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Advanced Near-Field Radar Imaging Approaches: An Overview with Emphasis on Signal Processing Aspects

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Abstract

Near-field (NF) microwave and millimeter-wave (mm-wave) imaging, extending into the terahertz (THz) frequency range, has seen remarkable advancements across diverse applications, including security screening, medical diagnostics, nondestructive testing, structural health monitoring, through-wall imaging and the food industry. These technologies benefit from the unique properties of microwaves and mm-waves, such as penetration, non-ionizing radiation, material sensitivity and weather independence. This paper provides an overview of the evolution and current state of NF radar imaging, emphasizing the critical role of signal processing in overcoming challenges related to hardware complexity, long acquisition times and image reconstruction quality. Advanced signal processing techniques, including Fourier-based algorithms, sparse imaging, low-rank matrix recovery and deep learning, are highlighted for their contributions to enhancing image resolution and processing efficiency. The paper also discusses recent innovations in antenna technologies, aperture configurations and scanning methods that have significantly improved NF radar imaging capabilities. Future research directions are suggested to further advance the field, highlighting the importance of continued exploration and innovation in NF microwave and THz imaging.

I. Introduction

Near-field (NF) microwave and millimeter-wave (mm-wave) imaging, along with its extension into the terahertz (THz) frequency range, has garnered significant attention and advancement across various domains over the past few decades [1–3]. The special features of microwaves and mm-waves, such as penetration and transparency, reasonable resolution, non-ionizing radiation, material sensitivity, versatility, and weather and environmental independence, make them suitable for various applications. Originating from radar technology, this field has evolved to find applications in security screening, medical diagnosis, nondestructive testing (NDT), structural health monitoring (SHM), through-wall imaging (TWI), the food industry, among others (see Fig. 1) [3–5]. Although each approximate range of the electromagnetic (EM) spectrum is commonly used for specific imaging applications and technologies, some imaging methods and applications may operate in multiple regions of the EM spectrum and use different wavelengths for different purposes in their imaging systems. For example, imaging research and technologies for security screening have been developed from low microwave frequency bands around 10 GHz up to mm-wave or sub-THz frequency bands at 220 GHz or 340 GHz thanks to the technological progress in signal processing. The history of NF microwave and THz imaging is marked by continuous innovation in physical, system, and processing layers, aimed at improving imaging capabilities and expanding its utility across diverse domains. Also, the history of NF signal processing in radar imaging can be traced back to the need for efficient and accurate detection systems capable of operating in close proximity to targets.

The motivation behind the continued research and development in NF microwave and THz imaging is multifaceted. One of the primary drivers is the critical need for advanced NF imaging technologies in areas such as security screening in public spaces like airports, train stations, and large gatherings. To achieve a reasonable image resolution for threat detection purposes, most of the security scanning systems tend to rely on reflection imaging operating on frequencies beyond 10 GHz [6]. Traditional imaging systems face challenges related to long acquisition times, high hardware complexity, inefficient signal processing algorithms for image reconstruction, and limited imaging quality, especially in the mm-wave and THz bands [2, 3, 7]. Addressing these challenges is imperative for enhancing security measures, ensuring public safety, and enabling efficient NDT practices.

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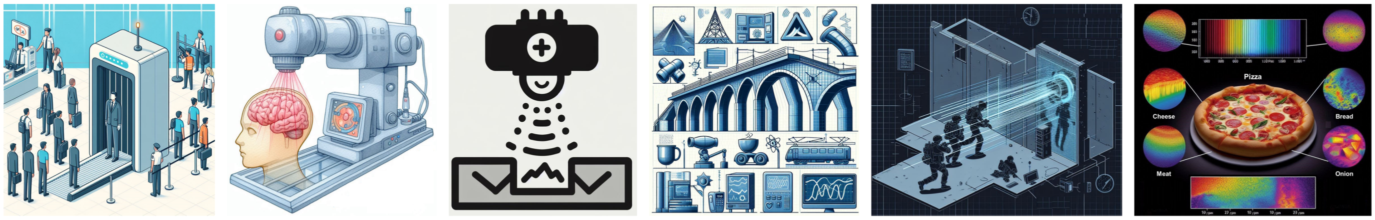

Body scanner in operation at airports | **Imaging for intracranial hemorrhage detection** | **Detect surface breaking cracks** | **SHM of pipes, plates, bridge cables and tubes, etc.** | **TWI with operational capabilities to military forces, etc.** | **Hyperspectral imaging in the food industry**

Fig. 1. Some examples of applications of NF Radar Imaging.

Moreover, NF microwave and THz imaging holds significant promise for revolutionizing medical diagnostics and healthcare practices. With the ability to penetrate materials and provide high-resolution images, these technologies offer new opportunities for early disease detection, tumor imaging, and minimally invasive surgical procedures [3, 5]. The potential impact on improving patient outcomes and reducing healthcare costs underscores the importance of advancing NF microwave and THz imaging techniques.

The significance of the topic for the Signal Processing Society (SPS) community is evident in its interdisciplinary nature and alignment with its core objectives. Microwave and THz imaging involves signal processing methodologies and techniques, EM theory, imaging algorithms, and hardware design, making it a fertile ground for collaboration and innovation within the SPS community. Researchers and practitioners in signal processing possess the expertise necessary to develop and optimize imaging algorithms for image reconstruction and target detection, analyze imaging data, and optimize system performance, thus playing a pivotal role in advancing the field. NF signal processing, in particular, plays a crucial role in extracting valuable information from microwave and THz signals acquired in close proximity to the target. Advanced signal processing techniques such as Fourier-based algorithms, sparse imaging, low-rank matrix recovery (LRMR) and deep learning (DL) are essential for reconstructing high-quality images from raw radar data acquired in NF conditions through microwave and THz imaging systems. These techniques play a critical role in extracting meaningful information from raw radar data and producing high-fidelity images of the target scene.

This article aims to showcase key challenges, and the latest advancements, innovations and state-of-the-art techniques in advanced NF radar imaging approaches, focusing on various aspects of radar signal processing. It reviews recent advances in NF microwave and THz imaging approaches that have enhanced radar imaging systems' capabilities and provides ideas for future research.

II. Challenges in NF imaging systems

As mentioned in the introduction, NF radar imaging systems play a vital role in a wide range of applications. However, these systems may encounter significant challenges that hinder their efficiency and effectiveness. This section provides an exploration of the key challenges faced by traditional NF imaging systems, discusses limitations in signal processing algorithms, and emphasizes the necessity for advanced techniques to drive advancements in NF imaging technology.

A. Hardware complexity and long acquisition times

Passive mm-wave or THz imaging systems rely on thermal radiations from targets to form the image, and the quality of the reconstructed image, including image resolution and contrast, is intrinsically low. This prevents this kind of system from developing and being implemented practically. In contrast, the active imaging approach uses transmitters (TXs) to illuminate the target and therefore enhance reflections from targets. This approach draws much attention from researchers and makes it widely studied. A synthetic aperture is usually focused in this active imaging system, which shares a similarity in technique with synthetic aperture radar (SAR).

In general, in active radar systems, there are several TX/receiver (RX) antennas (nodes) that are designed to make the system operate either as monostatic, bistatic, or multistatic radar. The radar is called monostatic radar if the TX and RX are placed in the same place; otherwise, the radar is bistatic or multistatic if both TX and RX(s) are located separately over a distance.

The data are sampled in a sampling plane far from the target plane by a raster scanning scheme with a single transceiver, or electronic scanning scheme with a linear array or planar array consisting of multiple TXs and RXs, both known as multiple-input multiple-output (MIMO) array imaging. Depending on the distance spacing TXs and RXs compared to the target distance, the MIMO array configurations include a monostatic scenario and a multistatic scenario.

Traditional NF imaging systems face substantial challenges related to hardware complexity and long acquisition times. One of the primary challenges is associated with synthesizing a 2-D aperture using large arrays of antenna elements. In conventional monostatic radar imaging systems, achieving high-resolution imaging with mechanical scanning often necessitates excessive acquisition times. While real aperture radar systems may alleviate some acquisition time constraints, they still encounter challenges in achieving high imaging resolution, particularly in NF scenarios, due to diffraction-limited performance [6, 7].

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Furthermore, the complexity escalates in multistatic radar systems, where separate TX and RX antennas are employed. While these systems provide flexibility in increasing the effective aperture virtually, they introduce challenges related to the number of antennas and channels. Array antennas, though effective in enhancing the effective aperture, often come with high costs, cumbersome form factors, and substantial power consumption due to complex control circuitry and numerous RF components. This complexity translates into extended data acquisition times, especially in scenarios requiring extensive spatial coverage, thereby limiting real-time applications.

The proliferation of antennas and channels in multistatic configurations exacerbates fundamental hardware limitations. Array antennas can be expensive to manufacture, exhibit poor form factors, and consume significant power, making them impractical for certain applications. Consequently, there is a pressing need to explore alternative solutions that streamline hardware complexity and reduce acquisition times without compromising imaging quality.

B. Limitations in signal processing algorithms

In addition to advances in the physical layer of imaging systems, the signal processing layer has also attracted the attention of researchers. Signal processing algorithms play a crucial role in NF imaging systems, facilitating tasks such as image reconstruction and target detection. However, these algorithms may encounter several limitations that impede their effectiveness. The effectiveness of image reconstruction techniques depends on both the quality of the reconstructed image and the computational requirements.

The amplitudes and phases of reflected waves from targets are sampled by RXs at a scanning plane. They are mathematically synthesised on the target plane to form (reconstruct) a target image. There are many techniques in the literature for image reconstruction. The widely used image reconstruction algorithms include holographic imaging, backpropagation (BA) algorithm, range migration algorithm (RMA) and their variations. The 2D image function $\rho(x, y, z_0)$ can be exactly reconstructed by the generalized synthetic aperture focusing technique (GSAFT), which is applicable to any scanning scheme and array configurations, described in (1) [8]

$$\rho(x, y, z_0) = \sum_{p=1}^{N_T} \sum_{q=1}^{N_R} s(p, q) e^{jk_0(R_p+R_q)}, \tag{1}$$

where j is the imaginary unit, $k_0 = 2\pi f_0/c$ is the wavenumber corresponding to the carrier frequency f_0, and c is the speed of light. $s(p, q)$ is the S-parameter between p-th TX and q-th RX, and N_T and N_R represent the number of TXs and RXs, respectively. TX and RX positions are assumed to be $(x_p, y_p, 0)$ and $(x_q, y_q, 0)$, respectively. R_p and R_q are the distance between TX and RX to the target point (x, y, z_0) described in (2)

$$R_p = \sqrt{(x_p - x)^2 + (y_p - y)^2 + z_0^2}, \quad R_q = \sqrt{(x_q - x)^2 + (y_q - y)^2 + z_0^2}. \tag{2}$$

When wideband imaging is applied, 3-D target image reconstruction $\rho(x, y, z)$ is possible with (3) [8]

$$\rho(x, y, z) = \sum_{n=1}^{N_f} \sum_{p=1}^{N_T} \sum_{q=1}^{N_R} s(p, q) e^{jk_n(R_p+R_q)}. \tag{3}$$

where N_f represents the number of frequency samples.

Conventional image reconstruction algorithms, often suffer from computational inefficiency and challenges in scenarios characterized by non-uniform sampling. For example, the above GSAFT reconstructions in (1) and (3) are exactly precise but they cost too much time to meet the fast imaging requirement. Therefore, a fast Fourier transform (FFT)-based image reconstruction algorithm has been proposed for a monostatic array imaging system where TX and RX separated spacing is much small compared to target distance or wavelength [9, 10]. It is acceptable to use the middle point of TX and RX to approximate the positions of TX and RX in calculating round trip paths and phases. This will not incur much phase errors and one space position of one sample corresponds to one space-frequency (wavenumbers) pair (k_x, k_y). So FFT-based image reconstruction is feasible as shown in (5) of the 2-D target image function and (6) of the 3-D target image function [8, 11]

$$\rho(x, y) = \text{FFT}_{\text{2-D}}^{-1} \left[\text{FFT}_{\text{2-D}} \left[s(x, y) \right] e^{-jz_0\sqrt{4k^2-k_x^2-k_y^2}} \right], \tag{4}$$

$$\rho(x, y, z) = \text{FFT}_{\text{3-D}}^{-1} \left[\text{Stolt\_interpolation} \left[\text{FFT}_{\text{2-D}} \left[s(x, y, \omega) \right] e^{-jz\sqrt{4k^2-k_x^2-k_y^2}} \right] \right], \tag{5}$$

where $\omega = 2\pi f$.

Although techniques that offer a solution to the EM inverse scattering problem in the Fourier domain are very computationally efficient, they require uniform sampling. A sampling at the Nyquist rate ensures that raw data can sample a complete set of Fourier components, such that a discrete Fourier transform (FT) can be defined over the set of data. Also, some image reconstruction algorithms typically require extensive computational resources and may yield reconstructed images with high sidelobes and poor quality, compromising the overall imaging fidelity. Additionally, signal processing algorithms tasked with

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target detection may struggle in environments rife with complexity and clutter, where distinguishing targets from background noise poses formidable challenges.

Furthermore, traditional algorithms may lack robustness and efficiency, hindering their performance in real-world scenarios. As NF imaging systems continue to evolve and expand into diverse applications, there is a growing demand for more advanced signal processing techniques that can overcome these limitations and deliver superior performance.

C. Advanced approaches

To address the challenges confronting traditional NF imaging systems and drive advancements in NF imaging technology, there is a critical need to embrace advanced approaches that offer innovative solutions.

One promising approach is the integration of dynamic metasurface antennas (DMAs), which can significantly reduce hardware complexity and power consumption while maintaining beamforming capabilities comparable to conventional phased array antennas [11, 12]. These antennas leverage tunable resonance responses and phase accumulation to achieve beam steering with minimal additional power requirements [11, 13]. By replacing conventional array antennas with metasurface antennas, NF imaging systems can achieve enhanced efficiency and performance.

Additionally, modified techniques based on principles like range migration and Kirchhoff migration present novel avenues for image reconstruction that can mitigate the limitations of traditional techniques [13, 14]. The basic principle of range migration involves back-propagating the received radar signal from the range cell associated with each point in the scene to a common reference range [14]. This process effectively aligns the signal phases and compensates for the range-dependent phase errors, enabling accurate image reconstruction. Kirchhoff migration involves back-propagating the measured field at the aperture plane to the migration plane, enabling the retrieval of 3-D spatial information of the target. By leveraging adapted Kirchhoff migration and other advanced techniques, NF imaging systems can overcome the challenges of hardware complexity and long acquisition times while enhancing image reconstruction quality and target detection efficiency.

Furthermore, advancements in machine learning (ML) and artificial intelligence (AI) hold immense promise for augmenting the capabilities of NF imaging systems [15, 16]. By leveraging DL algorithms for image processing and target recognition, NF imaging systems can achieve unprecedented levels of accuracy and efficiency in real-world applications.

The integration of advanced approaches such as the use of DMAs, and the derivation of novel algorithms based on fast Fourier calculations, Kirchhoff migration and ML is essential for overcoming the challenges faced by traditional NF imaging systems. These techniques offer innovative solutions to streamline hardware complexity, enhance signal processing algorithms, and drive advancements in NF imaging technology, thereby unlocking new opportunities for applications across various domains. Fig. 2 provides a summary of the information presented in Section II.

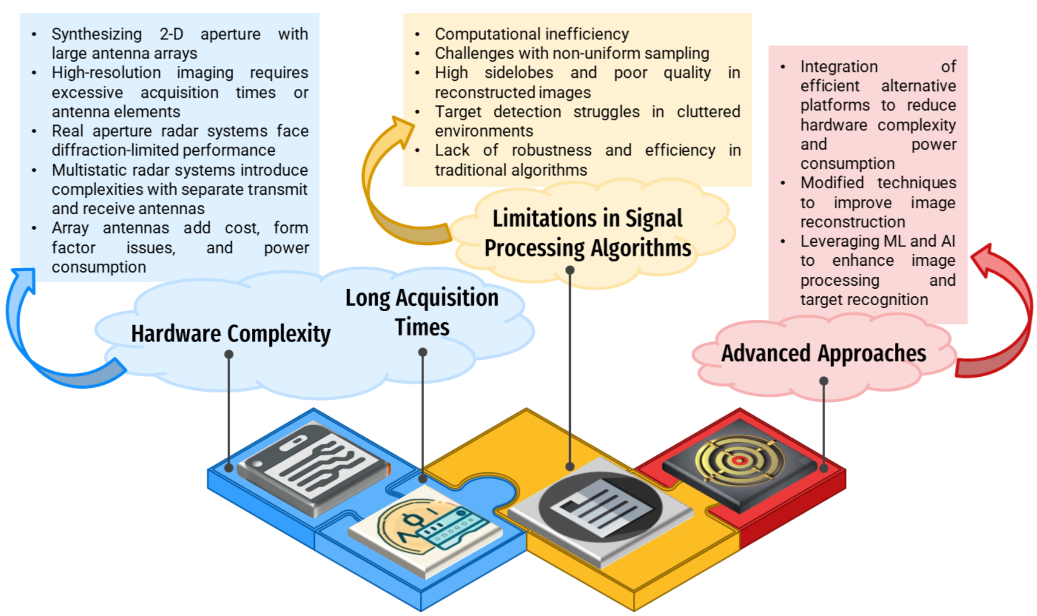

Fig. 2. Challenges in NF Imaging Systems.

III. Recent advances in NF radar imaging approaches

The landscape of NF radar imaging has evolved significantly with advancements in antenna technologies, aperture configurations and sophisticated signal processing techniques. Table I provides a comprehensive summary of various state-of-the-art NF radar imaging approaches, categorizing them based on key characteristics such as antenna types, aperture configurations, scanning methods, image reconstruction techniques, dimensions of reconstructed images, and primary contributions or achievements.

TABLE I
A SUMMARY OF THE KEY FEATURES OF THE VARIOUS APPROACHES

Feature	Antennas	Aperture Layout / Configuration	Scanning Type	Image Reconstruction Technique	Dimensions of Reconstructed Image	Main Contribution / Achievement
[6]	WR-28 open-ended waveguides	Multistatic	Electronically	Fourier based	3-D	The introduction of on-the-move imaging architecture
[17]	Isotropic antennas	Sparse MIMO arrays	Combined electronically and mechanically	Interpolation-free Fourier based	2-D	Establishing the analytical relationship between imaging ambiguities and the subsampled SAR aperture parameters
[1]	Cavity-backed metasurface antenna	Different polarization combinations of TX and RX	Electronically	Generalized minimal residue method (GMRES)	3-D	• Introduction of a 3 × 3 polarimetric matrix for representing the full vector polarimetric response of targets in the NF • Utilization of 3-D Jones vectors to describe the polarization states of non-planar vector sensing fields • Derivation and examination of 3-D polarimetric target parameters, providing detailed insights into the imaged object, including polarimetric features along the range direction • Validation of the effectiveness of this 3-D polarimetric imaging framework through experiments, demonstrating its potential for short-range microwave imaging applications
[5]	Monopoles / planar-slot / horn antennas	Multistatic / monostatic	Mechanically / electronically	Newton approach	3-D	A review of techniques developed for medical imaging, NDT, quality evaluation, TWI, and security screening, focusing on NF imaging and emphasizing the dependence of imaging on the electrical size of the antenna(s) and the target
[18]	Lens-loaded cavity-based metasurface	Monostatic	Electronically	Matched-filtering (MF)	3-D	• Increasing the number of effective measurement modes by 32% through lens loading of the coded aperture • Improving the conditioning of the imaging problem by more than a factor of two, enhancing the fidelity of the reconstructed images • Replacing the conventional pixel-by-pixel raster scanning with spatio-temporally varying, quasi-random bases for encoding back-scattered radar data, reducing hardware complexity
[19]	Isotropic antennas	Multistatic MIMO with 1-D uniform arrays	Combined electronically and mechanically	Multistatic-to-monostatic conversion + Fourier based	3-D	• Presenting the variational mode decomposition (VMD) of coded beat-frequency shifted signals algorithm for waveform diversity • Providing an efficient solution in terms of overall transmitting time and sampling rate in addition to robustness against channel noise
[20]	Isotropic antennas	MIMO with 1-D / 2-D uniform / Multistatic sparse arrays	Electronically / mechanically	Multistatic-to-monostatic conversion + fast Fourier based	2-D	Mathematical development of a Fourier-compatible method for NF MIMO THz imaging with sparse non-uniform apertures
[21]	Coded antennas	Bistatic	Electronically	MF	2-D	Development of a hardware-based solution using a field programmable gate array (FPGA) to significantly accelerate the signal processing required for computational imaging (CI) in real-time applications
[22]	Metasurface antennas	Frequency-diverse Mills Cross	Electronically	MF / GMRES	3-D	Development of a method to reduce latency and processing burden in frequency-diverse CI systems by employing dimensionality reduction on the sensing matrix that links measurements to the scene being imaged
[9]	WR3 (220–325 GHz) standard pyramidal horns	Multistatic MIMO with linear sparse periodic array (SPA)	Combined electronically and mechanically	Multipass synthetic aperture focusing and low-rank matrix completion (LRMC)	2-D	• Applying multipass interferometric technique into the NF THz imaging system with multistatic MIMO array for potential application of security/personnel screening • Integrating random undersampling sparse imaging into the multipass synthetic aperture focusing technique to reduce the sampling data, time and associated system cost • Proposing a systematic approach of CI simulation that involves the theoretical analysis in MATLAB and computational EM imaging simulation with FEKO

[23]	Isotropic antennas	Monostatic / multistatic MIMO	Mechanically / electronically	Compressive sensing (CS) based	2-D	Addressing two different mm-wave imaging structures, monostatic and multistatic, in the face of a sparse spatial sampling scenario
[24]	Isotropic antennas	Multistatic MIMO with 1-D uniform arrays	Combined electronically and mechanically	Multistatic-to-monostatic conversion + Fourier based	3-D	Development of an advanced method to enhance data acquisition efficiency in NF MIMO mm-wave imaging systems leveraging the superior sampling characteristics of frequency modulated continuous wave (FMCW) radar, and multi-resolution analysis
[16]	Isotropic antennas	Monostatic / MIMO	Mechanically	Conditional generative adversarial networks (cGAN)	2-D	Development and application of cGAN to significantly enhance the quality of high-resolution SAR images by mitigating artifacts
[14]	Panel-to-panel (1-D DMA panels)	Bistatic Mills Cross	Electronically	Fourier based	3-D	Proposing an adapted RMA with simplified interpolation
[11]	1-D DMA panel-to-probe	Fixed 1-D TX DMA + moving RX probe	Combined electronically and mechanically	CS-nonuniform inverse FFT (IFFT)	3-D	• Utilizing CS theory to optimize the conversion of raw measurements obtained by a DMA into Fourier bases • Presenting an efficient 3-D image reconstruction based on fast Fourier and sparse sampling without Stolt interpolation for NF microwave imaging using a DMA
[10]	WR3 (220–325 GHz) standard pyramidal horns	Multistatic MIMO with linear SPA	Combined electronically and mechanically	Reduced dimension Fourier (RDF)	2-D	• Developing multistatic-to-monostatic conversion for SPA • Mathematical derivation of a phase approximation to ensure the compatibility of Fourier-based solutions with the imaging scenario involving NF data collected by a sparse non-uniformly distributed MIMO effective aperture • Derivation of a Fourier-based closed-form expression leveraging dimensionality reduction for image reconstruction
[25]	Panel-to-panel (1-D DMA panels)	Multistatic MISO	Electronically	Fourier based	3-D	Development of an approach to deal with the combined measured signal scenario in which several TX antennas transmit signals simultaneously
[12]	Panel-to-panel (1-D DMA panels)	Multistatic square	Electronically	RMA based	3-D	Development of a multistatic DMAs-RMA for frequency domain
[4]	Cavity-backed polarimetric DMA	2-D dynamically reconfigurable metasurface aperture	Electronically	MF	2-D	Development of a two-stage method for TWI that does not require prior knowledge of the wall's structure, thus simplifying the process and reducing computational complexity
[2]	Patch antenna	Rectangular array	Electronically	Fourier based	2-D	Introduction of a novel transmissive programmable metasurface that enables high-resolution NF imaging and FF detection without the need for bulky lenses
[8]	WR3 (220–325 GHz) standard pyramidal horns	Multistatic MIMO with linear SPA	Combined electronically and mechanically	FFT MF (FFTMF)	3-D	• Proposing a fast image reconstruction algorithm for multipass synthetic aperture THz imaging of multistatic MIMO scenarios • Validation of a simple sparse imaging scheme with a linear SPA, which provides a practical and cost-effective solution to large-aperture imaging applications
[7]	Isotropic antennas	MIMO	Combined electronically and mechanically	BP and polar formatting	3-D	• Explore a toolbox that enables the rapid development of NF THz-SAR imaging systems and the generation of large NF THz imaging scenarios that can be used for data-driven applications as well as its potential for THz-based high-resolution and 2-D / 3-D imaging • Reporting the advantages of THz-based SAR over microwave SAR and optical imaging methods • Simulation of image reconstruction and NF THz imaging based on C-SAR scanning

[26]	Isotropic antennas	Multistatic MIMO	Electronically	Coded generalized RDF (CGRDF)	3-D	• Introduction of a special 2-D MIMO structure to fully electronically synthesize the 2-D aperture • Introducing an efficient model based on orthogonal coding to transmit simultaneously by all TXs and with the ability to extract channels information separately • Mathematical development of the RDF image reconstruction algorithm to a more general mode
[15]	Vivaldi	Multistatic MIMO	Electronically	Physics-based learned reconstruction	3-D	• Development of three novel 3-D image reconstruction methods for NF MIMO radar imaging using DL-based direct inversion and 3-D convolutional neural networks (CNNs) • Development of a synthesizer to generate 3-D scenes with extended targets to obtain large data for training the neural networks • Comprehensive experiments on synthetic 3-D scenes with quantitative and qualitative analysis by considering different compression and noise levels in the observations • Comparative performance evaluation by changing magnitude-only processing with complex-valued processing, 3-D convolution kernels with their 2-D counterparts, and U-Net architecture with ResNet • Resolution analysis at compressive imaging settings with sparse MIMO arrays • Performance analysis with experimental data, and comparison with the commonly used direct inversion and regularized reconstruction methods
[27]	Multiport switch and antenna array assembly	Sparse MIMO arrays	Combined electronically and mechanically	Fast factorized Kirchhoff migration algorithm (FFKMA)	3-D	Development of a FFKMA designed for 3-D NF microwave imaging using sparse MIMO arrays
[28]	Isotropic antenna	Monostatic	Mechanically	RMA based	3-D	Introduction of an NF mm-wave sparse imaging method that utilizes one-bit measurements
[29]	Metamaterial iris-based cavity antenna (MCA)	Bistatic	Electronically	LS	2-D	• Design and development of an MCA capable of generating dual-polarized, spatially-random illuminating patterns across the frequency range of 75 to 110 GHz • Significantly enhancing the capabilities of computational polarimetric imaging (CPI) systems
[3]	Non-reconfigurable EM skins (NR-EMSs)	Bistatic	Combined electronically and mechanically	BP	2-D	Delving into the usage of NR-EMSs for radar imaging in NLOS in a way that multiple modules generate an artificial sweeping useful for imaging
[13]	Panel-to-panel (1-D DMA panels)	Bistatic Mills Cross	Electronically	Data transformation from mask to spatial domain + adapted Kirchhoff migration	3-D	• Development of an adapted approach for NF radar imaging using the Kirchhoff migration principle, leveraging DMAs • Providing a comprehensive analysis of the characteristics of the masks

Scanning methods in NF radar imaging include mechanical, electronic, and combined approaches. Mechanical scanning, though slower, provides precise control over the imaging process, as seen in [16, 28]. Electronic scanning, on the other hand, offers faster data acquisition, which is crucial for real-time applications. Peng et al. [1] demonstrate the use of a cavity-backed metasurface antenna for electronic scanning to generate the random probing field set for the 3-D CPI purpose.

Image reconstruction techniques are pivotal in converting raw radar data into meaningful images. Table I indicates that techniques such as Fourier-based methods, least squares (LS), MF and Kirchhoff migration are commonly used. Recent innovations include the use of DL algorithms, which offer significant improvements in image quality and computational efficiency. Manisali et al. [15] highlight the potential of physics-based learned reconstruction methods, which combine traditional signal processing with DL to achieve real-time, high-quality 3-D imaging. The continual evolution in signal processing algorithms, particularly with the integration of DL, underscores the potential for achieving real-time, high-resolution imaging across various applications.

As Table I indicates, the dimensions of reconstructed images in NF radar imaging typically range from 2-D to 3-D. While 2-D imaging is simpler and faster, 3-D imaging provides more comprehensive information about the scene, which is essential for applications like security screening and medical imaging. For instance, Yurduseven et al. [18] demonstrate the use of MF

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techniques to achieve high-fidelity 3-D imaging using lens-loaded cavity-based metasurface antennas.

Each referenced study in Table I contributes unique advancements to the field. For example, Falconi et al. [18] focus on improving the conditioning of the imaging problem by a factor of greater than two times, while Shao et al. [5] review various techniques developed for NF imaging in different applications, emphasizing the dependency on the electrical size of the antennas and targets. The development of FPGA-based acceleration methods in [21] showcases the push towards real-time data processing, which is critical for practical implementations of NF radar imaging systems.

The studies reviewed in Table I employ a variety of antennas, including monopoles, isotropic antennas, horns, Vivaldi, NR-EMSs, phased arrays and metasurface antennas. Each antenna type is chosen for its specific advantages in different imaging scenarios. For instance, NR-EMSs are highlighted for their enhanced resolution imaging capabilities, as demonstrated in [3]. Metasurface antennas, particularly those with cavity-backed designs, show significant promise in enhancing polarization diversity and simplifying hardware configurations, as discussed in [1, 4].

Emerging DMA technology promises to achieve future wireless communications by reducing hardware costs, physical size and power consumption. Also, in the field of radar imaging, they can be used as an effective alternative platform for modern CI; because they can simplify the physical hardware and increase the data acquisition rate [11–13]. In fact, the hardware complexities can be simplified by replacing the antenna array with an electrically large metasurface antenna, which can be dynamically controlled to produce a sequence of field profiles. Furthermore, dynamically controlled metasurfaces can produce tailored radiation patterns without complicated hardware components, such as phase shifters, amplifiers, or mechanical scanning equipment. Each tuning state is called a mask [11–13]. As an example, in [14], the authors developed the first fast Fourier calculation technique that is applied to all electronic DMA-based (panel-to-panel) microwave CI systems for NF operation to achieve 3-D image reconstructions. This approach uses DMAs for both transmission and reception (see Fig. 3), enhancing system diversity and enabling real-time applications. Resulting from a numerical simulation in such a scenario, Fig. 3 shows the incident field at the centre frequency (19.75 GHz), and the output of the 2-D FT applied to it (in terms of wavenumbers k_x and k_y). Also, it indicates the output signal after applying the spatial filtering and Stolt interpolation for $k_x = 0$. Finally, in Fig. 3, the isosurface of the reconstructed image is shown. It can be seen that despite the compression of measurement data, the developed algorithm has succeeded in the 3-D reconstruction of the target image.

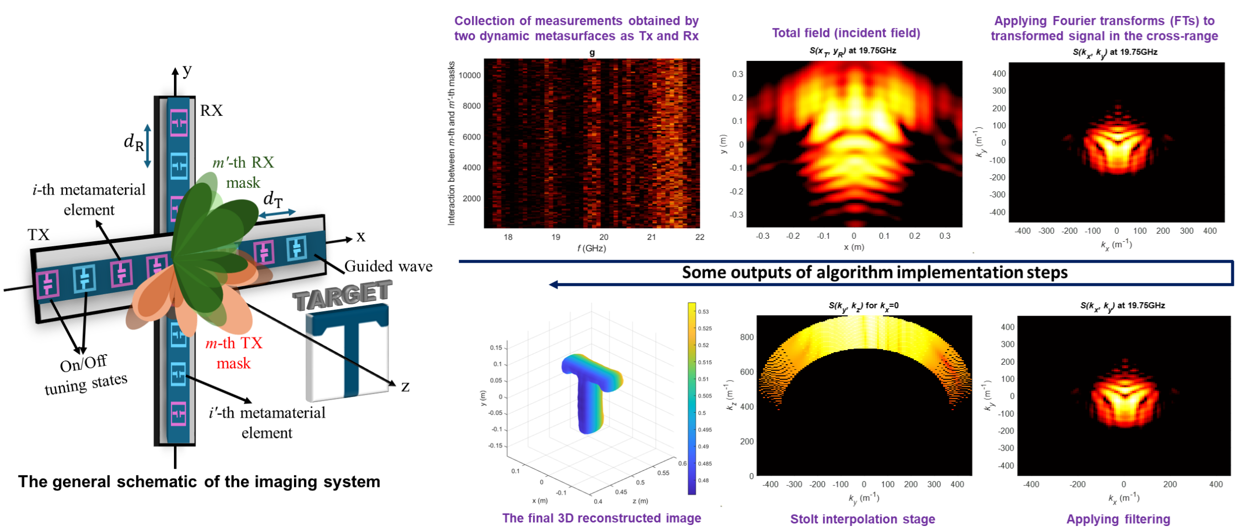

Fig. 3. NF panel-to-panel microwave imaging with DMAs [14].

The aperture layouts in Table I range from monostatic and bistatic configurations to more complex multistatic MIMO structures. The choice of aperture layout directly impacts the imaging resolution and system complexity. For example, multistatic MIMO configurations, such as those used in [8–10, 15, 19, 24, 26], allow for higher resolution imaging by leveraging the spatial diversity of multiple antennas.

An important challenge in using MIMO radar systems is the need to generate optimal signals that are orthogonal to each other (so-called waveform diversity). In other words, the transmitted waveforms, depending on the type of waveform (continuous or non-continuous (pulse wave)), must be designed and optimized in such a way that all pairs of individual TX-RX signals can be separated from the composite received signal at the RX. In [19, 24], an efficient waveform diversity for MIMO mm-wave imaging is developed (see Fig. 4). Consider an FMCW signal whose instantaneous frequency changes linearly with time as [19, 24]

$$s(t) = e^{j2\pi(f_0 t + 0.5Kt^2)}, \quad 0 < t < T_P, \tag{6}$$

where f_0 indicates the carrier frequency at $t = 0$, T_P is chirp pulse duration, and K indicates the range chirp. It is assumed that

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the two uniform linear arrays, as TX and RX, are used in a MIMO structure and perform the task of electronic scanning. To form a 2-D aperture, and thus obtain scene information in both the x- and y-directions, mechanical scanning is also performed horizontally by moving the arrays. On the TX-side, first, TX antennas are divided into L non-overlapping groups. The same carrier frequency is assigned to all chirp signals in the l-th group, where $l = 1, 2, ..., L$. The carrier frequency of each group has a small offset f_Δ compared to the previous group so that $f_\Delta \ll f_0$. Finally, before transmitting, the signals within the l-th group are encoded by assigning a binary phase in a time block. In the case of simultaneous transmission by all TX antennas, the challenge is that the raw data collected by the RXs cannot be processed directly for the image reconstruction process; because the individual data of each TX-RX pair are integrated into the combined signal. This is where applying a multi-resolution analysis can help separate the composite signals belonging to each group as well as retrieve the original content of the data. After recovering the composite signals of each group by a multi-resolution analysis, the composite signals are decoded to retrieve the signals corresponding to all pairs of TX-RX. In addition, after decoding, it is necessary to return the signal frequency content from the desired frequency to the beat frequency. The focus of research [19, 24] has been on two efficient VMD and successive VMD (SVMD) methods. Let us take a look at the spectrum of signals in Fig. 4. As can be seen, the frequency separation of the modes by the SVMD method is not as good as by the VMD method. In particular, the signal corresponding to group 0 contains more than one frequency component. The reason for this is the SVMD method's sensitivity to the modes' frequency distance.

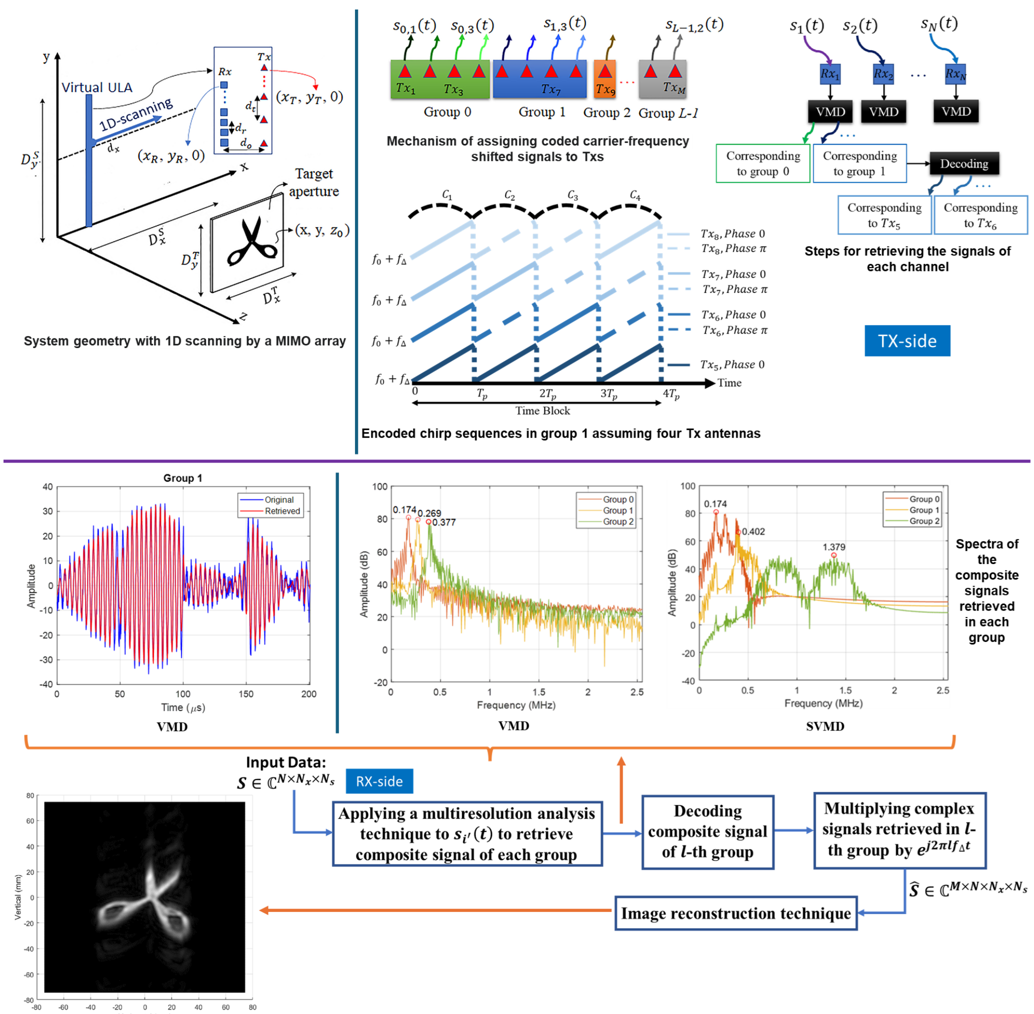

Fig. 4. An efficient waveform diversity for MIMO mm-wave imaging [19, 24].

Monostatic dense array requires sampling spacing on the order of $\lambda/2$ or being released to λ in practice by Nyquist sampling criterion to avoid aliasing, where λ is the wavelength. This will incur a large amount of antenna array elements and TX-RX channels. For example, the L3 ProVision ATD body scanner deployed in United States airports operates within the 24.25–30 GHz band and incorporates two vertical linear antenna arrays with 384 antenna elements in each array. This number will increase significantly with an increase in the operating frequency band, which is not acceptable for sub-THz and THz imaging considering system cost. To break this limit, multiple uses of TX and RX, multistatic MIMO array imaging systems and sparse imaging were proposed and studied. Linear sparse multistatic array with different multiple use ratios was initially

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investigated. In addition, planar multistatic sparse arrays with clusters, and other types of planar sparse arrays have been studied. In particular, multistatic linear SPAs with large inter-element spacing have recently been proposed for multistatic MIMO THz imaging systems [8, 10]. The work [10] focuses on developing a computationally efficient algorithm for image reconstruction compatible with SPAs in an NF multistatic THz imaging scenario. First, the structure of inter-element spacing in SPA is investigated and it is shown how this structure may create incompatibilities with conventional fast Fourier-based image reconstruction techniques. Then, for the mentioned scenario, a solution based on the FT with reduced dimensions adapted to the non-uniform spacing of the virtual array is presented. The efficiency of the proposed solution in [10], called RDF, has been assessed with both numerical and experimental data. The first target is a rectangular metal plate (see Fig. 5). It has several holes of different diameters. In addition, in Fig. 5, the target profile 2 with a different size is shown. Fig. 5 shows reconstructed images by GSAFT and RDF methods applied to experimental data obtained from an anechoic test environment and numerical data obtained from EM simulation by FEKO [10]. Also, the corresponding computational times for image reconstruction in the central processing unit (CPU) and graphics processing unit (GPU) are given.

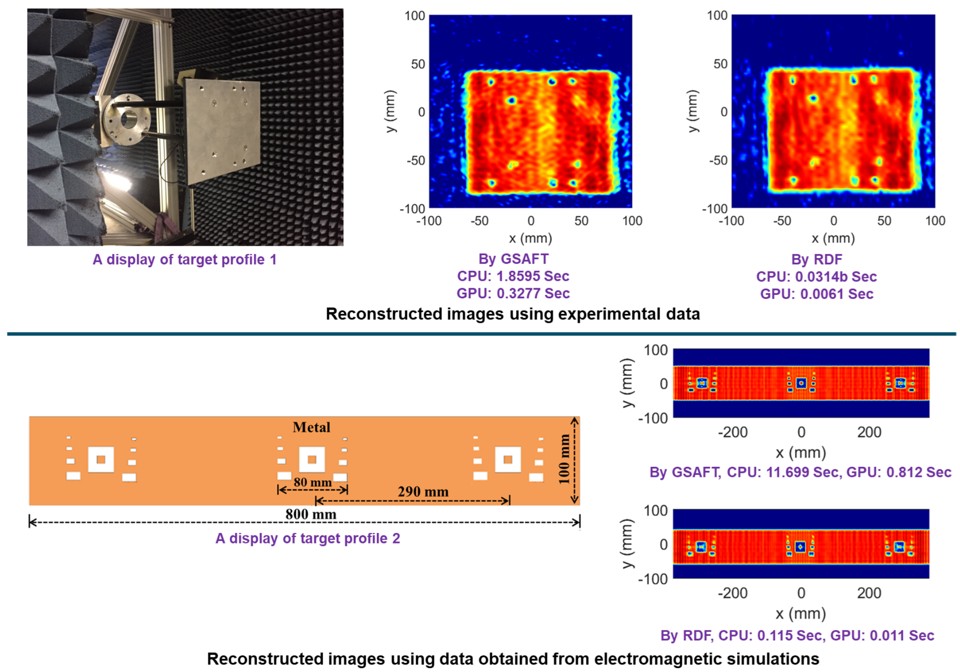

Fig. 5. Comparing the outputs of GSAFT and RDF (a fast processing approach) techniques in NF THz imaging with linear SPA [10].

In mm-wave imaging, although multiple uses of TXs and RXs are applied with a multistatic configuration, the number of array elements and channels is still very huge, especially for a large aperture application such as personnel screening. For example, there are a total of 736 TX antennas and 736 Rx antennas used in a planar 0.5 m $\times$ 0.5 m imaging system working at 72-80 GHz, which already uses a dedicated sparse array with a ratio of 5.75% of a total number of its counterpart dense array. This is developed to R&S®QPS scanning system that is capable of scanning a person. The system consists of front and back two panels. Each panel contains an array of 3008 TX and 3008 RX antennas. This number of antenna elements and channels might be acceptable for low frequency imaging systems because of well-developed technologies and low costs of devices. However, sub-THz and THz imaging are desired in the future because of their fine wavelength and superior performance on resolution comparable to wavelength. Therefore, new sampling schemes and corresponding transceiver arrays as well as image reconstruction algorithms are needed. As mentioned, linear SPA has been widely used in imaging in recent years because of its extended effective aperture and optimized radiation pattern with minimising side lobes. Its application in 220 GHz imaging with an array element spacing of 8.8λ has been studied and proved feasible with a ghost imaging suppressing approach [8, 9]. The findings are useful to guide the array and sampling design. Furthermore, a multipass interferometric synthetic aperture focusing technique has been proposed and studied to improve image quality at 220 GHz without increasing hardware complexity [9].

In addition to dedicated multistatic arrays for saving system channels and costs, sparse imaging is another promising technique to break the Nyquist sampling condition. To apply sparse imaging, two conditions should be fulfilled. One is to achieve a sparse sampling pattern with sparse arrays or an alternative approach, and the other one is an effective algorithm to recover the data such as CS and matrix completion techniques.

CS is a signal processing technique that offers compression of data below the Nyquist rate. It has emerged as a powerful tool in NF radar imaging, particularly for its ability to reconstruct high-quality images from sparse measurements. CS exploits the sparsity of the scene, enabling significant reductions in data acquisition time and computational resources. For example, Ge et al. [28] model one-bit measurements from a sparsity-driven perspective, based on CS theory, and introduce a convolutional reweighted l_1-norm constraint to promote the sparsity of clustered structures commonly found in NF imaging. Furthermore, to circumvent the computational complexities associated with constructing, storing, and optimizing large-scale matrix-vector multiplications within CS theory, the RMA and its inverse operator are used as an alternative.

Further advancements in CS techniques are illustrated by Molaei et al. [11, 20, 23], who integrate CS theory with fast Fourier-based sparse sampling methods. Especially in [20, 23], they first studied the effectiveness of CS theory in a monostatic imaging structure. However, when the TX and RX separated spacing is large compared to wavelength or target distance in a multistatic array imaging system, using the middle point of TX and RX as an approximation to their positions in a monostatic system cannot be directly applied which will incur much phase errors. Therefore, FFT-based image reconstruction in multistatic circumstances cannot be directly implemented by (4) or (5). Instead, a multistatic-to-monostatic conversion is required, as shown in Fig 6. Afterwards, an FFT-based approach like (7) can be applied to reconstruct an image [9]

$$\rho(x, y, z_0) = \mathrm{FFT}_{\text{2-D}}^{-1}\left[\mathrm{FFT}_{\text{2-D}}\,[\tilde{\mathbf{s}}]\,\mathrm{FFT}_{\text{2-D}}\left[\mathbf{H}_{z_0}^{*}\right]\right], \tag{7}$$

where $\mathbf{H}_{z_0}^{*}$ is a matrix of the conjugate of system response evaluated at the focusing point (x, y, z_0). Therefore, in the above scenario, a similar approach was generalized to a multistatic case by considering some compensators. The block diagram in Fig. 6 shows the main processing steps for preparing the data captured by the system for image reconstruction. Normally, to avoid aliasing in image reconstruction, the Nyquist criterion in spatial sampling must be met. This means that in the monostatic case a uniform sampling with sampling intervals, and in the MIMO case an inter-element spacing in the virtual array, must be implemented. However, according to CS theory, a sparse signal may be retrieved from much fewer measurements. Therefore, by imposing some additional processes to solve the problem of minimization (or data recovery), it is no longer necessary to obtain samples based on the Nyquist rate and uniform sampling. In Fig. 6, part of the experimental results are shown along with the measurement parameters. The target consists of a copper-clad laminate board containing rectangular cuts of different sizes. The reconstructed images from left to right show the reconstructed images using full data and compressed data at 25% and 35% rates, respectively.

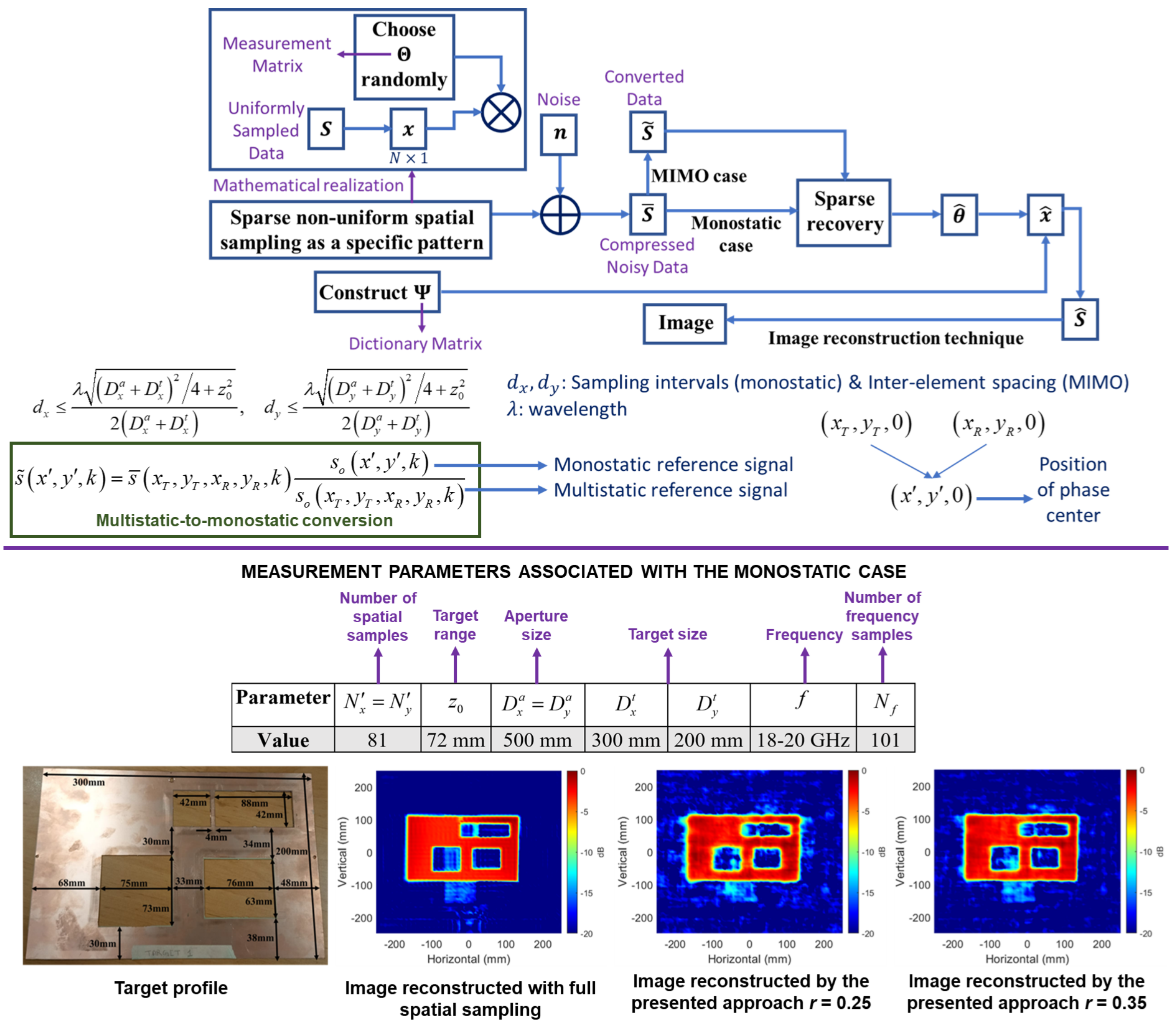

Fig. 6. A CS and Fourier-based image reconstruction [20, 23].

Also, the approach presented in [11] optimizes the conversion of raw measurements obtained by DMA into Fourier bases, facilitating efficient 3-D image reconstruction without the need for Stolt interpolation. The system uses a fixed DMA along the horizontal as the TX, and a single antenna moving along the vertical as the RX (see Fig. 7). The measurement signal with the presence of DMA has a more complicated form than the total field that is conventionally calculated for the model of single dipoles only with Green's function. Assuming full sampling, the measurement signal in this scenario can be written as [11]

$$g(f) = \int_V U_T(\vec{r}, f)\rho(\vec{r})G(\vec{r}, y_R, f)\, dV, \tag{8}$$

where $dV = dxdydz$ denotes a small volume element made of space intervals dx, dy and dz in the directions x, y and z, respectively, y_R corresponds to the position of RX, and $\vec{r}$ is the position vector to a point in the scene. In the above equation, U_T, ρ and G represent the field radiated from the aperture, target reflectivity and Green's function, respectively. A summary of the main steps of implementing the approach presented in [11], along with the final reconstructed image of a B-shaped target in the sparse spatial sampling scenario are given in Fig. 7. This approach demonstrates the potential of CS to significantly enhance the imaging capabilities of NF radar systems, especially in applications requiring rapid data acquisition and fast processing. Note that unlike wavenumbers k_x and k_y which have a uniform distribution, k_z and the corresponding data in this form are not amenable to applying the IFFT (see Fig. 7 where the pattern of k_z in terms of k_x and k_y according to the dispersion relation is shown). Using Stolt interpolation before applying inverse FT (IFT) is one of the conventional solutions to deal with it, which has a relatively high computational complexity.

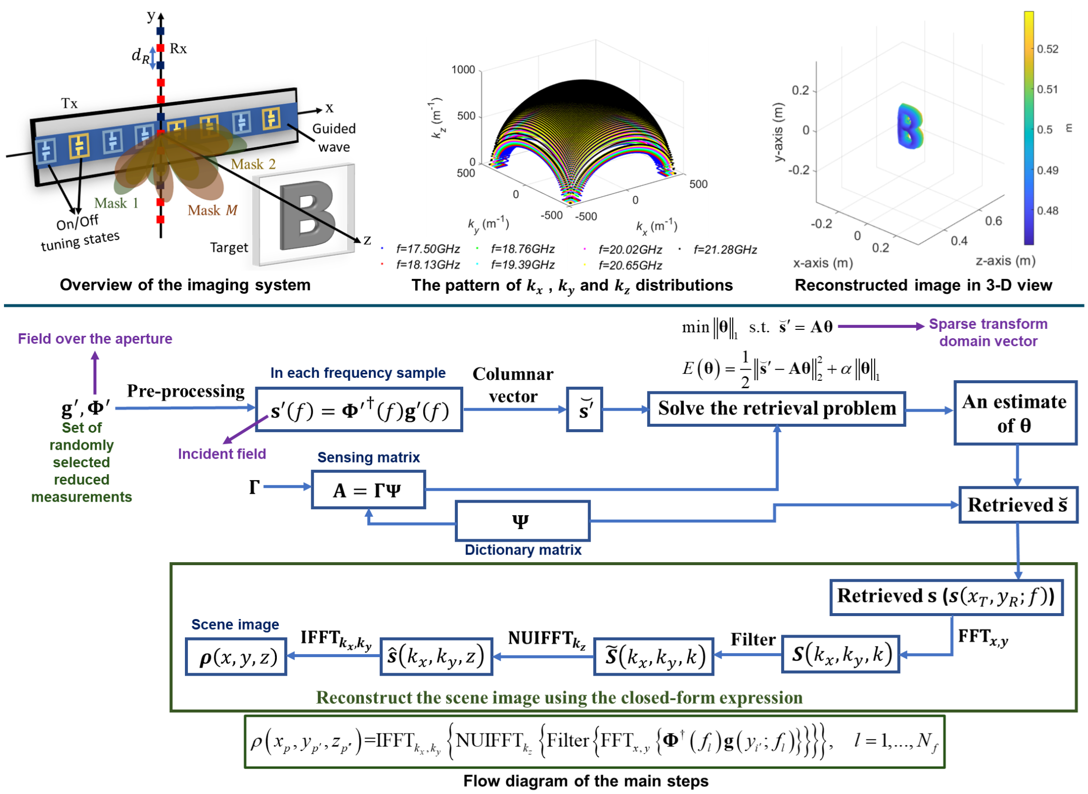

Fig. 7. An efficient 3-D image reconstruction for NF microwave imaging using a DMA [11].

LRMC or LRMR using the low-rank constraint is superior to CS because of its robustness against basis-mismatch, lower demand on computing resources and simplicity of exempting from the sparse representation. LRMR assumes a large data matrix $\mathbf{M}$ decomposed as a sum of a low-rank matrix $\mathbf{L}_0$ and sparse noise/error matrix $\mathbf{S}_0$ [8]. It aims to recover $\mathbf{L}_0$ from corrupted data $\mathbf{M}$. In some applications, however, the LRMC problem can be solved as a particular case of LRMR problem as some of the entries in $\mathbf{M}$ are missing. LRMC has gained significant interest in various applications such as W-band 0.4m-SAR imaging and 220 GHz 1.4m-SAR imaging for target detections [9]. Unlike classical LRMR also known as principal component analysis (PCA) in some applications, the novel use of error matrix $\mathbf{S}_0$ solely and together with $\mathbf{L}_0$ for image reconstructions has also been explored in experiments of 220 GHz 1.4m-SAR imaging and FFT reconstruction approach. This significantly improves the capability of target detection and reduces image reconstruction time [8].

IV. Future directions and opportunities

The future of NF radar imaging is bright, with numerous opportunities for advancements in technology and interdisciplinary research. By focusing on innovative signal processing techniques, sensor technologies, and collaborative efforts, the SPS community can significantly contribute to the evolution and application of NF imaging systems. Below are a few examples of future directions and opportunities in NF Radar imaging.

A. NF on-the-move imaging

The future of NF on-the-move imaging [6], particularly with mm-wave technology, offers promising avenues for advancements in personnel security screening and other applications. As the technology evolves, significant emphasis will be placed on improving signal processing techniques to enhance imaging systems' accuracy, speed, and reliability.

One key development area is the integration of advanced signal processing algorithms to manage the continuous flow of data as individuals move through the scanning corridor. Real-time processing capabilities are crucial for on-the-move imaging systems, and this can be achieved by implementing sophisticated techniques such as FFT and BP imaging. FFT is instrumental in transforming the collected time-domain data into the frequency domain, which facilitates the reconstruction of high-resolution images. On the other hand, BP imaging helps accurately reconstruct the scattered fields to generate clear and precise images of the moving subject.

Moreover, the sequential activation of multiple TXs and RXs requires robust synchronization and data fusion methods to compile coherent images from different angles. Advanced multistatic radar systems can provide a comprehensive view of the target by simultaneously collecting data from various perspectives. Signal processing algorithms must efficiently handle the vast amounts of data generated, ensuring that the resultant images are both high-resolution and timely.

Developing ML and AI algorithms for pattern recognition and anomaly detection represents another critical frontier. These algorithms can analyze the continuous stream of images to identify potential threats or concealed objects with high accuracy. Incorporating AI into NF on-the-move imaging systems can enhance their ability to adapt to different scanning environments and improve the robustness of threat detection.

Additionally, there is a growing need to improve the hardware aspects of NF imaging systems. Advances in DMAs can significantly enhance the flexibility and efficiency of mm-wave imaging systems. DMAs can steer beams dynamically without mechanical movement, which is ideal for on-the-move imaging applications. This advancement can lead to more compact and power-efficient systems, further facilitating the deployment of NF imaging technologies in various environments.

Interdisciplinary research will play a pivotal role in advancing NF on-the-move imaging. Collaboration between experts in EM, signal processing, computer science, and materials science is essential to develop innovative solutions that address the current limitations. For instance, combining EM theory with advanced computational techniques can result in more accurate and efficient imaging algorithms. Moreover, exploring new materials and fabrication techniques for antennas and sensors can lead to more durable and high-performance imaging systems.

In summary, the future of NF on-the-move imaging is poised for significant advancements through the integration of advanced signal processing techniques, AI and ML algorithms, and cutting-edge hardware innovations. These developments will not only enhance security screening processes but also open up new applications in medical diagnostics, industrial inspection, and beyond. The continued collaboration across disciplines will be key to overcoming the challenges and realizing the full potential of NF on-the-move imaging systems.

B. NF imaging with DL models

The integration of DL models into NF imaging represents a transformative approach with the potential to overcome longstanding challenges and introduce unprecedented capabilities in microwave imaging. This subsection explores the future directions and opportunities associated with utilizing DL, particularly focusing on the *measured microwave signals to image* model [30].

DL networks, especially CNNs, have demonstrated exceptional success in various imaging modalities, including magnetic resonance imaging (MRI), computed tomography and optical imaging. These successes suggest a promising future for their application in microwave imaging. The fundamental challenge in microwave imaging is the sparse nature of the measurement data due to the limited number of sensors, which leads to an underdetermined problem. DL models can address this by learning complex mappings from sparse measurements to high-resolution images, thus offering a viable solution to this inverse problem.

A significant innovation in this field is the two-stage training method that involves an autoencoder (AE) followed by a neural network mapping microwave signals to compressed features [30]. The AE reduces high-resolution images (128×128) to compact representations (256×1 vectors), facilitating easier training of the second neural network [30]. This network maps the measured microwave signals to these compressed features. By training these networks sequentially, the method reduces the overall training difficulty and enhances the network's ability to converge, even with sparse data.

Future research will focus on refining the algorithmic aspects of these DL networks to further improve the accuracy and efficiency of microwave image reconstruction. The use of advanced DL architectures, such as GANs and recurrent neural networks (RNNs), could provide significant improvements. GANs, for example, can help in generating high-fidelity images from sparse measurements by learning the underlying distribution of the imaging data, while RNNs can be utilized to model temporal dependencies in sequential data acquisition scenarios.

The quality and quantity of training data are crucial for the success of DL models. Future directions will involve generating more diverse and extensive datasets that encompass a wide range of object shapes, sizes, and dielectric properties. This can be achieved through sophisticated simulation models and real-world experiments. Additionally, data augmentation techniques

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can be employed to artificially increase the size and variability of training datasets, thereby enhancing the robustness of the trained models.

One of the most promising opportunities lies in the development of real-time imaging systems using DL. The fast inference capabilities of trained DL models make them suitable for applications requiring immediate feedback, such as security screening, medical diagnostics, and industrial NDT. Implementing these models in hardware-accelerated environments, such as GPUs or specialized AI chips, can further reduce latency and improve real-time performance.

Future work will also involve comparative analyses between DL-based methods and traditional techniques like the distorted Born iterative method and the phase confocal method. Understanding the strengths and limitations of each approach will guide the development of hybrid techniques that combine the best aspects of both. For example, initial reconstructions could be performed using traditional methods, followed by refinement through DL models to achieve higher resolution and better accuracy.

The advancement of NF imaging with DL will benefit significantly from interdisciplinary collaboration. Combining insights from fields such as signal processing, computer vision, ML, and EM can lead to innovative solutions and new theoretical frameworks. Collaborative efforts can also drive the development of standardized benchmarks and evaluation protocols, ensuring that advancements are robust, reproducible, and broadly applicable.

In summary, the future of NF imaging utilizing DL models to convert measured microwave signals into high-resolution images is bright and filled with potential. The two-stage training method and the application of advanced DL architectures are paving the way for more accurate, efficient, and real-time imaging solutions. With continued research and interdisciplinary collaboration, these innovations will not only enhance existing applications but also unlock new possibilities across various fields, from healthcare to security and beyond.

C. Factorisation of the sensing matrix

The previous sections have highlighted the main motivation behind CI techniques, which is to simplify complex and redundant active architectures, shifting constraints to the digital layer. Mathematics therefore plays a central role in these activities, from the development of models linking measurements to unknowns to the optimization of inverse problems enabling their estimation. In particular, this subsection focuses on the potential offered by the decomposition of sensing matrices. These techniques offer numerous prospects for analysing the diversity of radiating systems and optimizing acquisition.

In many CI studies, the definition of matrices linking the space to be imaged to the measured information is an essential design step. The most widely used formalism corresponds to the interaction between the transmitted and received fields is as follows [22]:

$$H_{m,n} = \mathbf{E}_m^{\mathrm{TX}}(\mathbf{r}_n) \cdot \mathbf{E}_m^{\mathrm{RX}}(\mathbf{r}_n), \tag{9}$$

where the reflectivity at each point of the space of index n is interrogated by measurements of index m. Considering M measurement modes and discretising the imaged scene into N voxels, the model can be reformulated in matrix form as follows [22]:

$$\mathbf{g} = \mathbf{H}\boldsymbol{\rho} + \mathbf{n}, \tag{10}$$

where $\mathbf{g} \in \mathbb{C}^{M\times 1}$ and $\boldsymbol{\rho} \in \mathbb{C}^{N\times 1}$ are respectively the vector of measured samples and the spatially discretised reflectivity of the scene to be imaged. $\mathbf{n} \in \mathbb{C}^{M\times 1}$ represents the additive Gaussian noise.

These formalisms involve a form of multiplexing towards a restricted number of ports of the information in a scene, via field distributions which can be reconfigured actively or by frequency scanning, forming a sensing matrix $\mathbf{H} \in \mathbb{C}^{M\times N}$. Successful execution of this operation depends above all on the ability to invert this matrix, since the measurements correspond to a superposition of linear combinations of the data to be reconstructed. The low correlation of these distributions is therefore a central issue for many activities, enabling the quantity of information that can be reconstructed from a series of measurements to be maximised. This principle is also strictly equivalent for conventional imaging systems, where the spatial sampling of the antenna array and the interrogated space affects the correlation of Green's functions and determines the number of independent components that can be estimated [22].

The singular value decomposition is the common starting point for all the analyses presented in this subsection. Assuming that $N < M$, the transfer matrix $\mathbf{H}$ can be factorised, here in its compact form, as follows [22]:

$$\mathbf{H} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^H, \tag{11}$$

where $\mathbf{U} \in \mathbb{C}^{M\times N}$ and $\mathbf{V} \in \mathbb{C}^{N\times N}$ are unitary matrices, bases of the decomposition of $\mathbf{H}$ into subspaces, weighted by $\boldsymbol{\Sigma} = \mathrm{diag}(\boldsymbol{\sigma})$, a diagonal matrix composed of the singular value vector $\boldsymbol{\sigma} \in \mathbb{C}^{N\times 1}$. Since the singular vectors composing the unitary matrices $\mathbf{U}$ and $\mathbf{V}$ carry no amplitude information, the singular values of $\boldsymbol{\sigma}$ alone play the role of weighting the different subspaces, being arranged by convention from the largest to the smallest contribution. An optimized imaging system must convert as much spatial information as possible into independent measured samples, which means obtaining singular values that are evenly distributed in amplitude.

Optimized systems tend to have a certain level of information redundancy, reflected in a fall in the amplitude of singular values above a certain threshold. This phenomenon may be the result of a voluntary approach, with the most significant contributions being made to make them more immune to noise, or it may simply be the translation of physical limits, particularly those associated with losses of various kinds. An illustration of this decomposition is shown in Fig. 8.

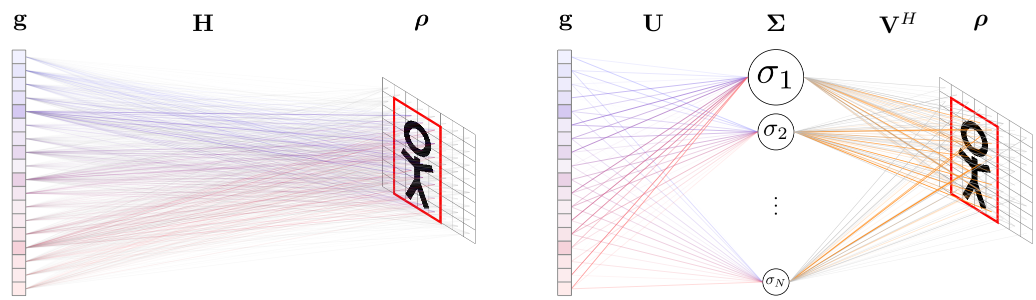

Fig. 8. Factorization of a sensing matrix to identify the principal components interrogating the space to be imaged. This decomposition can be coupled with support detection to restrict this domain by selecting vectors from the matrix $\mathbf{V}$ [22].

This decomposition allows, on one hand, to identify the linear combinations significantly contributing to the measurements and, on the other hand, to reduce the number of unknowns α [22]:

$$\mathbf{g} = \mathbf{P}\,\boldsymbol{\alpha} + \mathbf{n}, \tag{12}$$

where $\mathbf{P} = \mathbf{U}\boldsymbol{\Sigma}$ are the principal components of the system and where $\boldsymbol{\alpha} = \mathbf{V}^H\boldsymbol{\rho}$ corresponds to the unknowns to be estimated, allowing for the reconstruction of an image such that $\hat{\boldsymbol{\rho}} = \mathbf{V}\hat{\boldsymbol{\alpha}}$ [22]. By exploiting the correlation of data and measurements, this approach enables efficient compression of the datasets to be processed and accelerates measurement times. For a full-body security screening application where the memory footprint of the sensing matrix is 68 GB, this technique allows a reduction of this volume by a factor of 10 while halving the computation time, conceding a slight degradation of the reconstructed images [22].

PCA is also a promising path to optimize the reconstructions of datasets restricted to specific applications. If the illuminated objects are always of the same nature, there will necessarily be specific spatial structures associated with them, such as [22]

$$\boldsymbol{\rho} = \boldsymbol{\Psi}\mathbf{s} \tag{13}$$

where $\boldsymbol{\Psi} \in \mathbb{C}^{N\times K}$ is a decomposition basis adapted to a restricted application and where $\mathbf{s} \in \mathbb{C}^{K\times 1}$ is a vector of weights associated with this basis. This new factorization presents itself as an efficient method for achieving further data compression, focusing primarily on the reconstruction of the principal components specific to the studied datasets.

The factorization of sensing matrices also offers interesting perspectives for studying the propagation regimes exploited for imaging applications. Focusing here on an application exploiting frequency diversity to encode the spatial information of a scene. Facilitated by the illustration presented in Fig. 8, the unitary matrices $\mathbf{U}$ and $\mathbf{V}$ respectively contain vectors associated with perfectly decoupled frequency and spatial structures, composing the analyzed sensing matrix. Interestingly, it is possible to perform an IFT of the frequency data $\mathbf{U_t} = \mathfrak{F}^{-1}(\mathbf{U})$, identifying the temporal structures composing the matrices. This decomposition notably allows for classifying the different subspaces according to the propagation regimes composing the data, which can be both ballistic and strongly resonant for CI activities carried out with leaky resonant cavities. Such an approach presents itself as an interesting perspective in many applicative cases. Indeed, it becomes possible to remove the contribution of the most coherent subspaces in time and space, sources of potential artifacts during reconstructions. In the case of applications operating in a ballistic regime, it is also possible to identify and remove the contribution of multiple paths composing our datasets.

D. ML-assisted NF imaging hardware optimization

The integration of ML techniques in the physical layer side of the NF imaging system is expected to enhance hardware optimization. NF imaging, particularly in microwave and mm-wave frequency ranges, requires precise control of hardware to achieve high-resolution images. As discussed in Section II-A, SAR and MIMO arrays face challenges like long acquisition times and high hardware complexity. ML offers a promising solution by enabling dynamic optimization of hardware configurations. Although extensive literature exists on ML-assisted signal processing, there is little focus on real-time physical layer improvements in imaging systems. In addition to using ML models to learn complex mappings from sparse measurements to high-resolution images (refer to Section IV-B), ML can be applied directly to imaging hardware. This application can dynamically adjust the beamforming patterns of antenna arrays, enhancing imaging resolution and reducing redundant power

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leakage. Such adaptive hardware configuration is particularly beneficial in scenarios requiring highly precise beam control due to the proximity to the target.

Traditional systems often use static hardware configurations, which may not be optimal for all imaging scenarios, overstressing the capabilities of ML models implemented at the signal processing level alone. Hence, dynamically adjusting the hardware configuration based on low-complexity performance indicators seems the next logical step forward. This approach not only improves the imaging performance but also reduces the power consumption and complexity at both hardware and signal processing levels. For instance, a supervised learning method can be used to develop adaptive algorithms that adjust the antenna array configuration in real-time, based on the imaging environment and target characteristics. Dynamic optimization in imaging systems enables the hardware to operate at its optimal configuration, thereby enhancing imaging resolution and reducing acquisition time.

Consider an ML-enhanced NF imaging system. The system uses a dynamic aperture for imaging and employs ML algorithms to dynamically adjust the beamforming patterns and hardware configuration based on the target characteristics and imaging environment. During operation, the ML algorithms continuously analyze the incoming signal data and adjust the antenna configuration to optimize the imaging resolution. At the same time, the adaptive beamforming algorithms ensure that the system can accurately image targets at different distances and angles based on antenna performance indicators (such as correlation coefficient between radiated field modes), while the DL-based image reconstruction algorithms provide high-quality images even in the presence of noise and other interferences. The system can operate efficiently under different imaging conditions, providing reliable and high-resolution images. The block diagram of such a system is shown in Fig. 9.

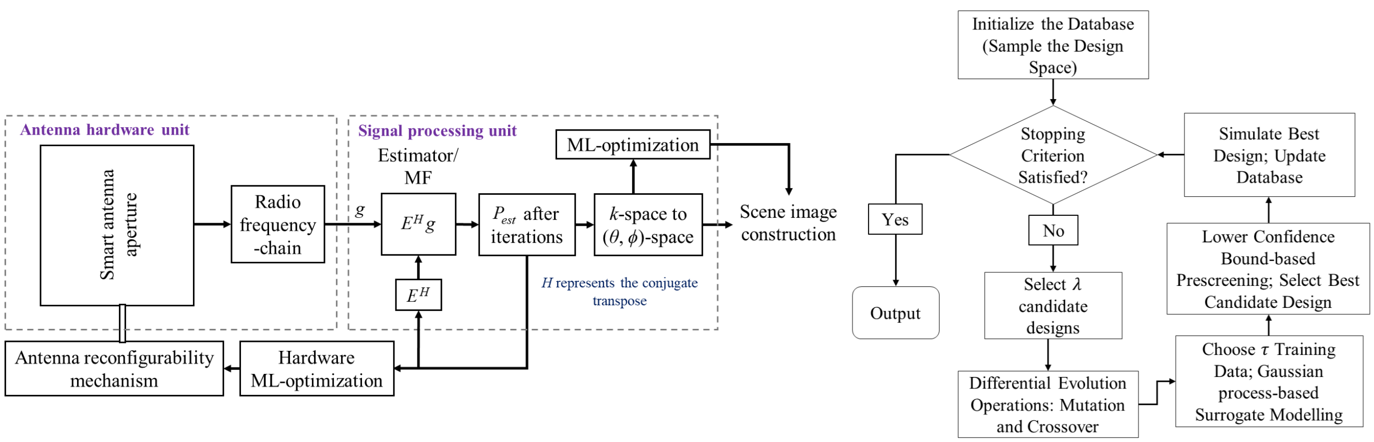

Fig. 9. Block diagram of an ML-enhanced NF imaging system.

E. Fast Kirchhoff migration for NF imaging

The development of fast and accurate imaging algorithms is crucial for advancing NF microwave imaging, particularly when using sparse MIMO arrays. The FFKMA [27] offers a promising approach, merging the high-quality imaging of traditional Kirchhoff migration algorithms (KMAs) with the computational efficiency of wavenumber domain algorithms. This subsection delves into the future directions and opportunities for enhancing NF imaging through FFKMA, emphasizing signal processing aspects.

A major advantage of FFKMA lies in its ability to reduce the computational burden typically associated with time-domain reconstruction algorithms. Traditional KMAs, while accurate, are computationally intensive due to the large number of TX-RX pairs and the high-resolution demands of NF imaging. By employing factorization techniques and dividing the full MIMO array into smaller, more manageable subarrays, FFKMA significantly decreases computational costs. Each subarray can be processed independently, allowing for parallel processing and faster overall image reconstruction. Future research can focus on optimizing these factorization techniques to further enhance efficiency, possibly incorporating ML methods to dynamically adapt the factorization process based on real-time data characteristics.

While computational efficiency is critical, maintaining high image quality and resolution is equally important. FFKMA achieves this by leveraging local spectrum properties of NF radar images to ensure efficient sampling of subimages. This approach minimizes the risk of aliasing and ensures that the reconstructed images retain the high resolution necessary for practical applications. Future developments could explore more sophisticated spectrum modeling techniques and adaptive sampling methods to further improve image quality. Additionally, integrating advanced signal processing techniques, such as sparse reconstruction and super-resolution methods, could push the resolution limits even closer to the diffraction limit.

One of the most promising opportunities for FFKMA is in real-time imaging applications, where rapid acquisition and processing are paramount. In scenarios such as security screening, industrial inspection, and medical diagnostics, the ability to quickly generate high-resolution images can significantly enhance operational efficiency and decision-making. Future research should focus on implementing FFKMA in hardware-accelerated environments, such as FPGAs or GPUs, to achieve the necessary speed for real-time applications. Furthermore, developing robust algorithms that can handle the noise and variability inherent in real-world data will be crucial for practical deployment.

A key strength of FFKMA is its applicability to generic sparse MIMO array configurations. This versatility makes it suitable for a wide range of NF imaging systems, from compact portable devices to large-scale industrial scanners. Future research can extend this adaptability by developing versions of FFKMA tailored to specific array geometries and application requirements. For instance, custom FFKMA implementations could be designed for cylindrical, planar, or irregularly shaped arrays, optimizing performance for each specific configuration.

Another exciting avenue for future research is the integration of FFKMA with other imaging modalities. Combining NF microwave imaging with techniques such as optical imaging, ultrasound, or MRI could provide complementary information, enhancing overall diagnostic capabilities. Developing multimodal imaging systems that seamlessly integrate FFKMA with other modalities will require sophisticated data fusion algorithms and real-time synchronization of different imaging streams. This multidisciplinary approach can lead to more comprehensive and accurate imaging solutions.

In summary, the FFKMA represents a significant advancement in NF microwave imaging, offering a balanced solution that combines high imaging quality with computational efficiency. By focusing on enhancing computational techniques, improving image quality, enabling real-time applications, and ensuring versatility, FFKMA opens up numerous future directions and opportunities. Continued research and development in these areas will not only enhance the capabilities of NF imaging systems but also expand their applicability across various fields, from security and industrial sensing to medical diagnostics and beyond.

F. NF imaging utilizing one-bit measurements

The future of NF imaging, particularly in the context of mm-wave technology, is poised for significant advancements through the adoption of one-bit measurement techniques [28]. This innovative approach addresses the challenges of high hardware costs and substantial data storage requirements associated with traditional high-precision quantitative imaging methods. By emphasizing the signal processing aspects of one-bit measurements, new horizons in efficient, cost-effective, and high-quality imaging can be explored.

One-bit measurements simplify the data acquisition process by quantizing the received signals to a binary format, indicating whether the signal is above or below a reference level. This method dramatically reduces the complexity and power consumption of analog-to-digital converters and minimizes the volume of data generated, thereby lowering hardware costs and easing data storage burdens. The crux of future advancements lies in enhancing the signal processing algorithms to maximize the potential of one-bit measurements.

Future research will continue to leverage CS theory, which allows for the reconstruction of signals with fewer samples than traditionally required by the Nyquist sampling theorem, particularly for sparse or compressible signals. By modeling one-bit measurements from a sparsity-driven perspective, new algorithms can be developed to reconstruct high-quality images even with limited data. The introduction of convolutional reweighted l_1-norm constraints, which promote the sparsity of clustered structures, represents a significant step forward. This approach not only improves image quality but also reduces artifacts and sidelobes, enhancing the overall imaging results.

One of the primary challenges in one-bit NF imaging is the computational complexity involved in matrix-vector multiplications and optimizations required for CS. To address this, future advancements will likely focus on integrating the RMA and its inverse operator. This integration combines the benefits of CS and MF, significantly reducing the computational load and storage requirements. The development of new algorithms that utilize logistic functions to measure the consistency between one-bit measurements and reconstructed signals can further streamline the imaging process. Logistic functions, being differentiable and log-concave, offer algorithmic advantages over traditional sign functions, facilitating more efficient and accurate signal reconstruction.

Adaptive quantization-level parameters and advanced optimization techniques will play a crucial role in future one-bit NF imaging systems. Techniques such as iterative hard thresholding and proximal splitting algorithms, which have shown promise in previous research, can be further refined to handle the unique challenges of one-bit measurements. The use of adaptive algorithms to update quantization parameters dynamically can mitigate noise-induced inconsistencies, thereby improving the robustness and accuracy of the imaging process.

The future of one-bit NF imaging will benefit greatly from interdisciplinary research and collaboration. Combining expertise from fields such as EM, signal processing, computer science, and materials science can lead to innovative solutions that address current limitations. Practical applications of this technology extend beyond security screening to include biomedical diagnostics and NDT, where the ability to produce high-quality images with minimal data is particularly valuable.

In summary, the future of NF imaging utilizing one-bit measurements is rich with opportunities for advancements in signal processing techniques. By focusing on CS, efficient algorithms, adaptive quantization, and interdisciplinary collaboration, the field can achieve significant improvements in imaging quality, cost-effectiveness, and practical applicability. These developments will not only enhance existing applications but also pave the way for new uses in various industries, showcasing the transformative potential of one-bit NF imaging technology.

V. Conclusion

We provided an overview of advanced NF radar imaging approaches with a focus on the critical role of signal processing. Our key findings and those of other researchers highlight the substantial progress in NF microwave and THz imaging, demonstrating its transformative potential across various applications such as security screening, medical diagnostics, NDT and SHM.

The importance of signal processing in advancing NF microwave and THz imaging cannot be overstated. Sophisticated signal processing techniques, including Fourier-based algorithms, sparse imaging, LRMR and DP, have been pivotal in enhancing image reconstruction quality and target detection efficiency. These advancements have significantly improved imaging capabilities and outcomes, making NF radar imaging systems more effective and versatile.

The topic of NF radar imaging is of paramount significance due to its broad applicability and potential to address critical challenges in various fields. As researchers continue to push the boundaries of imaging technology, the integration of advanced signal processing methods will be essential. Future research should focus on overcoming the remaining challenges related to hardware complexity, acquisition times, and computational inefficiencies. Additionally, exploring innovative solutions such as DMAs, ML algorithms, and novel image reconstruction techniques will be crucial in driving further advancements.

NF radar imaging, bolstered by cutting-edge signal processing techniques, holds great promise for future developments. Continued exploration and innovation in this field are encouraged to unlock new possibilities and enhance the impact of NF radar imaging across diverse applications. The journey towards more efficient, accurate and practical NF imaging systems is ongoing, and the contributions from the signal processing community will remain a driving force in this evolution.

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References

[1] R. Peng, O. Yurduseven, T. Fromenteze, and D. R. Smith, "Advanced processing of 3d computational microwave polarimetry using a near-field frequency-diverse antenna," *IEEE Access*, vol. 8, pp. 166 261–166 272, 2020.

[2] H. Li, Y. B. Li, G. Chen, S. Y. Dong, J. L. Shen, C. Y. Gong, S. Y. Wang, H. P. Wang, and T. J. Cui, "High-resolution near-field imaging and far-field sensing using a transmissive programmable metasurface," *Advanced Materials Technologies*, vol. 7, no. 5, p. 2101067, 2022.

[3] D. T. Bellini, D. Tagliaferri, M. Mizmizi, S. Tebaldini, and U. Spagnolini, "Multi-view near-field imaging in nlos with non-reconfigurable em skins," *arXiv preprint arXiv:2401.06891*, 2024.

[4] T. V. Hoang, R. Kumar, T. Fromenteze, M. García-Fernández, G. Álvarez-Narciandi, V. Fusco, and O. Yurduseven, "Frequency selective computational through wall imaging using a dynamically reconfigurable metasurface aperture," *IEEE Open Journal of Antennas and Propagation*, vol. 3, pp. 353–362, 2022.

[5] W. Shao and T. McCollough, "Advances in microwave near-field imaging: Prototypes, systems, and applications," *IEEE microwave magazine*, vol. 21, no. 5, pp. 94–119, 2020.

[6] B. Gonzalez-Valdes, Y. Álvarez, Y. Rodriguez-Vaqueiro, A. Arboleya-Arboleya, A. García-Pino, C. M. Rappaport, F. Las-Heras, and J. A. Martinez-Lorenzo, "Millimeter wave imaging architecture for on-the-move whole body imaging," *IEEE Transactions on Antennas and Propagation*, vol. 64, no. 6, pp. 2328–2338, 2016.

[7] M. Gezimati and G. Singh, "Curved synthetic aperture radar for near-field terahertz imaging," *IEEE Photonics Journal*, 2023.

[8] S. Hu, A. M. Molaei, O. Yurduseven, H. Meng, R. Nilavalan, L. Gan, and X. Chen, "Multistatic mimo sparse imaging based on fft and low-rank matrix recovery techniques," *IEEE Transactions on Microwave Theory and Techniques*, vol. 71, no. 3, pp. 1285–1295, 2022.

[9] S. Hu, C. Shu, Y. Alfadhl, and X. Chen, "Advanced thz mimo sparse imaging scheme using multipass synthetic aperture focusing and low-rank matrix completion techniques," *IEEE Transactions on Microwave Theory and Techniques*, vol. 70, no. 1, pp. 659–669, 2021.

[10] A. M. Molaei, S. Hu, V. Skouroliakou, V. Fusco, X. Chen, and O. Yurduseven, "Fast processing approach for near-field terahertz imaging with linear sparse periodic array," *IEEE Sensors Journal*, vol. 22, no. 5, pp. 4410–4424, 2022.

[11] A. M. Molaei, V. Skouroliakou, V. Fusco, and O. Yurduseven, "Efficient 3d image reconstruction for near-field microwave imaging using dynamic metasurface antenna," *IEEE Access*, vol. 10, pp. 68 491–68 498, 2022.

[12] V. Skouroliakou, A. M. Molaei, M. García-Fernández, G. Álvarez-Narciandi, and O. Yurduseven, "Frequency domain image reconstruction for imaging with multistatic dynamic metasurface antennas," *IEEE Access*, vol. 10, pp. 124 728–124 737, 2022.

[13] A. M. Molaei, M. García-Fernández, G. Álvarez Narciandi, R. Kumar, V. Skouroliakou, V. Fusco, M. A. B. Abbasi, and O. Yurduseven, "Application of kirchhoff migration principle for hardwareefficient near-field radar imaging," *IEEE Transactions on Computational Imaging*, vol. 10, pp. 876–892, 2024.

[14] A. M. Molaei, T. Fromenteze, V. Skouroliakou, T. V. Hoang, R. Kumar, V. Fusco, and O. Yurduseven, "Development of fast fourier-compatible image reconstruction for 3d near-field bistatic microwave imaging with dynamic metasurface antennas," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 12, pp. 13 077–13 090, 2022.

[15] I. Manisali, O. Oral, and F. S. Oktem, "Efficient physics-based learned reconstruction methods for real-time 3d near-field mimo radar imaging," *Digital Signal Processing*, vol. 144, p. 104274, 2024.

[16] J. Laviada, G. Álvarez-Narciandi, and F. Las-Heras, "Artifact mitigation for high-resolution near-field sar images by means of conditional generative adversarial networks," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–11, 2022.

[17] M. E. Yanik and M. Torlak, "Near-field mimo-sar millimeter-wave imaging with sparsely sampled aperture data," *Ieee Access*, vol. 7, pp. 31 801–31 819, 2019.

[18] O. Yurduseven, M. A. B. Abbasi, T. Fromenteze, and V. Fusco, "Lens-loaded coded aperture with increased information capacity for computational microwave imaging," *Remote Sensing*, vol. 12, no. 9, p. 1531, 2020.

[19] A. M. Molaei, O. Yurduseven, and V. Fusco, "An efficient waveform diversity based on variational mode decomposition of coded beat-frequency shifted signals algorithm for multiple-input multiple-output millimetre-wave imaging," *IET Radar, Sonar & Navigation*, vol. 15, no. 10, pp. 1266–1280, 2021.

[20] A. M. Molaei, S. Hu, V. Skouroliakou, V. Fusco, X. Chen, and O. Yurduseven, "Fourier compatible near-field multiple-input multiple-output terahertz imaging with sparse non-uniform apertures," *IEEE Access*, vol. 9, pp. 157 278–157 294, 2021.

[21] R. Sharma, O. Yurduseven, B. Deka, and V. Fusco, "Hardware enabled acceleration of near-field coded aperture radar physical model for millimetre-wave computational imaging," *Progress In Electromagnetics Research B*, vol. 90, pp. 91–108, 2021.

[22] T. Fromenteze, O. Yurduseven, P. del Hougne, and D. R. Smith, "Lowering latency and processing burden in computational imaging through dimensionality reduction of the sensing matrix," *Scientific reports*, vol. 11, no. 1, p. 3545, 2021.

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[23] A. M. Molaei, R. Kumar, S. Hu, V. Skouroliakou, V. Fusco, and O. Yurduseven, "A compressive sensing-based approach for millimeter-wave imaging compatible with fourier-based image reconstruction techniques," in *2022 23rd International Radar Symposium (IRS)*. IEEE, 2022, pp. 87–91.
[24] A. M. Molaei, S. Hu, V. Fusco, and O. Yurduseven, "A multi-resolution analysis-based approach to accelerate data acquisition for near-field mimo millimeter-wave imaging," in *Passive and Active Millimeter-Wave Imaging XXV*, vol. 12111. SPIE, 2022, pp. 90–101.
[25] A. M. Molaei, T. Fromenteze, S. Hu, V. Fusco, and O. Yurduseven, "Fourier-based near-field three-dimensional image reconstruction in a multistatic imaging structure using dynamic metasurface antennas," *IEEE Transactions on Computational Imaging*, vol. 8, pp. 1089–1100, 2022.
[26] A. M. Molaei, S. Hu, R. Kumar, and O. Yurduseven, "Mimo coded generalized reduced dimension fourier algorithm for 3-d microwave imaging," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–15, 2023.
[27] T. Song, X. Yao, L. Wang, Y. Wang, and G. Sun, "Fast factorized kirchhoff migration algorithm for near-field radar imaging with sparse mimo arrays," *IEEE Transactions on Geoscience and Remote Sensing*, 2024.
[28] S. Ge, S. Song, D. Feng, J. Wang, L. Chen, J. Zhu, and X. Huang, "Efficient near-field millimeter-wave sparse imaging technique utilizing one-bit measurements," *IEEE Transactions on Microwave Theory and Techniques*, 2024.
[29] M. Zhao, S. Zhu, R. Sharma, A. M. Molaei, X. Chen, and O. Yurduseven, "Metamaterial iris-based cavity antenna for mm-wave computational polarimetric imaging," *IEEE Antennas and Wireless Propagation Letters*, 2024.
[30] W. Shao and Y. Du, "Microwave imaging by deep learning network: Feasibility and training method," *IEEE transactions on antennas and propagation*, vol. 68, no. 7, pp. 5626–5635, 2020.