



Deep Learning and the Modern Radar

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Received: 29 September 2023 /Accepted: 10 January 2024 /Published: 28 February 2024

Abstract: For decades, radar Systems have been essential for detecting and tracking moving targets, such as aircraft, ships, and vehicles. Their tasks increase in difficulty with the development of more complex targets. A radar system operates by transmitting a high-frequency electromagnetic signal that travels through the air and bounces back when it hits an object. By measuring the time it takes for the signal to return, the radar can determine the distance to the object and its speed. Traditionally, radar signals are processed using classical signal processing techniques, such as filtering, matched filtering, and pulse compression. These methods are generally effective but require significant computational resources, particularly when dealing with large datasets or complex signals. As a result, conventional radar systems that rely on direct sampling of Radio Frequency (RF) signals can be too computationally intensive to obtain accurate range estimates within the required time frame. To address these limitations, recent research has focused on applying machine learning techniques for radar signal processing to process the radar return at machine speed. One such approach is the use of neural networks to perform sequence-to-sequence classification on radar signals. The neural network can be trained using a dataset of radar signals, allowing it to learn patterns and features that are indicative of different types of targets. In addition, the introduction of high-speed and highly maneuvering targets necessitates that the response time of the data and signal processor be fast and optimized to meet the close look track of the system requirements. This study's results show that using a trained neural network can significantly improve the accuracy and efficiency of radar range estimation. The neural network approach can accurately detect targets within the radar system's field of regard and estimate their ranges with an overall accuracy of 99 %, making it a promising alternative to traditional radar signal processing techniques. The use of machine learning techniques, particularly neural networks, has the potential to revolutionize the way radar signals are processed and analyzed. The promising results of this study highlight the importance of exploring innovative approaches to radar range estimation and signal processing, particularly in applications where real-time detection and tracking of targets are critical.

Keywords: Radar range estimation, Artificial intelligence, Machine learning, Deep learning, Neural networks, Sequence-to-sequence classification, Temporal Convolutional Network (TCN).

1. Introduction

Recent advancements in artificial intelligence have presented an exciting opportunity to revolutionize various engineering fields by providing new approaches to solving complex problems. With the

emergence of deep learning, there has been a proliferation of innovative network architectures that have significantly enhanced the field's performance and reliability. In fact, deep learning has become a ubiquitous technology integrated into many applications, ranging from vehicle traffic management

[1], medical [2, 3], wireless communications, the internet, retail, finance, and more. Notably, deep learning is particularly useful in applications where computational complexity is a challenge to traditional methods. This technology has already significantly impacted various areas and is expected to continue driving innovation in engineering in the coming years.

Radar systems engineering has a rich history spanning several decades and plays a crucial role in both commercial and military applications. For instance, in commercial applications, airport radar [4-6] facilitates the efficient management of passenger planes' arrivals and departures by providing real-time information on their range and altitude. Similarly, in military applications, radar systems are employed to detect, track, classify, and discriminate targets on the battlefield, with resource managers controlling the various modes of operation.

Radar systems are complex and composed of multiple subsystems [7, 8], including the receiver exciter, data processor, signal processor, and resource manager. This paper specifically focuses on the signal processor subsystem, its vital role, the conventional signal processing approach [7, 9], and recent advancements. The primary aim is to explore innovative techniques that could simplify the signal processor architecture and report target detection quicker than the traditional matched filtering approach.

By exploring novel techniques in signal processing, this paper seeks to identify strategies that can improve radar systems' efficiency, speed, and accuracy, particularly in target detection. Overall, this investigation could lead to the development of more advanced and reliable radar systems with enhanced capabilities that can effectively meet the needs of various applications.

In recent years, the field of radar systems engineering and design has experienced significant transformation thanks to the remarkable advances in CMOS technology [10-12]. These developments have led to the creation of more reliable Radio Frequency (RF) components, thereby enhancing system performance while simplifying receiver/exciter design. In particular, the latest analog-to-digital converters now possess a faster sampling rate [13-15], creating the opportunity to reduce the number of down-conversion stages required, which in turn gives rise to a more efficient receiver design at a reduced cost.

However, despite the significant improvements in receiver design, there are some drawbacks in the data and signal processor, primarily related to data throughput. To address this issue, one potential solution is the introduction of Artificial Intelligence (AI), especially deep learning. Deep learning can leverage the power of advanced algorithms and neural networks to improve data processing speed, accuracy, and efficiency [16-18].

Moreover, deep learning can enable the development of highly sophisticated algorithms capable of detecting patterns in radar signals that

traditional signal processing approaches might overlook [19-21]. By doing so, AI can enhance the performance and accuracy of radar systems in target detection, tracking, and classification. These recent advancements in AI have shown promising results and have the potential to revolutionize radar systems engineering and design.

Deep learning is a type of artificial intelligence and machine learning that uses neural networks to analyze and make predictions about specific types of data [16]. This technology is referred to as "deep" learning because the neural networks employed can have multiple layers, which allows for more sophisticated data processing and classification.

Deep learning has numerous applications, including facial recognition, natural language processing, and autonomous driving systems. In the context of radar systems, deep learning can be used to enhance the accuracy and efficiency of radar signal processing. Specifically, deep learning techniques can be applied to perform sequence-to-sequence classification on radar signals, which can be used to detect, track, and classify various types of targets.

The use of deep learning in radar systems has the potential to revolutionize the field, providing more accurate and efficient detection and classification capabilities. For example, deep learning can be used to identify subtle variations in radar signals that are indicative of specific targets, which traditional signal processing techniques might miss. Additionally, deep learning can be used to analyze large datasets generated by radar systems to extract valuable insights and identify patterns that are difficult for humans to discern. Overall, the application of deep learning in radar systems is an exciting development with significant potential for improving the performance and capabilities of these critical technologies.

Sequence-to-sequence classification is a widely used technique for analyzing temporal data, where each time step in a sequence is assigned a label. In this study, the researchers focus on classifying time steps in a reflected radar signal and use a neural network called the Temporal Convolutional Network (TCN) to perform this classification. TCN is a powerful deep learning architecture that has shown remarkable results in processing sequential data, including speech recognition and natural language processing.

The researchers aim to evaluate the efficacy of TCN in the context of radar signal processing. Specifically, they want to determine the accuracy of the network's predictions and assess whether it is a suitable candidate for this task. The results of this study may have practical implications for the use of TCN in other areas, such as medical signal processing, finance, and environmental monitoring.

This research is significant because radar signal processing is a complex and challenging task, and the development of accurate classification methods could have important applications, such as in national security and weather forecasting. By assessing the accuracy of the network's predictions, the researchers hope to contribute to the development of more

accurate and efficient radar signal processing techniques.

Overall, this study is an important step in exploring the potential of TCN in the context of radar signal processing. By evaluating the accuracy of the network's predictions and assessing its suitability for this task, the researchers aim to provide valuable insights into the effectiveness of this method and guide future research in this area.

The structure of the paper is organized as follows. In Section 2, the radar data model is formulated, which provides a clear understanding of the input data and the information it contains. In Section 3, the Temporal Convolutional Network (TCN) architecture used in the study is presented, which explains the network's design, structure, and key features. In Section 4, the training methodology used to train the TCN is described, including details on the dataset preparation, hyperparameter tuning, and optimization techniques used. Section 5 discusses the conventional radar signal processing. In Section 6, the deep learning signal processing is presented.

Section 7 presents the simulation results of the study, which includes the evaluation of the network's performance and the comparison of results against traditional methods. This section also includes an analysis of the model's strengths and limitations and how it can be improved in future work. Finally, in Section 8, the paper concludes with a summary of the research findings and the implications of the study, including potential applications and future directions for research in this area.

The paper is structured to provide a clear and concise understanding of the research process, including the formulation of the data model, the design of the TCN architecture, the training methodology, and the simulation results. By following this logical flow, the paper provides a comprehensive view of the study and its contributions to the field of radar signal processing.

2. Radar Model

The radar signal data model that will be used in the simulation is based on the constant low-velocity target model. The radar uses a linear frequency modulated (LFM) signal. The transmit signal for a single pulse is modeled by the signal

$$s(t) = u(t)e^{j2\pi f_0 t} = \text{rect}\left(\frac{t}{T}\right) e^{j2\pi\left(f_0 t + \frac{1}{2}Kt^2\right)}, \quad (1)$$

where $u(t)$ is the envelope of the LFM waveform, T is the pulsewidth, and K is the linear modulation rate. This transmit signal is then down-converted to a baseband signal given by

$$s_b(t) = \text{rect}\left(\frac{t}{T}\right) e^{j\pi Kt^2} \quad (2)$$

When the signal is incident upon a target, since the constant, low-velocity target model is being used, this

target is taken as static while the wave is reflected. Because of this, the reflected baseband signal is modeled by the equation

$$s_{rb}(t) = \text{rect}\left(\frac{t-t_r}{T}\right) e^{j\pi Kt^2} + N(\sigma), \quad (3)$$

where $t_r = 2R/c$ is the time delay for the signal to propagate to the target and back to the radar receiver, and $N(\sigma)$ is the random Gaussian noise of the environment. Since the detection of the target is of interest here, it is necessary to set up the return signal intensity for the single pulse system.

The intensity of the return will be based on the radar range equation (RRE). For the single pulse case, the RRE is given by

$$SNR = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^3 R^4 k T_0 B F L}, \quad (4)$$

where:

P_t is the Peak transmit power;

G is the Array gain;

λ is the Transmit signal wavelength;

σ is the Target radar cross section;

k is the Boltzman constant;

B is the Radar bandwidth;

F is the Noise figure;

L is the Total system losses.

It is assumed that a 13 dB signal-to-noise ratio is needed on the return for a general detection.

3. Temporal Convolutional Network Architecture

In recent years, deep learning has been a game-changer in many fields, including signal processing. Radar return signals, in particular, pose a significant challenge due to their large amounts of temporal data. This is particularly true when one considers reducing receiver design complexity by sampling the return signal at RF. As such, researchers have explored various deep-learning architectures to improve the processing of these signals, with the TCN architecture being one of the most promising.

The TCN architecture is a type of convolutional neural network (CNN) that incorporates dilated convolutions to capture long-range dependencies in the input signal. Compared to other network architectures, TCN offers several advantages, such as better memory size control and easy adaptability. The network can efficiently process long historical sequences, which is critical for our task of classifying radar signals.

The primary objective of our network is to perform sequence-to-sequence classification on the radar signal, as specified in Section 2. The sequence-to-sequence classification task involves labeling each time step in the input signal as "target" or "noise." To achieve this, we will employ a dilated causal convolutional layer.

The dilated causal convolutional layer is a type of convolutional layer that operates in a causal manner, meaning it only operates on past and present time steps Fig. 1. This characteristic makes it ideal for our task of classifying radar signals, as we only need to label the target and noise time steps based on past and present information. The layer's dilation parameter can be adjusted to expand its receptive field and capture long-range dependencies in the signal, allowing us to extract meaningful temporal features.

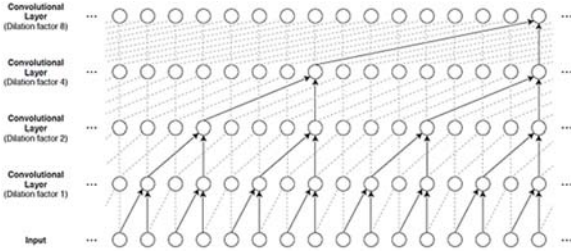


Fig. 1. Dilated Convolutional Layer (Photo Provided by MathWorks).

Overall, the combination of the TCN architecture and dilated causal convolutional layer is expected to significantly enhance our network's ability to classify radar signals accurately. By capturing important temporal features in the signal and efficiently processing long historical sequences, we hope to improve our understanding of radar return signals and support a variety of applications, including target detection, tracking, and recognition.

The defining feature of the convolutional layer is receptive field size. Receptive field size is defined as

$$R = (f - 1)(2^k - 1) + 1 \quad (5)$$

The temporal convolutional network (TCN) is a deep learning model that is particularly well-suited for processing time-domain signals, such as those commonly encountered in radar data analysis. The key idea behind TCNs is to use a series of stacked convolutional layers to extract features from a signal over time while retaining information on long-range dependencies between different temporal patterns. This is achieved by using dilated convolutions, which enable the receptive field of each convolutional layer to grow exponentially with each additional layer.

The two main hyperparameters that can be adjusted to optimize the performance of a TCN are the filter size (f) and the number of stacked convolutional layers (k). By increasing f , one can increase the size of the receptive field, which in turn allows the network to capture more temporal context and potentially improve classification accuracy. However, if the receptive field becomes too large, the network may start to encounter unnecessary data and experience performance degradation. On the other hand, increasing k allows for more complex feature

extraction but can also lead to overfitting and increased computational cost.

In addition to the convolutional layers, TCNs typically include several other layers that are used to improve training efficiency and prevent overfitting. Normalization layers are used to normalize the weights of the parameters in the network, which can help to prevent vanishing or exploding gradients during backpropagation. Spatial dropout layers are used to randomly zero out certain parameters in each layer during training, which helps to reduce the network's reliance on any particular set of features and mitigate the risk of overfitting. The dropout factor hyperparameter associated with each spatial dropout layer determines the proportion of parameters that are zeroed out. Finally, ReLU (rectified linear unit) layers are commonly used as activation functions, which introduce non-linearity into the network and help to capture complex patterns in the data.

The TCN architecture typically consists of a series of "sub-blocks," each of which contains multiple convolutional layers and other associated layers [22, 23]. In the architecture described, there are four main sub-blocks, each of which contains two convolutional layers, as well as normalization, dropout, and ReLU layers. The input radar signal is first passed through the initial sub-block, which contains a 1x1 convolution and skip connection to match the channel dimensions of the subsequent convolutional layers. The signal is then passed through the next three sub-blocks before reaching a fully connected layer, a SoftMax activation function layer, and finally, the classification layer Fig. 2. The number of sub-blocks used is another hyperparameter that must be tuned based on the specific data model being used.

TCNs are a powerful and flexible deep learning architecture that can be used for a wide range of time-domain signal processing tasks [24-26]. By adjusting the various hyperparameters and network architecture components, one can optimize the network's performance for a given dataset and classification task.

The novel radar signal processing technique is characterized by a two-step approach that integrates deep learning and conventional signal processing methodologies. In the initial step, a trained deep learning network rapidly determines the presence of a target or facilitates its detection, thereby yielding a swift response time. The range of the target is deduced in this step. Subsequently, in the second step, conventional signal processing techniques are employed in the vicinity of the target location to extract supplementary features, utilizing only a limited portion of the data. As an illustration, Section 7 demonstrates the utilization of a Range Doppler Map (RDM) to extract the Doppler associated with each target range.

Given the substantial volume of data generated by the employment of a fast ADC and high sampling rate, it is imperative for the signal processor to efficiently process the data stream in real-time to achieve optimal system performance.

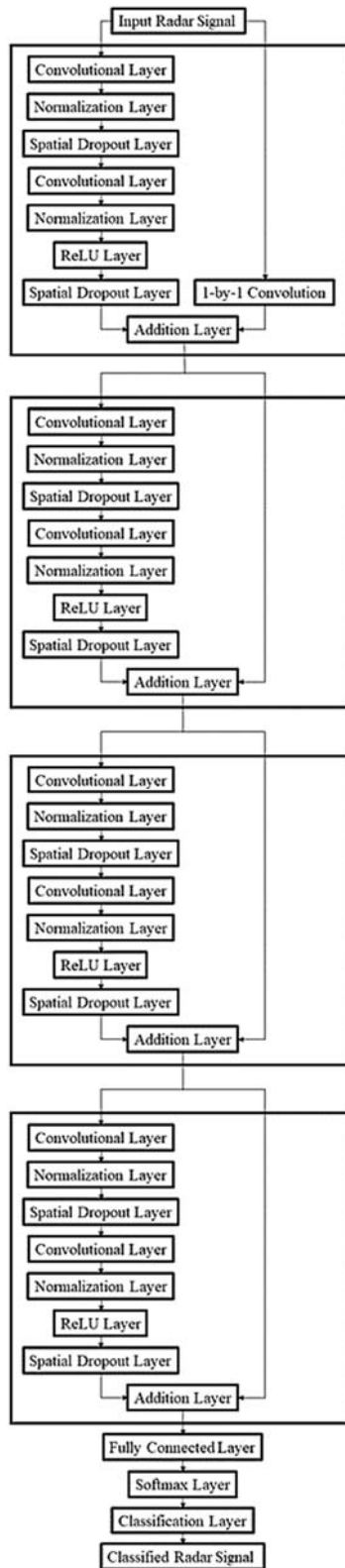


Fig. 2. TCN Architecture.

4. Training Methodology

The process of training a neural network involves feeding it with large amounts of data, and the quality and quantity of the data used can have a significant impact on the performance of the network. For this

particular project, we used radar signals as the training data to train the neural network to detect targets within a range of 100 to 1000 km.

To ensure optimal training results, we varied the ranges of the targets defined in the simulation. By doing so, we were able to generate a training dataset that would provide the neural network with the necessary input to learn how to detect any target within the range band specified. This approach allowed us to cover a wide range of scenarios that the neural network might encounter in real-world applications.

To further optimize the training process, we experimented with two different training methods, the uniform method and the random method. In the uniform method, we generated 10 radar signals with targets located at the lower limit of 100 km. We then incremented the range using a step size equal to the range resolution of the radar system. This approach ensured that the network was accurately trained at every incremental range, allowing it to detect targets with high precision. In contrast, the random method employed a larger and more diverse dataset of radar signals. This approach allowed the neural network to learn to detect targets across a wider range of scenarios and conditions. By doing so, the network was able to generalize better and detect targets within the range band specified more accurately.

Through the use of carefully selected training data and different training methods, we were able to successfully train the neural network to detect targets within a range of 100 to 1000 km with a high degree of accuracy. This achievement has important implications for various applications, such as military and security, where the ability to detect targets from a distance is crucial. This range was then incremented using a step size equal to the range resolution of the radar system, given by

$$\Delta R = \frac{c}{2B}, \quad (6)$$

where c denotes the propagation speed of light, and B denotes the modulation bandwidth of the radar. Again, 10 more radar signals were generated at this range to use as training data. This process is repeated until the upper range limit of 1000 km is reached, training the network along the way.

When it comes to training a neural network, choosing the right training method can significantly impact the model's accuracy, efficiency, and adaptability to different environments. In the case of radar signal detection, two main methods have been experimented with - the uniform method and the random method.

The uniform method involves generating radar signals with targets at different ranges, incrementing the range by a step size equal to the range resolution of the radar system. While this method provides a way to cover a wide range of values, it can lead to overfitting to lower range values and requires an impractical amount of time to train. In contrast, the random method involves generating a large number of

random signals within the defined range band, which reduces the risk of overfitting and makes the training process much faster.

One significant advantage of the random method is that it allows for greater flexibility in the training process. The random generation of signals means that the neural network can be trained to detect targets at various ranges, which makes it more adaptable to different real-world scenarios. This flexibility is crucial in situations where the radar environment is constantly changing, and the network must be able to adapt quickly to new conditions. Additionally, this method ensures that the network is less susceptible to memorizing specific range values and instead learns to identify targets in a more generalized way.

Another benefit of the random method is that it can help the neural network to become more robust to noise. By generating random signals with varying noise levels, the network can learn to recognize patterns in the radar signal despite the presence of noise. This adaptability is essential in real-world scenarios where the radar environment is often noisy and can significantly impact the accuracy of the detection system.

The random method provides many advantages over the uniform method in training neural networks for radar signal detection. Its flexibility, speed, and ability to adapt to changes in the environment make it a suitable approach for real-world applications. By utilizing this method, the neural network can be trained to detect targets over a wide range of ranges while being robust to noise levels, ensuring that the system performs accurately in various conditions.

5. Conventional Radar Signal Processing

Radar signal processing is a complex and sophisticated field that involves a wide range of techniques and methods to extract useful information from radar signals [27, 28]. Its main objective is to detect and interpret radar signals to identify objects or targets in the radar's detection range and to extract information about their location, speed, and size.

The process of radar signal processing begins with the transmission of electromagnetic waves by the radar transmitter. The waves travel through the air and bounce off objects in the radar's detection range, which then return to the radar receiver as echoes. These echoes are then processed by the signal processor to extract information about the detected objects.

One of the key challenges in radar signal processing is filtering the radar signals to remove unwanted noise and interference. Various filtering techniques can be used, such as low-pass, high-pass, and band-pass filters, to remove frequencies outside of the radar's bandwidth or filter out specific types of noise, such as electromagnetic interference.

Another important technique used in radar signal processing is target detection and tracking. This involves identifying and tracking objects in the radar's

detection range by analyzing the radar signals reflected off of them. Target detection algorithms can use various signal processing techniques, such as matched filtering, to distinguish between signals from targets and noise.

Doppler processing is another important technique used in radar signal processing to determine the velocity of a target by analyzing the frequency shift of the radar signals reflected off of it. Pulse compression techniques, such as frequency-modulated continuous wave (FMCW) radar, can increase the range resolution of the radar system by compressing the radar pulse width. Range gating techniques can also be used to isolate radar signals from specific ranges, allowing for more accurate target detection and tracking.

Radar signal processing is a critical component of modern radar systems, and the techniques used play a crucial role in the accuracy, reliability, and efficiency of radar-based detection and tracking systems. As technology advances, the field of radar signal processing continues to evolve, with new techniques and methods being developed to improve the performance and capabilities of radar systems.

6. Deep Learning Signal Processing

Deep learning signal processing combines the power of deep learning with traditional signal processing techniques to process and analyze signals. Alternatively, a Deep learning network can be trained to replace traditional signal processing [29-31]. In the context of sensor signal processing, deep learning techniques can be used to extract features from signals, such as radar signals, that are difficult to detect using traditional signal processing techniques. For example, a deep neural network can be trained to learn the characteristics of radar signals that are associated with specific types of targets or interference and then use this knowledge to detect and classify signals in real-time.

One advantage of deep learning in signal processing is that it can learn complex patterns and relationships in the data, even when the signal processing algorithms do not explicitly define them [32, 33]. This can lead to improved accuracy and reliability of signal detection and classification. Another advantage is that deep learning can be used to process signals in real-time, which is critical in applications such as radar systems for autonomous vehicles, where fast and accurate signal processing is essential for safe operation. More specifically, this is a game changer when it comes to data management and processing in large phased array radars.

Deep learning signal processing is still a relatively new field, and there are many challenges and opportunities for research and development. Some of the key challenges include developing neural network architectures that are optimized for signal processing tasks, dealing with issues such as data scarcity and transfer learning, and understanding the underlying principles and trade-offs involved in using deep

learning for signal processing. Despite these challenges, deep learning signal processing holds great promise for a wide range of applications, from improving the accuracy and reliability of radar systems to enhancing the capabilities of speech and image recognition systems.

7. Performance Analysis

Radar is a crucial technology used in a wide range of applications, including air traffic control, military surveillance, weather forecasting, and automotive safety systems. The performance of a radar system can be evaluated based on several metrics, each of which plays a vital role in determining its effectiveness and accuracy [7, 27].

The range is one of the essential metrics that affect early detection and the maximum distance at which a radar can detect and track a target for given system parameters and radar cross-section. The range depends on various factors, including the transmit power of the radar, the antenna gain, and the sensitivity of the receiver. Higher transmit power and antenna gain result in an increased range for the radar, enabling it to detect targets that are located farther away. Resolution is another crucial metric that measures the radar's ability to distinguish between two targets that are located close to each other. The resolution is determined by the radar's bandwidth, pulse duration, and the number of pulses transmitted. A higher bandwidth and a shorter pulse duration allow the radar to distinguish between targets that are located closer to each other.

Sensitivity is also an essential metric that refers to the minimum detectable signal that a radar can detect. A radar with higher sensitivity can detect weaker signals and is better at detecting small targets. This is particularly important in applications such as weather forecasting, where the radar needs to detect small particles, such as raindrops or snowflakes, and the military where the goal is to avoid detection. Accuracy measures how well a radar can estimate the position, velocity, and other characteristics of a target. Accuracy depends on various factors, including the radar's calibration, signal processing algorithms, and environmental conditions. A radar with high accuracy can provide more precise information about the target, enabling better decision-making in applications such as air traffic control or military surveillance.

Target detection and tracking capability refer to the radar's ability to detect and track targets in real-time. The performance of a radar in this area depends on the radar's signal processing algorithms, tracking filters, and other advanced techniques used for target tracking. A radar with high target detection and tracking capability can accurately track multiple targets simultaneously, even in challenging environments such as clutter and jamming. Largely, the performance of a radar system depends on its design, operating frequency, and the specific application for which it is used. Modern radars use

advanced signal processing techniques, such as adaptive beamforming and waveform diversity, to improve their performance in various applications. These techniques allow the radar to adapt to changing environmental conditions and provide more accurate information about the targets being tracked.

A. Single Target Detection.

Single target detection is an essential process in many radar applications, and the selection of the appropriate radar system and signal processing techniques depends on the specific requirements of the application. To detect a single target, the radar emits a signal and listens for the echoes that bounce back from the target. The radar system analyzes these echoes to determine the distance, direction, and speed of the target.

There are several techniques used for single target detection, including pulse radar, continuous wave radar, and frequency-modulated continuous wave radar. Pulse radar is the most common type of radar used for single target detection. It transmits a short burst of energy, called a pulse, and then listens for the echo. By measuring the time delay between the transmitted pulse and the received echo, the radar can determine the distance to the target [27]. Continuous wave radar, on the other hand, transmits a continuous wave of energy and measures the frequency shift of the reflected wave. This frequency shift, known as the Doppler shift, provides information about the speed of the target. Frequency-modulated continuous wave (FMCW) radar is another technique used for single target detection. FMCW radar transmits a signal with a continuously changing frequency. The radar system analyzes the frequency shift of the reflected signal to determine the distance to the target.

In addition to these techniques, there are several signal processing algorithms used for single target detection, such as matched filtering and thresholding [8]. Matched filtering is a technique that filters out noise and enhances the signal to detect weak echoes from a single target. Thresholding is a technique that sets a threshold level below which signals are considered noise and above which signals are considered a target.

B. Multiple Target Detection.

Multiple target detection refers to the ability of a radar system to detect and track multiple targets simultaneously within its coverage area. This is a crucial capability for many radar applications, including air traffic control, military surveillance, weather monitoring, and more. To achieve multiple target detection and extract additional target features, radar systems typically use a combination of signal processing techniques such as pulse compression, frequency diversity, angle of arrival estimation, and range doppler map Fig. 3. These techniques help to enhance the signal-to-noise ratio of radar returns and to separate the signals from different targets in the radar's field of view. One common approach to multiple target detection is to use a phased array radar system. Phased array radar employs multiple antenna elements that can be individually controlled to steer

the radar beam in different directions. This allows the radar to scan a large area rapidly and to track multiple targets simultaneously [9].

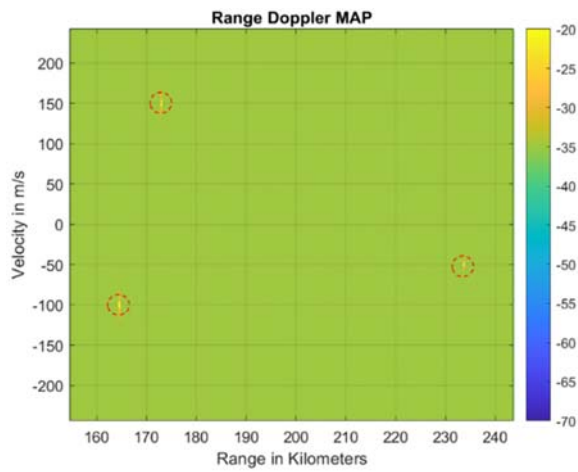


Fig. 3. Range Doppler Map showing three targets as the second step in the signal processor following target detection from the trained deep learning network.

Another approach to multiple target detection is to use advanced signal processing algorithms such as adaptive beamforming and waveform diversity. Adaptive beamforming can help to reduce interference from other radar sources or jamming signals, while waveform diversity can help to improve the detection and tracking of low-observable targets.

Overall, radar multiple target detection is a complex and challenging problem requiring advanced signal processing techniques, radar hardware design, and system integration. However, it is a critical capability for many radar applications and essential for ensuring safety and security in many domains.

C. Probability of Detection.

Radar probability of detection (P_d) is a measure of the likelihood that a radar system will detect a target that is present in its field of view. P_d is an important metric in radar performance evaluation and is typically expressed as a percentage or a decimal between 0 and 1.

The probability of detection depends on a variety of factors, including the radar's transmit power, antenna gain, receiver sensitivity, and signal processing algorithms. In general, higher transmit power and antenna gain will improve the radar's ability to detect targets at longer ranges and in adverse weather conditions. Similarly, more sensitive receivers and advanced signal processing algorithms can help to detect weaker radar returns and improve target discrimination.

In addition to hardware and software factors, the probability of detection also depends on the characteristics of the target itself, such as its size, shape, and reflectivity. Larger targets with higher radar cross-sections (RCS) will generally be easier to detect than smaller or low-observable targets.

To estimate the probability of detection for a particular radar system and target scenario, radar engineers typically use computer simulation or empirical testing. Simulation models can help to predict the expected performance of a radar system under different operating conditions Fig. 4, while testing can provide more accurate measurements of actual radar performance.

Radar probability of detection is a key performance parameter that is critical for many radar applications, including air traffic control, military surveillance, weather monitoring, and more. Improving the probability of detection is an ongoing challenge for radar engineers and requires a combination of hardware and software advancements, as well as a deep understanding of target characteristics and radar system behavior.

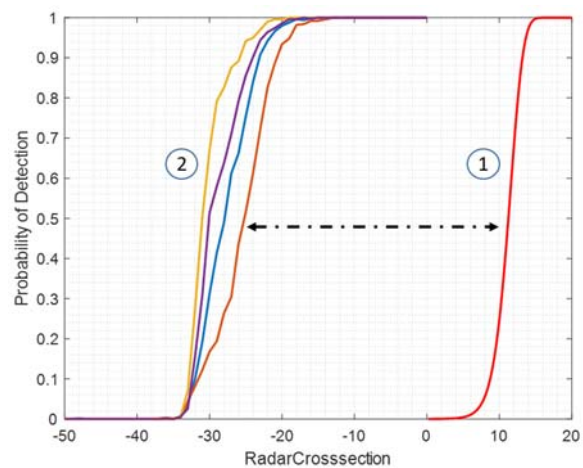


Fig. 4. Probability of detection curves for four probability of false alarms [$1e-4$ $1e-6$ $1e-7$ $1e-8$] and (1) the theoretical probability of detection curve in conventional radars. The trained deep-learning network shows considerable improvement in target detection for the same system parameters.

8. Conclusions

The paper introduces a state-of-the-art method for detecting radar targets, which utilizes deep learning and employs a sequence-to-sequence evaluation with a temporal convolutional network. The approach is novel and offers several advantages over traditional radar target detection methods. One key advantage is that recent advances in faster analog-to-digital converters have made it possible to simplify radar receiver designs, increase efficiency, and reduce costs.

However, these advances come with some challenges, such as high computational complexity for the signal processor when sampling the radar return at RF. The proposed detection scheme overcomes these challenges and demonstrates that real-time target detection on raw radar data can be achieved without the need for preprocessing. The experimental results show that this approach achieves high accuracy and

can be easily integrated into existing radar signal processors.

This method is particularly significant as it enables accurate detection of targets in complex and dynamic environments where traditional methods may fail to perform. Additionally, this approach offers flexibility in the design of radar systems, allowing for better adaptation to diverse applications. Overall, this work represents a major contribution to the field of radar target detection and offers a promising direction for future research in this area.



References

- [1]. V. Katariya, M. Baharani, N. Morris, O. Shoghli, H. Tabkhi, DeepTrack: lightweight deep learning for vehicle trajectory prediction in highways, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, Issue 10, 2022, pp. 18927-18936.
- [2]. S. Yang, *et al.*, Learning COVID-19 pneumonia lesion segmentation from imperfect annotations via divergence-aware selective training, *IEEE Journal of Biomedical and Health Informatics*, Vol. 26, Issue 8, 2022, pp. 3673-3684.
- [3]. L. A. Thomaz, S. M. M. Faria, L. M. N. Távora, L. Marcenaro, Automatic medical image diagnosis: highlights from the 2021 IEEE 5-minute video clip contest [SP competitions], *IEEE Signal Processing Magazine*, Vol. 39, Issue 3, 2022, pp. 130-134.
- [4]. T. Martelli, C. Bongioanni, F. Colone, P. Lombardo, L. Testa, A. Meta, Security enhancement in small private airports through active and passive radar sensors, in *Proceedings of the 17th International Radar Symposium (IRS'16)*, 2016, pp. 1-5.
- [5]. P. Lanzkron, E. Brookner, Solid state X-band airport surface surveillance radar, in *Proceedings of the IEEE Radar Conference*, 2007, pp. 670-676.
- [6]. H. Ghadaki, R. Dizaji, Target track classification for airport surveillance radar (ASR), in *Proceedings of the IEEE Conference on Radar*, 2006.
- [7]. D. K. Barton, *Radar Equations for Modern Radar*, Artech House, 2012.
- [8]. B. R. Mahafza, *Radar Systems Analysis and Design Using MATLAB*, 3rd Ed., CRC Press, 2013.
- [9]. M. A. Richards, *Fundamentals of radar signal processing*, 2nd Ed., McGraw-Hill Education LLC, Chicago, Ill., 2014.
- [10]. T. B. Ngo, Q. H. Do, S. W. Yoon, A wideband circulator leakage canceler for retro-directive RF system, *IEEE Microwave and Wireless Components Letters*, Vol. 32, Issue 10, 2022, pp. 1211-1214.
- [11]. S. Park, S. Hong, Millimeter-wave wideband differential four-way Wilkinson power divider with 90° rotational symmetric layout, *IEEE Microwave and Wireless Components Letters*, Vol. 32, Issue 10, 2022, pp. 1163-1166.
- [12]. F. Yu, *et al.*, A low phase noise VCO with placement reordered cores, high-Q bond wire array inductors, *IEEE Transactions on Circuits and Systems II: Express Briefs*, Vol. 69, Issue 9, 2022, pp. 3754-3758.
- [13]. V. Hiremath, S. Ren, An ultra high speed encoder for 5GSPS Flash ADC, in *Proceedings of the IEEE Instrumentation & Measurement Technology Conference Proceedings*, 2010, pp. 136-141.
- [14]. T. Li, Y. Zhang, Y. Ni, An ultra-fast ADC linearity test and calibration method, in *Proceedings of the IEEE 13th International Conference on Anti-counterfeiting, Security, and Identification (ASID'19)*, 25-27 Oct. 2019, pp. 282-285.
- [15]. Y. Zhang, T. Li, Z. Huang, Y. Ni, D. Fu, High-gain and fast-setting OTA for high speed and high resolution ADC, in *Proceedings of the IEEE International Conference on Electron Devices and Solid State Circuits (EDSSC'18)*, 6-8 June 2018, pp. 1-2.
- [16]. H. C. Kaskavalci, S. Gören, A deep learning based distributed smart surveillance architecture using edge and cloud computing, in *Proceedings of the International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML'19)*, 26-28 Aug. 2019, pp. 1-6.
- [17]. H. Phan, F. Andreotti, N. Cooray, O. Y. Chén, M. D. Vos, SeqSleepNet: end-to-end hierarchical recurrent neural network for sequence-to-sequence automatic sleep staging, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 27, Issue 3, 2019, pp. 400-410.
- [18]. Y. Tang, J. Xu, K. Matsumoto, C. Ono, Sequence-to-sequence model with attention for time series classification, in *Proceedings of the IEEE 16th International Conference on Data Mining Workshops (ICDMW'16)*, 12-15 Dec. 2016, pp. 503-510.
- [19]. Y. Deng, L. Wang, H. Jia, X. Tong, F. Li, A sequence-to-sequence deep learning architecture based on bidirectional GRU for type recognition and time location of combined power quality disturbance, *IEEE Transactions on Industrial Informatics*, Vol. 15, Issue 8, 2019, pp. 4481-4493.
- [20]. S. Arniriparian, M. Freitag, N. Cummins, M. Gerczuk, S. Pugachevskiy, B. Schuller, A Fusion of Deep Convolutional Generative Adversarial Networks and Sequence to Sequence Autoencoders for Acoustic Scene Classification, in *Proceedings of the 26th European Signal Processing Conference (EUSIPCO'18)*, 3-7 Sept. 2018, pp. 977-981.
- [21]. T. Ni, X. Ding, Y. Wang, J. Shen, L. Jiang, G. Zhang, Spectrum sensing via temporal convolutional network, *China Communications*, Vol. 18, Issue 9, 2021, pp. 37-47.
- [22]. M. Liu, H. Qin, R. Cao, S. Deng, Short-term load forecasting based on improved TCN and DenseNet, *IEEE Access*, Vol. 10, 2022, pp. 115945-115957.
- [23]. X. Yuan, S. Qi, Y. Wang, K. Wang, C. Yang, L. Ye, Quality variable prediction for nonlinear dynamic industrial processes based on temporal convolutional networks, *IEEE Sensors Journal*, Vol. 21, Issue 18, 2021, pp. 20493-20503.
- [24]. F. Luo, S. Poslad, E. Bodanese, Temporal convolutional networks for multiperson activity recognition using a 2-D LIDAR, *IEEE Internet of Things Journal*, Vol. 7, Issue 8, 2020, pp. 7432-7442.
- [25]. H. Wang, D. Hu, M. Zhang, N. Li, Y. Yang, Multiphase flowrate measurement with multimodal sensors and temporal convolutional network, *IEEE Sensors Journal*, Vol. 23, Issue 5, 2023, pp. 4508-4517.
- [26]. Y. Cheng, Y. Xu, H. Zhong, Y. Liu, Leveraging semisupervised hierarchical stacking temporal convolutional network for anomaly detection in IoT communication, *IEEE Internet of Things Journal*, Vol. 8, Issue 1, 2021, pp. 144-155.
- [27]. W. L. Melvin, Principles of modern radar, in *Radar Applications* (W. L. Melvin, J. A. Scheer, Eds.), Vol. 3, SciTech Publishing Inc., 2013.

- [28]. F. E. Nathanson, Radar Design Principles: Signal Processing and the Environment (J. P. Reilly, M. Cohen, Eds.), 2nd Ed., McGraw-Hill, 1991.
- [29]. Y. Liu, Y. Li, Y. Zhu, Y. Niu, P. Jia, A brief review on deep learning in application of communication signal processing, in *Proceedings of the IEEE 5th International Conference on Signal and Image Processing (ICSIP'20)*, 23-25 Oct. 2020, pp. 51-54.
- [30]. P. Y. Hsu, C. K. Cheng, Arrhythmia Classification using deep learning and machine learning with features extracted from waveform-based signal processing, in *Proceedings of the 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC'20)*, 20-24 July 2020, pp. 292-295.
- [31]. W. Li, K. Wang, L. You, Z. Huang, A new deep learning framework for HF signal detection in wideband spectrogram, *IEEE Signal Processing Letters*, Vol. 29, 2022, pp. 1342-1346.
- [32]. A. Jagannath, J. Jagannath, T. Melodia, Redefining wireless communication for 6G: signal processing meets deep learning with deep unfolding, *IEEE Transactions on Artificial Intelligence*, Vol. 2, Issue 6, 2021, pp. 528-536.
- [33]. A. M. Elbir, DeepMUSIC: multiple signal classification via deep learning, *IEEE Sensors Letters*, Vol. 4, Issue 4, 2020, pp. 1-4.

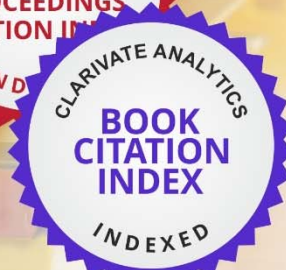


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