SANDIA REPORT
SAND2024-15543
Printed November 2024

Sandia National Laboratories

Applications of Artificial Intelligence to Radar

Joseph Geisz

Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185
Livermore, California 94550

Issued by Sandia National Laboratories, operated for the United States Department of Energy by National Technology & Engineering Solutions of Sandia, LLC.

Available to DOE and DOE contractors from

U.S. Department of Energy
Office of Scientific and Technical Information
P.O. Box 62
Oak Ridge, TN 37831

Telephone:	(865) 576-8401
Facsimile:	(865) 576-5728
E-Mail:	reports@osti.gov
Online ordering:	http://www.osti.gov/scitech

Available to the public from

U.S. Department of Commerce
National Technical Information Service
5301 Shawnee Road
Alexandria, VA 22312

Telephone:	(800) 553-6847
Facsimile:	(703) 605-6900
E-Mail:	orders@ntis.gov
Online order:	https://classic.ntis.gov/help/order-methods

National Nuclear Security Administration

ABSTRACT

In this report, we survey the current intersection between the fields of radar technology and artificial intelligence. Three main areas are highlighted - synthetic aperture radar automatic target detection, waveform optimization, and antenna design. Literature relevant to these applications and beyond are discussed and compiled in an annotated bibliography.

This page intentionally left blank.

CONTENTS

This page intentionally left blank.

1. OVERVIEW

Radar is present in many aspects of our society. Since the second world war, militaries with access to and knowledge of radar technology have had significant advantage over those without. Radar allows pilots to see through clouds and it gives advanced warning of attacks. Today, radar sensors provide rapid and high quality information to human analysts as well as autonomous systems, in particular through the application of synthetic aperture radar (SAR). However, even in peacetime and domestically radar is a hidden part of our daily life. Weather radar provides accurate data for the daily forecast. Airports monitor flight traffic with radar. Cars use radar to keep a safe distance from the vehicle in front of them while in cruise control. Radar is a highly useful technology.

Artificial intelligence (AI) has recently become a household term. While it has a history just as long as that of radar, only in the last decades has AI technology been applied successfully outside of academia. It has captured the attention of the public with it's generative capabilities and prompted philosophical debates about the structure of our society. It evokes fear and confusion in some, and wonder and hope in others. The public's opinion is evolving, but the underlying mathematical concepts are relatively straight forward and the quality of the results is often astounding. There are certain areas in which AI is showing incredible usefulness.

New technology has time and again changed our modern world. But sometimes "hype" causes moderately useful technology to over-promise and under-deliver. When considering applying AI technology to the field of radar, it is important to carefully consider where the strengths of AI can benefit the user, and where the weaknesses could introduce dangers. This report surveys the current literature on how AI has been applied in the field of radar and where successes and failures have been found.

This page intentionally left blank.

2. WHAT IS ARTIFICIAL INTELLIGENCE?

Artificial intelligence is a widely used and poorly understood term. It is broadly defined as "Intelligence" displayed by a machine. However, defining intelligence is no easy task; it is more a philosophical question than a technical one. In our current technological era, the use of the term AI is more often than not referring to machine learning (ML) and even more specifically neural networks (NN). However there are a number of other algorithms and techniques that are not neural networks that are lumped into this umbrella term.

It is important, especially for those tasked with projects relating to national and global security, that there is a clear view of when and how "AI" has already proved useful, where it shows potential, and where there are dangers. Like any tool, AI can be used for good or bad. In order to evaluate the uses of this tool in the literature, one must have a basic understanding of the types of algorithms and many terms used in the field. Below we define some common AI terms.

Artificial Intelligence (AI) This term is extremely broad and simply is defined as a computer or machine displaying "intelligence". It is used almost synonymously with machine learning (ML) which in reality is a subset of AI.

Machine Learning (ML) This is any AI algorithm that makes its decisions based on "learning" from data. Linear regression is a simple form of machine learning. Neural networks are more complex examples.

Artificial Nerual Networks (ANN/NN) A neural network is an algorithm that was originally modeled after the human mind. It takes in an input, and passes that input through a series of "neurons", resulting in an output. The input could be text, images, sound, or anything representable on a computer. The output could be a label for an image, a translation of the text, or a transcription of the sound. Almost all modern "AI" algorithms are NN's. NN's are often broken down into "layers" where the output of one layer becomes input for the next.

Convolutional Nerual Networks (CNN) A convolutional NN is a particular type of NN which is especially suited to gridded data such as images. The network includes at least one "convolutional" layer, in which the 2d input array is convolved with a kernel to produce another 2d array which becomes the input to the next layer. This maintains the 2-dimensional nature of the image, keeping information from adjacent pixels close together.

Deep Learning (DL) Deep learning is any NN where there are many layers. In general, experiments have shown that deep networks have a greater ability to learn than shallower networks and that more complex problems require deeper networks for high accuracy.

Genetic Algorithms (GA) This class of algorithms is modeled after the idea of natural selection. Numerous agents have their parameters assigned at random, and they are tested. They are each evaluated on their performance through a given objective function. The best performing algorithms "survive" and pass on their parameters to the next generation where they are combined in various ways to emulate genetics. When the objective function is well designed, this method can find optimal parameters in large search spaces.

Reinforcement Learning (RL) This type of machine learning can use NNs or other models. It is modeled after the manner in which humans and animals learn from their surroundings. An "agent" interacts with an "environment". It has an internal model for decision making and is given rewards, positive or negative, depending on its chosen actions and state within the environment. The parameters of the internal model are updated based on the reward given, with the intention of optimizing the reward. This has been used successfully, for example, to train computers to play complex video games.

3. APPLICATIONS OF AI TO RADAR

There are numerous applications of AI to radar. In order to narrow down the focus in such a wide field, three topics were chosen and investigated in depth. The first is synthetic aperture radar automatic target recognition (SAR ATR). The second is adaptive waveform design. The third is antenna design. Each is discussed in a separate section. An annotated bibliography includes a selection of relevant literature.

3.1. SAR Automatic Target Recognition (ATR)

Synthetic aperture radar (SAR) allows high-resolution images to be created from radar return data. See [1] for an introduction to SAR and [17] and [6] for more technical explanations of the technology. In the world of SAR, automatic target detection (ATD) is the process of automatically finding a target in a SAR image and automatic target recognition (ATR) is the processes of automatically classifying such a target into a category. In the world of computer vision (CV), object detection is the process of automatically finding an object in an image and classification is the process of automatically classifying the object into a category. In essence, these are exactly the same problems. We have an image (represented in a computer as a grid of numbers) and we wish to automatically find some object of interest, and classify it.

Object detection and classification have been studied extensively over recent year with high quality results due to the boom in deep learning (DL). DL, and in particular convolutional neural networks (CNN's) are extremely well suited to these issues. These algorithms owe their successes in major part to massive freely available datasets collected and transmitted through the internet. The standard published paper in the realm of CV/DL generally uses one of these datasets as a benchmark - a new algorithm or method is presented, it is trained using the "training" subset of the dataset, and it is tested using the "testing" subset. This, in in theory at least, gives a fair comparison of such algorithms as they have the same amount of data to learn from and are tested on similar data which should give researchers an even playing field to test the quality of the algorithms themselves.

SAR ATD and ATR, due to the similarity of the problem posed, have followed the same trend as the more general problem of object detection. The references [29, 3, 20, 25] are all review articles of modern ATR research with hundreds of sources. The conference talk [32] summarizes ATR's past, present, and future. Despite following similar trends, there are some key differences between ATR and object classification research.

Perhaps the most important difference is the lack of training data. To train a classifier differentiating the handwritten digits 0-9, a model can be trained on the MNIST dataset, consisting of 60,000 training and 10,000 testing samples [9]. To train a model to segment toasters and tables and bicycles and humans and other every-day objects from every-day images, one can use Meta's SA-1B dataset consisting of 11 million images with 1.1 billion segmentations [21]. No such dataset exists for SAR images. Not only are SAR images difficult and expensive to come by, many of the targets that consumers of ATR algorithms are interested in are generally top-secret or hidden by foreign governments. Some targets may simply never have been imaged to begin with.

While the lack of data remains an issue, the MSTAR dataset [28] has become the dataset of choice to fill this space in the realm of ATR. MSTAR is significantly smaller than other ML datasets, but offers a more or less fair comparison between algorithms. [5, 10, 30] all present deep learning models to solve the problem of ATR and all test their algorithms using MSTAR as a benchmark. However, issues with the dataset have been uncovered, and other datasets have been developed to solve problems unique to the field. The SAMPLE dataset [24] is derived from MSTAR, but includes synthetic data created using CAD models and EM simulations. This allows researchers to develop algorithms trained on synthetic data but tested on real data [16], a scenario that is relevant for many applications.

Another difference and difficulty associated with ATR and not with CV object recognition is the nature of SAR images. SAR images are different from EO images. While EO images can be blurry (Gaussian noise) SAR images are more often plagued with speckle noise. This is simply the nature of RF imaging. [10] uses artificially introduced speckle noise to augment the MSTAR dataset. This seems to improve robustness to noise. A camera image consists of real-valued intensity values, one channel if grayscale and 3 if color. On the other hand, a SAR image is generally a single channel, but complex-valued. These natural differences between optical and radar images stand in the way of immediate transfer of algorithms, similar to how humans seeing SAR images for the first time may misinterpret the phenomenology uniquely associated with SAR.

A third difference between the problem of SAR ATR and object detection is the consequences of incorrect results. A banana mis-identified as a kitten is a funny example of a deficiency of a detection algorithm. A school bus mis-identified as an enemy tank can have far more serious consequences. The bar for accuracy is much higher when creating algorithms that will be used for national security and in military applications. It is important that unknown targets are classified as unknown, rather than being forced into one of some number existing categories. [16] uses two different methods to score objects as "out of distribution" samples in order to avoid classifying unknown targets.

3.2. Waveform Optimization

When designing a radar system, the choice of waveform is important. In essence, designing a waveform is a constrained optimization problem. There are metrics one would like to maximize or minimize; for example, SAR image clarity or sidelobe interference. There are important constraints; for example, avoiding certain communications channels to eliminate interference or using certain power levels. These are difficult optimization problems, often non-linear, and can require large amounts of computation. In addition, with increasing use of cognitive and adaptive radar, one would like for these optimizations to be made on-the-fly during radar operations to be able to quickly adapt to changing conditions.

Especially in cases when communications systems are operating within the same spectrum, various methods have been proposed to design waveforms in such a way as to minimize interference. There are many traditional methods, dependent on the use case. Papers are often written either from a radar-centric viewpoint or a communications-centric viewpoint, both with the intention of avoiding interference from the other. Sometimes, collaborative approaches are suggested where radar and communication systems communicate in order to share the spectrum effectively. In certain cases, the idea of combining the systems into one piece of hardware has been explored so that a single waveform is used both for communication and for sensing/imaging. [4] and[34] each survey various techniques. [19] focuses on deep learning approaches.

The general waveform optimization problem can be thought of as a game of sorts. The radar has certain controls or "actions" it can take, for example switching between pre-determined modes, changing the duration of a waveform, and choosing between envelopes to modulate the waveform with. It is operating in an "environment" where it receives feedback in the form of return signals that can be of high or low quality, depending on a chosen metric. To have a fully cognitive radar, we need to teach the radar to play this game well.

Reinforcement learning (RL) has shown incredible success in teaching a computer to play video games, even ones that are difficult for humans to play. Rather than training a model via large labeled or unlabeled datasets, in RL an agent is essentially allowed to play around in a dynamic environment. The agent is given rewards based on its performance and the model is updated based on these rewards. If the agent's model is complex enough and the rewards are engineered correctly the model will be able to learn to play the game. [2] is a great review of RL research to date. [8, 31] are both examples which use RL to optimize a radar waveform. [33] uses RL specifically for radar jamming in electronic warfare situations.

One issue that can arise with RL is that the agent can "cheat" by finding an solution for the given optimization problem that is not what the user wanted or expected. This is caused by a poorly chosen reward system. [31] illustrates an example of this problem when the chosen algorithm finds a solution that gets high rewards but does not truly satisfy the desired constraints.

3.3. Antenna Design

Antenna design is a complex task. Depending on the use case there are various requirements and constraints that must be met, measures of quality to optimize, and parameters to optimize over. Often, simulations are slow and compute intensive. Expert knowledge is still vital in the design of antennas, because the problem has such a large space of parameters to explore. However, much of machine learning is based on the idea of optimization, so applications are numerous. The survey article [27] describes various machine learning and genetic algorithms that have been applied to this field.

Array design is an optimization problem, but unlike waveform optimization it does not require interacting sequentially with an environment. Once the antenna is built, it will not be changing. RL is therefore not the best algorithm to apply. Instead, genetic algorithms (GA) currently seem to be the fit for this challenge. GA's are effective for complex optimization problems, even when the space of parameters to be explored is extremely large and complex. These algorithms have been used for many years; the 1995 paper [15] discusses lessons learned in using GA's to optimize antenna parameters and the 1997 review [18] demonstrates a number of applications. The authors of [26] conducted a bibliometric survey of antenna design article and found that AI applied in this field has followed the general trends of AI research. While GA are common and have been used for many years, and discussed in more detail here, DNN's have been used increasingly in the literature while GA's show signs of plateauing.

GAs heuristically work like evolution does. A population of potential solutions is created and tested in some way to measure their fitness. The ones that perform the best are allowed to pass on their "genes" to the next generation. A new population is created based on these survivors, combining their genes in various methods analogous to breeding. This process is iterated over many generations until an optimal or near optimal solution is found.

These algorithms have been applied to optimizing antenna design in many forms. In a collaboration between the private company Meta and academia, [22] uses a genetic algorithm to design optimal planar antenna. The designs are unconventional yet show high performance on the optimized metrics. This is often the case with GA's, and the advantage is often that they do not have the same built in preconceived notions and biases that even human experts posses.

3.4. Other Applications

There are many applications of ML in the field of radar beyond these three chosen topics. [23, 13] both survey the field and include more applications beyond what was discussed. [11] extends the idea of NeRF, a successful ML model, to radar. [14] has a full chapter explaining the use of ML in cognitive radar. Other ideas include synthetic data generation, sidelobe filtering, SAR image registration/orthorectification, and microdoppler analysis for articulated targets.

4. CONCLUSION

From target detection, to adaptive waveforms, to antenna design, AI and ML has been increasingly solving complicated problems in the field of radar. This trend is true in other scientific and technological domains as well. ML algorithms that can make quick, high-quality decisions are already transforming everything from war to finance to graphic design. The book [12] discusses the complexities of an algorithm-filled world and the lessons are broadly applicable. In particular, [7] discusses how "black box" algorithms must have their “values” aligned with the human users. When applying AI to radar, it is important that careful steps are taken to ensure the results are good both technically and ethically.

This page intentionally left blank.

BIBLIOGRAPHY

[1] T. Ager. *The Essentials of SAR: A Conceptual View of Synthetic Aperture Radar and Its Remarkable Capabilities*. INDEPENDENTLY PUBLISHED, 2021. ISBN: 9798512864487. URL: https://books.google.com/books?id=H_3JzgEACAAJ.

This book covers SAR at a high level so that little technical background is required. It discusses the basic physics required to understand signal processing and is a great intro to SAR.

[2] Kai Arulkumaran et al. "Deep Reinforcement Learning: A Brief Survey". In: *IEEE Signal Processing Magazine* 34.6 (2017), pp. 26–38. DOI: 10.1109/MSP.2017.2743240.

This is a thorough review of reinforcement learning, with a focus on the new successes of deep RL. It describes the basis for RL mathematically as a markov decision process and discusses the various techniques for learning optimal policies for agents to interact with their environments. It also discusses research avenues and challenges. While not directly related to radar, this review is great for understanding RL in general terms and in its current state.

[3] Erik Blasch et al. "Review of recent advances in AI/ML using the MSTAR data". In: *Algorithms for Synthetic Aperture Radar Imagery XXVII*. Vol. 11393. https://www.spiedigitallibrary.org/conference-proceedings-of-spie/11393/2559035/Review-of-recent-advances-in-AI-ML-using-the-MSTAR/10.1117/12.2559035.full ; https://ui.adsabs.harvard.edu/abs/2020SPIE11393E..0CB/abstract. SPIE, May 19, 2020, pp. 53–63. DOI: 10.1117/12.2559035. URL: https://lens.org/056-921-243-130-917.

A short summary of SAR ATR development over the years through a focus on MSTAR. They highlight how ATR research has followed the waves of machine learning. They split the discussion into classical ML and deep learning. This review is helpful to see SAR ATR development in a historical perspective, but it doesn't go into much technical detail. Despite this it still uses a lot of radar and DL jargon.

[4] Ashoka Chakravarthi Mahipathi et al. "A Survey on Waveform Design for Radar-Communication Convergence". In: *IEEE Access* 12 (2024), pp. 75442–75461. DOI: 10.1109/ACCESS.2024.3404628.

This survey introduces the problems that come with coexistence between radar and communications systems that share the same spectrum. It gives examples of relevant situations (airport traffic/radar, autonomous cars, and more) and then divides the discussion into two types: cooperative radar communication systems (CRCS) and dual function radar communication systems (DFRC). The first focuses on ways to optimize waveforms for both systems to avoid mutual interference. The second focuses on designing systems that use a single waveform both for sensing and data transmission. ML is mentioned when relevant throughout. This review gives a picture of the current research and possible future work. Its organization is lacking and it is not very concise.

[5] Sizhe Chen et al. "Target Classification Using the Deep Convolutional Networks for SAR Images". In: *IEEE Transactions on Geoscience and Remote Sensing* 54.8 (2016), pp. 4806–4817. DOI: 10.1109/TGRS.2016.2551720.

[6] Margaret Cheney and Brett Borden. *Fundamentals of Radar Imaging*. Society for Industrial and Applied Mathematics, 2009. DOI: 10.1137/1.9780898719291. eprint: https://epubs.siam.org/doi/pdf/10.1137/1.9780898719291. URL: https://epubs.siam.org/doi/abs/10.1137/1.9780898719291.

This book is an introduction to radar imaging with mathematicians as the intended audience. It introduces the technical concepts involved in radar imaging with rigorous mathematics.

[7] B. Christian. *The Alignment Problem: Machine Learning and Human Values*. W. W. Norton, 2020. ISBN: 9780393635836. URL: https://books.google.com/books?id=Lh_WDwAAQBAJ.

This book discusses how AI/ML researchers attempt to teach algorithms "human values". It discusses the intricacies of defining this problem, the partial solutions that have been developed, and the future of ethics in AI. It is a popular-science book with no technical expertise required for reading.

[8] Mario Coutino and Faruk Uysal. "Reinforcement Learning for Radar Waveform Optimization". In: *2023 IEEE Radar Conference (RadarConf23)*. 2023, pp. 1–6. DOI: 10.1109/RadarConf2351548.2023.10149794.

This paper uses a reinforcement learning model to find an optimized waveform. The problem is defined mathematically as a markov decision process and an agent is trained using proximal policy optimization. The agent can choose an up-chirp, down-chirp, or up-down-chirp, can choose how long to wait between pulses, and the duration of each pulse. The model optimizes the waveform to aim for a particular duty cycle and a certain maximum sidelobe level. The paper gives a good description of the problem in exact mathematical terms, but doesn't evaluate performance in depth or explore other training methods.

[9] Li Deng. "The Mnist Database of Handwritten Digit Images for Machine Learning Research". In: *IEEE Signal Processing Magazine* 29.6 (2012), pp. 141–142.

[10] Jun Ding et al. "Convolutional Neural Network With Data Augmentation for SAR Target Recognition". In: *IEEE Geoscience and Remote Sensing Letters* 13.3 (2016), pp. 364–368. DOI: 10.1109/LGRS.2015.2513754.

This short letter compares a simple CNN to older methods like SVM's at target classification on MSTAR. It addresses 3 issues with SAR data: translation variability (targets not centered), speckle noise, and lack of variety in poses of targets. It uses data augmentation techniques to introduce simulated data by translating images, introducing speckle noise, and interpolating between poses to add training samples. It shows that a model trained with all 3 augmentations achieved 93% accuracy on the original test data. This paper is concise. It outlines the issues, suggested solution, and results. It is cited in many of the ATR reviews, likely because of its understandability and good results.

[11] Thibaud Ehret et al. "Radar Fields: An Extension of Radiance Fields to SAR". In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2024, pp. 564–574.

This paper extends the ideas of radiance fields and NeRF's to SAR imagery. The extension is fairly straight forward: the main difference is integrating across rays instead of along rays, the same as the difference between an optical and radar image. The results from simulated data show good performance. This paper is an exciting transfer of technique from the CV/ML world to the SAR/radar world. It had promise, but more research should be done to incorporate InSAR and other existing 3D techniques with this one.

[12] Hannah Fry. *Hello world: Being human in the age of algorithms*. WW Norton & Company, 2018.

This book discusses the prevalence of algorithms in our daily lives. It is a popular-science book and requires no technical background and poses interesting questions about how algorithms affect us personally and at a societal level.

[13] Zhe Geng et al. "Deep-Learning for Radar: A Survey". In: *IEEE Access* 9 (2021), pp. 141800–141818. DOI: `10.1109/ACCESS.2021.3119561`.

This is a general overview of how deep learning algorithms have been used in various ways to solve problems in the general field of radar. It splits its discussion into 4 main categories: 1) waveform and array design, 2) LPI/passive waveform recognition, 3) automatic target recognition and 4) interference suppression. It includes tables summarizing many works in each section. This is a high quality review of the use of deep learning in radar. It is organized and effectively compares techniques without overselling deep learning or making outlandish claims. It discusses the good and bad of ML, including issues and over-hype. It has organized citations and easy to access information.

[14] J.R. Guerci. *Cognitive Radar: The Knowledge-aided Fully Adaptive Approach*. Artech House radar library. Artech House, 2010. ISBN: 9781596933651. URL: `https://books.google.com/books?id=8Mn_C-iOzeEC`.

This book covers many topics that make up cognitive radar. This includes multiple-input, multiple-output (MIMO) radar, scheduling, knowledge aided (KA) adaptive radar, and more. It includes a chapter on applications of ML techniques to cognitive radar.

[15] R.L. Haupt. "An Introduction to Genetic Algorithms for Electromagnetics". In: *IEEE Antennas and Propagation Magazine* 37.2 (1995), pp. 7–15. DOI: `10.1109/74.382334`.

This short article introduces using genetic algorithms for optimizing the parameters of an antenna design. It describes the technical details of implementing the optimization in MATLAB. It describes the problem in mathematical terms and gives results of various tests. It includes a lessons learned section at the end. This is an old, highly cited paper showing how GA's have been used in antenna design for many years.

[16] Nathan Inkawhich et al. "Bridging a Gap in SAR-ATR: Training on Fully Synthetic and Testing on Measured Data". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 14 (2021), pp. 2942–2955. DOI: 10.1109/JSTARS.2021.3059991.

This paper investigates the problem of training an ATR model to detect targets in real, measured SAR images, but using only simulated data in the training process. Using data augmentation, a variety of model architectures, a number of training functions, and model ensembling, they find a model that ultimately achieves 95% accuracy on the SAMPLE dataset using only synthetic examples for training and measured for testing. They use accuracy metrics, saliencey maps, and feature space visualization to analyze the models. They also investigate out of distribution detection for identifying targets that are not in the models knowledge base. This is a very relevant paper in ATR with deep learning. It addresses a huge issue in SAR ATR which is a lack of good training data. Using exclusively synthetic/modeled data eliminates cost associated with collecting lots of data. The results are also promising with 95% accuracy despite the use of no real images in training.

[17] C.V. Jakowatz et al. *Spotlight-Mode Synthetic Aperture Radar: A Signal Processing Approach*. Springer, 1996. ISBN: 9780792396772. URL: https://books.google.com/books?id=kw_Ovq82zc0C.

This book covers the mathematical basis for SAR. It was written by employees at Sandia and is a high quality reference for learning how radar pulses can be formed into high resolution images. It is very mathematical and technical.

[18] J.M. Johnson and V. Rahmat-Samii. "Genetic algorithms in engineering electromagnetics". In: *IEEE Antennas and Propagation Magazine* 39.4 (1997), pp. 7–21. DOI: 10.1109/74.632992.

This review from 1997 explains genetic algorithms with emphasis on applications in electromagnetics. GA's are described analogously to biological evolution, and the encoding of parameters as chromosomes and the updating of chromosomes from generation to generation is explained. It discusses applications to beam forming for linear arrays, reducing side lobes, and patch antenna design. This is a well laid out review that shows the GA's have been used successfully for many years in the world of antenna design.

[19] Bosung Kang et al. "Deep Learning for Radar Waveform Design: Retrospectives and the Road Ahead". In: *2023 IEEE International Radar Conference (RADAR)*. 2023, pp. 1–6. DOI: 10.1109/RADAR54928.2023.10371126.

This summary gives an abstract overview of radar waveform design. It describes waveform design as a constrained optimization problem. It descries the use of fully connected networks, residual networks, and mentions GAN's LSTM, and autoencoders. It then discusses the use of "unrolled" iterative algorithms - taking standard iterative algorithms and converting them into NN's. with tunable parameters, to combine the interpretability of the iterative algorithm with the flexibility of the ML.

This paper doesn't focus on applications, but it is concise in its description of the waveform design problem and solutions and focuses on interpretation of algorithms, which is not always common.

[20] Odysseas Kechagias-Stamatis and Nabil Aouf. "Automatic Target Recognition on Synthetic Aperture Radar Imagery: A Survey". In: *IEEE Aerospace and Electronic Systems Magazine* 36.3 (2021), pp. 56–81. DOI: 10.1109/MAES.2021.3049857.

This review article compares and explores various ATR algorithms focusing on those using MSTAR as a benchmark. While many of the algorithms are DNN's, it also includes more classical algorithms such as feature based methods, sparse representation classification methods, attributed scattering center methods, and low rank matrix factorization methods. It additionally discusses deep learning models beyond CNN's, including autoencoders, Boltzmann machines, and long short term memory (LSTM) networks. It concludes with a direct comparison of accuracies of the models. The article is a god review of MSTAR-tested algorithms, which is a quantitative and scientific way to compare. However it also points out that this methodology may have problems, for example it refers to papers that suggest the background clutter of the targets in MSTAR is correlated to the target, gibing higher accuracy scores than are realistic in wider-ranging applications.

[21] Alexander Kirillov et al. *Segment Anything*. 2023. arXiv: 2304.02643 [cs.CV]. URL: https://arxiv.org/abs/2304.02643.

[22] Slawomir Koziel et al. "On Unsupervised Artificial Intelligence-Assisted Design of Antennas for High-Performance Planar Devices". In: *Electronics* 12.16 (2023). ISSN: 2079-9292. DOI: 10.3390/electronics12163462. URL: https://www.mdpi.com/2079-9292/12/16/3462.

This collaboration between academia and Meta describes an AI approach to antenna design. A flexible parameterization of planar antennas is developed. Then an algorithm is developed which optimizes both the geometry and dimensions of the antenna. It does this using a genetic algorithm first followed by a fine tuning/optimization step. This technique requires only the problem constraints and then produces an antenna meeting those requirements without any need for expert knowledge or manual fine tuning.

[23] Ping Lang et al. *A Comprehensive Survey of Machine Learning Applied to Radar Signal Processing*. https://arxiv.org/abs/2009.13702. 2020. arXiv: 2009.13702 [eess.SP].

This is a survey paper published on the arXiv, but not published through any journal. It gives a survey of AI/ML techniques applied to radar signal processing (RSP). It was uploaded in September 2020 so some of the most recent advances are not included. It includes background on ML algorithms, including multi-representation models. It has an extensive bibliography with citations to relevant papers and other reviews.

[24] Benjamin Lewis et al. "A SAR dataset for ATR development: the Synthetic and Measured Paired Labeled Experiment (SAMPLE)". In: *Algorithms for Synthetic Aperture Radar Imagery XXVI*. Vol. 10987. https://www.spiedigitallibrary.org/conference-proceedings-of-spie/10987/109870H/A-SAR-dataset-for-ATR-Development--the-Synthetic-and/10.1117/12.2523460.full ; https://ui.adsabs.harvard.

edu/abs/2019SPIE10987E..0HL/abstract. SPIE, May 14, 2019, pp. 39–54. DOI: 10.1117/12.2523460. URL: https://lens.org/005-497-399-726-59X.

This paper is a description of the Synthetic and Measured Paired Labeled Experiment (SAMPLE) dataset, derived from the MSTAR dataset. This dataset contains synthetic and real SAR image paris for 10 different targets. The synthetic images were created with realistic CAD models and radar simulations, matching the metadata of the real images. This dataset is released publicly to develop ATR algorithms. Three experiments are outlined to measure different algorithms, 1) train with some percentage of synthetic/real images and test with real images, 2) test with real data of some targets and synthetic data of others and 3) remove some classes completely to identify classes that are out of distribution to avoid false detections. The SAMPLE dataset is important because comparing algorithms for ATR requires a common dataset to work with. this dataset and associated experiments encapsulate the difficulties of SAR ATR by replicating common conditions that would arise for those interested in ATR.

[25] Jianwei Li et al. "A Comprehensive Survey on SAR ATR in Deep-Learning Era". In: *Remote Sensing* 15.5 (2023). ISSN: 2072-4292. DOI: 10.3390/rs15051454. URL: https://www.mdpi.com/2072-4292/15/5/1454.

[26] G. Mani and S. Pohekar. "Growth Profile of Using AI Techniques in Antenna Research Over Three Decades". In: May 2023, pp. 647–663. ISBN: 978-981-99-1413-5. DOI: 10.1007/978-981-99-1414-2_47.

The authors of this paper preformed a bibliometric study of the state of AI techniques used in antenna research. They find that genetic algorithms are the most widely used, but research has plateaued in this area and deep neural network techniques have surged, correlated to the similar trend in general AI research. The authors offer a landscape view of the field and suggest topics which have not seen significant attention. This statistical way of measuring the field offers interesting insights into the trends in this field and gives a high level overview of the field.

[27] Hilal M. El Misilmani and Tarek Naous. "Machine Learning in Antenna Design: An Overview on Machine Learning Concept and Algorithms". In: *2019 International Conference on High Performance Computing & Simulation (HPCS)*. 2019, pp. 600–607. DOI: 10.1109/HPCS48598.2019.9188224.

This short review describes ML at a high level and gives examples of its application to antenna design. It splits applications into two types: ML for parameter optimization and evolutionary algorithms for antenna design. The first use databases of antenna designs to predict performance in order to find optimal parameters with fewer simulations. The second optimize the array design by iteratively evolving the parameters to approximate an optimal antenna. This paper gives a good intro to how ML can be useful in antenna design, but is a bit lacking on some of the details about how the algorithms worked and how much they help.

[28] *Moving and Stationary Target Acquisition and Recognition (MSTAR) Dataset*. The Sensor Data Management System, U.S. Air Force. 2015. URL: https://www.sdms.afrl.af.mil/.

The MSTAR dataset was collected in 1995 and 1996 by Sandia, under a DARPA program. The publicly released dataset consists of a total of 7,171 SAR images of 10 target types imaged at 15° and 17°. It is split into a training and a testing set. This has become the standard dataset for comparing ATR algorithms due to it's consistency and size, similar to the way MNIST, ImageNet or COCO datasets are frequently used for comparing image detection, classification, and segmentation algorithms in the deep learning community. The MNIST dataset, which contains images of handwritten digits 0-9 frequently used to test image classification algorithms, consists of 60,000 training samples and 10,000 test samples. Compared to MSTAR, this shows how the availability of high quality data is an issue for effective ATR algorithms.

[29] Alicia Passah et al. "Synthetic Aperture Radar image analysis based on deep learning: A review of a decade of research". In: *Engineering Applications of Artificial Intelligence* 123 (2023), p. 106305. ISSN: 0952-1976. DOI: `https://doi.org/10.1016/j.engappai.2023.106305`. URL: `https://www.sciencedirect.com/science/article/pii/S095219762300489X`.

This review article summarizes recent research which uses deep learning - in particular CNN's - to preform target detection and target classification in SAR imagery. It details particular issues faced, including speckled/noisy images, lack of training data, and issues with scalability and robustness. It concludes that using updated architectures, more data augmentation techniques, and hybrid networks could further improve results. For the two specific problems posed, this review is very helpful and informative. It gives clear next-step options for future research based on a variety of published papers. It's focus is fairly narrow on CNN architectures, but this is the most relevant network for this task. It only mentions attention networks once despite being published in 2023.

[30] Ronghua Shang et al. "SAR Targets Classification Based on Deep Memory Convolution Neural Networks and Transfer Parameters". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 11.8 (2018), pp. 2834–2846. DOI: `10.1109/JSTARS.2018.2836909`.

[31] Graeme E. Smith and Taylor J. Reininger. "Reinforcement Learning For Waveform Design". In: *2021 IEEE Radar Conference (RadarConf21)*. 2021, pp. 1–6. DOI: `10.1109/RadarConf2147009.2021.9455187`.

This conference paper attempts to use deep RL to train a model that adapts waveforms into "notched" waveforms by choosing various phases which modulate the carrier frequency. to avoid communication channels. It is a simplified example to show the possibility of using such algorithms. The reinforcement learning approach fails because the reward function is formulated such that the algorithm can "cheat" to get high rewards. However, using supervised training the network is able to preform well. While the authors fail to display the use of DRL, this failure is important. It shows the challenges of using an incorrect reward function and how this can cause issues. This is an important negative result.

[32] Edmund G. Zelnio. "Automatic target recognition: past, present, future". In: *Radar Sensor Technology XXVI*. Ed. by Kenneth I. Ranney and Ann M. Raynal. Vol. PC12108. International

Society for Optics and Photonics. SPIE, 2022. DOI: 10.1117/12.2632771. URL: https://doi.org/10.1117/12.2632771.

This conference talk summarizes the unique challenges of ATR. It is a good broad overview, including a history of relevant ML and statistical approaches used in the past. It discusses the needs of good data and getting by with less data It also discusses the need to understand the inner workings of the models. In all, it is a good overview of the state of the art in ATR and general roadmap of where the field may be headed.

[33] Chudi Zhang et al. "Radar Jamming Decision-Making in Cognitive Electronic Warfare: A Review". In: *IEEE Sensors Journal* 23.11 (2023), pp. 11383–11403. DOI: 10.1109/JSEN.2023.3267068.

This review summarizes how decision making is modeled and implemented for Cognitive Jamming in Cognitive Electronic Warfare. It covers traditional methods as well as more modern methods like Q-learning, deep Q-learning, and actor-critic algorithms. These decisions include jamming style, waveform optimization, and resource scheduling. It discusses the research trends in this area.

[34] Le Zheng et al. "Radar and Communication Coexistence: An Overview: A Review of Recent Methods". In: *IEEE Signal Processing Magazine* 36.5 (2019), pp. 85–99. DOI: 10.1109/MSP.2019.2907329.

This review paper summarizes recent methods that have been proposed to solve the issue of radar and communication transmissions sharing the same band of spectrum. They do not discuss ML methods instead they look at various methods to share the spectrum, methods to choose different sub-bands with cognitive radar, and functional coexistence where radar and communication transmissions come from the same transmitter allowing for better coexistence. This is a good review for someone unfamiliar with the general problems in radar and communication coexistence.

DISTRIBUTION

Email—Internal

Name	Org.	Sandia Email Address
Technical Library	1911	sanddocs@sandia.gov

Sandia National Laboratories

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.