

A Review on Image Processing Techniques on FOPEN Radar Clutter Cancellation

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Abstract: Foliage-penetration (FOPEN) radar systems operating in VHF/UHF bands enable detection of man-made targets concealed beneath dense vegetation, yet their performance is significantly constrained by strong, non-Gaussian, and temporally varying foliage clutter. Traditional signal-domain techniques such as MTI/MTD filtering, CFAR variants, adaptive LMS/RLS cancellation, entropy-weighted coherent integration, and blind-source separation methods provide only partial suppression under wind-induced decorrelation, multipath propagation, and low signal-to-clutter ratios. In parallel, image-processing strategies including diffusion filtering, Total Variation and Forward-Backward Diffusion models, anisotropic diffusion, RPCA/TV-RPCA decomposition, and background-subtraction families enhance clutter rejection in Range-Time-Intensity (RTI), Range-Doppler (RD), and spectrogram formats by exploiting spatial-temporal structure. Recent advances in machine learning and deep networks such as CNNs, autoencoders, hybrid feature-fusion architectures, and learned Doppler-feature representations further improve target localization and classification by modeling nonlinear clutter characteristics directly from radar imagery. Also, Synthetic Aperture Radar (SAR)-based FOPEN imaging provides a complementary pathway for clutter suppression. Techniques including coherent and incoherent change detection, spectral intersection filtering, circular-aperture angular correlation (ACF/FCF), physical-optics modeling, deterministic-aided STAP, and multi-channel interferometric imaging significantly improve background suppression and moving-target detection in dense forests. This paper presents a comprehensive review of signal-domain, image-domain, machine-learning, and SAR-based clutter-cancellation techniques for FOPEN radar. The review focuses on a number of key aspects, including theoretical principles, algorithmic implementation, strengths, limitations, and realistic performance in a wide range of forest environments. Such unification of classical radar processing with modern SAR imaging and deep learning presents a comprehensive reference to guide future research toward high-accuracy detection, classification, and tracking of hidden targets beneath dense vegetation.

Keywords: FOPEN, STAP, ACF/FCF, SAR, FBD, Image Processing, Clutter cancellation.

I. INTRODUCTION

Foliage-penetration radar (FOPEN) design requires an effective signal propagation strategy, adaptive beam control and accurate detection mechanisms capable of extracting weak target signatures buried under heavy clutter. Although the existing literature provides the overview on RF sensing, micro-Doppler radar, SAR imaging, digital beamforming and free-space optics which covers the underlying concepts of turbulence mitigation, adaptive steering, interference suppression, and intelligent feature extraction that provides the base for tackling the challenges associated with radar operation in dense foliage environments. Various works have been done in order to compensate for atmospheric turbulence and restore beam stability in free-space optical communication systems under highly dynamic propagation conditions. Raj et al. analysed

beam wandering compensation strategies for maintaining link quality under varying turbulence regimes [1], while cognitive and intelligent steering controllers were later developed to autonomously adapt the beam direction in response to environmental fluctuations [2]. Prediction-driven control algorithms further leveraged machine learning to mitigate amplitude and phase instabilities under severe turbulence [3]. Although these works originate from optical communication, their underlying principles—adaptive pointing, real-time environment sensing, and intelligent compensation—directly translate to foliage-penetration radar, where the radar beam must dynamically counteract scattering, attenuation, and multipath induced by dense vegetation.

Parallel advances in RF radar systems have produced several techniques that are highly relevant to detecting targets obscured by foliage. Early feature-extraction techniques for LPI waveforms [4] and digital receiver architectures for CW radars [5] established frameworks for robust acquisition and processing of weak, noise-buried signals—conditions frequently encountered in forested environments. Infrared tracking work using classical detection pipelines [6] demonstrated the importance of resilient feature extraction in clutter-rich backgrounds, a requirement that directly extends to foliage-induced clutter scenarios.

A significant research on micro-Doppler signatures and small RCS target detection provides further insight into recovering weak motion signatures hidden within strong environmental scattering. UAV classification using propeller-modulation features [7] and nonlinear micro-Doppler imaging using SP-WVD with adaptive filter banks [8] highlight the importance of time–frequency representations and clutter-resilient processing, both essential for resolving target motion obscured by foliage. Enhanced DOA estimation via modified MUSIC algorithms [9] and velocity-sensitive CW radar processing [10] offer techniques for improving angular and Doppler discrimination, which becomes challenging when foliage adds decorrelation and attenuation.

Pulse-Doppler and FMCW radar advancements provide direct building blocks for foliage-penetration systems. Digital pulse-Doppler processors with improved clutter suppression [11] and FMCW radars designed for moving target detection in dense environments [12] explicitly demonstrate methodologies that can be repurposed for foliage environments. Foliage-penetration radar principles continue to be well-established, particularly regarding detection and characterization of obscured targets in dense vegetation [13]. β -tuning techniques based on Spectrum localization and Hough-transform [13] offers strong tools for extracting micro-doppler features in scenarios where foliage generates much lower frequency clutter and masking. In [14] the studies have been conducted on radar waveform design, which helps to understand the importance of types of waveforms in different applications. The C-band FMCW radar hardware setup is explained in details [15], and multi-bit digital receivers [16] provides the insights for waveform selection, bandwidth optimization, and hardware considerations, helpful for maximizing the penetration depth while preserving resolution. Early VHF-band SAR systems such as CARABAS-II highlights the advantages of low-frequency operation for foliage penetration and wide-area surveillance [128].

Phased-array processing literature contributes methods for improving target localization when scattering from leaves and branches increases angular uncertainty. Modified subarray monopulse algorithms for precise angle estimation [17], DSP-based FMCW altimeters [18], and OFDM-based SAR imaging approaches [19] showcase techniques for increasing angular robustness, mitigating inter-range-cell interference, and improving imaging fidelity under complex propagation. X-band automotive Doppler processors [20], deep-learning-based ornithopter classification [21], and interference-resilient SAR techniques [22] further demonstrate that AI-enabled feature extraction and interference mitigation can significantly strengthen detection performance under adverse foliage conditions.

Deep-learning-enabled radar processing, explored through maritime SAR ship classification [27], drone recognition [29], and UWB-based human detection [24], provides a promising foundation for foliage-penetration applications where traditional matched-filtering struggles against dense clutter. Digital beamforming and MIMO radar studies [28] illustrate how adaptive transmit–receive strategies can be leveraged to steer nulls toward foliage-induced interference and enhance target echoes. Additional developments in mobile-target ranging [25] and low-RCS imaging systems [26] align closely with the need to detect human, vehicular, or UAV targets whose signatures are severely attenuated by vegetation. Collectively, these works lay a strong technical foundation for foliage-penetration radar by contributing critical methodologies in adaptive beam control, clutter suppression, intelligent feature extraction, robust waveform design, digital receiver engineering, and machine–learning–supported radar interpretation. Their combined insights directly support the development of a next-generation FOPEN radar capable of penetrating dense vegetation, suppressing foliage-induced clutter, and reliably detecting concealed targets.

II. FUNDAMENTALS OF FOPEN RADAR CLUTTER

A. Scattering Phenomena in Forests

FOPEN radar clutter originates from a combination of complex scattering mechanisms:

- 1) Volume scattering: Caused by leaves, branches, and undergrowth. This generates diffuse, decorrelated returns across coherent pulses.
- 2) Trunk-ground double bounce: Strong deterministic component produced by interaction between tree trunks and the underlying ground.
- 3) Canopy layer scattering: Produces high backscatter that varies significantly with wind, moisture, and tree density.
- 4) Temporal decorrelation: Tree motion leads to rapidly fluctuating clutter statistics, making adaptive processing difficult.
- 5) Speckle: A coherent phenomenon caused by the constructive and destructive interference of numerous small scatterers. These factors make foliage clutter significantly stronger than concealed target returns, often masking targets completely, especially in VHF/UHF systems.

FOPEN systems operate primarily in the VHF and UHF frequency bands, enabling detection of man-made targets hidden beneath dense vegetation [50, 51]. Unlike conventional higher-frequency radars, FOPEN radars take advantage of the longer wavelengths to penetrate the tree canopies and therefore are appropriate for military surveillance, border security, and search-and-rescue operations in forested areas. However, electromagnetic waves propagating through foliage introduce significant clutter, including volume scattering from the leaves and branches, trunk-ground double-bounce reflections, and canopy layer scattering [52]. Dominated by these clutter components, the radar returns often present low signal-to-clutter ratios (SCR) and severely complicate target detection. Clutter suppression in FOPEN radar is further exacerbated by temporal decorrelation due to wind-induced motion of foliage, multipath propagation, and non-Gaussian statistics of clutter returns [53]. For initial clutter mitigation in FOPEN radar, MTI, CFAR filtering, and adaptive LMS/RLS filters have been widely used, which are traditional signal processing methods. While effective against a stationary or slowly varying clutter, these methods often fail to preserve a weak target echoes embedded within highly dynamic and spatially correlated foliage clutter.

B. Foliage Electromagnetic Propagation Characteristics

The propagation of electromagnetic waves in forested media is dominated by volumetric attenuation, multiple scattering, and dielectric losses. While radar waves navigate through vegetation, the energy will be absorbed and scattered by leaves, branches, and trunks, rendering the channel highly dispersive and variable. Within the VHF and UHF bands, the wavelength of the signal is comparable to the physical dimensions of trees, enabling partial penetration but still resultant in strong diffuse and coherent scattering. This results in delayed multipath returns and waveform distortion that reduce clarity of target signatures. Seasonal conditions, such as leafy and non-leafy cycles, additionally impact depth of penetration and clutter level, which complicates clutter modeling and suppression.

C. Clutter Statistics and Non-Gaussian Behaviour

Foliage clutter demonstrates definitely non-Gaussian features due to the interaction of radar signals with a great number of randomly oriented scatterers. Foliage clutter, measured for different forest environments, is well modelled by heavy-tailed distributions like log-normal, Weibull, K-distribution, generalized Gaussian, and symmetric alpha-stable distributions. These distributions model the strong fluctuations, impulsive interference, and large variance that are characteristic of most radar returns from foliage. Since the behavior is inherently non-Gaussian, these traditional detectors based on Gaussian noise assumptions perform poorly under conditions of strong wind motion, variable moisture, and heterogeneous vegetation density. Artificial-intelligence-based classifiers have also been applied for direct clutter identification and segmentation using polarimetric features and statistical learning techniques [60].

D. Doppler Characteristics of Foliage Motion

Wind-induced motion has a profound impact on the Doppler characteristics of foliage. Leaves, branches, and whole structures from trees will all move at different velocities, producing a well-dispersed Doppler frequency spectrum that could overlap with the Doppler signatures from slow-moving targets. Human or vehicle micro-Doppler patterns cannot easily be distinguished from foliage-induced Doppler spread because of that. A broad, time-varying Doppler ridge in Range-Doppler

maps is what such clutter resembles. This limits the performance of MTI and MTD filters, which need stable clutter behavior. Due to this variability in Doppler, advanced learning-based Doppler-feature extraction or adaptive normalization techniques have to be employed.

E. Multipath, Ground Interaction, and Double-Bounce Effects

Forested environments create strong multipath propagation due to reflections from the ground, tree trunks, and intermediate layers of vegetation. Trunk-ground double-bounce reflections often generate strong, deterministic returns that mask weak target signals at similar ranges. Lateral waveguiding along the forest floor and multiple canopy-ground interactions also produce extended clutter tails and distort the temporal signature of returns. This effect is particularly pronounced in VHF-band FOPEN SAR systems such as CARABAS, where the interaction between the ground and vertical trunks is one of the dominant clutter components. For these reasons, physical-optics models and digital elevation models are often employed to better understand and mitigate these propagation-induced clutter sources.

F. Spatio-Temporal Correlation and Clutter Decorrelation

Foliage clutter is highly spatially correlated, since radar echoes from neighboring trees are frequently similar. Yet, temporal correlation decays rapidly due to wind-driven vegetation motion. The combination of large spatial coherence and fast temporal decorrelation challenges processing techniques requiring consistent clutter statistics across pulses or antenna elements. Long coherent integration becomes unreliable, and STAP algorithms struggle when homogeneous training data are limited or foliage motion is unpredictable. Techniques such as RPCA, TV-RPCA, and angular-correlation imaging exploit spatial structure, while adaptive filtering attempts to manage the temporal variability.

G. Frequency Dependence of Clutter and Penetration Depth

Foliage clutter behavior is strongly related to the radar operating frequency. For VHF frequencies, radar signals penetrate deeply into dense vegetation but suffer from increased multipath and reduced spatial resolution. UHF frequencies offer a balance between penetration and resolution but are more sensitive to canopy-layer scattering. At higher frequencies in the L-band and S-band, the penetration is limited, although the radar acquires an enhanced capability for distinguishing surface and canopy features. These frequency-dependent trade-offs need to be carefully considered in the design of FOPEN radar systems, in particular for applications which require deep penetration and at the same time accurate localisation.

H. Impact of Environmental Factors on Foliage Clutter

Effect of Environmental Factors plays important role in determining the intensity and variability of foliage clutter. Wind speed, humidity, rainfall, moisture content, temperature, and soil conductivity determine the actual interaction of the radar signal with vegetation. Wind-induced motion is especially critical because it causes rapid temporal decorrelation and produces large Doppler spreads. Moisture increases the dielectric constant of leaves and trunks and strengthens backscatter and attenuation. Seasonal changes, including leaf growth or shedding, can alter clutter statistics several decibels, which in turn makes clutter suppression techniques highly sensitive with respect to environmental variability. Forest type in general may be tropical, deciduous, or coniferous; it influences the scattering mechanisms and the overall clutter complexity.

III. SIGNAL-DOMAIN CLUTTER SUPPRESSION METHODS

Signal-domain clutter mitigation forms the earliest stage of FOPEN radar processing, operating directly on raw time-domain or frequency-domain data before generating RTI or RD images. The work in [103] presents the design of an X-band FMCW radar incorporating a digital Doppler processor to enhance velocity estimation accuracy and real-time signal analysis. The architecture enables efficient extraction of micro-motion signatures and improved clutter discrimination. Such digital processing frameworks are highly relevant for FOPEN radar, where precise Doppler sensitivity is essential for detecting slow-moving targets behind foliage. A hybrid clutter-suppression framework for foliage-penetration radar has shown improved separation of target returns from dense vegetation by combining statistical and signal-processing approaches [110]. High-resolution W-band studies further illustrate effective cancellation of strong stationary clutter, enabling clearer detection of weak moving targets [111]. The methods used, attempt to remove stationary or slowly varying clutter using statistical filtering, adaptive cancellation, blind source separation, or compressed sensing. This section compiles classical and advanced signal-level techniques including MTI/MTD filters, CFAR variants, adaptive LMS-based cancellation, entropy-weighted coherent integration, compressed sensing, and Blind Source Separation (BSS) approaches such as PPSA.

A. Range-Time-Intensity (RTI) Background Subtraction

A simple yet effective clutter-cancellation method for foliage environments is presented in [46] using a C-band FMCW radar. After mixing transmitted and received signals, a running average background is continuously subtracted from the Inverse FFT output to generate clean Range-Time-Intensity (RTI) plots. Stationary foliage clutter disappears almost completely, leaving bright, continuous traces only for moving human targets even at slow speeds. The technique requires only basic FFT/IFFT operations and average subtraction, making it extremely lightweight and suitable for real-time implementation on low-cost hardware. Results from real foliage measurements confirm reliable detection and ranging of moving targets inside vegetation where conventional methods struggle. The background is estimated across successive slow-time frames using:

$$B(n, k) = \alpha B(n-1, k) + (1 - \alpha)X(n, k) \quad (1)$$

where $X(n, k)$ is the RTI intensity at range bin k and slow-time index n , α is a smoothing factor and $B(n, k)$ is the smoothed estimate of stationary background. Subtracting B from X yields moving-target-enhanced RTI images. Such techniques effectively suppress stationary clutter but fail under nonstationary foliage returns, motivating more advanced adaptive methods.

B. Ordered-Statistic Constant False Alarm Rate (OS-CFAR) as a Classical Clutter-Rejection Baseline

From [31, 37, 38, 43] literature, Ordered-Statistic CFAR (OS-CFAR) and the similar variant Cell-Averaging CFAR (CA-CFAR) is used as the standard classical clutter-rejection and detection stage after background subtraction or 2D-FFT processing. In low-frequency multistatic foliage-penetration systems operating in the VHF/UHF band, OS-CFAR is applied after Exponential Average Background Subtraction (EABS) and reliably detects human targets in range profiles once stationary tree clutter and most multipath clutter have been removed, it enables the subsequent data association and Kalman tracking [37-38]. The same papers note that clutter suppression performance remains weather-dependent, but OS-CFAR consistently provides stable false-alarm regulation in these harsh environments. The OS-CFAR threshold is:

$$T = \alpha Z_{(k)} \quad (2)$$

where $Z_{(k)}$ is the k -th ranked value among training cells, and α ensures a constant false-alarm rate. In contrast, when the same OS-CFAR with simple peak detection is applied to highly noisy short-range 77 GHz automotive Range-Doppler maps (NXP TEF810X, 12.8 m max range), it exhibits extremely poor performance, especially for low-reflectivity pedestrians that fall below the noise floor; here it is comprehensively outperformed by convolutional autoencoders by 76.8% while generating far more false alarms [31]. Similarly, in urban automotive 76–77 GHz scenarios, CA-CFAR (a closely related ordered-statistic variant) followed by DBSCAN clustering is routinely used as the first hard gate to reject clutter points before feeding potential targets to deep classifiers [43]. Collectively, these references establish OS-CFAR as the most common traditional clutter-controlled detector, effective when clutter is largely stationary or pre-subtracted, yet fundamentally limited in high-noise, short-range, or rapidly varying clutter conditions where these learned methods take over. Clutter distribution in forests is known to be non-Gaussian; thus, OS-CFAR outperforms CA-CFAR. Advanced CFAR variants such as CA-CM and CM-CM CFAR further adapt detection thresholds to clutter intensity fluctuations.

C. CFAR Variants and FPGA Real-Time CFAR Implementations (CM-CM CFAR)

Advanced constant false alarm rate (CFAR) algorithms, such as the censored mean clutter map CFAR (CM-CM CFAR), integrate multiple CFAR strategies to achieve more reliable performance under diverse and heterogeneous clutter conditions. Fig. 1 provides a high-level overview of the system architecture via a detailed block diagram, highlighting the interconnected components of the improved CFAR algorithm [56]. Classical CFAR variants often fail in dense target environments or in scenes with significant clutter non-stationarity, which leads to degradation in the probability of detection and instability in the probability of false alarm. The CM-CM CFAR framework addresses this limitation by forming a composite detector that combines cell averaging CFAR, ordered statistic CFAR, mean level detectors and clutter map based CFAR, thereby maintaining a controlled false alarm rate while improving detection performance across varying background conditions [56]. This integrated approach is also suitable for implementation on field programmable gate arrays for real time operation, making it practical for airborne and wide area FOPEN imaging systems. In operational settings, CM-CM CFAR can be employed in conjunction with physics based or learning based pre-processing stages to normalize clutter statistics and enhance robustness to spatial variability [56].

D. Convolutional Autoencoders

The strongest clutter-cancellation method with best performance is the convolutional autoencoder (CAE) approach described in [31]. Traditional OS-CFAR with peak detection performs poorly in highly noisy environments, especially when low-reflectivity targets like humans fall below the noise floor and get buried under stationary clutter. The proposed CAEs (single, parallel, and sequential configurations) are trained to reconstruct only genuine moving objects while completely removing stationary clutter and random noise. The results mentioned in this research show that all CAE variants significantly outperform classical processing, with the best model (three parallel CAEs + three sequential frames) achieving 94.6% correct object reconstruction and only 1.6% false object frames. An overall improvement of 76.8% over OS-CFAR with peak detection is observed. Activity classification accuracy achieved is 94.2%. This is a fully learned, threshold-free clutter cancellation stage that needs no background modelling or statistical assumptions. The authors conclude that neural networks succeed where traditional methods fail because they can extract hidden features and learn patterns from the data.

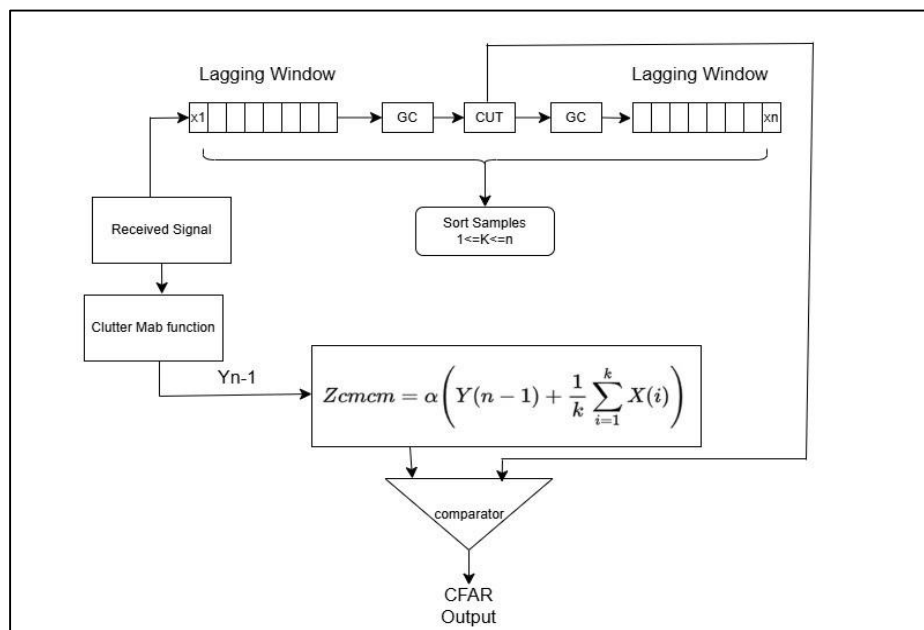


Fig. 1. An improved CFAR algorithm for multiple environmental conditions

E. Entropy-Weighted Coherent Integration (EWCI) with MTI and Hough Transform for Foliage Clutter Suppression

A highly effective non-learning clutter-cancellation technique specifically tailored for dense foliage is the Entropy-Weighted Coherent Integration (EWCI) method combined with MTI and Hough transform, demonstrated on real 675–825 MHz bistatic LFMCW field data [45]. Moving Target Indication (MTI) uses temporal filtering to suppress static clutter. A two-pulse canceller:

$$y[n] = x[n] - x[n - 1] \quad (3)$$

where $x[n]$ represents the complex radar return from a given resolution cell at the current pulse index n , while $x[n-1]$ denotes the return from the same cell acquired at the previous pulse repetition interval (PRI). The output $y[n]$ corresponds to the difference between consecutive slow-time samples and forms the MTI-filtered signal used for further processing. Acts as a high-pass filter in slow time, removing zero-Doppler foliage clutter but creating blind speeds. Three-pulse cancellers reduce blind spots but remain limited against nonstationary forest clutter. Moving Target Detection (MTD) performs FFT across slow-time pulses, generating Doppler bins. Wind-induced foliage motion spreads clutter across Doppler frequencies, broadening the clutter ridge in RD space. Thus, pure MTD often fails under dense-foliage environments. EWCI enhances coherent integration under nonuniform clutter by assigning higher weights to pulses with lower entropy. Thus, EWCI with MTI and Hough Transform overcomes the limitation. The pipeline first applies two-pulse Moving Target Indication (MTI) to cancel zero-Doppler stationary clutter, then uses EWCI as the core stage: local entropy is computed in the range-slow-time domain, and integration gain is adaptively reduced in high-entropy cells dominated by random multipath clutter from wind-blown leaves, while preserving full gain for low-entropy coherent human motion. This entropy-based weighting dramatically suppresses multipath clutter that completely masks targets when conventional uniform coherent integration is

used. The resulting cleaned range-slow-time map allows a standard Hough transform to reliably extract straight-line walking trajectories. This method can effectively suppress not only the stationary clutter but also the multipath clutter, which is good to improve the Hough detection performance with field measurements confirming successful human detection where classical integration fails [45]. The adaptive weighting philosophy of EWCI complements the weather-dependent and background-subtraction-based clutter mitigation strategies employed in related low-frequency multistatic foliage-penetration systems [38, 39]. The advantages of hough transform is implemented for search and track radar[123,124,125].

F. Classical Adaptive Filters and LMS / RLS Variants for High-Resolution Small-Target Detection

Adaptive filter-based clutter suppression models clutter as a slowly varying process. LMS and RLS filters update their weights to cancel clutter components iteratively. The LMS update rule is:

$$w(n+1) = w(n) + \mu e(n)x(n) \quad (7)$$

where $w(n)$ is the adaptive filter coefficient (weight) vector at the n th iteration, and $w(n+1)$ denotes the updated weights for the next iteration. The vector $x(n)$ represents the input data vector. The term $e(n)$ is the instantaneous estimation error. The scalar μ is the step-size or learning-rate parameter. Hybrid adaptive filters such as LMS-STD (Structure Tensor-Driven LMS) or frequency-domain adaptive cancellation have been proposed for forest environment suppression. They adapt more effectively to nonstationary foliage motion and outperform conventional MTI filters. These algorithms are designed to suppress quasi stationary clutter components by continuously adapting filter weights based on incoming data, which directly addresses the problem that weak man-made targets are often masked by strong vegetation returns in VHF and UHF FOPEN imagery. Adaptive filters have demonstrated significant improvement in recovering low radar cross section targets embedded in heavy environmental clutter, as shown in outdoor measurement studies where modified LMS implementations achieved more reliable clutter suppression and target extraction than standard LMS and RLS methods under low signal to clutter ratio conditions [78]. Their computational efficiency and real time feasibility make them suitable candidates for onboard or near real time FOPEN processing chains where rapid clutter mitigation is required before further imaging or detection steps. Although their performance can be affected by nonstationary clutter dynamics and parameter sensitivity, adaptive filters remain valuable for FOPEN because forest clutter often exhibits slow temporal variation relative to platform dwell times, allowing stable adaptation. When combined with FOPEN specific pre-processing such as range or Doppler domain normalization, adaptive filtering can reduce dominant foliage responses and produce cleaner residual signals that improve downstream detectors and image formation algorithms [78].

G. Blind Source Separation: Parallel Principal Skewness Analysis

Blind Source Separation (BSS) techniques aim to obtain target signals from mixtures dominated by clutter or interference without explicit knowledge of the underlying mixing matrix. Among these techniques, the Parallel Principal Skewness Analysis (PPSA) algorithm is an advanced higher-order-statistics-based method that separates sources by maximizing signal skewness in parallel subspaces. Parallel Principal Skewness Analysis (PPSA) extends PSA by extracting multiple sources simultaneously via parallel subspace estimation. The overall architecture of the proposed Parallel Principal Skewness Analysis (PPSA) radar clutter suppression scheme is illustrated in Fig. 2 PPSA maximizes third-order cumulants (skewness):

$$\max_W \text{skew}(Wx) \quad (8)$$

where W is the separation matrix, x represents the observed radar return vector (containing both clutter and target components) and $\text{skew}(\cdot)$ denotes the third-order cumulant (skewness), a measure of signal asymmetry and non-Gaussianity. Unlike conventional approaches such as Independent Component Analysis (ICA) or Principal Component Analysis (PCA) that rely mainly on second-order statistics, PPSA exploits third order statistical structure, making it highly effective in scenarios where clutter and target echoes exhibit distinct non-Gaussian characteristics. This allows PPSA to suppress strong, nonstationary clutter while preserving weak target components, enabling improved detection and parameter estimation in radar systems operating under severe masking conditions. Wang et al. [112] proposed an enhanced radar clutter suppression method using Blind Source Separation (BSS), specifically the Parallel Principal Skewness Analysis (PPSA) algorithm. Their approach performs BSS in both the range domain and Doppler domain, enabling accurate localization and velocity estimation of moving targets even when the clutter Doppler spectrum fully masks the target. BSS techniques can extract the desired signals from mixed signals and effectively achieve noise reduction. Compared to traditional MTI/MTD and classical

BSS methods such as FastICA and PSA, the PPSA-based scheme achieved superior clutter suppression with reduced signal-energy loss and improved capability under strong masking conditions. The methods were validated using both simulated and real data, showing significant improvements in signal-to-clutter-ratio (SCR) and detection performance under dense clutter environments.

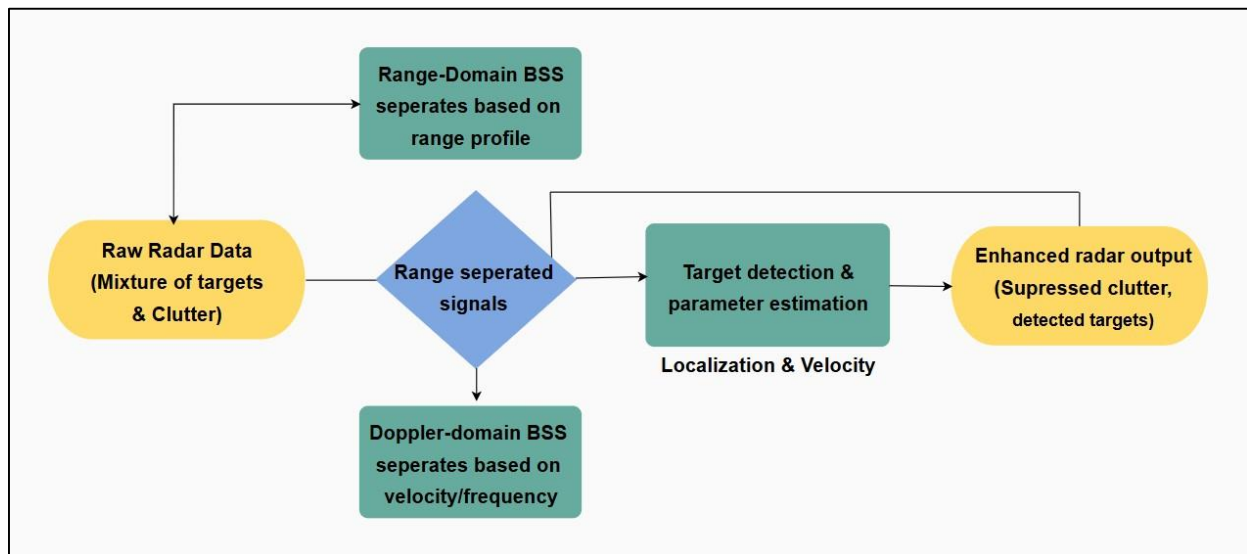


Fig. 2. Parallel Principal Skewness Analysis (PPSA) Radar Clutter Suppression Scheme

IV. SIGNAL-DOMAIN CLUTTER SUPPRESSION METHODS

Image-processing techniques operate on radar outputs such as RTI, RD, or spectrogram representations by treating them as images. These methods exploit spatial, temporal, and morphological properties of clutter to suppress foliage-induced disturbances while preserving weak target signatures. Classical image filters, diffusion methods, low-rank decomposition, and statistical enhancement methods fall under this category. This section consolidates all classical image-domain clutter suppression strategies found in literature, including Total Variation methods, diffusion filtering, component decomposition, CFAR-based image detectors, morphological operators, and advanced statistical enhancement techniques.

A. Forward-Backward Diffusion Total-Variation Denoising (TV-FBD) for Radar Spectrogram Cleaning

A distinctive clutter and noise suppression technique present in the dataset is the Forward-Backward Diffusion Total-Variation model (TV-FBD) proposed in [35]. Conventional Total Variation (TV) denoising removes small-scale noise and clutter effectively, yet it introduces severe contrast loss and staircasing effects that blur target edges in Range-Doppler maps and micro-Doppler spectrograms. Total Variation (TV) minimization is widely used to denoise radar images while preserving structural edges such as ground or target boundaries. The classical TV model minimizes:

$$\min_u \int |\nabla u| dx + \lambda \|u - f\|^2 \quad (9)$$

where u denotes the reconstructed or denoised radar image and f represents the observed noisy image affected by foliage clutter, thermal noise, speckle, or RF interference. The operator ∇u is the spatial gradient of the image u , which measures directional intensity changes across pixels. The scalar λ is the regularization parameter that controls the trade-off between noise suppression and signal preservation. To address this drawback, the authors incorporate a non-convex forward-backward diffusion term into the TV energy functional: forward

diffusion smooths noise/clutter regions, whereas backward diffusion actively sharpens real target boundaries. Forward-Backward Diffusion (FBD) enhances TV denoising by alternating between forward diffusion (denoising) and backward diffusion (edge sharpening). The combined TV-FBD approach is highly suitable for RTI/RD images with strong clutter gradients. The resulting TV-FBD model is efficiently solved via a two-step splitting method. Experimental results confirm that TV-FBD successfully eliminates speckle-like clutter while simultaneously preserving and even enhancing edge contrast of moving objects, capability the standard TV and isotropic diffusion methods lack. The authors explicitly conclude that the proposed TV-FBD approach can effectively solve the problem of the contrast loss in TV regularization [35]. The

lightweight implementation and edge-preserving nature, TV-FBD serves as an excellent pre-processing filter for any FMCW radar pipeline before CFAR detection, clustering, or deep classification stages.

B. Deep Learning on Radar Images with Implicit Clutter Suppression

The deep convolutional networks learn everything directly from raw data. Unlike classical pipelines that explicitly remove clutter using CFAR, background subtraction, or clustering, these networks are trained on real-world scenarios containing strong stationary and dynamic clutter (roadside objects, buildings, trees, rain, ground bounce). As a result, they automatically learn to suppress clutter and focus only on genuine micro-Doppler signatures of moving targets. A multi-domain feature attention fusion network that intelligently combines RT and DT maps achieved 97.58% accuracy in human activity recognition, with its attention mechanism naturally ignoring static background clutter [40]. Similarly, a dual-channel ResNet-18 augmented with CBAM attention delivered near-perfect classification of six different human motions on a 77–81 GHz TI IWR1642 sensor, where the attention modules act as a learned clutter gate that discards stationary returns [41]. Real-world automotive experiments on an NXP 77 GHz platform showed that ResNet and CNN-RNN hybrids can reliably distinguish cars, single pedestrians, groups of pedestrians, and bicycles in real time with accuracy consistently above 97%, even when micro-Doppler extraction runs on a low-power DSP, proving robust learned suppression of typical urban clutter without any dedicated pre-filtering stage [48]. Multi-input CNNs that simultaneously process Range-Doppler maps and point-cloud data further improve clutter invariance while keeping computational cost manageable [46]. The deep-learning approaches consistently deliver 97–99% classification accuracy in heavily cluttered environments by performing implicit, data-driven clutter cancellation as a result of training the data. The main setback is the need for large labelled datasets captured under realistic clutter conditions and edge-AI hardware capable of large MFLOPs per frame. Also the continuous non-segmented motion streams, overlapping or crossing targets, and reliable performance under severe weather clutter (heavy rain, fog, snow) where purely implicit clutter suppression is challenging. [40, 41, 46, 48].

V. MACHINE LEARNING-BASED CLUTTER SUPPRESSION

Machine learning (ML) techniques extend traditional clutter suppression by learning statistical patterns directly from radar images or Doppler spectra. Unlike classical filtering methods, ML-based approaches can model nonlinear clutter behavior, adapt to varying foliage conditions, and generalize across different environments. This section compiles your ML content, including feature-engineered classifiers, deep CNN models, autoencoders, and advanced learned representation techniques. Recent advances in artificial intelligence have further expanded radar clutter mitigation techniques through end-to-end learning, adaptive detection, and intelligent imaging workflows [59].

A. Doppler-Spectrum Feature Extraction with Classical & Hybrid Machine Learning

A highly effective and lightweight approach for distinguishing humans from vehicles and rejecting the clutter relies on extracting features directly from the Doppler spectrum rather than full Range-Doppler images.

Algorithms	x1	x2	x3
typical algorithm #1	-	-	MCV
typical algorithm #2	SPC	-	-
proposed algorithm #1	SPC	SPD	-
proposed algorithm #2	SPC	SPD	MDR

TABLE I: Four classification algorithms used with a combination of three features. MCV—magnitude current value; SPC—scattering point count; SPD—scattering point difference; MDR—magnitude difference rate.

The most prominent work in [33] as given in Table I, where three novel features are derived from two consecutive Doppler frames of a 24-GHz FMCW radar: 1. Scattering Point Count (SPC) – number of significant Doppler peaks (captures body + limb returns for humans). 2. Scattering Point Difference (SPD) – change in the number of peaks between frames (higher for walking humans due to swinging limbs). 3. Magnitude Difference Rate (MDR) – rate of change of reflected energy across frames (vehicles show stable magnitude, humans fluctuate). These three features are fed to classical classifiers: Support Vector Machine (SVM) and Binary Decision Tree (BDT). Results from real measurements show classification accuracy exceeding 99% for humans and 96% for vehicles using either classifier, with the three-feature combination improving performance by approximately 8% (human) and 5% (vehicle) over using only SPC [33]. The same philosophy is extended in a hybrid pipeline [43], where classical Doppler features first provide coarse separation and suppress clutter-induced false detections, then cropped Range-Doppler patches are refined by a lightweight CNN. This combination

leverages the interpretability and low computational cost of hand-crafted features for clutter rejection while retaining deep networks only for final fine-grained classification, making it ideal for resource-constrained automotive platforms. Similar FFT-domain statistical features have also been reported for classification of targets using mmWave FMCW radar systems [64].

B. Convolutional Neural Networks (CNNs) and Deep Learning Detectors for Clutter Suppression and Target Detection

Deep learning methods, especially Convolutional Neural Networks (CNNs), have become important tools for clutter suppression and target detection in foliage penetrating (FOPEN) radar imagery. Deep Convolutional Neural Networks (CNNs) automatically extract spatial and temporal features from radar images without requiring hand-crafted features. CNNs have been applied for clutter suppression in RD maps, moving target detection under foliage, noise reduction in spectrograms, and persistent Range–Doppler target recognition [50]. Classical detection approaches such as CFAR, matched filtering, and correlation based similarity measures often assume Gaussian clutter and stationary noise statistics. These assumptions do not hold in VHF/UHF FOPEN conditions where foliage produces strong volume scattering, multipath effects, and non Gaussian, spatially varying clutter that can mask weak man made targets. CNNs overcome these limitations by learning hierarchical and shift invariant representations directly from radar imagery including Range–Doppler maps, range FFT based images, and micro Doppler signatures. This allows the network to distinguish target scattering from foliage related clutter patterns more effectively than handcrafted features [50, 53, 58]. Studies report substantial improvements in detection accuracy compared to traditional methods. For example, Doppler based CNN architectures have reached classification accuracies close to 98.99%, and Faster R CNN detectors have shown improved performance for identifying small objects in the presence of dense clutter [50]. These improvements arise because CNNs capture texture patterns, Doppler variations, and reflectivity structures that are characteristic of targets but not of natural clutter. Despite these strengths, CNNs require large labelled datasets, which are difficult to obtain for realistic FOPEN environments. They may overfit to specific radar frequencies or geometries, and the decision process is not easily interpretable. To address these issues, researchers have used physics guided feature fusion, such as combining CNN outputs with range FFT or angular correlation features, along with data augmentation and transfer learning to improve generalization [50, 56, 58]. Overall, CNN based approaches are effective for clutter cancellation in FOPEN radar imagery because they can model complex nonlinear scattering effects that are difficult to capture with traditional rule-based detectors. The work in [101] introduces DIAT-RadSATNet, a lightweight deep convolutional network optimized for micro-Doppler–based detection and classification of small UAVs. The study in [102, 105, 109] presents the DIAT- μ RadHAR micro-Doppler signature dataset along with RadNet, a lightweight DCNN designed for human activity recognition using radar echoes and classification of ornithopter. The work highlights the effectiveness of micro-Doppler features for distinguishing human motion patterns even in cluttered environments, making it valuable for foliage-penetration scenarios where conventional motion cues are heavily masked [106]. The authors in [108] demonstrates synthetic aperture radar (SAR) imaging of small UAVs, highlighting the capability of SAR to resolve low-RCS airborne targets with high spatial precision. The work emphasizes motion-compensation and focused imaging techniques that remain effective even under clutter-dominated conditions. Additional efforts have integrated noise-signal modeling and compressed sensing to directly mitigate wave-induced clutter components, reducing artefacts in high-resolution reconstructions [113]. Empirical L-band evaluations confirm that clutter-cancellation algorithms can significantly refine ground-scene radar outputs under real measurement conditions [114]. Multi-channel approaches extend this capability by exploiting spatial diversity to isolate dynamic targets in clutter-rich environments [115]. More recent deep-learning-based radar classifiers demonstrate that data-augmented convolutional models can handle radar-based suspicious human activity recognition even in challenging cluttered scenes, offering improved detection [116]. Multi-element radar signal processing systems have also been shown to benefit from optimized receiver and feature-extraction strategies that enhance clutter resilience in distributed sensing setups [117]. Lightweight CNN architectures and adaptive background mixture models contribute by enabling real-time classification performance on embedded radar platforms without compromising clutter-suppression capability [118, 119].

C. Convolutional / Deep Autoencoders (CAE / Auto-ED) for denoising and target enhancement

Convolutional autoencoders and encoder–decoder networks have recently been adopted for clutter suppression and target enhancement in FOPEN radar imagery, where conventional Constant False Alarm Rate (CFAR) and peak-based detectors fail under dense foliage, low SNR, and heavy environmental noise. Convolutional Autoencoders learn to reconstruct clean target images from cluttered inputs. A CAE consists of an encoder $E(\cdot)$ and decoder $D(\cdot)$:

$$\hat{X} = D(E(X)) \quad (10)$$

where X is the cluttered radar image and \hat{X} is the clutter-suppressed output. The main limitation of the classical methods is the assumption of homogeneous or Gaussian clutter which breaks down in foliage- penetrating situations when multipath, volumetric scattering, and vegetation-induced fluctuations dominate. In this context, autoencoder-based models contribute by learning a compact representation of background clutter and rebuilding a denoised image where hidden or low-contrast targets become easily distinguishable. Studies using Convolutional Autoencoder (CAE) frameworks: Sequential CAE that processes entire radar images end- to-end and Parallel CAE where Multiple CAEs process frequency or range subbands independently. These frameworks for range-Doppler and FMCW radar maps report substantial false-alarm reduction and improved reconstruction fidelity even when the raw imagery contains severe structured clutter, occlusion, or weather-driven distortions [65, 66]. Their strengths include robustness to nonlinear clutter characteristics, preservation of target geometry, and the ability to operate without handcrafted filters once trained. However, their performance depends on the availability of representative FOPEN training data, and there is a risk of inadvertently suppressing weak or rare target classes during reconstruction. Computational cost is another constraint, mainly during the training phase. Despite these limitations, autoencoder-based denoising remains a strong candidate for FOPEN radar clutter cancellation because it learns clutter statistics directly from data and generalizes well to complex, non- stationary environments. Related neural-network-based studies have also reported accurate target classification and reliable range estimation in continuous-wave millimeter-wave radar systems [67].

D. Low-Rank and Sparse Decomposition (RPCA / TV-RPCA) for clutter suppression

Low rank and sparse decomposition methods, including Robust Principal Component Analysis (RPCA) and its total variation regularized extension Total Variation-Robust Principal Component Analysis (TV RPCA), are widely used for clutter suppression in FOPEN radar imagery because they model vegetation clutter as a correlated low rank background and man-made targets as sparse anomalies. These methods were developed to address limitations of traditional MTI, STAP and SVD-based clutter cancellers, which have difficulty handling complex Doppler spectra, require high hardware resources, or depend heavily on manually tuned parameters. The TV RPCA framework replaces the standard l_1 penalty with a total variation term, which preserves spatial smoothness in the low rank background while retaining sharp localized features associated with targets. This has been shown to improve clutter suppression performance in pulse Doppler experiments [51]. The approach provides effective separation between structured foliage clutter and isolated targets, and the total variation term helps maintain important edges without over smoothing the scene. However, performance may degrade when clutter does not follow a low rank model, such as in scenes dominated by man-made structures, and the method can be sensitive to the choice of patch size. It is also computationally demanding for large SAR images, so practical implementations often apply RPCA locally and then use CFAR on the sparse residual for final target detection [51]. Overall, RPCA-based decomposition offers a mathematically principled and practically validated framework for clutter cancellation in FOPEN radar when the clutter exhibits strong spatial correlation.

E. Change Detection (Coherent & Incoherent CCD/ICD, SPD) and Single-Pass Detection (SPD)

Change-detection methods exploit temporal revisits to suppress stationary canopy clutter and detect newly introduced or moved man-made objects beneath foliage. CARABAS experiments show that coherent change detection (CCD) and incoherent change detection (ICD) provide substantial background suppression (5–12 dB) and raise detection probability for vehicle-sized targets compared to single-image methods. Single-Pass Detection (SPD) and spatial averaging variants are also used where repeat passes are limited [70, 73, 74]. The inherent problem these methods solve is that single-image detectors suffer high false alarm rates in FOPEN because canopy and ground scatter vary with aspect and wavelength, temporal differencing isolates non-stationary returns. Strengths include major clutter suppression and improved PD vs FAR, limitations include sensitivity to platform motion, registration errors, seasonal/phenological changes that mimic change, and requirement for multi-pass data (except SPD variants). Accurate motion compensation and precise geocoding are essential for improving the stability of FOPEN radar imagery, and spatial averaging can be applied to achieve an appropriate balance between resolution and robustness in heterogeneous clutter environments. In addition, model-based Bayesian classification frameworks have been shown to enhance target inference by incorporating prior knowledge of expected target statistics and clutter behaviour, thereby improving discrimination performance in challenging forested scenes [70, 74]. To ensure reliable angular and frequency correlation across multi-pass SAR acquisitions, precise image matching and spectral normalization are required, especially when circular or near-repeat flight tracks are used for clutter cancellation. In low-frequency FOPEN SAR systems such as CARABAS, differences in sensor geometry, platform motion and propagation conditions introduce variations in impulse response and spectral support between image acquisitions. These inconsistencies degrade correlation-based suppression unless compensated at the image processing stage. To address this, SAR images are

first geocoded onto a common ground plane and then spectrally equalized using two-dimensional bandpass filtering. As illustrated in Fig. 6, only the intersecting spectral components between two SAR images are preserved in the frequency domain, while non-overlapping frequency bands are rejected. This operation systematically removes distortions caused by differing incidence angles, aperture extents and transfer functions, and enforces spectral compatibility before correlation or change detection. The resulting filtered images exhibit enhanced radiometric consistency, reduced phase decorrelation and improved suppression of foliage-induced clutter. This spectral intersection processing is therefore a necessary preprocessing step that strengthens angular correlation, stabilizes frequency-domain responses and enables robust clutter cancellation in FOPEN SAR change detection frameworks [54].

F. Physical-Optics (PO) Ground–Stem Double-Bounce Models and Topography-Aware Correction

Physical-optics double-bounce models explicitly simulate ground–stem interactions and account for deterministic topography Digital Elevation Model (DEM) to explain and correct large variations in VHF/UHF backscatter. The problem addressed is that small-scale topography and stem geometry substantially modulate HH backscatter and can mask or mimic vehicle signatures. The overall methodology for detecting concealed ground targets using change detection in CARABAS SAR images is illustrated in Fig. 3 [73]. PO models validated on CARABAS/LORA show that including topography yields much better prediction of observed variability than flat-ground models. Physical optics models provide a principled framework for analyzing the angular dependence of scattering in FOPEN radar and offer valuable guidance for DEM based motion compensation and physics aware pre-processing. These models also supply informative priors that support hybrid systems that combine physical modelling with data driven learning. Although their accuracy can be affected by uncertainties in dielectric parameters, small scale surface roughness, stem tilt and branch contributions, and although the simulations can be computationally demanding, physical optics-based formulations remain essential for interpreting FOPEN radar imagery and for improving the performance of model-based detectors and physics informed neural networks [77].

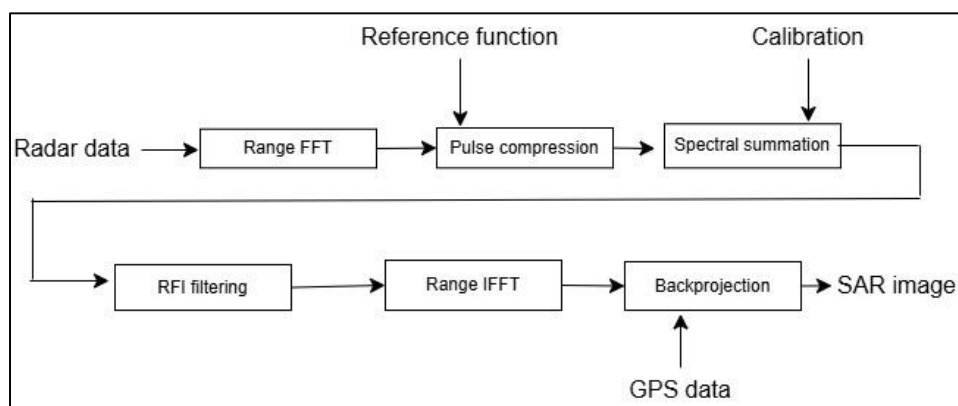


Fig. 3. Detection of Concealed Ground Targets in CARABAS SAR Images using Change Detection

G. CARABAS / VHF-band Ultra-Wideband SAR, DEM Estimation and Campaign Datasets (LORA, LORAM)

Sensor and dataset development efforts, particularly through the CARABAS, LORA and LORAM campaigns, form the foundation of modern FOPEN radar research. VHF ultrawideband SAR provides deep canopy penetration and reduced speckle at moderate resolution, which enables the detection of resonant man-made objects and supports more reliable estimation of digital elevation models beneath dense forest cover. The reported literature describes system design considerations, antenna and radio frequency constraints, back projection-based processing, and the successful generation of DEMs with mean height errors below 1.5 m in dense forests, demonstrating the value of these datasets for validating clutter suppression and imaging techniques. Operational challenges remain, including radio frequency interference, antenna installation requirements, motion compensation accuracy and the scarcity of labelled target examples in real deployments. Consequently, algorithmic developments for FOPEN clutter cancellation should be evaluated using CARABAS and LORA datasets, and DEM or lidar ground truth should be incorporated to calibrate and assess the performance of topography aware methods [70, 75, 76].

H. PSD Modelling & Matched Filtering Robustness (Gaussian / Exponential / Power-Law)

Statistical clutter modelling, particularly the characterization of the power spectral density (PSD) of the background, plays a central role in the design of matched filter and whitening based detectors for FOPEN radar, because the accuracy of these detectors depends strongly on the underlying PSD characteristics of the clutter. Measurements of L band ground clutter

have shown that exponential spectrum shapes frequently provide the best fit, and that mismatches between the assumed and actual PSD can significantly degrade the interference factor, the probability of detection and the probability of false alarm. Classical matched filters typically assume Gaussian stationary clutter, and their performance deteriorates when the observed PSD deviates from this assumption. Incorporating explicit PSD modelling through log normal least squares estimation improves clutter suppression and leads to better matched filter design by aligning the detector with the true spectral structure of the clutter [57]. A key limitation is that PSD parameters vary with terrain type, vegetation density and operating frequency, which makes fixed models unreliable across diverse scenes. Therefore, practical FOPEN detectors should estimate PSD characteristics online and adapt the whitening or matched filter accordingly, or integrate PSD dependent features within Bayesian detection frameworks to maintain robustness under changing clutter conditions.

I. Compressed Sensing and Sparse Reconstruction for Direct-Wave & Clutter Suppression

Compressed sensing (CS) based approaches exploit the inherent sparsity of target returns in range Doppler, time domain or transform domain dictionaries, enabling separation of direct wave components and clutter from the sparse target signals. This class of methods is relevant for foliage penetration (FOPEN) radar because man-made targets beneath vegetation typically occupy only a few coefficients in an appropriate basis, while foliage clutter is more distributed. Recent work shows that noise assisted CS formulations reduce the computational burden of classical CS reconstruction by generating sparse sensing bases through random noise modulation, thereby avoiding multiple iterative refinement stages required in standard CS pipelines. These formulations directly address the problem of high computational complexity and inconsistent clutter suppression observed in traditional CS based cancellation. Experiments indicate that noise assisted CS can achieve equal or superior clutter cancellation performance with significantly reduced processing cost [79]. CS methods are particularly effective when targets are sparse and sub Nyquist sampling is desired, which aligns well with FOPEN scenarios where bandwidth and data volume are constrained. However, their performance may degrade when the assumed sparse basis does not accurately represent the true target and clutter structure, making robust dictionary design and regularization essential. For FOPEN radar, integrating CS with physics guided dictionaries or learned sparse representations can improve separation of vegetation clutter and enhance recovery of weak target signatures beneath foliage.

J. Background-Subtraction Families & Classical Denoising / Diffusion (Anisotropic Diffusion, Scale-Space, Edge Detection)

Background subtraction techniques such as running Gaussian averaging, temporal median filtering, mixture of Gaussians, kernel density estimation and eigen background modelling are widely used as low complexity pre-processing tools to reduce background clutter and extract target dominated regions in radar imagery. These methods are applicable to foliage penetration (FOPEN) radar because vegetation clutter often exhibits slow temporal variations, making it possible to suppress persistent background components through temporal modelling. Complementary image denoising and enhancement techniques including transform-based filtering, anisotropic diffusion and Canny edge detection further improve target visibility by removing speckle like artifacts and enhancing structural discontinuities associated with man-made objects. Comparative studies indicate that simple filters provide fast processing but can blur edges and reduce target definition, while kernel density estimation and eigen background approaches deliver better background modelling performance at the expense of higher memory usage and computational cost [58, 61, 63]. Anisotropic diffusion is particularly effective in FOPEN applications because it preserves edge structures and junction geometry while smoothing homogeneous clutter regions, leading to improved multiscale feature extraction compared to isotropic Gaussian smoothing [63]. These techniques are well suited as front-end processing stages in FOPEN pipelines, where they generate improved representations or candidate regions that can later be refined by model-based detectors or learning driven classifiers. Their effectiveness depends on careful parameter selection and assumptions of background stationarity, and performance may degrade in highly dynamic forest environments where clutter statistics vary rapidly [58, 61, 120].

K. Bayesian Detection and ROC-Centered Statistical Decision Frameworks

Bayesian detection frameworks model radar measurements using probabilistic formulations that combine prior information with observed data to estimate the posterior probability of target presence. This approach is relevant to foliage penetration (FOPEN) radar because clutter statistics vary significantly with terrain, vegetation type and acquisition geometry, which makes fixed threshold detectors unreliable. Bayesian analysis addresses the limitations of single threshold constant false alarm rate decisions by explicitly quantifying uncertainty and enabling improved control of the tradeoff between probability of detection and probability of false alarm through posterior distributions and enhanced receiver operating characteristic analysis. In addition, Bayesian methods support the sequential fusion of multiple observations, which is particularly

important in FOPEN scenarios where weak target signatures gradually emerge over multiple looks. These formulations also allow the integration of prior knowledge about expected target characteristics and clutter behaviour, resulting in detection strategies that are more robust to environmental variability. Their effectiveness, however, depends on the availability of meaningful prior distributions and accurate clutter models, and in practice they are often combined with data driven calibration or adaptive thresholding to ensure stable performance across operating conditions [62].

VI. SAR BASED FOLIAGE CLUTTER SUPRESSION

A. SAR-Based FOPEN Radar Systems and Environmental Effects

Accurate estimation of forest canopy height is essential for ecological and forestry studies[121, 122]. The use of TanDEM-X X-band PolInSAR allowed canopy height retrieval over tropical forests in the Western Ghats, India, employing a modified Random Volume over Ground (RVoG) model. Multi-baseline acquisitions were analyzed, and the optimal wavenumber, incidence angle, and precipitation were found to significantly influence height inversion accuracy. The merged height approach improved RMSE to 1.9 m with $r^2 = 0.92$, demonstrating the capability of spaceborne X-band PolInSAR for large-scale forest mapping [80]. Foliage- penetrating (FOPEN) ultra-wideband SAR imaging faces challenges due to impulsive noise and high clutter. A statistical-physical model was proposed using symmetric alpha-stable (SaS) distributions, linking clutter parameters to physical characteristics such as foliage density and attenuation coefficient. Empirical tests using exploratory data analysis (EDA) confirmed the model’s suitability for accurate clutter representation, helping reduce false alarms in target detection [81]. Non-line-of-sight (NLOS) propagation in foliage environments was investigated using both narrowband and ultrawideband (UWB) radars. CLEAN algorithm removes strong clutter reflections from the signal and uncovers weaker paths, giving a cleaner CIR. Then, the Poisson process model organizes the remaining multipath into clusters and identifies normal clutter arrival behavior, helping separate clutter from meaningful reflections. The log-logistic amplitude distribution (LLD) models the strength of each path more accurately, allowing clutter and noise to be filtered out based on amplitude statistics. The model provides frequency-dependent channel characterization and is extendable to seasonal or other foliage environments, improving simulation and planning of wireless systems [82]. Analytic alpha-stable noise modeling has been explored to characterize Poisson-distributed interferer and scatterer environments, offering improved robustness for radar signal interpretation [126]. Fig. 4 illustrates the linear decision boundaries generated by Bayesian classification under Gaussian statistics [73].

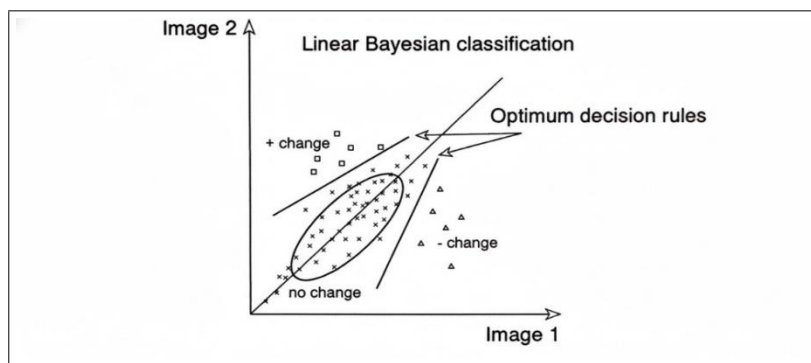


Fig. 4. Linear Bayesian Classification Decision Boundaries under Gaussian Statistics

Radio wave propagation in tropical rainforests of India was studied at 50–800 MHz over various distances and antenna heights. Attenuation increases exponentially up to 0.4 km Beyond 0.4 km, loss increases 40 dB per decade. Higher frequencies leads to higher attenuation. Vertical polarization suffers more loss. Horizontal polarization performs better. Higher antenna height reduces attenuation.. Modes of propagation were distinguished as through-the-foliage (short distances) and tree-top/lateral-wave (long distances), providing empirical models for forest propagation and highlighting polarization and distance effects [83]. Simulation of FOPEN radar range detection addressed target detection through trees under receiver noise and ground clutter. By constructing an ideal ground reflection model and introducing attenuation and reflection coefficients, a method was proposed to calculate maximum detection range. Simulations varying antenna height and topography demonstrated improved estimation of radar range through dense vegetation, providing a framework for practical radar deployment in forested areas. The new radar range equation is:

$$R_{max} = \frac{\sigma F_T^4 I}{(S/C)_{min} \sigma^0 F_C^4 \theta_B^4 (c\tau/2) sec\phi L_{csc}}$$

where, σ is the RCS of the target, I is the improvement factor of the radar, $\min(S/C)$ is the minimum detectable signal-to-clutter and noise ratio, τ is the pulse width after pulse compression, B is the bandwidth, c is the speed of light, θ is the incidence angle, and FT is the clutter pattern factor [84].

Clustering-based clutter suppression methods have also been demonstrated for detecting moving targets in environments dominated by stationary reflectors, such as the QuickSAR approach [132]. Additionally, multistage Wiener-filter-based algorithms have been developed for non-side-looking SAR configurations, achieving improved clutter mitigation and enhanced target visibility [133]. Statistical analysis of bistatic X-band radar ground clutter in German rural environments revealed significant variation among terrain types (fields with low/high vegetation, small tree plantations, and forests) across seasons. Processed range-Doppler maps were used to derive amplitude PDFs and CDFs. Differences in skewness, standard deviation, and interquartile range emphasized the need for terrain-specific adaptive detection and knowledge-aided CFAR and STAP approaches for improved radar performance [85]. For border control and homeland protection, low-power unattended FOPEN radar was developed for dense forest environments, integrating Unattended Ground Sensors (UGS) to detect moving targets, people, or vehicles. The system demonstrates feasibility for long-term, low-maintenance monitoring in challenging terrains and could be integrated with other radar systems to enhance security applications [86]. The study in [104] proposes a low-complexity interference mitigation method tailored for IRCI-free SAR imaging algorithms. The technique effectively suppresses narrowband interference while preserving spatial resolution, enabling robust imaging performance in challenging electromagnetic environments. The work in [107] investigates deep CNN-based ship recognition using SAR imagery captured in maritime environments. The proposed framework enhances feature extraction from complex sea clutter and improves classification robustness under varying sea states with 90% accuracy. The sample images in the dataset are taken from satellites, Sentinel-1 and RADARSAT-2.

B. Range-Doppler Based Multistatic Clutter Suppression and STAP Enhancements

Human target detection and tracking in radar systems faces challenges when targets are close or overlapping, particularly in foliage-penetration environments. To address this, a range-Doppler (RD)-based centralized framework is proposed for multistatic radar, incorporating clutter reduction, RD calculation, target detection, measurement estimation, target localization, and tracking. Key innovations include a 2D OS-CFAR detector for RD detection and a minimum root-mean-square error pruning algorithm for multi-target localization, reducing wrong association probability compared to range-only methods [87]. In FMCW radar systems, asynchronization between transmitter and receiver can corrupt RD maps, affecting detection accuracy. A reconstruction method is presented that identifies corrupted maps using image entropy and restores them via linear estimation based on adjacent normal maps, ensuring accurate target range and velocity detection [88]. In heterogeneous clutter environments where conventional STAP fails due to the lack of homogeneous training data, a deterministic-aided single dataset STAP (DA-SDS-STAP) method is proposed. Using only cell-under-test data, a high-resolution angle-Doppler power spectrum is obtained via sparse recovery, and a deterministic-aided GIP algorithm selects clutter components for covariance matrix estimation, enabling effective STAP filtering without secondary data [89]. Fig. 5 presents the block diagram of the DA-SDS-STAP method for effective clutter suppression in heterogeneous environments[133].

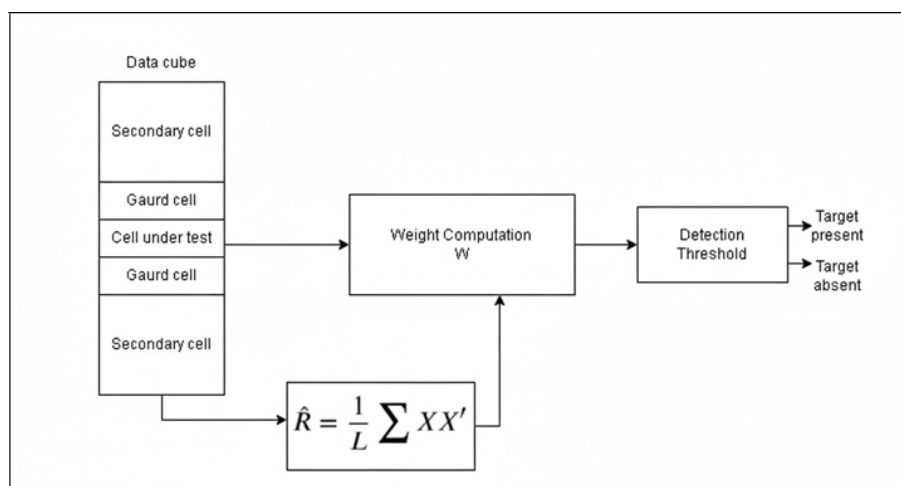


Fig. 5. A Single Dataset STAP (DA-SDS-STAP) method for heterogeneous clutter

C. Correlation-Based Angular / Frequency Techniques (ACF / FCF) and Circular SAR

Angular correlation function (ACF) and frequency correlation function (FCF) methods often implemented with circular-aperture SAR exploit angular/frequency coherence to suppress speckle and incoherent clutter and to enhance point like resonant scatterers (stems, vehicles). Controlled X-band experiments and circular SAR field tests show ACF imaging outperforms conventional SAR and FCF for imaging point scatterers in heavy clutter because correlation across aperture isolates coherent double-bounce/resonant returns while averaging incoherent clutter [69, 71, 72]. The core advantage is physics-aligned discrimination of coherent target mechanisms, limitations are the need for wide angular sampling (circular tracks or multi-angle acquisitions), demanding motion and geometry accuracy, and higher computational burden. For FOPEN applications, ACF with circular SAR is effective where platform geometry allows dense angular coverage, practical systems combine ACF outputs with CCD/ICD and CFAR to produce operational detections [69, 70, 71]. Fig. 6 provides a comprehensive overview of the geometric alignment and spectral component extraction[73].

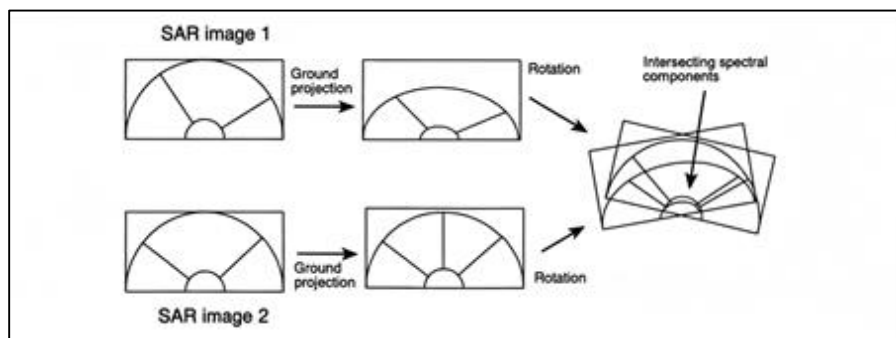


Fig. 6. Geometric Alignment and Spectral Component Extraction from Dual SAR Imagery

D. Clutter Cancellation with Advanced Imaging Techniques for Radar Target Classification and Micro-Motion Analysis

This paper proposes a deep learning approach for radar emitter classification using an improved EfficientNetv2-s model. By replacing the two-dimensional convolution with one-dimensional convolution and optimizing the channel attention mechanism, the method processes spectrum images generated from 16 radar signal types. Despite its strong performance on the experimental dataset, the method has limitations regarding generalization to new datasets, model simplification, and varying working conditions. The proposed approach achieves a top-1 accuracy of 98.12%, Lower model complexity and faster classification. Enhanced attention mechanism preserves important features. Effective for radar frequency-domain spectrum images [90]. A nonlinear edge-preserving diffusion method called speckle reducing anisotropic diffusion (SRAD) is presented for radar and ultrasonic imaging. Unlike conventional diffusion methods, SRAD directly processes speckled data by exploiting the instantaneous coefficient of variation, preserving edges and features while reducing noise. Comparative simulations show that SRAD outperforms traditional Lee, Frost, and standard anisotropic diffusion filters in terms of edge preservation, variance reduction, and mean preservation. The method is suitable for various radar and ultrasound applications requiring noise suppression without compromising image quality [91]. This study introduces a method for target classification using frontal radar images captured by 77 GHz MW-MIMO radar. The images contain both shape and reflection characteristics of targets, which are classified using deep convolutional neural networks. The method achieved classification rates of 87.1% for six classes (sedans, SUVs, trucks, humans, poles, and trees) and 92.6% for three broader classes (vehicles, humans, clutter). Although the accuracy is slightly lower than range-Doppler-based methods, the study demonstrates that frontal images can serve as a complementary modality for situational awareness in autonomous vehicles and ground surveillance [92]. A novel feature extraction method for micro-motion targets is proposed using time-frequency spectrograms obtained via short-time Fourier transform. Spectrogram pre-processing enhances image features, and three types of features—entropy, third-order statistical moments, and directionality—are extracted to classify targets. Using support vector machines, the method achieves high classification accuracy for humans and vehicles while maintaining robustness across varying signal-to-noise ratios and sample sizes. It is concluded that only 0.53% human samples are recognised as vehicles, and 6.92% vehicle samples are regarded as human. The probability of correct classification rate higher than 90% when the training sample number is larger than 20 if it is less than it gives 80% accuracy. This approach effectively combines spatial, temporal, and frequency information for micro-motion target recognition [93]. This paper presents time-integrated range-Doppler maps as a tool for visualizing micro-Doppler features of moving targets. By compiling range-Doppler maps over time, the approach creates a spectrogram-like representation that retains range information while compressing time. This visualization allows operators to classify moving humans, vehicles, and animals

effectively. While challenges such as detecting grazing animals and handling overlapping targets remain, the method significantly improves operator-assisted classification and provides a foundation for automated detection and enhanced radar data interpretation [94].

E. Feature-Based, Fusion, and Deep Learning Approaches for Radar and SAR clutter cancellation and Moving Target Detection

Support vector machine-based SAR image recognition techniques have shown reliable performance for target classification in varied environments [129] but the identification of radar targets gets difficult since RCS values change with viewing angle. To reduce this problem, central moments of RCS signals are calculated, making the features more stable. PCA is then used to shrink the feature size and remove noise. These cleaner features are classified using an SVM. Tests with different SNR levels and different PCA dimensions show that the PCA-based method gives better accuracy than traditional methods, although it takes more time to compute. When accuracy is more important than speed, the PCA-SVM approach is the better choice [95]. Autonomous systems need to detect objects clearly even in darkness, clutter, and noisy environments. A fusion method is developed that combines radar data with camera images. Radar gives the rough location of objects, which is used to create accurate ROIs on the image. A deep network then learns micro-Doppler features from radar and texture features from the camera, and merges them for classification. A day/night dataset is created to test the model. The fusion system achieves up to 89.42% mAP, performing much better than radar-only methods and standard Faster R-CNN, especially in low-light and high-clutter scenes [96]. Deep learning is applied to SAR images using a ResNet-18 model trained on the MSTAR dataset. The system reaches around 99% accuracy for classifying ten types of targets. The work also studies how to handle a new target type that has very few training samples. Two training choices are tested: freezing the earlier layers or training the whole network from scratch. Freezing layers protects accuracy for known targets but performs poorly on the new target. Training from scratch helps the new target but reduces accuracy for older ones. The results show that the best training method depends on whether the priority is existing targets or new targets [97]. SAR target recognition usually struggles with overfitting because training data is limited and traditional ConvNets have too many parameters. In order to reduce the number of trainable parameters, A-ConvNets eliminate fully connected layers and only use convolutional layers. Without the need for human processing, the network automatically extracts valuable features from SAR images. Tests on the MSTAR dataset show 99% accuracy for ten target classes, and the method performs better than standard ConvNets, especially when classifying slightly different versions of the same target [98]. Detecting moving targets in high-resolution SAR images is challenging because stationary ground clutter can mask slow-moving targets, and moving targets appear smeared and displaced due to long integration times. To address this, the authors used an 8-channel QuickSAR system from General Dynamics and applied multi-channel phase interferometry to generate clutter-cancelled SAR images. A clustering-based detection algorithm was then applied, which uses magnitude and phase thresholds to identify potential moving targets, groups contiguous pixels into target clusters, and compares detections across channels to reduce false alarms. Using GPS truth data for validation, this method achieved a probability of detection greater than 90% with a false alarm density of 100 FA/km², demonstrating that the combination of clutter cancellation and clustering algorithms provides a robust and accurate solution for automated moving target detection in SAR imagery [99]. From [100] the target can be identified and described using the range-cross range profile that is acquired for a particular spatial arrangement of point scatterers. The work has been done with respect to ISAR imaging.

VII. FUTURE SCOPE

The advancements reported across these works reveal several promising research directions that can directly support the development of next-generation foliage-penetration (FOPEN) radar systems. Atmospheric turbulence modeling and compensation techniques originally proposed for optical wireless communication such as the prediction frameworks in [136] and adaptive control strategies in [134] can inspire analogous correction mechanisms for mitigating vegetation-induced amplitude scintillation and phase distortion in forested environments. Antenna innovations, including dual-band shared-aperture reflectarray designs demonstrated in [135], highlight opportunities for compact, electronically steerable antenna systems suitable for airborne or ground-based FOPEN missions. A significant research done on photonics-enabled radar including X-band micro-Doppler-based target characterization [130, 137], empirical wavelet transform-assisted cadence frequency imaging [138], OptiSystem-based photonic radar modeling for high-resolution detection [139], and photonics-assisted FMCW/ISAR imaging of small UAV targets [140], demonstrates the capability of optical domain processing to overcome bandwidth limitations, phase noise degradation, and RF front-end nonlinearities. These features are directly beneficial for FOPEN radar, where wideband, low-phase-noise illumination is essential for penetrating dense foliage. The dual-band RF-photonics radar modeling reported in [141] further emphasizes the feasibility of multi-band,

flexible sensing architectures, which can be exploited to optimize penetration depth at lower frequencies while maintaining fine resolution at higher bands. The comprehensive survey on photonics technologies for radar widens the potential of optical carriers, ultra-stable oscillators, wavelength-division multiplexing, and integrated photonic front-ends to elevate FOPEN radar performance in dense clutter and low-visibility environments. These works point towards a probability in which turbulence-aware modeling, photonic signal generation, adaptive beam control, and micro-Doppler-assisted feature extraction converge to enable highly resilient and high-resolution FOPEN sensing platforms.

Future research in FOPEN radar clutter suppression should focus on developing standardized large-scale datasets across diverse forest types and environmental conditions to support robust training and benchmarking of advanced algorithms, while also integrating physics-guided deep learning frameworks that fuse physical- optics scattering models, DEM-aware corrections, and angular/frequency correlation features with data-driven neural architectures. There remains a strong need for adaptive clutter modelling capable of responding to wind speed, moisture, rainfall, and seasonal variations by dynamically adjusting statistical parameters and suppression weights. Additionally, future algorithms must increasingly exploit joint spatial-temporal-spectral processing that unifies MTI/MTD dynamics, Doppler signatures, and multistatic/angular diversity to maximize clutter invariance. Enhanced low-rank and sparse decomposition methods, including patch-adaptive RPCA and physics- constrained sparse dictionaries, will be essential for isolating weak target returns under dense multipath foliage. Furthermore, improving multi-pass SAR change-detection pipelines through more robust image registration, spectral equalisation, and motion compensation will enhance clutter suppression in VHF/UHF SAR datasets, such as CARABAS and LORA. Advancing FOPEN architectures, such as drone-mounted, multistatic, and ground-air integrated systems can provide complementary geometries and frequency diversity for improved detection. Finally, establishing a unified benchmarking framework with standardized metrics for signal-to-clutter ratio improvement, detection probability, false-alarm rate, and computational efficiency will be critical for comparing classical, learning-based algorithms and SAR-driven clutter-suppression approaches.

VIII. CONCLUSION

This review presented a comprehensive synthesis of clutter-suppression methodologies for foliage-penetration (FOPEN) radar spanning signal-domain processing, image-domain techniques, machine-learning frameworks, and SAR-based approaches. Reliable discrimination of targets from clutter by a single method is not possible because the foliage clutter varies with frequency, wind-induced motion, canopy density, multipath behaviour, and environmental conditions. Signal-domain techniques - including MTI/MTD filtering, CFAR variants, LMS/RLS adaptive cancellation, entropy-weighted coherent integration, and blind-source-separation approaches - offer low-complexity and real-time feasibility. These methods reliably suppress stationary or slowly varying clutter. However, under strongly nonstationary, non-Gaussian, and multipath-dominated conditions, which are typical in dense forests, their performance is very poor. Image-domain strategies including Total Variation denoising, Forward-Backward Diffusion, anisotropic diffusion, RPCA/TV-RPCA decomposition, and background-subtraction families effectively exploit spatial and morphological structure of radar imagery, preserving target geometry while removing distributed clutter. Their effectiveness depends on the quality of RTI/RD representations and parameter stability. This study also suggests that machine-learning and deep-learning algorithms significantly outperform classical approaches when clutter is highly nonlinear or multimodal. Convolutional autoencoders, CNN-based detectors, and Doppler-feature fusion networks learn clutter characteristics directly from data, achieving strong target reconstruction and classification even at low SNR. Yet, these methods require large labelled datasets physics-consistent augmentation, and careful regularization to avoid overfitting to specific forest or frequency conditions. SAR-based techniques including coherent/incoherent change detection, spectral intersection filtering, angular/frequency correlation methods, DEM-informed physical-optics modelling, and deterministic-aided STAP provide powerful clutter rejection by exploiting aperture diversity and physical scattering models. Their limitations stem from platform motion sensitivity, DEM dependence, frequency/angle decorrelation, and the logistical constraints of multi-pass data acquisition. Among all these categories, a consistent trend is observed:

- 1) Signal-domain methods excel in real-time, low-complexity processing but fail under rapidly varying clutter.
- 2) Image-domain methods preserve structural features but depend on stable spatiotemporal representation.
- 3) Deep learning achieves the best clutter suppression under complex environments but requires extensive datasets and compute resources.
- 4) SAR-based techniques provide the strongest clutter rejection using multi-aperture physics, but are operationally very challenging.

A combination of physics-guided modeling, statistical clutter characterization, adaptive signal processing, and deep learning offers the path to next-generation FOPEN radar systems. This requires a unified framework that contains the strengths of all four domains for reliable detection, tracking, and identification of concealed targets beneath dense vegetation.

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