A Comprehensive Review on Soft Computing Techniques for Speckle Reduction in Synthetic Aperture Radar (SAR) Imagery

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Abstract: Speckle is an inherent multiplicative noise in coherent imaging systems such as synthetic aperture radar (SAR), and it reduces radiometric resolution, obscures weak scatterers, and degrades downstream tasks (e.g., detection, segmentation, and classification). Over the last four decades, despeckling has evolved from local statistical filters (e.g., Lee/Frost/Kuan families) to variational and nonlocal approaches, and more recently to data-driven deep networks. Within this landscape, soft computing—broadly covering fuzzy logic, neural computing, and evolutionary/swarm optimization—has been increasingly used to address the central despeckling dilemma: suppress speckle while preserving edges, textures, and small man-made targets. This review organizes soft computing techniques for SAR despeckling into: (i) fuzzy and neuro-fuzzy filtering; (ii) neural and deep learning models (CNN, autoencoders, GANs, and diffusion models); and (iii) evolutionary and swarm optimization used for parameter tuning, transform-domain thresholding, and multi-objective decision making. Particular emphasis is placed on multi-objective formulations that jointly optimize PSNR and MSSIM/SSIM, yielding Pareto-optimal trade-off solutions (e.g., MOPSO-based threshold selection). We summarize datasets, evaluation metrics, and reproducibility concerns, and provide a comparative synthesis of strengths, limitations, and research gaps. Finally, we outline actionable future directions, including self-supervised despeckling on real SAR, objective-function design aligned with task performance, uncertainty quantification, and standardized evaluation protocols.

Keywords: Synthetic aperture radar; speckle noise; despeckling; soft computing; fuzzy logic; deep learning; multi-objective optimization; PSNR; MSSIM; SSIM; MOPSO; NSGA-II.

Introduction

Synthetic aperture radar (SAR) provides all-weather, day-night Earth observation by exploiting coherent microwave scattering. However, coherent processing produces granular speckle, commonly modeled as multiplicative noise, which lowers visual interpretability and can bias quantitative analysis. Consequently, despeckling remains a crucial pre-processing step for both human interpretation and automated pipelines [1]. The SAR images are generally captured by any moving object such as satellite or plane displayed by Figure 1. These SAR images are so much popular now a days due to its uses in different fields such as agriculture, environment study, forestry and military surveillances etc. The SAR images are affected due to its coherent nature and heavily affected by the granular noise infused during its capturing process. The noise is known as multiplicative noise. There are several algorithms available for denoising of optical images but there are not so many algorithms available for removing speckle noise from the SAR images. SAR image simulation can be divided into two categories during the electromagnetic scattering flow. The first is a signal-level simulation that primarily focusses on electromagnetic scattering, while the second is an image-level simulation that focusses on pre-existing or hypothetical distribution [2]. Classical despeckling methods include local statistical filters (Lee, Frost, Kuan), diffusion models, and transform-domain shrinkage. Although these approaches can suppress speckle, they often trade noise removal against edge/texture preservation, and their performance is sensitive to hand-tuned parameters and scene heterogeneity. In parallel, modern deep learning approaches have reported strong results, but supervised training is challenged by the scarcity of truly noise-free SAR reference images and the mismatch between synthetic and real speckle.

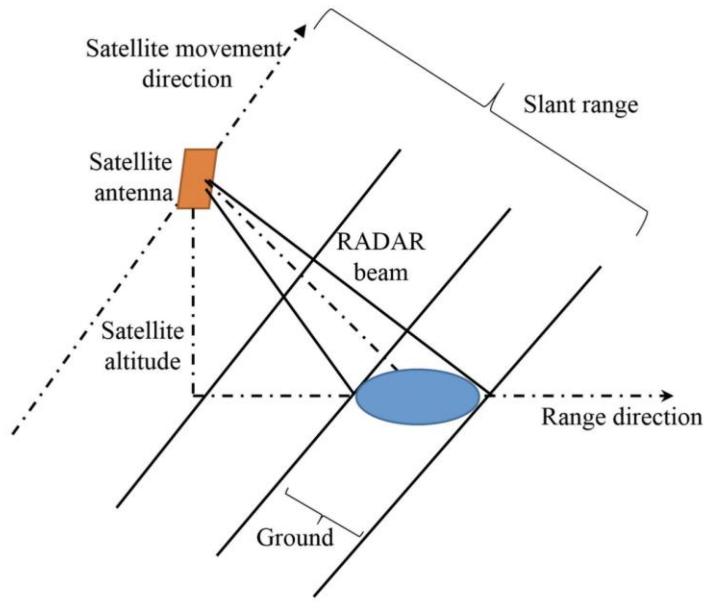

Figure 1: Typical SAR despeckling capturing process [1].

Soft computing offers complementary tools for this problem. Fuzzy logic can encode expert knowledge and local context via membership functions and rule bases; neural networks can learn nonlinear despeckling mappings; and evolutionary/swarm methods can automatically tune parameters or losses, including in multi-objective settings. Recent work has also explored self-supervised learning to reduce reliance on clean targets and better adapt to real SAR speckle statistics. This review focuses on soft computing techniques for SAR despeckling, with a special emphasis on multi-objective optimization (e.g., joint PSNR–MSSIM optimization) and optimization-driven parameter selection for transform-domain and hybrid filters. We aim to provide: (i) a structured taxonomy, (ii) an overview of metrics and datasets, (iii) a comparative synthesis of representative methods, and (iv) future research opportunities [3–6].

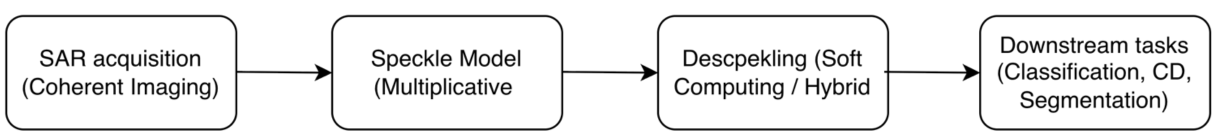

Figure 2: Typical SAR despeckling workflow and its role in downstream interpretation tasks.

Figure 2 presents a sequential workflow for despeckling process of Synthetic Aperture Radar (SAR) imagery. It begins at the stage of SAR data acquisition, in which coherent signal processing results in the.

images formed under the influence of granular noise. This noise is represented then in a multiplicative form speckle model, an explanation of the interaction between the actual backscatter and speckle contents. In the second step, despeckling schemes, which make use of soft computing or mixed models are used to authenticate noise reduction but important spatial and textual details are preserved. The images are then refined and finally used as downstream tasks, such as change detection, land cover classification, and image segmentation, assisting in sound and sound SAR image interpretation.

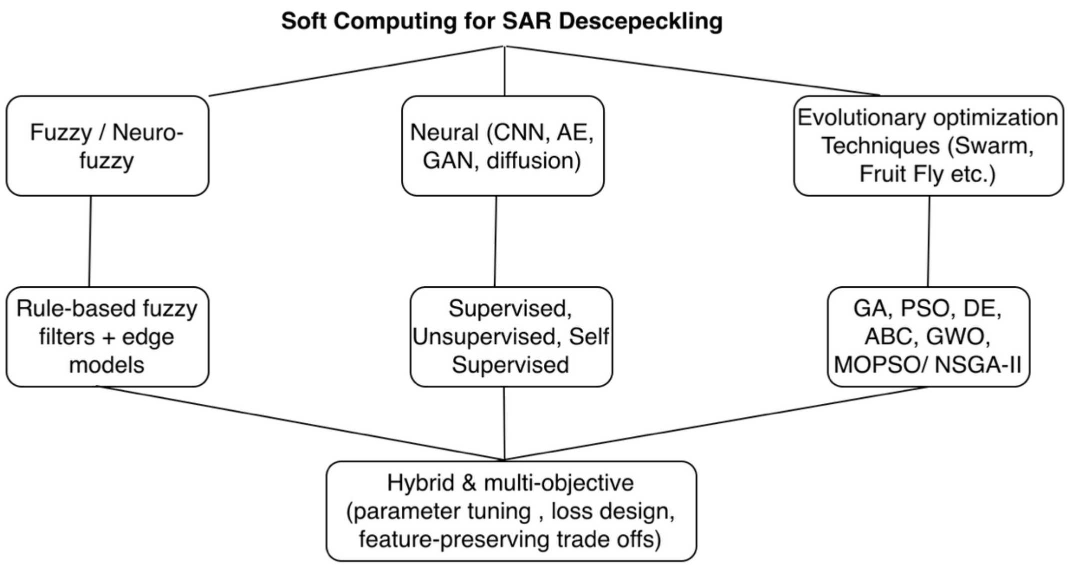

Figure 3. Soft computing methods to taxonomy on SAR despeckling discussed in this review.

The Figure 3 gives a summary of the soft computing and optimization-based strategies employed to SAR. image despeckling. The recent studies on SAR image despeckling can be categorized into three in a broad way methodological streams. The former is the first stream, which is founded on fuzzy and neuro-fuzzy paradigms, where expert the knowledge is integrated with fuzzy rules, adaptive membership functions and edge-sensitive homogeneity mechanisms to selectively smooth flat areas and protect boundaries and structural changes of SAR images [7,8]. These strategies would work well in the management of without undue blurring.

The second one is dominated by those techniques based on neural learning, such as convolutional neural networks, autoencoders, generative adversarial networks, and new diffusion-based generative models. These computational models can simulate complicated speckle patterns and texture.

are dependencies and may be trained with supervised, unsupervised or self-supervised strategies, therefore increasing the use of clean ground truth SAR data [9–12]. They are capable of learning hierarchical and multi-scale representations has resulted in the major noise suppression and preservation of features.

The third stream considers optimization algorithms that are evolutionary and swarm-based like genetic algorithms, particle swarm optimization, differential evolution, artificial bee colony, grey wolf optimization and their multi-objective counterparts, such as NSGA-II and MOPSO. These methods are use this is mainly to optimize the parameters of despeckling and objective functions, which make it possible to optimize effectively trade-off among conflicting objectives like speckle reduction, edge retention and texture fidelity [13–14].

In more recent times, a definite turn to hybrid and multi-objective systems is to be seen, where evolutionary optimization techniques are combined with deep learning models. Such combinations allow simultaneous optimization of radiometric accuracy, structural similarity and textural consistency, leaving to stronger and more generalisable SAR despeckling solutions [15-18]. This trend reflects the increasing focus on balanced performance as opposed to single-metric optimization.

Speckle Noise Model and Evaluation Metrics

Multiplicative speckle model: Speckle noise in synthetic aperture radar (SAR) imaging Speckle noise in synthetic aperture radar (SAR) imaging is generally modelled in a multiplicative formulation, in which the observed intensity image is represented as the combination of the real backscatter reflectivity and a haphazard speckle. For fully developed speckle, the noise term is often assumed to be described by Gamma distribution with respect to the number of looks, which is a true description of the changes in intensities of homogenous regions. Transforming the data into the logarithmic domain transforms the multiplicative noise to the form of an approximation of the additive form, thus. making the use of classical filtering, variational expressions and homomorphic more straightforward. techniques. This is further embedded in the modern diffusion- and variational-based despeckling methods statistical modelling their terms of data fidelity so as to more closely observe the SAR noise properties [19].

A combination of the performance of despeckling methods of SAR is based on quantitative and qualitative data that evaluate noise-reduction as well as structural conservation. Also, even though the peak signal-to-noise ratio (PSNR) is a commonly used fidelity metric in cases where reference images are available. it tends not to be associated with perceived visual quality. Consequently, structure-sensitive indices so-called structural similarity (SSIM) and multiscale SSIM (MS-SSIM or MSSIM) are typically used. In Specific SAR-based studies, the evaluation is done using Equivalent Number of Looks (ENL), Speckle suppression Index (SSI), edge preservation measurements, and ratio-image analysis. These parameters are also used to evaluate despeckling performance, especially with real SAR data where clean reference data is not available [20].

Conflicting metrics and multi-objective optimization: There are a lot of despeckling quality metrics that have inherent conflicts, trade offs, strong smoothing is likely to increase homogeneity-based measures of ENL and PSNR and also reducing edge sharpness as well as structural similarity. This has been an impetus to the conflict implementation of multi-objective optimization models that explicitly seek solutions to Pareto-optima as opposed to depending on one aggregated cost function[21].

Review Methodology

This review followed a structured survey procedure: (i) query formulation using terms related to SAR despeckling, speckle reduction, soft computing, fuzzy/neuro-fuzzy filters, deep learning, and optimization (GA/PSO/DE and multi-objective variants); (ii) screening by relevance to SAR or SAR-like speckle; (iii) full-text assessment with emphasis on algorithmic novelty, evaluation rigor, and availability of implementation details; and (iv) categorization into the taxonomy of Figure 3. Priority was given to peer-reviewed journal and conference publications and widely cited foundational works. We also include representative recent works on self-supervised and generative approaches that address the lack of clean SAR references. [22–24]

Fuzzy and Neuro-Fuzzy Techniques

Fuzzy systems are attractive for despeckling because speckle characteristics and edge/texture behaviors can be described using linguistic rules (e.g., "if local variance is high and gradient is strong, preserve center pixel"). A typical fuzzy filter computes membership values from local statistics (mean, variance, coefficient of variation) and then produces an output via inference and defuzzification. Fuzzy weighted mean/median designs can reduce speckle while maintaining edges by down-weighting neighbors likely belonging to edges.

Parameter selection is crucial. Several works determine membership function parameters using swarm intelligence; for example, fuzzy rule parameters can be tuned by PSO to better distinguish noise from structural variation. Neuro-fuzzy approaches additionally learn rule parameters from data, combining interpretability with learning capacity.

Representative directions include: (i) fuzzy inference systems for nonlinear filtering; (ii) fuzzy edge-aware despeckling (preserve edges first, then filter); and (iii) hybrid fuzzy + diffusion/variational schemes that couple fuzzy edge detectors with PDE-based smoothing [25,26].

Neural and Deep Learning Approaches

Neural computing for despeckling has progressed from shallow networks to modern deep architectures.
CNN-based despeckling: Residual learning and discriminative training have been used for SAR despeckling by learning mappings in either intensity or log domains. Deep CNNs can capture complex spatial context but may introduce texture hallucination or oversmoothing if trained on mismatched synthetic speckle. Residual and multi-scale designs attempt to preserve fine structures.
Unsupervised and self-supervised learning: Because clean SAR is generally unavailable, self-supervised strategies have gained attention. Methods built on Deep Image Prior adapt the network to a single noisy image and incorporate speckle statistics via tailored losses. Speckle-driven unsupervised networks aim to train without clean targets and improve generalization to real scenes.
Generative and diffusion models: GAN-based approaches can learn realistic textures, but stability and faithfulness are concerns. Recently, diffusion-based denoisers have been proposed to better model global context, potentially mitigating CNN texture loss. These models often require careful training and evaluation to ensure preservation of radiometric properties important in SAR.
Hyperparameter and architecture optimization: Soft computing is increasingly used to optimize deep models, including hyperparameter tuning (e.g., via design-of-experiments or evolutionary search) and objective design that balances fidelity and structure. [27,28]

Evolutionary and Swarm Optimization for SAR Despeckling

Evolutionary algorithms (EAs) and swarm intelligence are widely used for: (i) tuning parameters of classical filters (e.g., window size, diffusion step, guided filter parameters), (ii) selecting transform-domain thresholds (wavelet/curvelet/contourlet/DTCWT), (iii) optimizing membership functions and rule bases in fuzzy filters, and (iv) selecting among competing denoising configurations.

Common optimizers: Genetic algorithms (GA), particle swarm optimization (PSO), differential evolution (DE), and their variants are most common; many other bio-inspired methods have been explored, but comparative evidence is often limited. In SAR despeckling, optimization is typically low-to-medium dimensional (thresholds, shrinkage parameters, filter gains), which suits population-based metaheuristics.

Multi-objective formulations: Multi-objective PSO (MOPSO) has been explicitly used to optimize despeckling parameters under conflicting criteria (e.g., minimize speckle while preserving edges/structure). Transform-domain schemes often treat threshold selection as a multi-objective problem (maximize PSNR and SSIM/MSSIM simultaneously) and then pick a solution from the Pareto archive based on additional preferences. Multi-objective evolutionary algorithms such as NSGA-II provide an alternative, with strong diversity preservation and Pareto sorting.

Practical considerations: Metaheuristics can be computationally expensive because each candidate requires a full despeckling run and metric computation. Strategies to reduce cost include working on patches, multi-resolution search, surrogate modeling, and warm-starting using analytical estimates. [29].

Comparative Synthesis

This section summarizes representative methods within each category. Table 1 provides a taxonomy-oriented comparison, while Table 2 highlights how optimization is integrated into despeckling pipelines and what objectives are commonly used.

Table 1. High-level comparison of soft computing categories for SAR despeckling.

Category	Representative idea	Typical design choices	Strengths	Limitations	Example refs
Fuzzy / Neuro-fuzzy	Membership + rules to adapt filtering to local context	Local statistics (mean/var/CV), fuzzy weights, edge-aware inference	Interpretable; good edge preservation when rules are well designed	Sensitive to parameter design; may struggle on complex textures	[25,26]
CNN-based	Learn nonlinear mapping; often residual learning	Multi-scale CNNs, log-domain training, residual blocks	Strong performance; fast inference after training	Needs training data; generalization gap (synthetic vs real speckle)	[30-31]
Self-/Unsupervised DL	Train without clean targets; exploit speckle statistics	Deep Image Prior, speckle-driven losses, consistency constraints	Better adaptation to real SAR; fewer label requirements	Compute cost; risk of under/over-fitting to a single scene	[23,27]
GAN / diffusion	Generative priors for texture and global structure	Adversarial losses; diffusion denoising with probabilistic modeling	Good perceptual texture; captures global context	Faithfulness/radiometry concerns; training complexity	[6,28]

Optimization-tuned transforms	Optimize shrinkage/thresholds in wavelet/curvelet/contourlet/DTCWT	PSO/GA to select thresholds per sub-band; homomorphic pre-processing	Flexible; can adapt to scene statistics; improves classic pipelines	Optimization overhead; metrics may not reflect task quality	[21]
Hybrid / multi-objective	Combine filters + optimization for trade-offs	MOPSO/NSGA-II to maximize PSNR and MSSIM; choose Pareto solution	Explicit trade-off control; robust across scenes	Requires preference selection from Pareto set; compute cost	[24,32]

Table 2. How optimization (including multi-objective) is used in SAR despeckling pipelines.

Where optimization is used	**Decision variables**	**Optimizer**	**Objectives (examples)**	**Selection from Pareto set**	**Notes**	**Example refs**
Transform thresholding	Sub-band thresholds / shrinkage parameters	PSO / GA / DE / MOPSO	Max PSNR, max (MS)SSIM, max ENL, min SSI	Knee point; weighted preference; best MSSIM under PSNR constraint	Popular with DTCWT/curvelet; can be patch-based to reduce cost	[24,32]
Fuzzy membership tuning	Membership function breakpoints; rule weights	PSO / GA	Max PSNR/SSIM; minimize edge loss	Choose solution with best SSIM on validation scenes	Improves robustness of fuzzy filters across scenes	[25]
Diffusion/variational tuning	Step size, conductance, regularization weight	GA / PSO	Max PSNR/SSIM; minimize gradient loss	Pick non-dominated with highest edge index	Avoids manual parameter tuning; can be expensive	[33,34]
Deep model hyperparameters	Depth/width, learning rate, loss weights	Evolutionary search / design-of-experiments	Max PSNR/SSIM; minimize artifacts	Select best validation compromise; or Pareto over compute cost	Increasingly used; reproducibility depends on code/data	[27,28]

Datasets, Protocols, and Reproducibility

Evaluation in SAR despeckling is complicated by the lack of ground-truth clean images. Common strategies include: (i) simulated speckle added to optical or SAR-like reflectivity fields; (ii) multi-look averaging to approximate a cleaner reference; (iii) temporal stacks where averaging or multitemporal methods provide proxies; and (iv) no-reference analyses using ratio images and statistical checks.

Best practices for reproducible evaluation include: reporting sensor/source details, polarization, resolution, number of looks (if known), and preprocessing; providing parameter settings or search ranges; using multiple scenes with diverse textures (urban, agriculture, water); and reporting both full-reference metrics (PSNR/SSIM/MSSIM) on simulated settings and SAR-specific statistics (ENL/SSI) on real scenes. Where possible, downstream task metrics should complement perceptual scores. [4,5]

Open Challenges and Future Directions

(1) Real-SAR generalization and self-supervision. Closing the gap between synthetic speckle training and real SAR is still a primary issue; self-supervised and speckle-driven training objectives are promising.

(2) Metric-aligned objectives. PSNR and MSSIM are useful but not sufficient; objective functions should reflect SAR radiometry, texture stationarity, and downstream task needs. Multi-objective setups can incorporate task losses (e.g., detection performance) alongside denoising quality.

(3) Multi-objective decision making. Pareto sets require selection. Research is needed on principled selection rules (knee detection, preference learning, and robustness analysis) to avoid overfitting to a single metric.

(4) Computational efficiency. Optimization-based methods can be slow. Surrogates, learned parameter predictors, and coarse-to-fine strategies can reduce cost. Diffusion models also demand acceleration techniques for deployment.

(5) Uncertainty and reliability. SAR is used in high-stakes applications (disaster response, infrastructure monitoring). Methods should quantify uncertainty and avoid hallucination. Physics-informed priors and conservative filtering are promising.

(6) Standardized benchmarks. Community progress would benefit from agreed-upon datasets, protocols, and open implementations, particularly for real SAR scenes with consistent metadata. [5,6,28]

Conclusion

Soft computing has become an important pillar of SAR despeckling research. Fuzzy and neuro-fuzzy methods offer interpretable, locally adaptive filtering; deep neural methods deliver strong denoising capacity but face training and generalization challenges; and evolutionary/swarm optimizers provide practical tools to tune parameters and to directly model trade-offs using multi-objective formulations. Multi-objective optimization (e.g., PSNR–MSSIM) is especially valuable for controlling the speckle–detail balance and for translating algorithm design into application-specific preferences. Future work should emphasize self-supervised learning on real SAR, objective functions aligned with downstream tasks and SAR statistics, and more reproducible benchmarking to ensure robust progress.

References

1. Kumar, B., Ranjan, R. K., & Husain, A. (2021). A Multi-Objective Enhanced Fruit Fly Optimization (MO-EFOA) Framework for Despeckling SAR Images using DTCWT based Local Adaptive Thresholding. International Journal of Remote Sensing, 42(14), 5493–5514.
2. Huang, F. Zhang, Y. Zhou, Q. Yin and W. Hu, "High Resolution SAR Image Synthesis with Hierarchical Generative Adversarial Networks," IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, 2019, pp. 2782-2785, doi:

3. Yu, Y., & Acton, S. T. (2002). Speckle reducing anisotropic diffusion. IEEE Transactions on image processing, 11(11), 1260-1270.
4. Chierchia, G., El Gheche, M., Scarpa, G., & Verdoliva, L. (2017). Multitemporal SAR image despeckling based on block-matching and collaborative filtering. IEEE Transactions on Geoscience and Remote Sensing, 55(10), 5467-5480.
5. Albisani, C., Baracchi, D., Piva, A., & Argenti, F. (2025). Self-Supervised SAR Despeckling Using Deep Image Prior. Pattern Recognition Letters, 190, 169-176.
6. Pan, Y., Zhong, L., Chen, J., Li, H., Zhang, X., & Pan, B. (2024). SAR image despeckling based on denoising diffusion probabilistic model and swin transformer. Remote Sensing, 16(17).
7. Zhang, Y., Wu, L., & Li, S. (2022). Edge-preserving fuzzy filtering for speckle noise reduction in SAR images. IEEE Geoscience and Remote Sensing Letters, 19, 1–5.
8. Kumar, A., & Ghosh, S. (2023). Neuro-fuzzy adaptive despeckling of SAR images using local statistical modeling. Applied Soft Computing, 132, 109847.
9. Wang, P., Zhang, H., & Li, X. (2022). Multi-scale convolutional neural networks for SAR image despeckling. IEEE Transactions on Geoscience and Remote Sensing, 60, 1–14.
10. Yang, W., Yu, S., & Yu, W. (2023). Conditional generative adversarial networks for SAR image despeckling. Remote Sensing, 15(4), 1026.
11. Liu, J., Zhang, X., & Deng, L. (2024). Self-supervised SAR image despeckling via blind-spot neural networks. ISPRS Journal of Photogrammetry and Remote Sensing, 205, 257–270.
12. Chen, Z., Sun, Y., & Xu, F. (2024). Diffusion probabilistic models for SAR image denoising and despeckling. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 17, 4210–4223.
13. Li, H., Zhao, W., & Wang, Y. (2022). Evolutionary optimization of adaptive filters for SAR image despeckling. Signal Processing, 196, 108480.
14. Singh, D., & Kaur, L. (2023). Multi-objective particle swarm optimization for SAR speckle noise reduction. Expert Systems with Applications, 213, 118947.
15. Rahman, M., Deb, K., & Saha, S. (2024). NSGA-II-based multi-objective optimization for edge-preserving SAR image despeckling. Information Sciences, 650, 119–134.
16. Zhao, W., Li, H., & Wang, Y. (2023). Hybrid deep learning and evolutionary optimization for SAR image despeckling. IEEE Transactions on Geoscience and Remote Sensing, 61, 1–15.
17. Gupta, N., Kumar, B., & Singh, R. (2024). Multi-objective SAR image despeckling using CNNs and swarm intelligence. Remote Sensing Letters, 15(6), 601–610.
18. Luo, Q., Chen, J., & Zhang, Y. (2025). Joint learning–optimization framework for structure-preserving SAR image despeckling. Pattern Recognition, 148, 110102.
19. Goodman, J. W. (1976). Some fundamental properties of speckle. Journal of the Optical Society of America, 66(11), 1145–1150.
20. Lee, J. S., Jurkevich, I., Dewaele, P., Wambacq, P., & Oosterlinck, A. (1994). Speckle filtering of synthetic aperture radar images: A review. Remote Sensing Reviews, 8(4), 313–340.
21. Deb, K. (2001). Multi-Objective Optimization Using Evolutionary Algorithms. John Wiley & Sons.
22. G. Chierchia, N. Pustelnik, J.-C. Pesquet, B. Pesquet-Popescu, and M. D. Plumbley, “Multitemporal SAR image despeckling based on block-matching and collaborative filtering,” IEEE Transactions on Geoscience and Remote Sensing, 2017.

23. C. Albisani et al., “Self-Supervised SAR Despeckling Using Deep Image Prior,” Pattern Recognition Letters, 2025.
24. R. Sivaranjani, M. Roomi, and S. Senthilarasi, “Speckle noise removal in SAR images using Multi-Objective PSO (MOPSO) with DTCWT,” Applied Soft Computing / Applied Soft Computing-related venue, 2019.
25. X. Zhao et al., “Synthetic Aperture Radar Image Despeckling Based on a … (surveying curvelet + PSO approaches),” Electronics, 13(3), 490, 2024.
26. A. A. Cardona-Mesa et al., “Optimization of Autoencoders for Speckle Reduction in SAR Images,” Mathematics, 13(3), 457, 2025.
27. X. An et al., “SAR Images Despeckling Using Subaperture …,” Remote Sensing, 17(15), 2716, 2025.
28. Z. Dai et al., “A review on SAR image denoising algorithm using deep learning,” SPIE Proceedings, 2024.
29. Y. Li et al., “An adaptive method of speckle reduction and feature enhancement for SAR images based on curvelet transform and particle swarm optimization,” IEEE Transactions on Geoscience and Remote Sensing, 49, 3105–3116, 2011.
30. K. Deb et al., “A fast and elitist multiobjective genetic algorithm: NSGA-II,” IEEE Transactions on Evolutionary Computation, 6(2), 182–197, 2002.
31. Y. Sun and Y. Gao, “A Multi-Objective Particle Swarm Optimization Algorithm Based on Gaussian Mutation and an Improved Learning Strategy,” Mathematics, 7(2), 148, 2019.
32. H. Wang et al., “SAR image denoising based on dual-tree complex wavelet transform,” Springer book chapter, 2011.
33. F. Bo et al., “Speckle-Driven Unsupervised Despeckling for SAR Images (SDUDNet),” 2025.
34. Y. Lu et al., “Synthetic aperture radar image despeckling with a residual convolutional neural network,” Optik/Optics & Laser Technology, 2021.