Advances in Radar Signal Processing: Integrating Deep Learning Approaches

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Abstract. In the military, in daily life, and in scientific research, radar technology is widely used. Radar signal processing has long been an essential component in target detection and imaging. The development of deep learning technology in recent years has given radar signal processing new approaches and resources. With its exceptional feature extraction and pattern recognition skills, deep learning has made amazing strides and has been applied to radar signal processing to enhance tasks like target detection, tracking, and recognition. Traditional radar signal processing is based on models. It mainly uses the prior information of the model and related signal processing criteria to design signal processing methods. It uses Gaussian, linear, and stationary assumptions. The deep learning method is a data-based method that does not require prior knowledge of the model and can spontaneously find the relationship between the input of the algorithm and the expected output. This article will review traditional methods and deep learning methods in radar signal processing, focusing on the application and future development direction of deep learning methods in radar signal processing, briefly sorting out the research progress in recent years, and analyze some existing problems or shortcomings of existing methods.

Keywords: Radar signal processing; Deep learning Radar target detection; Automatic target recognition; Moving target tracking.

1. Introduction

Radar is an electromagnetic system that uses electromagnetic energy for target detection, tracking and identification. Radar systems are mainly composed of antennas, transmitters, receivers, signal processors and terminal equipment. The antenna transmits high-power signals and receives target echo signals. The transmitting end mainly includes waveform generation and power amplification. The receiving end performs power amplification, frequency down conversion and analog-to-digital conversion (A/D) of the received signal. Signal processing performs a series of processes on the received digital signals to generate target traces and sends them to the back-end data processing. For active radar, it detects targets by emitting electromagnetic signals and forming a judgment on whether there is a target echo in the received signal. The received signal of radar consists of possible target echo, clutter, interference and noise. The target echo is related to factors such as the detected target characteristics, distance and atmospheric loss. Clutter, interference and noise are related to the radar working environment.

2. Radar signal processing method

2.1. Traditional radar signal processing methods

The primary techniques for processing radar signals now in use include pulse Doppler processing, digital beam shaping, waveform matching filtering, and moving target detection [1]. For signal processing in the fast time dimension, waveform matching filters are mainly used. It uses over-threshold detection to distinguish signals and noise by exploiting the difference in waveforms between signals and noise. When the noise is Gaussian white noise, waveform matching filtering is optimal for this deterministic signal. When the noise no longer obeys the Gaussian distribution, this signal processing method will no longer be optimal. The main goals of signal processing in the slow time dimension are to suppress clutter and coherently accumulate moving targets. For moving targets, the echo signal contains unknown phase terms, which is no longer a deterministic signal and therefore is not suitable for matched filtering. For the detection of moving targets, existing methods are mainly pulse Doppler processing based on DFT, which distinguishes signals and noise in the Doppler domain.

The design of existing radar signal processing methods is mainly derived from modeling of the physical characteristics of signal propagation and the statistical characteristics of noise. For example, assuming that the noise obeys Gaussian distribution and the target signal is a deterministic signal, the waveform matching filter is derived from the optimal detection theory. The distribution of clutter and targets in the frequency domain is different, so a clutter suppression algorithm and a pulse Doppler processing algorithm are designed. Model-based signal processing is the name given to this type of signal processing that is created using the signal model, which includes the physical model of the signal and the measurement of noise [2]. The design of model-based signal processing methods mainly considers three aspects: criteria, models and algorithms. Criteria describe the objectives and constraints for detector design. A model is a formal representation of a physical process. It formalizes prior information such as signal generation, propagation characteristics, receiver characteristics, noise characterization, etc. Criteria and models determine the design of algorithms. In existing model-based signal processing methods, the design of the model depends on the study of physical phenomena by human experts, using a large number of Gaussian, linear and stationary assumptions [3]. The deep learning approach is a data-based technique that may automatically determine the relationship between an algorithm's input and its anticipated result. It does not require any prior understanding of the model. Deep learning has also shown remarkable promise in solving some challenging modeling challenges in recent years, such as computer vision [4], speech signal processing [5], natural language processing [6], etc. The following therefore outlines how deep learning methods can be applied in radar signal processing. Numerous research have examined the use of deep learning in radar, with the majority focusing on target identification and detection.

2.2. Deep learning methods in radar signal processing

2.2.1 Convolutional Neural Network (CNN)

One kind of artificial neural network is the convolutional neural network. Both the number of weights and the complexity of the network model are decreased by its weight-sharing network topology. This benefit is especially clear when a multi-dimensional picture is used as the network's input. In CNN, the data is sent to several levels sequentially, with the image serving as the input at the base of the hierarchical structure. By using multi-layer learning, the intricate structure inside the data may be automatically identified, eliminating the need for the laborious feature extraction procedure found in conventional algorithms. In radar signal processing, convolutional neural networks are extensively employed for feature extraction and target recognition. CNN can enhance signal processing performance and efficiently capture important information in both the time and frequency domains by creating convolution kernels that adjust to the unique properties of radar data.

2.2.2 Recurrent Neural Network (RNN)

Neural network models also heavily depend on Recurrent Neural Networks (RNN). It is frequently utilized in the field of natural language processing because of its unique structural unit, which also gives it great memory capabilities and the capacity to convey pertinent sequence data. RNN enhances the tracking and prediction skills of moving targets by capturing the temporal dependencies of the data. Its primary distinction from CNN is the presence of recurring hidden layers.

2.2.3 Application of Deep Neural Network (DNN)

DNN is composed of many neuronal layers, usually consisting of an input layer, multiple hidden layers, and an output layer. Multiple neurons are present in each layer, and weights are used to connect the neurons in neighboring layers. A deep neural network is called "deep" because it has multiple hidden layers, which allows it to learn more complex and abstract feature representations. When training deep neural networks, the backpropagation technique is typically used to minimize the loss function and modify the network's weights in order to get the output as near to the true value as feasible. The network may learn the intricate mapping relationship between input and output during the training process by using the back propagation technique. This allows for representation learning and the extraction of features from the input data.

3. Radar signal processing applications based on deep learning

3.1. Radar target detection (RTD)

Neural networks typically have neurons, weight vectors, activation functions, biases, and other components. A neural network with numerous hidden layers and interconnected neurons in each layer is called a multilayer perceptron (MLP). Neural networks' capacity for learning makes it possible to use them for radar target detection. The radar target identification problem is actually better understood as a pattern recognition problem, which is a good fit for artificial neural networks' capabilities [7]. Deep learning models are used in radar target detection, which is the process of autonomously identifying and localizing targets from radar data. Since radar data has special timing and physical characteristics, compared with image-based target detection, radar target detection based on deep learning needs to take into account the sparseness of the data, the Doppler effect and other characteristics. Recurrent neural networks (RNN) are frequently used to process the temporal aspect of radar data, and convolutional neural networks (CNN) are frequently utilized to extract spatial and temporal characteristics.

There are several methods that show that using artificial neural networks (ANNs) as nonlinear detectors can improve detection performance. Conventional radar signal processing techniques are applied as training data preparation techniques, which help to improve detection performance and extract useful characteristics. However, since the DNN model can automatically extract features from the input and perform matching filtering and coherent accumulation, which are essentially convolutional calculations similar to classic processing methods, DNNs can be used to identify targets from unprocessed radar echoes. Jiang et al. [8] proposed a CNN-based RTD model that directly processes radar echo signals, thus avoiding the traditional signal processing process. Compared with traditional methods, CNN-based models have better detection accuracy and performance. Deep learning technology has made significant progress in radar target detection and recognition tasks. Through the end-to-end learning framework, the model can automatically extract the characteristics of the target and achieve efficient target detection and classification.

In addition to determining if the radar echo to be measured is comprised of noise or a target signal, the primary goal of RTD is to acquire multi-dimensional position and motion information. The facts demonstrate DNN's excellence and qualification in RTD. DNN features a more intricate architecture and distinct training techniques for more complicated RTD scenarios. Furthermore, several preprocessing techniques for radar data processing might help enhance detection performance by efficiently extracting characteristics. RTD based on deep learning has broad application prospects in practical applications. It can overcome the reliance on feature engineering in traditional methods, better process complex radar data, and achieve efficient and accurate detection of targets. As a result, combining new deep learning principles with established detection techniques has emerged as a viable trend and solution for RTD applications.

3.2. Automatic target recognition

Target identification, battlefield reconnaissance, and long-range remote sensing are all possible with the radar while it is operating in image mode. After imaging to identify targets of interest, picture interpretation is necessary to gain more accurate information. Traditional manual image interpretation has low efficiency, high error rate, consumes a lot of resources, and cannot meet the needs of time-sensitive applications. Data-based deep learning methods provide a new technical route that eliminates the need for manual feature engineering and target modeling. Using measured data, the deep neural network approach may extract a variety of hidden properties from targets, eliminating the need for laborious high-frequency electromagnetic computations or the construction of intricate, high-fidelity models. In the present field of automatic radar target detection, it has emerged as a new hot zone. Convolutional neural network (CNN) does not require feature extraction and selection, and has excellent image classification performance. As a result, it has drawn increasing attention from researchers studying radar automatic target recognition. CNN can extract features in radar images through convolutional layers and pooling layers. Convolutional layers can effectively capture local features in images, while pooling layers can reduce the dimensionality of features while retaining important information, thereby speeding up calculations and reducing the risk of overfitting. Targets in radar images may have different scales, so CNN usually designs multi-scale convolution kernels to capture features at different scales. This allows the network to better adapt to targets of different sizes and improves recognition accuracy.

The model can be pretrained on other large-scale data sets as the initial model, and then refined on the radar data set, if the training data set is tiny. This is known as the transfer learning approach [9]. This speeds up model training and improves model performance. CNN plays an important role in automatic radar target recognition. By designing appropriate network structures and training methods, efficient and accurate recognition of targets in radar images can be achieved. Radar data with temporal properties, like time series data from radar scans, can be processed using recurrent neural networks (RNN). This technique can help increase the accuracy of target recognition by capturing the target's changing properties over time.

3.3. Moving target tracking

Technology such as target tracking is vital. Its basic idea is to use sensors to gather measurement data from the target, record its motion characteristics, and then use a filtering algorithm to estimate and forecast the target's current condition [10]. Single target and multi-target tracking technologies are the two categories of target tracking technology. Among them, multi-target tracking technology is compatible with single target tracking problems, has a broad variety of applications, and is challenging. It is now at the forefront of target tracking technology for radar image sequences.

Combined with the timing processing capabilities of deep learning, it is possible to track moving targets detected by radar. Use deep learning models to extract features in radar images to capture the motion and morphological characteristics of targets. These features can be used to distinguish different targets and help the tracker better understand the target's movement patterns. Target detection is used to identify the location and shape of targets in radar images, while target tracking continuously tracks the target's movement trajectory and updates the target's location and status information. The deep learning model is used for motion prediction to forecast the target's future position and trajectory of movement based on its properties. This makes it easier to anticipate reactions and keep a closer eye on the target's movement. It is possible to think of the radar target tracking problem as a type of time series prediction problem. Many works of literature currently exist that demonstrate how the Long Short-Term Memory (LSTM) network [11] can be used to solve time series prediction issues. Later researchers also made significant contributions to time series problems with their suggested network models, which included the Transformer, Temporal Convolutional Network (TCN), and Convolutional Long Short Term Memory (ConvLSTM) network [12]. Regarding time series prediction problems and visual tracking problems, deep learning technology has shown great advantages. Therefore, exploring the application of LSTM, Transformer, TCN and other networks in radar multi-target tracking is a forward-looking research direction.

4. Challenges and future prospects

4.1. Existing neural network-based detectors have certain limitations

Treating signal detection as a regression problem, the neural network is trained using the mean square error loss function. However, supervision data for the regression problem is difficult to obtain, which limits the scope of use of this type of neural network-based detector.

The neural network's detection performance will decline if the signal-to-noise ratio of the test data differs from the training data since it only uses data with a single signal-to-noise ratio for training and testing.

4.2. Difficulties in data labeling and acquisition

The training of neural networks requires large and complete training data support, otherwise it will easily lead to overfitting. The difficulty of model-based methods lies in modeling physical phenomena, while the main difficulty of model-free, data-driven methods such as neural networks lies in the collection of large amounts of complete data. How to use prior knowledge to reduce the data set requirements for neural network training has been the main research task of small sample learning in recent years.

Radar signal data usually requires a large amount of annotation to be used for deep learning model training. Annotating large-scale radar data is still a challenge, especially for complex scenes and multi-category targets. In addition, how to effectively obtain representative data sets is also a problem that needs to be solved. The following methods can be used for further research in the future: (1) Develop learning-based methods, such as transfer learning [9], thereby reducing reliance on large amounts of annotated data. (2) Data enhancement [13]. Rotation, translation, scaling and other operations can be performed on the existing small amount of annotated data to generate more diverse data, thus increasing the diversity of training data.

4.3. Real-time and computing resources

Radar signal processing usually requires real-time response, and deep learning models usually have high computational complexity. The real-time nature and demand for computing resources of deep learning models is an ongoing challenge. In order to use deep learning models to radar signal processing effectively, it is imperative to design models that are lightweight or efficient DNN models.

4.4. Data fusion and integration

Radar signal processing usually requires fusion with other sensor data, which involves the fusion and integration of different data types and features. In the future, multi-modal fusion deep learning models [14] can be used to design network structures suitable for multi-modal data processing, or methods such as feature fusion and multi-task learning can be used to achieve data fusion and integration.

In the future, these challenges can be overcome through more effective data annotation methods, optimized model architecture, and the introduction of multi-modal information fusion to promote the further development of radar signal processing technology based on deep learning. The combination of deep learning and radar technology is expected to bring greater innovation and performance improvement to the field of radar applications.

Numerous current studies demonstrate that there is a clear trend toward the deep merging of deep learning-based solutions with conventional signal processing techniques. Traditional radar signal processing techniques, like coherent accumulation and pulse compression, are useful for improving features and, consequently, detection performance as a data preprocessing technique. Moreover, we believe deep learning-based models are able to provide a "end-to-end" framework that combines judgment, processing, and perception. Without a doubt, deep learning research and application will lead to significant advancements in the field of radar signal processing, even though it is still in its infancy and confronts several difficulties.

It is anticipated that more cutting-edge deep learning-based techniques and technologies will be achieved in the field of radar signal processing in the future as a result of the technology's ongoing development and implementation. These techniques should increase the effectiveness and precision of radar data processing and encourage the use of radar technology in a variety of industries.

5. Conclusion

This paper reviews traditional model-based radar signal processing methods and data-based deep learning methods, focusing on radar signal processing applications based on deep learning. Lastly, a summary of the current issues and potential solutions for radar signal processing is provided. Without a doubt, deep learning research and application will lead to significant advancements in the future, even though the subject of radar signal processing is still in its infancy and confronts many obstacles. Radar system advancements and deep learning algorithm advancements are bound to complement one another.

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