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Research Progress and Prospect of Radar Data Intelligent Processing

Yaqi Cui[1], You He[1], Shutao Xia[1,*], Wei Xiong[1], Pingliang Xu[1,*], Yu Liu[1], Ziling Wang[1], Xiangqi Gu[1], Weiwei Sun[1], Jianjuan Xiu[1], Zhan Kong[1], Haoran Li[1], Yuan Lu[1] and Hao Tang[1]

[1] Institute of Information Fusion, Naval Aviation University, Yantai 264001, China

Abstract

With the continuous expansion of the application field of artificial intelligence, radar data processing has also begun to fully enter the era of intelligence, and new achievements have emerged in the research fields of target detection, target tracking, and target recognition. At a time of rapid development of artificial intelligence technology, it is necessary to think about the future development of radar data intelligent processing. To this end, combining the research history and the superficial understanding of radar data intelligent processing in the past ten years, our team analyzes the main research progress and challenges of radar data intelligent processing, examines the new requirements for autonomous, multi-modal, and multi-mode radar data intelligent processing, and explores new opportunities in the era of large models, etc. Furthermore, along a research path of "1 domain foundation model + 3 core task models + N typical application implementations", the research conceptions and main contents of radar data large model are put forward in order to enable the research of intelligent radar.

Keywords: artificial intelligence, deep learning, large model, radar data processing, target detection, target tracking, target identification.

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***Corresponding authors:**
Shutao Xia
1123103211@qq.com
Pingliang Xu
xu_pingliang@163.com

1 Basic conception

Modern radar information processing is generally categorized into two main components: radar signal processing and radar data processing. Radar signal processing directly performs matching filtering, constant false alarm rate (CFAR) and other processing on the intermediate frequency signal and video signal output by the radar receiver. The output is radar measurement or target track point, including spatial position information such as distance and azimuth, and target characteristic information such as echo intensity and polarization. Radar data processing is conducted after radar signal processing, the radar measurement is further refined with the processing such as tracking and identification, so as to achieve

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the radar measurement of "discarding the dross and selecting the essential" and "discarding the false and retaining the true", and the output is the track information of the target of interest, including motion state information and characteristic information. The motion state information includes position, speed, course, and other information, and the characteristic information includes military and civilian information, enemy and friendly information, type and category information [1]. Radar data processing is mainly used to track the target and identify the target, and solve the problem of where the target goes and what the target is.

From a traditional perspective, radar data processing in the narrow sense primarily refers to target tracking. However, the broader interpretation encompasses all post-signal-processing operations, incorporating target detection, tracking, and recognition as integral technical components.

1.1 Target detection

Radar target detection theory is constantly developed based on researchers' expansion of radar signal dimensionality. For one-dimensional radar signals, the one-dimensional CFAR detection method was developed [2–4]. Regarding two-dimensional radar signals, the Range-Doppler moving target detection approach emerged [5, 6]. When processing three-dimensional radar signals, the Track-Before-Detect (TBD) method composed of range-azimuth-frame was established [7–9].

In complex environments characterized by strong clutter, interference, and weak targets, where the target signal-to-noise ratio (SNR) remains suboptimal and radar detection exhibits instability with intermittent target presence across frames, direct detection approaches frequently result in missed targets.

Typical TBD methods can be divided into two categories: 1) Tracking-based TBD, which employs motion priors to extract multidimensional target information from sequential radar raw data frames; and 2) Detection-based TBD, implementing batch processing of multi-frame radar data for trajectory detection prior to target state estimation via track filtering. Representative methods of tracking-based TBD include dynamic programming [10] and particle filtering [11]. Notable methods of detection-based TBD include Hough transform [12], three-dimensional matching filter [13] and probabilistic multiple hypothesis of histogram [14].

1.2 Target tracking

Target tracking is the core of radar data processing. Through the association filtering of single or multiple radar data from the same target at different times, the mapping relationship between radar data and different real targets is established, so as to obtain accurate and reliable target state information such as position and speed, achieve continuous and accurate grasp of individual targets, and real-time and effective monitoring of regional situation. In the 1960s, relevant researches began to appear at home and abroad, mainly using the mathematical modeling ideas and probability statistical method to solve. According to the difference of the number of radars, target tracking can be divided into single radar target tracking and multi-radar target tracking, and according to the difference of the data processed, it can be divided into point-to-track target tracking and track-to-track target tracking.

In the single radar target tracking problem, there are many researches on point-to-track target tracking technology. Typical technical frameworks include association-based target tracking, Multiple Hypothesis Tracking (MHT) and Random Finite Set (RFS). There are few researches on track-to-track target tracking technology, which mainly consists of interrupted track continuity tracking.

1. The association-based target tracking takes point-to-track association as the core technology, and mainly consists of four processing parts, including track initiation, point-to-track association, track filtering, and track management. Track initiation mainly uses logic method and Hough transform method. point-to-track association mainly uses the nearest neighbor [15], probability data association (PDA) [16], joint probability data association (JPDA) [17], and other algorithms to establish the corresponding relationship between radar measurement and track. Track filtering is sometimes called target state estimation, algorithms such as α-β filter [18], α-β-γ filter [19], Kalman Filter [20] and Interacting Multiple Model (IMM) were used to eliminate the effects of random measurement errors on target state estimation to obtain a stable and accurate target state estimation. In track management, the cost function, Bayes, and other algorithms are used to realize timely and efficient conversion of target track between the three states of uncertainty, confirmation, and cancellation.

2. Multiple Hypothesis Tracking processes track initiation, point-to-track association and track management in a unified framework through track hypothesis, which consists of four processing parts, including multiple hypothesis generation, hypothesis probability calculation, optimal hypothesis output, and hypothesis quantity management [21, 22]. Among them, the multi-hypothesis generation step is used to generate all possible hypotheses. Each hypothesis represents a set of possible target tracks. The hypothesis probability calculation step mainly uses Kalman filter, Gaussian mixture model and other methods to score hypotheses to determine which hypotheses are more likely to be correct. The optimal hypothesis output step selects the hypothesis with the highest score as the best tracking result of the current frame. The hypothesis quantity management step uses clustering, low-probability hypothesis deletion, N-scan pruning, similar hypothesis merging and other algorithms to reduce the number of hypotheses and avoid the exponential growth of the number of hypotheses.

3. The research on random finite set target tracking originates from the Probability Hypothesis Density (PHD) filtering algorithm proposed by Mahler based on RFS framework in 2003 [23]. It assumes that all measurements may be associated with all targets, and calculates their estimated likelihood functions. The state estimates of all targets can be obtained by deleting the smaller likelihood probabilities without data association. Typical algorithms include Gaussian mixture probability hypothesis density filter (GM-PHD) [24], sequential Monte Carlo probability hypothesis density filter (SMC-PHD) [25], a multi-sensor multi-Bernoulli filter (MeMBer) [26], labeling-enhanced variants [27], and numerous derived algorithms employing different filtering approaches [28–30].

In the multi-radar target tracking problem, track-to-track target tracking technology focuses on track association research, and there are many technologies, such as sequential track association, statistical double threshold track association, fuzzy double threshold track association, gray track association, etc., while the track fusion after track association is less researched. The research of multi-radar point-to-track target tracking technology is mainly the extended application of single-radar point-to-track target tracking technology in multi-radar scenarios, and the technical framework remains unchanged.

1.3 Target recognition

Target recognition refers to the process of utilizing identity-related information such as echo intensity and target contour extracted from radar measurements, combined with motion characteristics derived from target trajectories, to determine size attributes, military vs. civilian classification, and target categories. Typical techniques include echo-intensity-based recognition, high resolution range profile (HRRP) analysis, and SAR imagery target identification.

2 Main Work

Driven by information technologies such as big data, cloud computing, and the Internet of Things, Artificial Intelligence (AI) has been widely used in image, video, text, voice, and other industries, and has even made breakthroughs in basic science fields such as mathematics, physics, chemistry, meteorology, and algorithm design. And it has become a new driving force for rapid progress in all walks of life. In recent years, our team has systematically carried out research on the integration of radar data processing with artificial intelligence, yielding notable achievements in intelligent target detection, tracking, and recognition methodologies.

2.1 Intelligent target detection

In the case of a large number of false alarms in radar measurement, the existing TBD method is prone to problems such as excessive computation, poor detection performance, and insufficient use of multi-dimensional information. To this end, our team combined deep learning and multi-frame measurements to propose a two-stage TBD method based on deep learning [31], and the schematic diagram is shown in Figure 1. This method first employs a low-threshold DB-YOLO target detection network for single-frame detection, reducing the amount of data and alleviating the pressure on subsequent processing. Then, it uses a model-based approach to determine potential tracks, transforming discrete measured data into track data with spatial-temporal correlation. Finally, convolutional neural networks (CNN) and recurrent neural networks (RNN) are used to extract track position information, innovation scores, and target structure information, thereby achieving accurate

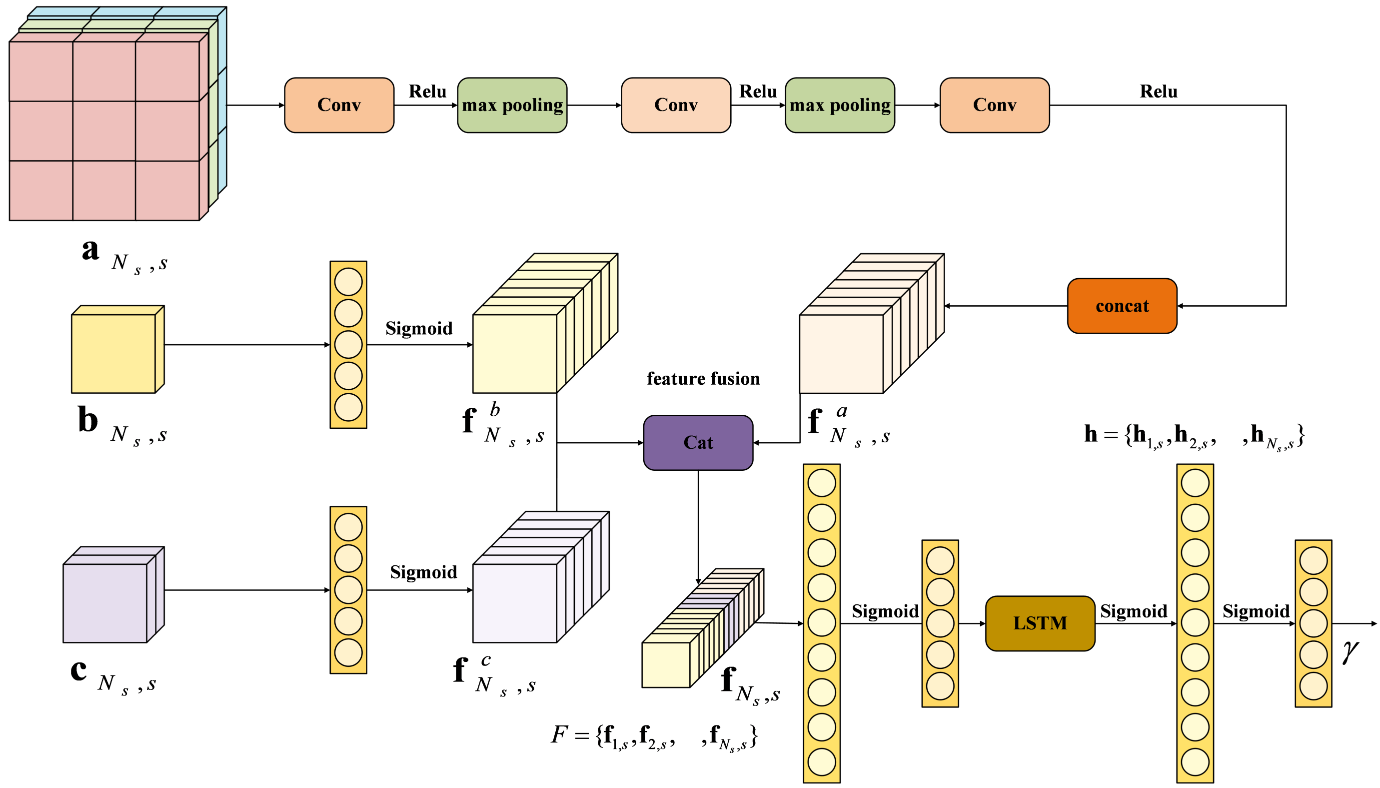

Figure 1. The schematic diagram of a two-stage TBD method based on deep learning.

target localization. In the network, $a_{N_s,s}$ represents the preprocessed output from a low-threshold target detection network. The structural feature vector $f^a_{N_s,s}$, obtained by processing $a_{N_s,s}$ through a convolutional network, encapsulates the target's structure information. The innovation scores $b_{N_s,s}$ generated by the Singer model is transformed into feature vector $f^b_{N_s,s}$ via a fully connected network, while the positional information $c_{N_s,s}$ from detection results is converted into location feature vector $f^c_{N_s,s}$ through a separate fully connected network. These three feature vectors are integrated to form a track feature sequence $F = \{f_{1,s}, f_{2,s}, \cdots, f_{N_s,s}\}$ with length N_s. This sequence is fed into an LSTM network, followed by confidence score mapping through fully connected layers. A track is validated as true when its confidence score surpasses the predefined threshold γ. Experimental results show that this method can accomplish multi-target detection and localization in a strong clutter environment, and possesses certain real-time processing capabilities. These findings highlight the method's practical significance and showcase promising potential for real-world applications in complex detection scenarios.

In addition, some researchers used CNN to directly process radar echoes to distinguish targets from clutter and achieve target detection. Ningyuan et al. [32] used CNN to process the time-frequency graph of radar echoes obtained by the short-time Fourier transform (STFT), and divided radar echoes into clutter and targets to realize the detection of maritime targets. Also for the target detection of one-dimensional radar signals, Ning et al. [33] arranged the one-dimensional radar signals after pulse compression into a two-dimensional matrix in the slow time dimension, obtained the range-slow time image of radar echo signals, and input it into the YOLO v5 network composed of CNN for target detection. In order to improve the performance of target detection in clutter environment and improve the generalization of target detection, Xiaoqian et al. [34] proposed a clutter suppression and sea surface moving target detection method for navigation radar images based on INet. In this method, a fusion network INet for clutter suppression and target detection is designed, and the INet target detection model is optimized by pre-training and interframe accumulation, and the optimized INet target detection model is obtained, which greatly improves the detection probability and generalization ability of target detection methods based on neural networks. Considering that the target detection method based on deep learning will produce a large number of redundant candidate boxes in radar echo images, resulting in reduction of detection accuracy and detection efficiency, Lan et al. [35] proposed a Faster R-CNN network combined with reinforcement learning. Through reinforcement learning, this method adaptively searches regions that may contain targets in the feature map, and selects candidate boxes within the search region for target detection, which can effectively reduce the influence of complex background clutter and reduce the computational cost of Faster R-CNN.

2.2 Intelligent target tracking

Intelligent target tracking primarily focuses on three core components in association-based target tracking: 1) track prediction, 2) data association, and 3) track filtering, along with supporting methods including interrupted track continuity tracking and track association.

2.2.1 *Multi-source track association dataset construction*

Data, algorithms and computing power are the troika for the development of artificial intelligence technology, of which data is the raw material and the basis for the application of general artificial intelligence technology industry. In the field of radar target tracking, the lack of standard and special datasets hinders the development of intelligent target tracking technology to some extent. To this end, our team constructed a Multi-source Track Association Dataset (MTAD) based on global AIS through processing steps including grid division, automatic interruption, and noise addition [36]. It can be directly applied to the training and testing of intelligent target tracking algorithms for tracks such as interrupted track continuity tracking and track association, and can also be applied to the research of intelligent target tracking algorithms for points such as track prediction, data association, and track filtering after simple processing. The sample of the MTAD is shown in Figure 2 and the dataset has been downloaded more than 7000 times since it was published in 2022.

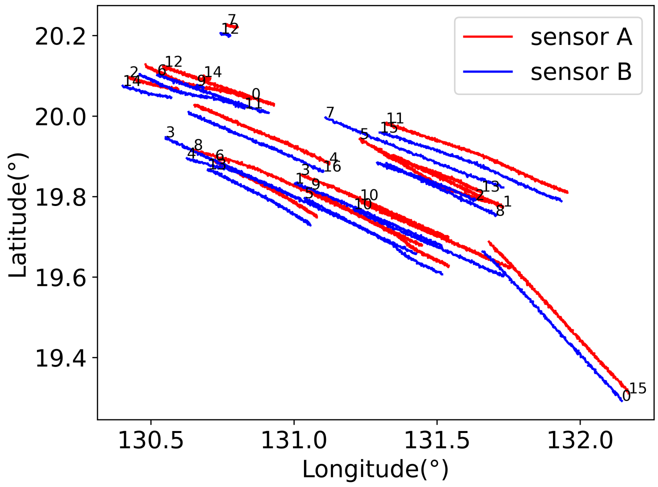

Figure 2. The sample of the MTAD.

2.2.2 *Intelligent track prediction*

Track prediction primarily focuses on predicting the potential future positions of a target based on its historical movement tracks. It is a crucial component of track initiation and track filtering. Traditional track prediction methods mainly rely on target motion models for prediction, such as constant velocity, constant acceleration, coordinated turn, Singer, current statistical, and Jerk models. These methods remain constrained by inherent limitations in model representational capacity and insufficient adaptability to complex hybrid motion patterns, leading to inconsistent performance in practical implementations. To this end, our team modeled track prediction as a process of pattern information extraction (I-step) and a process of predicted position generation (E-step) through theoretical derivation. In addition, Recurrent Neural Network (RNN) and Multi-Layer Perceptron (MLP) are used to construct the neural network structure for track prediction [36]. The intelligent track prediction network is shown in Figure 3. Experiments based on simulation data and actual data show that the constructed neural network structure can extract and recognize the existing motion patterns while generating high-fidelity predictions, effectively resolving domain-specific track prediction challenges across diverse operational environments with demonstrable efficacy.

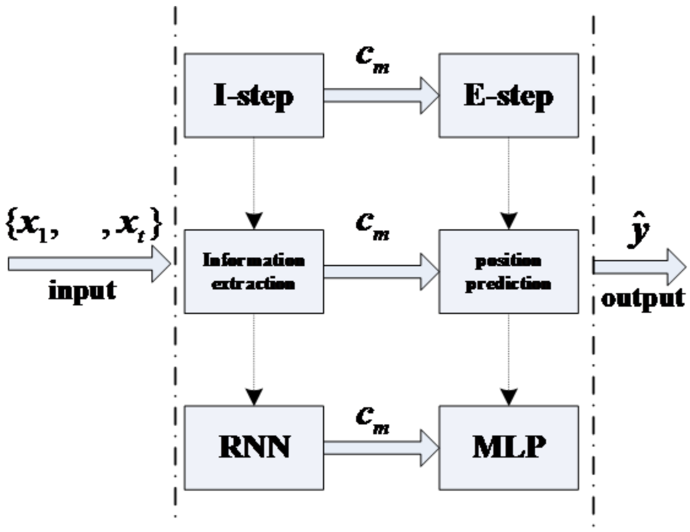

Figure 3. The intelligent track prediction network.

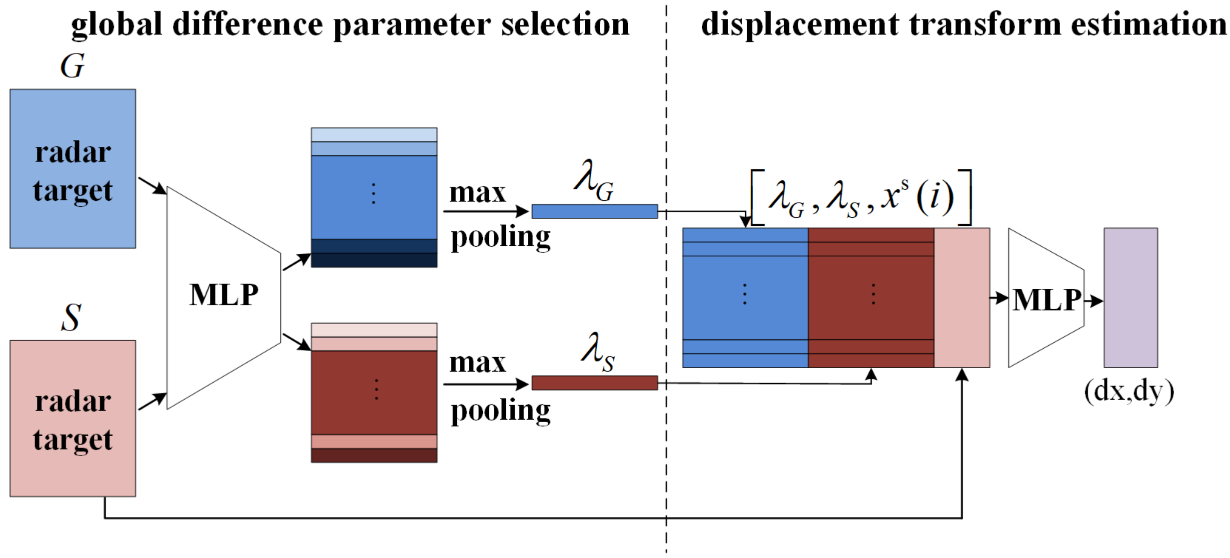

Figure 4. The intelligent point-to-track association network.

2.2.3 Intelligent point-to-track association

Because of the simple decision logic, the traditional point-to-track association method based on statistical distance often causes problems such as association failure and association error in dense, formation, and other complex multi-target tracking environments. To this end, our team proposed an intelligent point-to-track association model [37, 38], as shown in Figure 4. First, the overall difference parameter extraction network was designed based on MLP to extract the overall difference parameters of track points and measurement points, respectively. Then, the extracted difference parameters are integrated in series to get the global difference parameters. Next, the global difference parameters are aligned with the track points and measurement points by means of the designed displacement transformation network. Finally, the registered target points are judged for association according to the defined association criterion. The experimental results show that the model can well adapt to scenarios such as target formation changes, radar false alarms, and missed detections, effectively improving the speed and accuracy of association.

2.2.4 Intelligent track filtering

Traditional track filtering mainly uses Kalman, IMM, and other filtering methods based on target motion model. Whether the motion model used matches the actual movement of the target has a decisive influence on track filtering. Although IMM filtering method can integrate multiple motion models and solve the problem of incompatibility of target motion models to a certain extent, its integration number of motion models is limited due to competition and pollution effects among motion models, resulting in limited performance of existing track filtering algorithms. To this end, our team conducted a computational structure analysis of typical α-β filtering and Kalman filtering methods, concluding that both filtering methods possess a typical RNN structure and are a type of RNN with constrained weights. Then, based on this conclusion and considering the capability of RNN to recognize target motion patterns, our team proposed an intelligent track filtering network, which achieved structural unification, environmental adaptability, and performance expansion of existing filtering methods [39, 40]. The schematic diagram of the intelligent track filtering network is shown in Figure 5. According to the function and effect of the α-β filter, the smooth network that is composed of feedforward and recurrent structures is designed to smooth the fluctuant measurements and obtain stable estimations of the target state. According to the structure of Kalman filter, the evaluation network that is composed of feedforward structures, recurrent structures, and an attention mechanism is designed to calculate the gain. Meanwhile, an additional attention mechanism is used to transfer the gain information from the evaluation network to the smooth network and integrate the two network parts closely. The experimental results show that the overall performance of the intelligent track filtering network is significantly superior to traditional filtering methods. In addition, based on the transformer model, a deep data association and track filtering network (DeepAF) was constructed in this paper to achieve the function of data association and end-to-end track filtering [1]. A predictive regression network with the capability of processing time series (DeepAF-B) is designed to extract track features. The DeepAF network, composed of DeepAF-P and DeepAF-V, is designed to estimate the target position and velocity. The schematic diagram of DeepAF-B is shown in Figure 6. Experimental results show that DeepAF can stably and effectively track targets moving in different models such as constant velocity, constant acceleration, and constant turn rate.

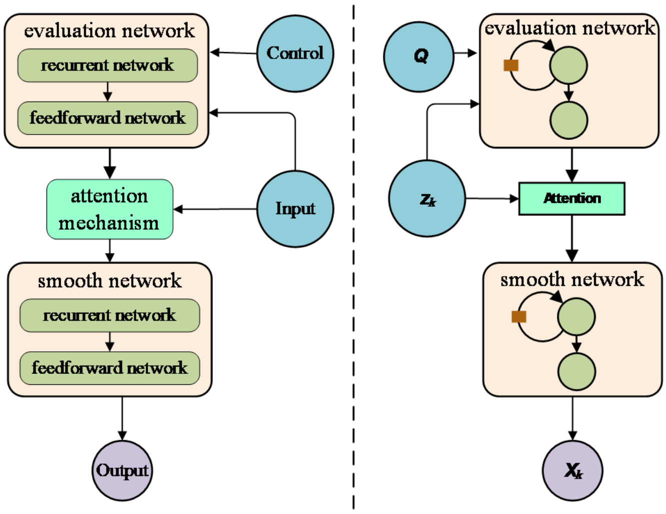

Figure 5. The schematic diagram of the intelligent track filtering network.

2.2.5 *Intelligent interrupted track continuity tracking*

Due to the rapid movement of the platform such as turning, acceleration, or attitude change, the maneuvering radar is easy to cause the loss of target measurement and track interruption, which leads to the instability and discontinuity of target tracking. To this end, based on metric learning, generative adversarial networks (GAN), and graph representation networks, our team respectively studied and proposed a variety of intelligent interrupted track continuity tracking networks, such as discriminant, generative, and graph representation, to achieve effective and continuous tracking of interrupted tracks in complex scenarios [41, 42]. The generative interrupted track continuity tracking network is shown in Figure 7.

2.2.6 *Intelligent track association*

Similar to the point-to-track association, traditional track association (track-to-track association) is mainly based on multidimensional statistical distance such as position, speed, and heading, which has the problem of simple decision logic and poor applicability in complex scenarios. To this end, our team adopts a deep learning approach, constructing all tracks in the to-be-associated scenario into a track tensor similar to the shape of association matrix, utilizing transformers to conduct overall processing on the track tensor, extracting global features of the track tensor and detailed features of each track, segmenting the track tensor to obtain associated track pairs, achieving end-to-end transformation from the track tensor to the association matrix. The intelligent track association network is shown in Figure 8. The experimental results show that the intelligent track association network can realize the effective association of multi-source tracks and has a high accuracy.

In the research direction of intelligent target tracking, in addition to the above works of our team, domestic and foreign scholars have also carried out in-depth and detailed research. In the direction of intelligent track prediction and intelligent track filtering, Gao et al. [43] adopted both Bayesian LSTM and non-Bayesian LSTM for target tracking. Bayesian LSTM learns the conditional probability of the target motion and predicts the probability density, while non-Bayesian LSTM directly learns the motion mapping of the target and predicts the position of the target. Moon et al. [44] and Deng et al. [45] combined LSTM and IMM to predict the probability of each motion model. Using the learning ability of neural networks, this method can obtain the weights of different motion models quickly and accurately, and minimize the estimation time delay of traditional IMM algorithm. Jouaber et al. [46] proposed an adaptive Kalman filter based on neural networks, which uses LSTM to predict the covariance matrix of process noise required by traditional Kalman filtering to improve the scenario adaptability and noise robustness of Kalman filtering. Chen et al. [47] developed a target tracking framework based on XGBoost that establishes a nonlinear mapping between target measurements and true kinematic states, implementing a sliding window mechanism to continuously process streaming measurements while maintaining real-time target tracking capabilities [48].

In the direction of intelligent point-to-track association, Zhang et al. [49] proposed a TrMTT radar maneuvering target tracking model, which uses the encoder and decoder in Transformer network to realize target tracking. Aiming at the difficulty in obtaining prior information such as target motion model and clutter density, Wenna et al. [50] proposed a data association algorithm for multi-target tracking based on Transformer network. In this method, virtual

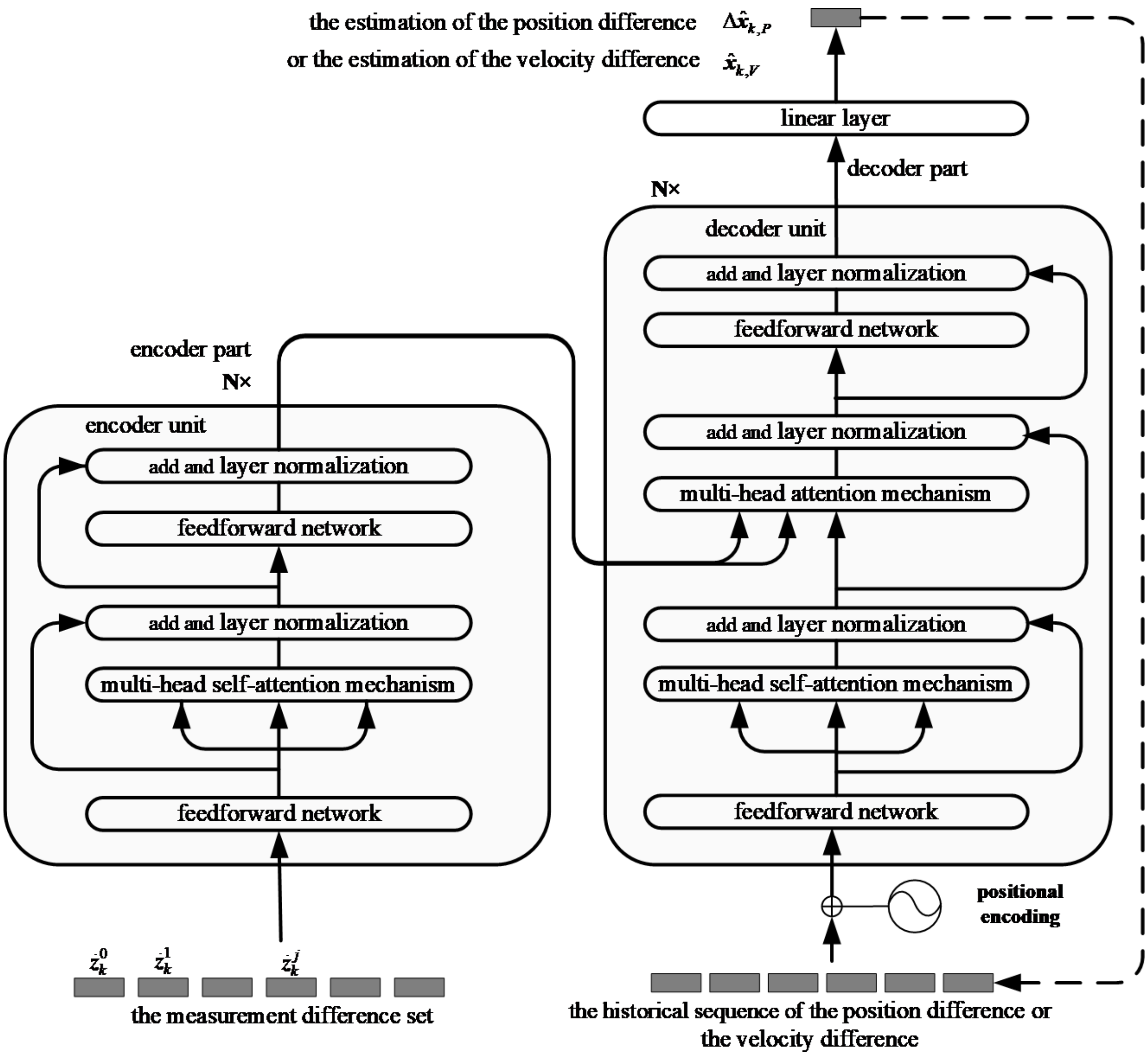

Figure 6. The schematic diagram of DeepAF-B.

measurement is introduced to solve the problem of missing detection, and a loss function combining a mask cross entropy loss and an overlap loss is designed to optimize the network parameters. To address the challenge of association between established tracks and newly detected observations, Chen et al. [51] developed Track-MT3 – an end-to-end multi-target tracking model leveraging the Transformer network. This innovative approach incorporates dual query mechanisms (detection queries and tracking queries) that implicitly perform data association between measurements and tracks, and state estimation at the same time. This model implements a cross-frame alignment strategy to ensure time consistency of tracks, while featuring two specialized components: 1) A query transformation module that preserves target identity coherence, and 2) A time feature encoder specifically engineered to capture complex motion state of targets.

2.3 Intelligent target recognition

At present, the target recognition algorithm mainly focuses on the High Resolution Range Profile (HRRP) and SAR images, which contain abundant target contour features, while the target recognition methods based on track features are rarely researched.

2.3.1 *Target recognition for SAR images*

Research on target recognition for SAR images has been extensively explored and remains a prominent research focus to date. Tian et al. [52] combined CNN and SVM, utilizing CNN for feature extraction from SAR images and SVM for feature classification to achieve recognition results. Zhang et al. [53] extracted three features of SAR images, including principal component features, wavelet transform

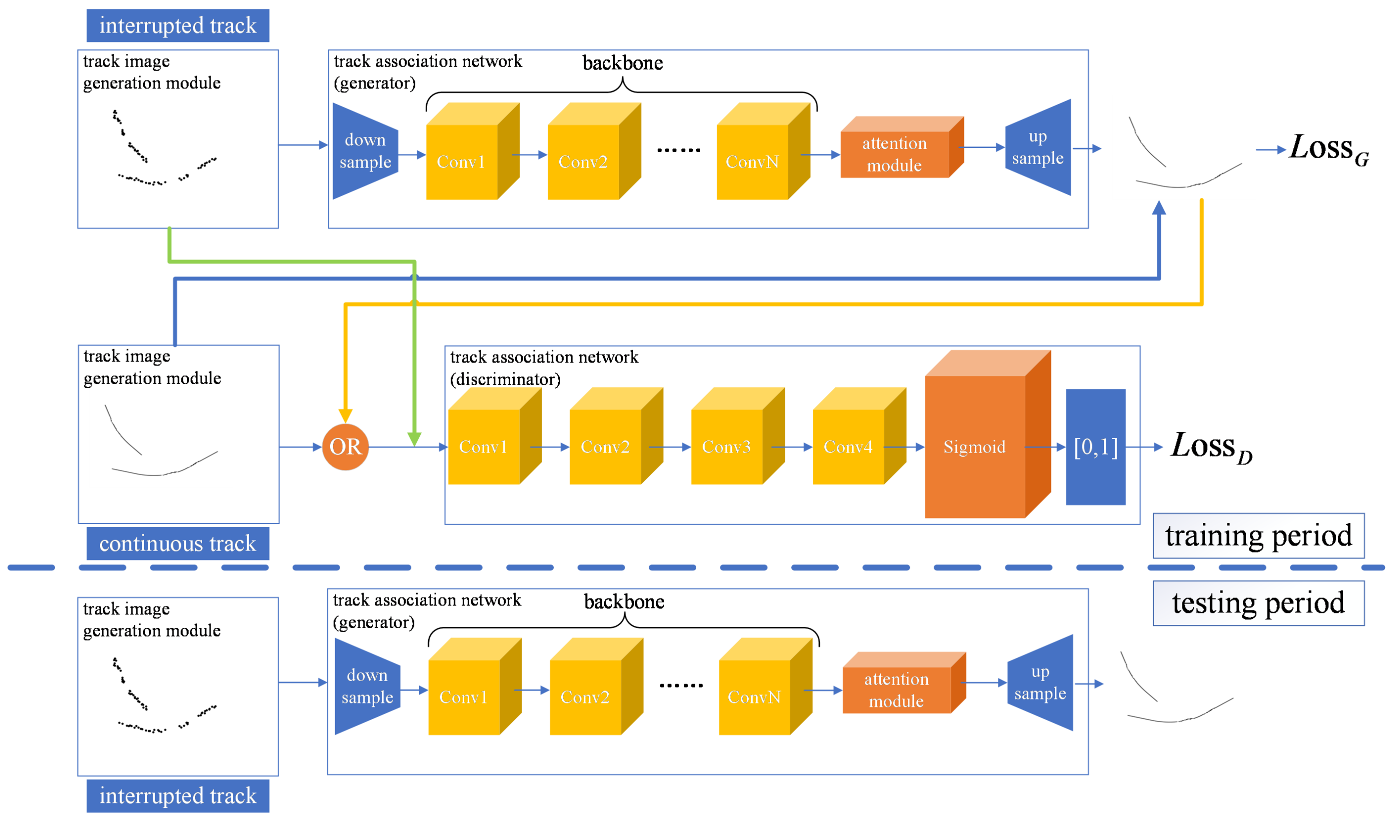

Figure 7. The schematic diagram of the generative interrupted track continuity tracking network.

features, and 2D slice Zernike features. These features were then separately input into sparse representation classifiers and collaborative representation classifiers for pre-classification, generating six prediction labels. Classifier fusion was applied to these labels to obtain the final recognition decision. To address the requirement of large labeled training samples for SAR image recognition, Yu et al. [54] proposed a target recognition method for SAR images based on Fully Convolutional Neural Network (FCNN) and an improved convolutional autoencoder. They initialized partial parameters of FCNN using network parameters from an unsupervised-trained improved convolutional autoencoder, followed by fine-tuning with a small number of labeled samples to reduce reliance on labeled SAR data. To leverage rich feature information from multi-aspect SAR image sequences, Zhao et al. [55] developed a multi-angle SAR target recognition model integrating EfficientNet and Bidirectional Gated Recurrent Unit (BiGRU). This model combines CNN for spatial feature extraction and GRU for sequential feature extraction from image sequences to enhance recognition accuracy. To tackle the challenge of widely distributed spatial structures among different targets in SAR images, Lü et al. [56] designed an associated scattering classifier to quantify target discreteness and guide the network to learn more discriminative feature representations. Additionally, they proposed an adaptive feature refinement module to mitigate background noise interference by directing network attention to target-critical regions. While improving CNN parameters and scales enhances SAR image recognition capability, it demands large training datasets. Addressing limited SAR data availability, Li et al. [57] introduced a deep network based on Attribute Scattering Center (ASC) convolutional kernel modulation. This network employs modulated kernels to extract scattering structures and edge features aligned with SAR characteristics in shallow layers, while leveraging standard CNN kernels for semantic feature extraction in deeper layers, effectively balancing electromagnetic scattering properties and CNN advantages to reduce training sample dependency. To enhance the interpretability of SAR recognition networks and clarify decision mechanisms, Cui et al. [58] integrated perturbation concepts into Class Activation Mapping (CAM), proposing a SAR Clutter Characteristics CAM (SCC-CAM) method. By progressively adding globally distributed perturbations to SAR images and analyzing neuron activation changes during recognition flip points, this approach enables dynamic observation and quantification of salient regions in network decision

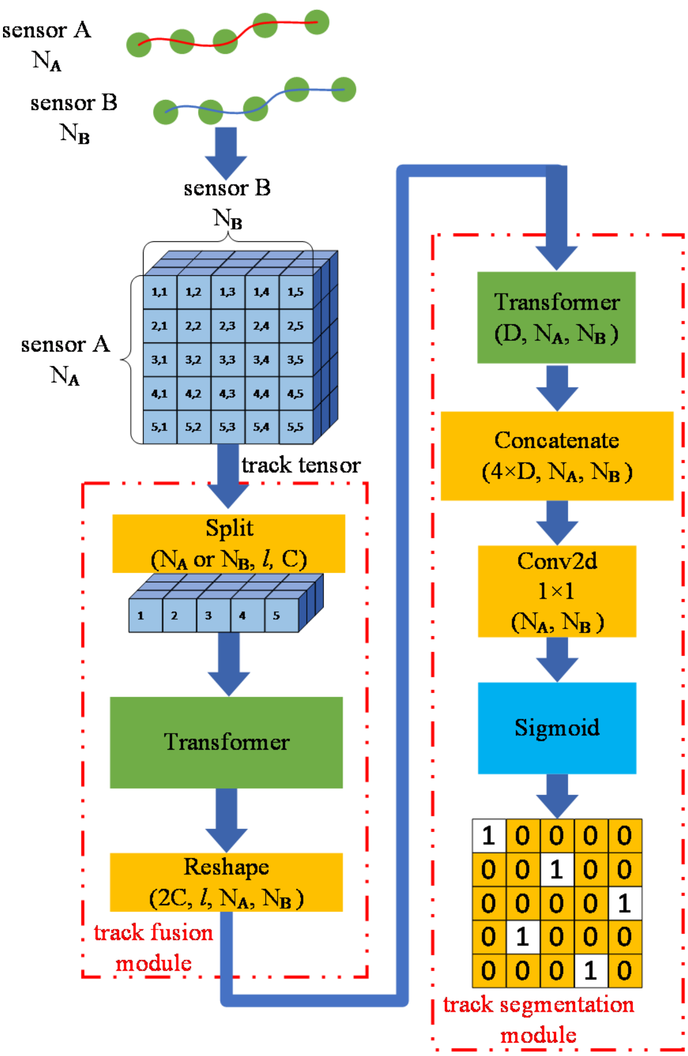

Figure 8. The schematic diagram of the generative interrupted track continuity tracking network.

processes.

2.3.2 *Target recognition for HRRP*

Considering that traditional target recognition methods for HRRP focus solely on envelope information of samples while neglecting temporal correlations between range cells, Liu et al. [59] proposed an attention-based bidirectional recurrent neural network model. This approach divides time-domain HRRP data into forward and reverse sequences via a sliding window, processes them independently through two parallel Gated Recurrent Unit (GRU) networks for temporal feature extraction, and concatenates features from both sequences at each timestep to leverage bidirectional temporal information. Aiming at the challenges posed by data discrepancies between multiple cooperative radar stations for HRRP target recognition, Guo et al. [60] developed an angle-guided transformer fusion network. The network comprises single-station processing and multi-station processing components: Using Transformer as the core architecture, it extracts both local and global features from individual station HRRP data. Three new auxiliary modules including the angle-guided module, the pre-feature interaction module, and the deep attention feature fusion module are designed to enable cross-station feature fusion learning, thereby significantly enhancing HRRP target recognition performance in multi-static cooperative radar systems.

2.3.3 *Target recognition for tracks*

The target tracks can be widely obtained, and more importantly, it can be obtained at a long distance, so it is of great application value to use the target track information to recognize the targets. To this end, our team constructs a Bayes-Transformer neural network, which can be used to complete track feature extraction, track feature representation, and different types of target classification, so as to realize end-to-end target recognition based on track information [61, 62]. The schematic diagram of the Bayes-Transformer neural network is shown in Figure 9. The experimental results based on AIS data shows that the proposed network can recognize 9 types of targets, including fishing boats, military ships, search and rescue ships, tugboats, passenger ships, cargo ships, oil tankers, and other ships, and the recognition accuracy is more than 90%.

3 Challenges and opportunities

3.1 Main challenges

With the continuous expansion of human activity space, the rapid development of unmanned control technology, the emergence of new means of unmanned platform detection, new modes of space-air cooperative detection, near space targets, unmanned cluster targets and other high-threat targets, have brought serious challenges to radar data processing, and put forward new requirements for radar data intelligent processing technology.

3.1.1 *New means of unmanned platform detection*

On March 16, 2021, the United States Department of the Navy officially released 'Department of the Navy Unmanned Campaign Framework', pointing out that one-third of the Navy's fleet and half of the Marine Corps' aviation equipment may be based on unmanned systems in the future, and should achieve seamless integration of manned and unmanned forces in all areas to provide lethal, survivable, and scalable combat effects to support future maritime missions. This strategic shift foresees unmanned

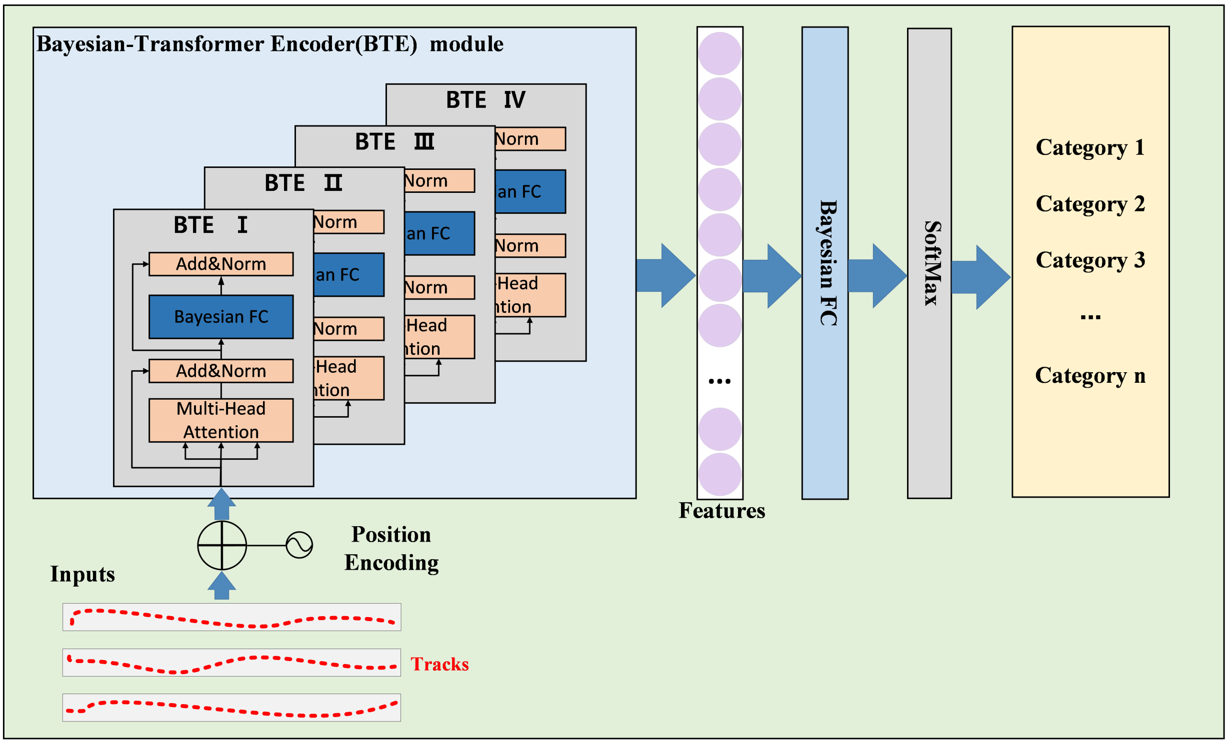

Figure 9. The schematic diagram of the Bayes-Transformer neural network.

combat systems - including unmanned aerial vehicles, underwater unmanned devices, surface unmanned vehicles, and land unmanned machines - forming complementary operational architectures with their manned counterparts.

Unmanned platform detection has the new characteristics such as long-range, autonomy, and collaboration, which pose higher requirements for the automation, intelligence, and autonomy levels of radar data processing. A prime example is the U.S. Navy's MQ-4C Triton UAV, which employs a multi-mode active radar system capable of alternating between maritime surface search and inverse synthetic aperture imaging modes. This advanced system enables automated target detection, tracking, and identification, while autonomously executing the complete "Observation-Orientation-Decision-Action" (OODA) cycle for comprehensive maritime surveillance.

3.1.2 *New modes of space-air cooperative detection*

By combining the advantages of space-based and air-based radars, it is possible to achieve rapid wide-area search and observation while also enabling detailed detection and recognition of key areas and targets, meeting the requirements for extensive and precise surveillance in remote seas and oceans. However, there are significant differences between space-based and air-based radars in terms of observation azimuth, observation distance, resolution, and scan period, among other aspects. Essentially, they can be considered as two different modalities of radar data that originates from the same physical observation space and can be mapped to the same semantic space. This poses new requirements for the capability of processing multi-modal radar data.

3.1.3 *Complex target scenarios*

The rapid development of near-space hypersonic technology and the widespread application of unmanned systems require radar to possess complex multi-mode data processing capabilities, and be capable of adapting to intricate and variable scenarios. The complex electromagnetic and atmospheric environments within the near-space airspace, along with the unique motion characteristics of hypersonic vehicles, provide near-space hypersonic vehicles with a natural advantage of multiple "protective umbrellas." However, individual unmanned systems are generally of small scale, and their signals are easily drowned out by background noise, leading to measurement loss and interrupted tracks, and even the failure of track initialization. For more complex unmanned clusters, the high density of targets and frequent formation changes make detection, tracking, and recognition even more challenging.

3.2 New opportunities for development

In November 2022, ChatGPT powered by GPT-3.5 emerged as a groundbreaking innovation, demonstrating realistic natural language interaction and multi-scenario content generation capabilities that ignited the AI large model revolution. In July 2023, Huawei's Pangu meteorological large model were published in the journal Nature [63]. Compared with the global most advanced European Centre for Medium-Range Weather Forecasts (ECMWF) integrated forecasting system, the forecasting timeliness was improved by about 0.6 days, the computing speed was increased by more than 10000 times compared with numerical methods, and the tropical cyclone track forecasting error was reduced by 25% compared with the ECMWF forecasting system. In February 2024, OpenAI launched a new large model for text-to-video generation, Sora [64], which once again caused a global sensation.

At present, artificial intelligence research can be divided into two modes: specialized AI research and general large model research. Specialized AI systems are designed for specific tasks. Due to their single task focus, clear requirements, well-defined application boundaries, rich domain knowledge, and relatively simple modeling, they have achieved breakthroughs in specific areas of AI, and in some intelligence level test of specific tasks, they can even surpass human intelligence. However, specialized AI systems corresponding to different tasks require repeated design, evaluation, and iteration, resulting in extremely high costs. They face problems such as difficulties in large-scale deployment and limited performance, making it challenging to adapt to the fragmented and diverse demands of artificial intelligence.

In 2020, Kaplan et al. [65] proposed the concept of scaling laws, indicating that model performance is strongly correlated with model size and weakly correlated with model architecture, where model size includes the number of model parameters, dataset size, and computational resources of models. This means that increasing the number of model parameters and expanding the dataset size can predictably improve model performance. Additionally, research has found that when the model size is small, the model generally lacks the ability to solve downstream tasks. However, when the model size reaches a certain threshold, surpassing a critical value, the model experiences a sudden insight (Grokking), with a dramatic increase in performance and the emergence of previously unattained capabilities. As a result, research on general large models has begun to receive significant attention, and the approach of "pre-trained large models followed by fine-tuning for downstream tasks" has started to become a new paradigm for AI industry application development.

General large models can effectively capture knowledge from a vast amount of labeled and unlabeled data. By storing this knowledge in a large number of parameters and fine-tuning for specific tasks, they greatly expand the model's generalization capabilities, offering advantages such as strong versatility, wide application scope, and high accuracy. These models have received significant attention from both academia and industry, with rapid development and iteration. Depending on the types and characteristics of the input data, general large models can be categorized into Large Language Models (LLM), Large Vision Models (LVM), Multimodal Large Language Models (MLLM), and Large Time Series Models (LTSM), among others. Typical LLMs include OpenAI's GPT series [66–68], Google's PaLM [69], Meta's Llama series [70, 71], Baidu's ERNIE [72–74], Alibaba's QWEN [75, 76], Zhipu AI's ChatGLM [77], and DeepSeek's DeepSeek [78, 79]. Visual large models include OpenAI's DALL-E series [80, 81], NVIDIA's StyleGAN [82–84], and Huawei's Pangu CV large model [85]. Multimodal language large models include OpenAI's GPT-4 [86], Google's Gemini [87], Tencent's Hunyuan series [88], SenseTime's INTERN large model [89], and Huawei's Pangu multimodal large model. In January 2025, the complete open-source release of DeepSeek brought the research on large models to a new peak.

It is evident that current general large models are in a period of rapid development. The perfect combination of big data, large computing power, and advanced algorithms has significantly enhanced the intelligence level and multi-scenario application capabilities of large models. Large models are at the forefront, a focal point, and a key area of the development in artificial intelligence technology. They also provide a feasible and effective solution to meet the new demands for autonomous, multi-modal, and multi-mode radar data processing.

Radar data processing can be seen as a time series processing problem and the challenges of them are often common. At present, a large number of time series large models have been proposed and these models can provide reference for the research of radar data intelligent processing. According to the size of the models, these models can be divided into time series large language models and time series pre-trained foundation models. The model scale of the time series large language model is larger than that of the time series pre-trained foundation model. According to the input data, the time series large language model can be divided into text (PromptCast [90], LLMTime [91], TEST [92], Time-LLM [93]), original sequence (Lag-Llama [94], TEST [92]), sequence patch (One Fits All [95], TEMPO [96], LLM4TS [97], Time-LLM [93]), and quantized sequence (Chronos [98]); and the time series pre-trained foundation model can be divided into original sequence (Voice2Series [99], TF-C [100], TS2Vec [101]) and sequence patch (STEP [102], MTSMAE [103], PatchTST [104], SimMTM [105], TSMixer [106]). The achievements of time series large models can be applied to radar data intelligent processing to promote its developments. However, compared with the general time series data, radar data has the characteristics of high noise, strong heterogeneity, and dynamic change of data quality, which makes it difficult to apply the existing time series large models directly to radar data, so it is necessary to carry out targeted research on the characteristics of these radar data.

4 Prospect of future development

In the field of time-series data processing, to which radar data processing belongs, several large models have recently emerged, including time-series large language models and time-series pre-trained foundation models. Among them, time-series large language models include PromptCast [90], LLMTime [91], One Fits All [95], LLM4TS [97], TEST [92], and Time-LLM [93], etc. Time-series pre-trained foundation models include Voice2Series [99], TF-C [100], TS2Vec [101], STEP [102], MTSMAE [103], and TSMixer [106], etc. In November 2023, the American company Nixtla released the industry's first time-series foundation model, TimeGPT [107], claiming it to be the first foundation model that is capable of surpassing other time-series processing methods with minimal complexity. Its dataset covers various areas of daily life, including finance, economics, demographics, healthcare, weather, IoT sensor data, energy, website traffic, sales, transportation, and banking.

Therefore, judging from the research trends in time-series large models, radar data processing will soon enter the stage of general large model. Below, based on our team's research journey and superficial understanding, with track as the core, a research concept for radar data large models is proposed.

4.1 Basic framework

In response to the new demands for autonomous, multi-modal, and multi-mode radar data processing capabilities posed by new means of unmanned platform detection, new modes of space-air cooperative detection, and complex target scenarios, and in conjunction with the development trends of large language models and time-series large models, following the "pre-trained foundation model + downstream task fine-tuning" large model research approach, facing the foundation, technological core, and practical application, it is envisioned to proceed along a research path of "1 domain foundation model + 3 core task models + N typical application implementations." Specifically, this involves conducting research on the radar track foundation model, three core task models for track generation, track association, and track classification, as well as various typical application implementation research such as target detection, target tracking, target recognition, and integrated detection-tracking-recognition. Ultimately, we aim to construct a radar data intelligent processing model to effectively address the current challenges. The research concept for radar data large model is shown in Figure 10.

4.2 Research on foundation model

To train the radar track foundational model, it is crucial to focus on solving three major problems: the construction of large-scale datasets, the design of large-scale neural networks that is suitable for radar spatial-temporal data, and the large model pre-training. In terms of large-scale dataset construction, considering practical factors such as the diversity of track scenarios, the scale of track acquisition, and the cost of track acquisition, AIS data and ADS-B data with long accumulation times and wide distribution ranges can be used as data sources. Targeted research on data compilation and processing methods such as abnormal track deletion and missing track completion should be conducted to generate an accurate, unambiguous large-scale track dataset.

In architecting large-scale neural networks, existing frameworks such as contrastive, predictive, and generative self-supervised learning methods offer valuable references. Innovative approaches including temporal chunk aggregation and spatial grid encoding

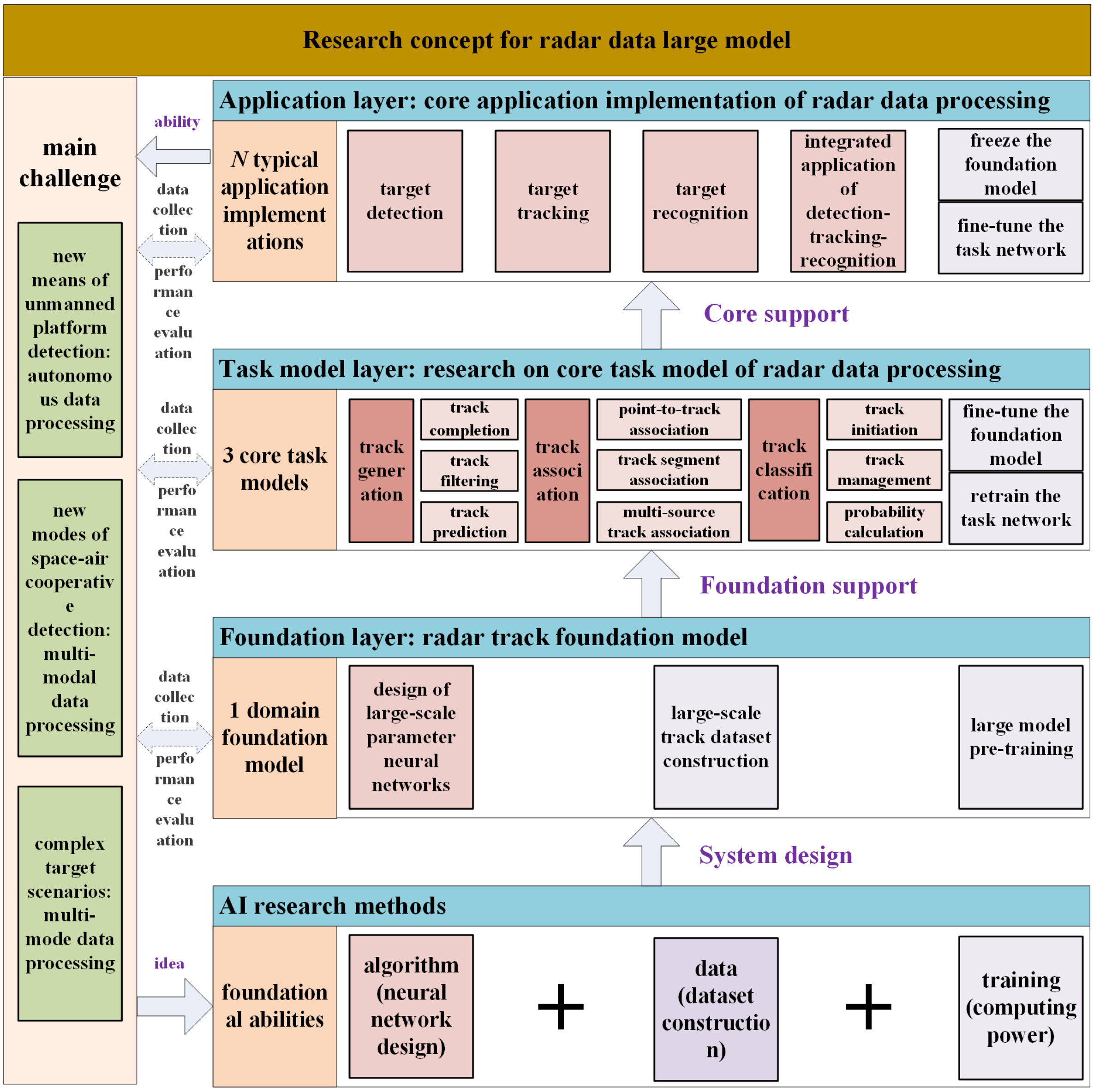

Figure 10. The schematic diagram of the Bayes-Transformer neural network.

should be explored for input-output configuration. Through systematic experimentation and rigorous evaluation, network architectures incorporating CNN, LSTM, Transformer, and Mamba components can be progressively optimized. This ensures that the constructed networks possess the capability to adapt to asynchronous data with different update time and multi-source mixed heterogeneous data. It also possesses the capability to learn representations of target track data characterized by continuous spatial-temporal variations, long time spans, and wide area spatial distributions. This provides a foundational model support for subsequent research on three core tasks: track generation, track association, and track classification.

Large model pre-training primarily aims to enhance the efficiency and accuracy of model training by optimally utilizing limited computational and communication resources. Existing techniques mainly include large-scale distributed training and low-precision training. Among these, large-scale distributed training encompasses data parallelism, tensor parallelism, pipeline parallelism, and 3D parallelism. In addition, in terms of large model pre-training, our primary focus lies in constructing effective input-output data structures to facilitate self-supervised pre-training of large models.

4.3 Research on core task model

Based on the radar track foundation model, radar data is used as the data source. According to the respective characteristics of core tasks such as track generation, track association, and track classification, targeted research and design are conducted on the construction method of domain datasets, network input and output, loss functions, network structures of tasks, and the joint approach of the foundation model and the task network. Following the network optimization methods of fine tuning the foundation model and retraining the task network, specific task models for track generation, track association, and track classification are trained and generated. These models serve as core modules to provide direct support for typical applications in radar data processing.

Track generation primarily utilizes existing target state information from multiple moments, such as position and velocity, to complete missing moments, estimate the current moment, or predict the target state information for the next moment. The network structure of track generation mainly considers the use of LSTM or Transformer for design, and the foundation model and the task network are directly combined through series connection with residual connection.

Track association mainly involves associating multiple existing tracks with newly acquired multiple measurement points from a single radar, or multiple measurement points from multiple radars, or multiple tracks from a single radar, or multiple tracks from multiple radars. The network structure of track association mainly considers the use of MLP, CNN, or Graph Neural Networks (GNN) for design. The foundation model and the task network are combined through feature fusion, with the deep features obtained from the foundation model enhancing the task network in the form of situational knowledge.

Track classification mainly involves classifying whether a track is a real target track, or assessing the quality of the track, or recognizing the type of target corresponding to the track based on a segment of historical track information. The network structure of track classification mainly considers the use of MLP for design, and the foundation model and the task network are directly combined in a series manner.

4.4 Research on core application implementation

Under the existing typical processing frameworks for target detection, target tracking, and target recognition, core task models for radar data processing such as track generation, track association, and track classification are utilized to replace relevant algorithm modules. These core task models are then integrated and optimized to achieve intelligent processing throughout the entire process of target detection, target tracking, and target recognition. According to the network optimization method of freezing the foundation model and fine-tuning the task network, oriented towards specific radar scenarios, online or offline rapid learning is conducted through a small number of samples, and the system integration is optimized for specific applications, so as to obtain radar data processing applications that can be actually deployed and applied. For instance, in target tracking, the association-based target tracking framework can replace, optimize, and integrate track initiation (supported by the track classification task model), point-to-track data association (supported by the track association task model), track filtering (supported by the track generation task model), and track management (supported by the track classification task model). The multiple hypothesis target tracking framework can replace, optimize, and integrate hypothesis probability calculation (supported by the track classification task model) and track filtering (supported by the track generation task model).

5 Conclusion

The rapid development of unmanned control technology, the emergence of new means of unmanned platform detection, new modes of space-air cooperative detection, near space targets, unmanned cluster targets and other high-threat targets, have put forward autonomous, multi-modal, and multi-mode processing capabilities of radar data. At the same time, the general large model has built powerful capabilities for generating content such as language and vision through technologies like unsupervised learning, Reinforcement Learning with Human Feedback (RLHF), and Chain of Thought (CoT). These models not only represent the frontier and focal point of artificial intelligence development, but also offer feasible and effective solutions to address emerging requirements in radar data processing.

In view of this, by reviewing the research process and content of radar data intelligent processing in the past decade, we consider the future development of radar data intelligent processing technology in view of the current challenges faced by radar data intelligent processing and combined with the development opportunities of large model, and puts forward the research concept of radar data large model. The research path of "1 domain foundation model + 3 core task models + N typical application implementations."

is designed, with a view to providing a reference for the research of radar data.

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Not applicable.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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Yaqi Cui received the B.S., M.S. and Ph.D. degrees in Information and Communication Engineering from Naval Aviation University, Yantai, China, in 2008, 2011 and 2014, respectively. From 2024, he was an Associate Professor with Naval Aviation University. His research interests include information fusion, machine learning, and deep learning with their applications in information fusion. (Email: cui_yaqi@126.com)

You He You He, an academician of the Chinese Academy of Engineering, is a professor at the Naval Aviation University. He received his B.S. and M.S. degrees from the Naval University of Engineering in 1982 and 1988 respectively, and obtained his Ph.D. in Communication and Information Systems from Tsinghua University in 1997. He once studied in Germany.

He was a representative of the 17th National Congress of the Communist Party of China and a member of the 12th National Committee of the Chinese People's Political Consultative Conference. He was also awarded the title of National Excellent Teacher.

He has served as a fellow of CAAI, CIE, CAA, CIC, CSF, CICC, and IET; a member of the National Discipline Evaluation Group; a member of the National Natural Science Foundation of China's Outstanding Youth Science Fund Review Committee; and a member of the Information Science Department Consultative Expert Committee of the National Natural Science Foundation of China. He is the vice president of the Chinese Association for Artificial Intelligence and the director of the Intelligent Fusion Professional Committee, the honorary vice president of the Chinese Aeronautical Society and the director of the Information Fusion Branch, and the supervisor of the China Command and Control Society.

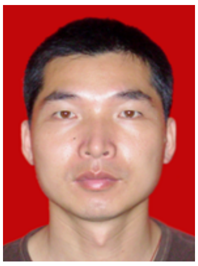
His main research fields include signal detection, information fusion, intelligent technology and applications, etc. As the first author, he has won four second prizes of the National Science and Technology Progress Award, one first prize and one second prize of the National Teaching Achievement Award, and 11 first prizes at provincial and ministerial levels. He has been granted over 60 Chinese invention patents and software copyrights.

He won the National 100 Excellent Doctoral Dissertations Award, and has published over 260 important papers in IEEE journals and other publications, and authored six monographs. His works have been cited over 20,000 times. He has trained over 200 postdoctoral fellows, doctoral and master's students.

He has been selected into the National Program for Hundreds, Thousands and Tens of Thousands of Talents, and has won the Ho Leung Ho Lee Science and Technology Progress Award, the Qiushi Project Award, the National Achievement Award for Returned Overseas Chinese, and the Shandong Province Science and Technology Top Award, among others.

(Email: heyou_f@126.com)

Shutao Xia received the B.S. degree in Electronic Information Technology from Yantai University, Yantai, China, in 2003. And received the M.S. degree in Communication and Information System from Naval Aviation University, Yantai, China, in 2008. Now, he is an associate professor with Naval Aviation University. His research interests include information fusion, deep learning, and target tracking. (Email: 1123103211@qq.com)

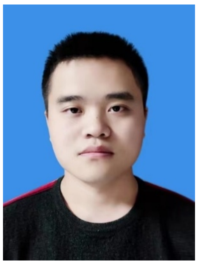


Wei Xiong received the B.S., M.S., and Ph.D. degrees from Naval Aviation University, Yantai, China, in 1998, 2001 and 2005, respectively. From 2007 to 2009, he was a Post-Doctoral Researcher at the Department of Electronic Information Engineering, Tsinghua University, Beijing. He is currently a Full Professor at the Naval Aviation University, Yantai, China, where he teaches random signal processing and information fusion. He is one of the Founders and the Directors of the Institute of Information Fusion, Naval Aviation University. He is the Member and Director General of Information Fusion Branch of Chinese Society of Aeronautics and Astronautics. His research interests include pattern recognition, remote sensing, and multi-sensor information fusion. (Email: xiongwei@csif.org.cn)

Pingliang Xu received B.S. degrees and M.S. degrees from Naval Aviation University, Yantai, China, in 2019 and 2021 respectively, and is currently pursuing a Ph.D. degree in Information and Communication Engineering at Naval Aviation University. His research interests include track association, information fusion, and deep learning. (E-mail: xu_pingliang@163.com)

Jianjuan Xiu received the B.S. degree in Biochemical Engineering from Yantai University in 1994, the M.S. degree in Signal and Information Processing from Naval Aviation University in 2000, and the Ph.D. degree in Communication and Information System from Naval Aviation University in 2004. She is currently a Full Professor at the Naval Aviation University, Yantai, China. Her research interests include information fusion, target tracking, and radar data processing. (Email: xiujianjuan@163.com)

Yu Liu received the B.S., M.S. and Ph.D. degrees in Information and Communication Engineering from Naval Aviation University, Yantai, China, in 2008, 2011 and 2014, respectively. He is currently a Professor at the Naval Aviation University, Yantai, China. His research interests include information fusion, machine learning, and deep learning with their applications in information fusion. (Email: liuyu77360132@126.com)

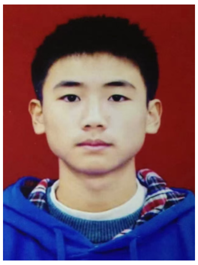


Zhan Kong received the B.S. and M.S. degrees from Naval Aviation University, Yantai, China, in 2020 and 2022 respectively, and is currently pursuing the Ph.D. degree in Information and Communication Engineering at Naval Aviation University. His research interests include target recognition, tracking, and cross-disciplinary applications involving artificial intelligence. (Email: kz2020001@163.com)

Ziling Wang received the B.S., M.S. and Ph.D. degrees in Information and Communication Engineering from Naval Aviation University, Yantai, China, in 2008, 2011 and 2014, respectively. From 2024, he was an Associate Professor with Naval Aviation University. His research interests include information fusion, machine learning, and deep learning with their applications in information fusion. (Email: wzl001213@163.com)

Haoran Li received the B.S. and M.S. degrees from Naval Aviation University, Yantai, China, in 2020 and 2022 respectively, where he is currently pursuing the Ph.D. degree in Information and Communication Engineering. His research interests include information fusion, and deep learning with their applications in remote sensing. (Email: rizhaolihaoran@163.com)

Xiangqi Gu received the B.S. degree from Changchun Institute of Technology, Changchun, China, in 2017, and received the M.S. and Ph.D. degrees in Information and Communication Engineering from Naval Aviation University, Yantai, China, in 2019 and 2023, respectively. His research interests include information fusion, and reinforcement learning with their applications in target tracking. (Email: guxiangqi1314@163.com)



Yuan Lu received the B.S. and M.S. degrees from Naval Aviation University, Yantai, China, in 2021 and 2023 respectively, where he is currently pursuing the Ph.D. degree in Information and Communication Engineering. His research interests include TF analysis, Track-before-Detect, and STAP with their applications in bistatic radar target detection and tracking. (Email: 15267003758@163.com)

Weiwei Sun received the M.S. degree in Computer Science and Technology from Liaoning Normal University, Dalian, China, in 2015. From 2015, she was a lecturer with Naval Aviation University. Her research interests include information fusion, deep learning, and remote sensing image processing. (E-mail: cui_yaqi@126.com)

Hao Tang received the B.S. and M.S. degrees from Naval Aviation University, Yantai, China, in 2022 and 2024 respectively, where he is currently pursuing the Ph.D. degree in Information and Communication Engineering. His research interests include information fusion, and deep learning with their applications in sensors. (Email: tang_haomail@163.com)