employing statistical mechanics for deriving accurate test statistics and thresholds under the row-orthogonal design model [66]. ISTANet enhances flexibility and performance by translating the iterative steps of the Iterative Shrinkage-Thresholding Algorithm (ISTA) into a deep learning framework with learnable nonlinear transforms [67].

The ATP-Net framework utilizes a ternary sampling matrix with an attention mechanism to optimize the sampling process, highlighting attention-based mechanisms' potential to enhance sensing matrices' efficiency and accuracy [57]. Adaptive sampling-reconstruction frameworks like H1.5 provide tailored approaches for each input, addressing joint optimization and adaptive sampling limitations [40]. Innovations in deterministic sequences, such as Frank-Zadoff-Chu (FZC) and Golay sequences, improve coherence parameters, enhancing sensing matrices' efficiency compared to random approaches [68]. The AMP-UD method combines approximate message passing with a universal denoiser to improve signal recovery without needing input signal bounds knowledge, further enhancing CS robustness [65].

Comparative analyses of optimization algorithms like RecPF, TwIST, and SALSA, tailored for MRI image reconstruction, provide insights into their relative performance, guiding appropriate algorithm selection in SAR imaging contexts [69]. These innovations in sensing matrices have advanced CS capabilities in SAR imaging, offering robust solutions that enhance image quality, computational efficiency, and adaptability across diverse scenarios. Ongoing advancements in SAR imaging methodologies, particularly through innovations like multi-static imaging and deep learning techniques, are expected to broaden SAR applications' scope, enhancing scientific research and practical implementations in fields like automatic target recognition and image despeckling [30, 41, 39, 31, 24].

4.3 Data Acquisition and Sampling Strategies

Effective data acquisition and sampling strategies are crucial for optimizing compressed sensing (CS) techniques' efficiency and accuracy in synthetic aperture radar (SAR) imaging. These strategies focus on capturing critical information through limited measurements, reducing data acquisition costs and computational demands while maintaining high-quality image reconstruction. CS enables simultaneous acquisition and compression of signals through fewer random linear measurements, ensuring reliable reconstruction quality as long as the number of measurements exceeds a certain threshold. Advancements in iterative reconstruction algorithms and structured low-rank matrix completion enhance the capability to recover high-dimensional signals from sparse data, particularly beneficial in applications like Magnetic Resonance Imaging (MRI), where reduced sampling times lead to faster scans and improved accuracy, especially in pediatric cases where patient movement is a concern [34, 27, 70, 24, 59].

Figure 5 illustrates key strategies, challenges, and innovations in data acquisition and sampling for compressed sensing in SAR imaging, highlighting advancements such as adaptive selection and CSRN networks. Adaptive selection methods improve sampling strategies by dynamically choosing sampling masks and reconstruction networks based on input data, leading to enhanced image reconstruction quality. The adaptive selection framework optimizes the sampling process tailored to specific scene characteristics [40]. The divide-and-conquer approach refines sampling strategies by employing various under-sampling masks, such as 1D Cartesian, 2D random, and pseudo radial sampling, demonstrating versatility and effectiveness across different imaging contexts [44].

Despite CS advantages, practical implementation faces challenges due to high computational costs and storage requirements of random measurement matrices, complicating real-world applications [57]. To address these challenges, methods like Convolutional Compressed Sensing leverage deterministic filters constructed from sequences with favorable autocorrelation properties, followed by random sampling of the output, enhancing sampling efficiency while maintaining high reconstruction quality [68].

The Lightweight Recurrent Learning Network (CSRN) integrates a sampling sub-network, an initial reconstruction sub-network, and a residual reconstruction sub-network to achieve efficient image reconstruction, showcasing the potential of advanced network architectures in optimizing sampling and reconstruction processes in SAR imaging [71]. Additionally, utilizing previous scans as reference images in Longitudinal Adaptive Compressed Sensing-MRI (LACS-MRI) allows for informed sampling decisions by optimizing measurement selection based on historical data, exemplifying the potential of leveraging prior information to enhance sampling efficiency [70].

These data acquisition and sampling strategies are crucial for advancing compressed sensing in SAR imaging, offering robust solutions that enhance image quality, computational efficiency, and adaptability across diverse applications. Ongoing advancements in SAR imaging methodologies, particularly through innovative approaches like multi-static SAR with overcomplete dictionaries and the application of deep learning for Automatic Target Recognition (ATR), are expected to significantly broaden the scope and effectiveness of SAR imaging, improving the imaging of moving targets while addressing challenges related to data biases and overfitting in deep learning models [31, 41].

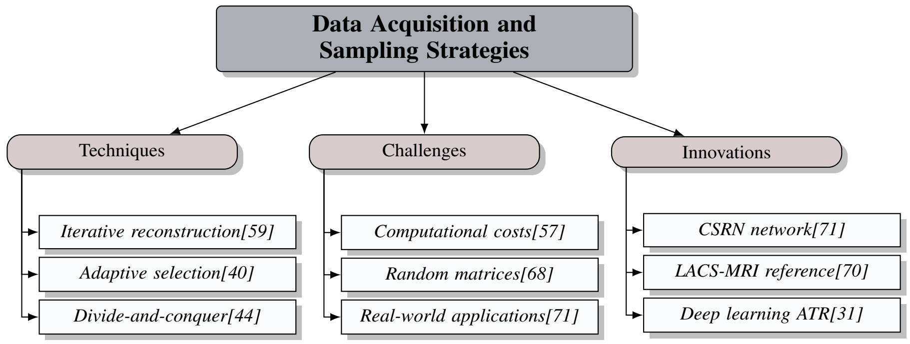


Figure 5: This figure illustrates key strategies, challenges, and innovations in data acquisition and sampling for compressed sensing in SAR imaging, highlighting advancements such as adaptive selection and CSRN networks.

5 Deep Learning for 3D SAR Imaging

5.1 Integration of Deep Learning in SAR Imaging

Deep learning has revolutionized synthetic aperture radar (SAR) imaging by enhancing image reconstruction and computational efficiency. These models excel in identifying complex data patterns, surpassing traditional methods in accuracy and speed. CASNet exemplifies this by employing a sampling, initialization, and recovery subnet for adaptive sampling and superior image reconstruction [72]. The Multi-scale Dilated Convolution Neural Network (MsDCNN) merges measurement and reconstruction, streamlining the process [73]. ISTA-Net combines the iterative structure of the Iterative Shrinkage-Thresholding Algorithm (ISTA) with deep learning for comprehensive parameter learning [67].

Frameworks like JDPS optimize across multiple domains, achieving higher compression ratios and improved image quality, crucial for SAR's diverse environmental conditions [16]. Deep learning integrated with physics-based optimization enhances radar imaging quality and efficiency, as demonstrated by physics-assisted deep learning frameworks [56]. The Deep Image Prior offers a novel reconstruction approach using untrained convolutional networks optimized for specific measurements [74].

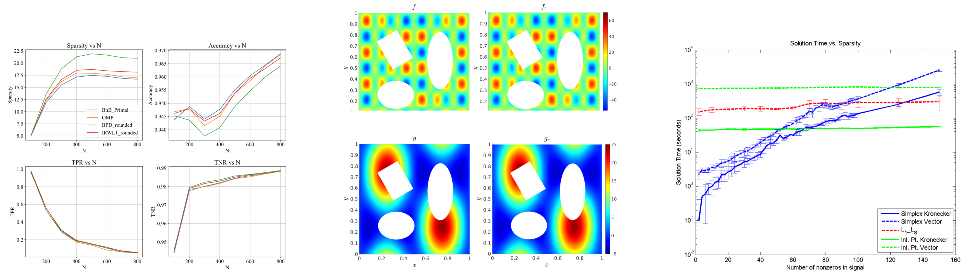
In target recognition, deep learning's impact is profound, with modified AlexNet CNN versions significantly improving SAR capabilities [46]. These advancements enhance SAR systems' image quality, efficiency, and adaptability, broadening applications in military and civilian sectors. By tackling data bias and model overfitting, these innovations propel scientific research and practical implementations in automatic target recognition, multi-sensor data fusion, and real-time processing [31, 4, 8].

5.2 Optimization and Efficiency Enhancements

Deep learning optimizes SAR imaging through methodologies that streamline image reconstruction. The Scalable Convolutional Sparse Coding Network (SCSNet) refines image quality with a hierarchical structure [75]. Bayesian Convolutional Neural Networks (BCNNs) demonstrate superior performance in noisy environments, maintaining high reconstruction quality [76]. These methods exhibit robustness against statistical and adversarial noise, surpassing traditional benchmarks like total-variation minimization [25].

The ISTA-Net framework balances speed and accuracy, merging traditional optimization with deep learning performance [67]. Recent advancements improve despeckling, crucial for mitigating speckle noise, enhancing reconstruction accuracy, and increasing efficiency in tasks like segmentation and recognition [7, 30]. Continuous development promises further enhancements across scientific and practical domains.

Figure 6 illustrates deep learning's role in optimizing 3D SAR imaging. The first subplot compares sparse recovery methods, highlighting algorithmic complexity versus image quality. The second



(a) Comparison of Different Sparse Recovery Methods for Image Reconstruction[77]

(b) Two-dimensional plots of functions f, $f_r, g, and g_r$[78]

(c) Solution Time vs. Sparsity[79]

Figure 6: Examples of Optimization and Efficiency Enhancements

subplot visualizes functional variations, and the third examines solution time relative to signal sparsity, showcasing deep learning's potential in enhancing 3D SAR imaging through strategic optimization [77, 78, 79].

5.3 Handling Speckle Noise and Artifacts

Speckle noise significantly challenges SAR imaging by degrading image quality. Recent deep learning advancements effectively mitigate this issue, enhancing SAR image quality by learning complex despeckling mappings [30]. Multilook processing within compressed sensing frameworks enhances speckle reduction while maintaining efficiency [39]. Combining multilook processing with deep learning achieves a balance between noise reduction and detail preservation, leading to more accurate SAR data interpretations.

The Image Despeckling Convolutional Neural Network (ID-CNN) enhances reconstruction quality and efficiency through convolutional layers, batch normalization, and activation functions, improving interpretability for automated systems and analysts [7, 30]. Continuous development promises further enhancements in SAR capabilities across various domains.

6 Neural Networks in SAR Image Reconstruction

The integration of neural networks into synthetic aperture radar (SAR) image reconstruction holds immense potential, yet it presents certain challenges. As deep learning technologies progress, assessing these models' effectiveness in terms of accuracy, computational efficiency, and noise robustness becomes crucial for their practical application. This section delves into the evaluation and benchmarking of neural network models, focusing on performance assessment methodologies and their implications for SAR imaging.

6.1 Evaluation and Benchmarking

Benchmark	Size	Domain	Task Format	Metric
CS-AP[80]	256	Neural Signal Processing	Signal Reconstruction	Compression Ratio, Signal-to-Noise Ratio
DNN-RIP[25]	1,594	Medical Imaging	Image Reconstruction	PSNR, SSIM
UAVSAR-DS[2]	20	Land Use Land Cover	Semantic Segmentation	Pixel Accuracy, F1 Score
QXS-SAROPT[32]	20,000	Remote Sensing	Image Matching	Accuracy, Precision
SEN1-2[8]	282,384	Remote Sensing	Data Fusion	Accuracy, F1-score
CS-MRI[69]	3	Medical Imaging	Image Reconstruction	PSNR, Relative Error
CS-Benchmark[61]	1,000,000	Compressed Sensing	Reconstruction	MSE, RMSE

Table 6: Table ef presents a detailed comparison of various benchmarks used in neural signal processing, medical imaging, land use land cover analysis, remote sensing, and compressed sensing. It highlights the size, domain, task format, and evaluation metrics for each benchmark, providing a comprehensive overview of the datasets utilized for performance evaluation in these fields.

AI-generated, for reference only.

Evaluating neural network models in SAR imaging is critical for their application in real-world scenarios. A comprehensive evaluation framework uses large-scale datasets to ensure model generalizability. For instance, analyses using datasets from the UCI Machine Learning Repository offer insights into model performance [37]. Comparisons with traditional methods like MapReduce and Spark highlight deep learning advancements. Table 6 provides a detailed comparison of benchmarks used to evaluate neural network models in SAR imaging and related domains, illustrating the diversity of datasets and metrics employed in this field.

Key evaluation metrics include accuracy, computational efficiency, and noise robustness, essential for assessing neural network applicability in SAR imaging. Benchmarking systematically compares neural network architectures to identify those offering optimal accuracy for Automatic Target Recognition (ATR) tasks. Addressing challenges like data biases and overfitting is crucial, as recent studies quantify their impact on recognition accuracy. Employing datasets like MSTAR and approaches such as the Shapley value to measure overfitting, researchers strive to pinpoint architectures adept at handling SAR imaging complexities [31, 4, 8]. This ensures selected models meet technical and operational needs, enhancing SAR image reconstruction quality.

6.2 Interpretability and Robustness

Interpretability and robustness are pivotal for neural network models in SAR imaging, especially in ATR applications where data bias and background clutter can impact performance. Recent research focuses on quantifying image region contributions to target recognition using metrics like the Shapley value, aiding in understanding model behavior and developing reliable architectures for SAR applications [30, 4, 7, 25, 31]. Interpretability involves understanding neural networks' decision-making, fostering trust and transparency in SAR image analysis, while robustness refers to maintaining performance across various noise conditions.

Advancements in deep learning have enhanced interpretability by developing models that clarify features learned from SAR data. Techniques such as layer-wise relevance propagation and saliency maps visualize input feature contributions to network outputs, improving decision-making transparency [25]. These methods enhance user understanding of neural network processing in SAR images, facilitating informed interpretations.

Robustness is vital for ensuring reliability in SAR imaging. Deep learning models have shown resilience to diverse noise types and perturbations, often outperforming traditional methods in maintaining high reconstruction quality under challenging conditions [25]. This robustness is achieved through advanced training techniques incorporating noise modeling and data augmentation, allowing models to generalize effectively across different scenarios.

Combining interpretability and robustness enhances neural networks' applicability in SAR imaging, providing reliable and transparent solutions for complex tasks. As deep learning evolves, rigorous research on model reliability and robustness is increasingly essential. This includes developing architectures excelling in sparse reconstruction and signal separation while demonstrating resilience to adversarial perturbations. Innovations like Neurally Augmented ALISTA and ADMM-DAD networks exemplify adaptive approaches and deep unfolding techniques that enhance performance while maintaining theoretical guarantees. Ensuring model trustworthiness through rigorous validation is critical, especially in safety-critical domains like medical imaging and remote sensing [81, 8, 15, 25, 82].

6.3 Computational Complexity and Resource Demands

The computational complexity and resource demands of neural networks in SAR imaging significantly influence the feasibility and scalability of deploying these models. Deep learning architectures require substantial computational resources due to their complexity and the vast data they process. The computational burden in SAR imaging is pronounced, necessitating high-resolution data acquisition and rapid processing. This challenge is exacerbated by data biases, such as background correlation, which can lead to overfitting in deep learning models for ATR. As these models aim for accuracy, they exploit clutter characteristics correlating with target classes, necessitating sophisticated algorithms for efficient data processing. Recent advancements in compressive sensing techniques underscore the need for innovative multilook processing approaches to enable effective speckle reduction and image reconstruction even at sub-Nyquist sampling rates [31, 39].

Managing computational complexity involves addressing the high dimensionality of SAR data, requiring efficient algorithms capable of processing large-scale inputs without sacrificing performance. Techniques such as model compression, including pruning and quantization, have been employed to reduce the size and computational demands of neural networks, enhancing their suitability for resource-constrained environments [71]. These methods streamline network architecture, minimizing parameters and operations required for inference while maintaining acceptable accuracy levels.

Integrating efficient training algorithms, such as approximate message passing and iterative shrinkage-thresholding, can alleviate computational demands by optimizing the learning process [65]. These algorithms exploit SAR data's inherent sparsity to accelerate convergence and reduce computational load, enabling faster and more efficient neural network training.

Deploying neural networks in SAR imaging necessitates hardware resource considerations, as deep learning models often require specialized hardware accelerators, such as GPUs or TPUs, for real-time performance. The resource demands of high-performance computing can create operational challenges, particularly in remote or field-deployed environments where access to such infrastructure is limited. This limitation can hinder implementing advanced techniques like Compressed Sensing and structured low-rank algorithms, critical for efficiently processing large datasets and enhancing image reconstruction accuracy in applications like MRI. Thus, effectively managing resource constraints is crucial for leveraging cutting-edge computational methods in practical settings [78, 27, 26, 83, 59].

Ongoing research aims to develop lightweight neural network architectures balancing computational efficiency and performance. Techniques like the Lightweight Recurrent Learning Network (CSRN) exemplify efforts to design models achieving high-quality image reconstructions with reduced computational overhead [71]. These advancements are vital for applying deep learning in SAR imaging, ensuring neural networks can be effectively deployed in diverse environments without overwhelming computational resources.

Continuous exploration of strategies to optimize computational complexity and resource demands is essential for advancing neural network integration in SAR imaging. By enhancing SAR models' efficiency through advanced deep learning techniques, researchers can significantly improve high-resolution imaging and enable real-time analysis. This progress addresses challenges like data bias and model overfitting while expanding SAR technology applicability across fields such as military reconnaissance, environmental monitoring, and multi-sensor data fusion, unlocking new opportunities for innovative applications [4, 8, 39, 23, 31].

7 Challenges and Future Directions

7.1 Adaptability to Diverse Imaging Conditions

The adaptability of synthetic aperture radar (SAR) imaging to varied conditions is vital for its deployment in dynamic environments. Current techniques, such as compressed sensing (CS) and sparse reconstruction, show promise but struggle with extreme variations in target appearance and environmental factors, necessitating more robust methods [13, 16]. Models like JDPS face challenges in adaptability due to the high dimensionality of the forward model, which makes training time-intensive.

Noise and clutter sensitivity significantly impact image quality, while robust infrastructures for distributed processing remain a challenge, as methods like DDPF are often infeasible due to complexity and resource demands [37]. Resource-intensive strategies such as Divide-and-Conquer further emphasize the need for optimization to improve scalability [44]. Frameworks like AETomo-Net offer potential for adapting to different scenarios [5], though methods like CS-DIP may falter at low sample ratios, underscoring the need for lightweight models for real-time applications [74, 4].

Integrating deep learning can enhance SAR adaptability, improving reconstruction quality and efficiency [27]. Refinements in adaptive thresholding and generative adversarial networks (GANs) are necessary for managing complex signal environments and generalizing to real-world conditions. Enhancing SAR adaptability requires refining methodologies, expanding datasets, and integrating innovative approaches. Research should focus on extending methods to higher-order tensors and exploring adaptive coherence measures to improve robustness in complex signal environments [12].

7.2 Technological Advancements and Emerging Applications

Technological advancements in SAR imaging, driven by innovations in signal processing and machine learning, are opening new application avenues. Key developments involve optimizing deep neural network (DNN) architectures for efficiency in resource-constrained environments, refining feature compression, and exploring alternative array configurations to boost radar imaging performance. Sophisticated models, like Bayesian approaches and enhanced GANs, are being explored to manage complex real-world data [15].

Emerging applications drive new methodologies in compressed sensing (CS) and signal reconstruction. Developing structured sensing matrices that require less randomness and memory, alongside hybrid designs informed by coding theory and communication systems, offers promising research directions [14]. These advancements aim to enhance SAR robustness and performance, especially in applications requiring real-time processing and high data throughput.

In channel estimation, the Generative Channel Estimator (GCE) provides advantages such as reduced pilot overhead and independence from the sparsifying basis, indicating substantial technological potential [10]. Exploring additional random matrix ensembles and integrating machine learning can optimize reconstruction processes based on existing benchmarks [61].

Future research should expand datasets and explore algorithms to enhance benchmark robustness [69]. Advancements in model-aware regularization could optimize computational efficiency and broaden applicability to various inverse problems [47]. Non-linear methods within radar systems and real-time processing enhancements are promising areas for further exploration [17].

The integration of deep learning with SAR technology is poised to significantly enhance imaging capabilities, enabling more accurate Automatic Target Recognition (ATR) and innovative applications like multi-sensor data fusion and real-time target tracking. These developments open new avenues for scientific exploration and practical implementations across fields such as military surveillance, environmental monitoring, and urban planning. Comprehensive datasets like SEN1-2 support these advancements by providing valuable resources for training deep learning models, expanding SAR imaging's potential in diverse domains [31, 41, 4, 8]. These ongoing developments are expected to improve SAR systems' precision, efficiency, and adaptability, cementing their role as essential tools in modern imaging and analysis.

8 Conclusion

The survey highlights the profound impact of advanced reconstruction techniques on three-dimensional synthetic aperture radar (SAR) imaging, emphasizing improvements in image quality and computational efficiency. Sparse reconstruction and compressed sensing capitalize on signal sparsity to enable high-resolution imaging from limited data, thus enhancing radar system performance. Incorporating deep learning amplifies these advancements, with neural network-based methods offering superior reconstruction quality and reduced computational demands, applicable to a wide range of imaging modalities.

Notable progress includes frameworks like AETomo-Net, which significantly reduce computational time while improving imaging quality compared to traditional methods. The QXS-SAROPT dataset has become an essential asset for advancing deep learning models in SAR-optical data fusion, paving the way for future research and applications. Furthermore, physics-assisted deep learning frameworks have demonstrated substantial improvements in reconstruction accuracy and processing speed, underscoring their robustness and adaptability across various datasets and conditions.

Future SAR imaging research is poised to build on these developments, focusing on refining reconstruction techniques to further enhance image quality and computational efficiency. The potential for real-time recognition and the integration of contextual information to boost processing capabilities is promising. As the field progresses, the exploration of innovative methodologies and the adoption of cutting-edge technologies are expected to expand SAR systems' capabilities and applications, solidifying their role as indispensable tools in contemporary imaging and analysis.

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