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Generative AI in Radar Systems: A Survey of Emerging Techniques and Sectoral Applications

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Abstract – In the contemporary era of technological advancements, integrating Generative Artificial Intelligence (AI) with radar systems has emerged as a groundbreaking approach to enhance the quality and clarity of radar data. This fusion has paved the way for significant improvements in data accuracy and interpretation and, expanded the potential applications of radar technology across various industries; including defense, meteorology, aviation, and autonomous vehicles. Generative AI algorithms, through their ability to learn from vast datasets and generate high-resolution radar imagery, have revolutionized how radar data is processed and analyzed. This paper provides a comprehensive survey of the current state-of-the-art Generative AI technologies applied to radar systems, highlighting critical methodologies, such as deep learning models and neural networks, that have been instrumental in achieving these advancements. Furthermore, it explores the challenges faced in the integration process, including data privacy concerns, computational demands, and the need for robust models capable of handling real-world variability. Through a detailed analysis of recent case studies and experimental results, this survey underscores the transformative impact of generative AI on enhancing radar data quality and clarity, thereby offering insights into future directions and potential breakthroughs in the field.

Keywords – Radar, GAN, VAE, SAR, Image Fusion, Signal Generation

I. Introduction

This work explores the integration of Generative AI in radar applications, discussing its advantages and disadvantages. Thus, understanding these technologies is essential to understand the topic better.

Radar technology was developed in the early 20th century to detect ships in fog. It has been operated with certain algorithms and models based on the principle of using electromagnetic waves for many years. Therefore, it is a technology that has been around for a long time and has a constantly developing structure. Radar technology is used in a variety of fields spanning military, civil, aviation, and space to track objects with data such as location and speed to provide crucial details about the objects it follows [1]. Because the areas in which radar technology is used are sensitive, we conclude that various improvements should be made to the accuracy and sensitivity of the radar, and existing applications should be optimized. Unlike traditional methods, radar technology can work in a way that has not been encountered before with Generative AI. For instance, radar signals can be optimized by using features of Generative AI, considering its ability to synthesize signals and information extraction [2].

Generative AI is built on the foundations of machine learning [3]. Artificial intelligence trained with deep learning techniques, including Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), is used to generate new and unique data, to be then used for improving the evaluation and understanding of the data. This paper examines previous studies of radar applications with implementations based on GANs and VAEs. GANs work on the idea of two neural networks to generate new data based on a given dataset. One of the neural networks generates synthetic data (generator), and the other network (discriminator) judges its reliability. These two networks are in constant competition, trying to deceive each other [4]. Another generative model is VAE, which learns to encode data into a compressed representation and then decode it. The encoder learns latent variables from the input, and the decoder generates an output based on samples of the latent variables. This translation happens in a latent space, where the data's essence is captured. VAEs attempt to generate a model that accurately represents the data's fundamental pattern [5].

By taking advantage of the capabilities of Generative AI, it is possible to talk about innovative developments in radar technology. Multiple studies with different sub-domains about the use of Generative AI in radar applications will be explained further in *Related Work* section: Image Fusion and Enhancement, SAR Image Generation and Target Recognition, Radar Signal Generation and Enhancement. Each of these categories proves that Generative AI can help the radar produce more information about the objects it detects by improving accuracy, reducing noise, and increasing the augmentation of data.

In this study, various Generative AI approaches and their outcomes will be compared to lead the research towards a conclusion where algorithms used in different studies are evaluated in terms of performance and efficiency. While doing the analysis, it is crucial to take into account the protection of sensitive radar data as much as possible [6]. Rather than the superiority of one algorithm over another, the efficiency achieved, the advantages and limitations in real-world scenarios will be discussed. Conducting these reviews is essential in terms of maximizing the potential of these technologies while ensuring that Generative AI does not mislead radar applications with inaccurate data.

II. PREVIOUS WORK

Radar technology is still under improvement. Therefore, it must be considered that there are still issues with the technology's efficiency under different circumstances. To be more specific, the traditional methods used in radar applications face particular challenges when it comes to managing and analyzing complicated data to gather information [7]. The challenges include how traditional radar methods have difficulties in understanding large and noisy datasets, which makes the recognition, clutter suppression, and classification processes of the objects challenging. Considering the dynamic and unpredictable nature of the radar environment, these challenges significantly influence the accuracy of radar systems and their overall effectiveness [8]. The approach to overcoming these challenges to obtain more accurate target detection, navigation, and safety within the radar systems is possible with generative AI.

After carefully analyzing the selected articles, the paper aims to examine different methodologies of Generative AI in radar applications. These analyses will help us to understand the innovations caused by the potential combination of the two powerful technologies in the field. Additionally, every article under each category mentioned in this section will discuss the performance and accuracy of the proposed methods to decide on their advantages and disadvantages. Thus, what kind of results can be concluded from this powerful combination in real-world scenarios will be revealed.

A. *Image Fusion and Enhancement*

This subcategory assumes significant importance within radar applications owing to its potential to positively impact the enhancement of radar image quality and clarity, thereby facilitating improved object detection and identification across diverse operational scenarios.

Grohnfeldt, C. *et al*. [9] provide a cGAN (conditional GAN) based approach, specifically named SAR-Opt-cGAN, for fusing Synthetic Aperture Radar (SAR) images and using it to remove cloud and fog obstructions from Sentinel-2 satellite images. The research aims to use Generative AI to provide better imaging for situations where atmospheric conditions are challenging and various. The study uses a subset of the SEN1-2 dataset and achieves a lower Root Mean Square Error (RMSE) (0.017) and Structural Similarity Index (SAM) (0.006) compared to the Opt-cGAN method where RMSE is 0.023 and SAM is 0.009.

Similarly focused on the objective of image fusion, Li, F. *et al*. [10] present an alternative approach for enhancing the resolution of images obtained from airborne radar systems. To overcome the limitations of traditional radar imaging methods, as these methods generally produce low-resolution images, the proposed method GAN is suggested to create high-resolution images from low-resolution radar data. The results of the study show a significant increase in image resolution. The research is conducted with both simulation and real data with an improvement in azimuthal resolution, which refers to how precisely the radar can determine the horizontal positions of targets.

Addressing the enhancement of marine radar images, Ai, J. *et al.* [11] target the augmentation of ship target contrast within SAR images. Increasing the contrast is important to distinguishing and recognizing the ship targets better from environmental noise. The proposed method ISRGAN, is a GAN-based advanced super-resolution algorithm developed using a Residual Dense Network (RDN) for detailed feature extraction. The results show that the proposed method offers significant improvements in increasing target contrast with a low ATTR (measures the contrast between ship targets and clutter) and low ISR (loss function of the proposed method).

Consistently across all articles within this category, a GAN-based approach has been employed for image fusion and enhancement. Analogous to the preceding subcategory, each article delineates its respective limitations and advantages, as summarized in Table 1.

Table 1. The Advantages and Limitations of the Proposed Methods for Image Fusion and Enhancement

Method	Advantages	Limitations
SAR-OPT-cGAN	Effective removal of cloud and fog	Effectiveness depends on the quality of SAR images
SRGAN	Increasing the resolution of images	High computational cost and the need for large training data set
ISRGAN	Azimuth ambiguity suppression by increasing target contrast	High computational cost

From Table 2, SAR-Opt-cGAN is effective for cloud and fog removal, but the accuracy depends on the SAR image quality; SRGAN provides high resolution but has a high computational cost; ISRGAN reduces azimuth uncertainty and increases target contrast, but computational costs are limited. Therefore, algorithm selection should be tailored to specific requirements and resource constraints.

B. *SAR Image Generation and Target Recognition*

This subcategory within radar applications is critical because it can generate synthetic radar imagery and augment target identification accuracy, particularly in scenarios where real-world data may be inaccessible.

In the study of Zeng, Z. *et al.* [12], the aim is to overcome a challenge where data for training is limited for Automatic Target Recognition (ATR) of SAR images. The proposed method combines two well-known generative models, GAN and VAE, and is named as VAE-Dis. The main purpose is to create images with VAE and use a discriminator to compare the generated images with the real ones. Examining the results of the paper, with the MSTAR dataset being used, it is seen that the model is capable of generating more realistic images than both VAE and GAN methods, with Inception Score (IS) = 1.74 higher than the result of both GAN and VAE models, and Fréchet Inception Distance (FID) = 104.31 lower than the results of the models, two classic metrics for measuring the generative models.

Qin, J. *et al.* [13] have the same aim but a different approach to the study [12]. The authors proposed a new model called CWDCGAN to generate different target categories. It focuses on improving the quality and diversity of generated SAR images. The results of the article show that the method is effective at producing higher-quality images at different training rates and improving recognition accuracy using the MSTAR dataset. In the article, as an example, the mean for CWDCGAN is 0.1096, and for the real sample, it is 0.1089, representing how evaluation values for CWDCGAN are close to the real samples.

Similarly, Peng, G., *et al*. [14] focus on the case where the training data set is limited for ATR. Unlike the previous two articles, the article aims to generate SAR images having a specific feature using cGAN. The approach offers the ability to generate more unique SAR images for ATR models' training data. The obtained results using the MSTAR dataset show that the cGAN has a huge potential for improving ATR systems with an accuracy of 95.94% and 98.99% for AlexNEt and A-ConvNets (deep learning-based algorithms), respectively.

Similarly to the preceding subcategory, the methodologies within this category exhibit their respective advantages and limitations, as delineated in Table 2.

Table 2. The Advantages and Limitations of the Proposed Methods for SAR Image Generation and Target Recognition

Method	Advantages	Limitations
VAE-Dis	Improvement of the accuracy of ATR	High computational cost and long training time
CWDCGAN	Ability to work with limited data	High computational cost and long training time
cGAN	Ability to work with limited data and generate high-resolution SAR images	High computational cost and long training time with a need of high-quality training data

Table 2 indicates high computational costs and lengthy training times for all methods. Despite this, they show promise in achieving their objectives. Method selection should consider these factors, which may pose implementation challenges.

C. Radar Signal Generation and Enhancement

Radar signal generation and enhancement play a critical role in creating precise radar data for object identification in situations with limited data collection capabilities.

T. *et al*.'s study [15] proposes using a GAN specifically tailored to enable hidden object tracking by radar signal generation. Their goal was to meet the challenge of gathering high-quality radar signal data for security and access control systems and integrating this technology. Their results indicate that their method produces realistic radar signals that are not distinguishable by human observers from training data, with very low mean squared error (MSE) (9e-7 at most) for various object sizes.

Charlish, A. *et al*. [16] used VAEs as another and different approach for producing radar signal data by creating Non-Linear Frequency Modulated (NLFM) radar waveforms quickly and flexibly utilizing frequency modulation effects; their method easily created these wave modulation effects. Results indicate that VAE was successful at producing desired wave shapes.

Saarinen and Koivunen [17] employ GANs as an approach to synthesizing radar waveforms with desirable Ambiguity Functions (AFs) and constant modulus properties, including AFs. A Wasserstein GAN (WGAN), trained on Frank & Oppermann codes known for their favorable autocorrelation and cross-correlation properties, synthesizes synthetic waveforms that closely resemble those from their training set while remaining within acceptable cross-correlation levels; results demonstrate close similarities while maintaining low cross-correlation levels - suggesting their potential use within modern radar systems with modern radar systems striving towards increasing adaptability & performance.

Table 3 is provided to evaluate the strengths and weaknesses of the distinct methodologies serving the same objective.

Table 3. The Advantages and Limitations of the Proposed Methods for Radar Signal Generation and Enhancement

Method	Advantages	Limitations
GAN	Generates the required radar signal	Effectiveness depends on the quality of real data and might have challenges in generalization of the real-world scenarios
VAE	Generating fast and flexible radar waveforms	Effectiveness depends on the quality of real data
WGAN	Synthesizes waveforms with good autocorrelation and novelty	Requires complex-valued data handling and high computational cost

In the radar signal generation process, the fidelity of the output is contingent upon the quality of the real data, as evidenced in Table 3. Consequently, careful consideration should be given to the selection of data during the implementation phase.

III. METHODOLOGY

In this section, we present the methodology for comparative analysis. Our primary goal is to evaluate different Generative AI approaches within radar technology, as introduced in the Previous Work section. The criteria for analysis include a review of AI techniques, their advantages, limitations, performance outcomes, and potential applications in the field (see Fig. 1).

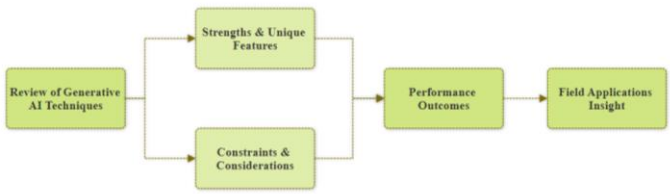

Fig. 1 A criteria flowchart for comparative analysis.

Fig. 1 displays our methodology. In the first step, we investigate generative AI technology; thereafter, we evaluate its limitations, performance potentials and applications in radar manufacturing.

At our research institute, we conducted an intensive assessment of each method's applicability and efficacy for radar applications. Our analyses of AI generative methods shed further insight into their strengths, weaknesses, industry impact and overall applications.

IV. RESULTS

In this section of the paper, the comparative analysis results of generative AI approaches across various radar application subcategories are examined using the metrics mentioned in the *Methodology* section. Each subcategory represents a distinct side of radar technology where generative AI has an important role. The key findings, methodologies, and outcomes for each group of articles will be shared, keeping light on the general trends observed in recent literature, strengths, and limitations of these approaches. Furthermore, how the techniques presented in each subcategory can complement and improve the existing methods in this field will be explored.

A. Image Fusion and Enhancement

General Trends in Current Methods: Recent studies reveal a growing interest in GANs for radar image fusion and enhancement, particularly atmospheric interference removal and resolution enhancement. Notable studies include those by Grohnfeldt *et al.* [9], who use cGAN-based approaches to fuse SAR and optical images for the removal of clouds and haze; Li *et al.* [10] employ GAN models to enhance forward-looking radar images resolution; Ai *et al*. [11] contribute with an aim of increasing ship target contrast using an improved super-resolution GAN model.

Conflicts and Limitations of Methods: Although GANs are widely utilized among researchers, studies that employ them encounter difficulties related to computational demands as well as poor data quality, which limits their scalability.

Gaps and Future Directions: As with any application area, each needs customized radar image enhancement solutions tailored specifically to its own image enhancement requirements. Despite progress made with radar image enhancement techniques, issues with model adaptability and computational efficiency still need addressing - this will require future research in this area to address them effectively. Variability in results highlights the significance of data context when using GAN techniques - thus suggesting new areas to investigate for increasing effectiveness, reliability, and efficiency when performing radar image enhancement techniques.

B. SAR Image Generation and Target Recognition

General Trends in Current Methods: The pattern observed across articles suggests a shift towards advanced generative models (particularly GANs) as an effective solution to SAR image processing challenges for ATR. Challenges related to data scarcity and image generation for target recognition capabilities remain central. Zeng *et al.* [12] proposed using a VAE/GAN combination known as VAE-Dis, while Qin *et al.* [13] employed their new CWDCGAN model, while Peng *et al.* utilized CWDCGAN. [14] offered cGAN; however, there was a conflict regarding its balance between model complexity and computational demands and effectiveness. Methodological disparities, including few-shot learning and Wasserstein GAN adaptations, highlighted the need for tailored solutions tailored specifically for SAR ATR tasks.

Conflicts and Limitations of Methods: Despite advancements, significant gaps still remain between model generalizability, computational efficiency, and image fidelity.

Gaps and Future Directions: Future research should address these gaps by creating adaptable models, exploring unsupervised learning methods, and integrating domain knowledge. Variation in results emphasizes the complexity of SAR image processing; for its continued progress in ATR technologies, it requires a more nuanced understanding.

C. Radar Signal Generation and Enhancement

General Trends in Current Methods: Studies on radar waveform generation examine various advanced generative models such as VAEs employed by Charlish and Schwalm [16], Saarinen and Koivunen [17] with GANs used by Truong and Yanushkevich [15]. This trend marks an apparent move to employing machine learning to increase radar systems' adaptability by creating novel waveforms with specific properties.

Conflicts and Limitations of Methods: Methodological limitations arise when trying to balance model complexity with practical applicability, including computational costs and training stability challenges. Methodological differences highlight diverse approaches, such as waveform synthesis using WGANs for autocorrelation optimization or VAEs for NLFM waveform generation.

Gaps and Future Directions: Current gaps include the lack of models capable of handling complex-valued data efficiently while being applicable across radar systems. Future research may look towards hybrid models or novel training methodologies as a solution, and their variability underscores how closely model architecture, training data, and desired waveform characteristics interact. Tailor-made solutions may present themselves for these issues.

V. DISCUSSION

In this paper, we examined how Generative AI could be integrated with radar systems to enhance data quality and expand applications. Through various studies, we discovered that machine learning models such as GANs and VAEs could significantly increase radar accuracy and functionality across diverse fields such as defense, meteorology, and aviation. Furthermore, our comparative analysis framework enabled a structured evaluation of Generative AI approaches and their impacts on radar technologies.

Our findings illustrate how Generative AI can optimize radar signal generation and image quality through advanced techniques like image fusion and super-resolution - essential components in modern radar applications. Though these results are promising, they also reveal significant computational requirements as well as insufficient data sources required for implementation of these AI models effectively.

Research demonstrated a rise in radar applications' adoption of increasingly complex AI models, in line with general technological progress. Unfortunately, this shift encountered many hurdles regarding model complexity and computational efficiency - an ongoing battleground where Generative AI potential is restricted by practical considerations like resource requirements.

As a result, while Generative AI combined with radar technologies can bring many advantages, there are also some drawbacks that need further investigation. Future efforts should focus on refining AI models to better reflect real-world variations and researching hybrid models that might overcome certain hurdles for more robust and adaptable radar systems.

VI. CONCLUSION

Our research provides concrete proof that Generative AI is an invaluable tool for improving Radar system capabilities. It can both increase data quality and expand its range of applications; however, its integration into existing radar technology is not without challenges; computational complexity must be managed while providing users with high-quality information. Future research should be focused on improving these AI models in order to increase their adaptability and efficiency under real-world conditions. This will ensure that the full potential for Generative AI can be realized. This will improve performance and expand the practical application of radar systems in various industries.

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