Multi-radar collaborative networking method based on T-GCN

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Abstract. Multi-radar collaborative networking is the development direction and research hotspot of radar detection technology. In recent years, with the rise of artificial intelligence, researchers have introduced neural networks and other artificial intelligence methods into multi-radar collaborative networking and achieved remarkable results. In this work, we abstract the radar network as an un-weighted graph, and then introduce the GCN, and combine the characteristics of the GRU with the temporal context, apply the Temporal Graph Convolutional Network to multi-radar collaborative network. We solve the problem of low efficiency and slow speed of radar network without data fusion.

1. Introduction
With the change of the world's military strategy and the continuous deepening reform of the world's military struggle system, information-led systematic combat and confrontation have become the main form of future wars. Cross-formation and cross-platform systematic collaborative operation will also become the basic form of war. As the core equipment of battlefield target perception, radar detection system is also facing more severe challenges. We focus on two of them to analyze and give our solutions. i) In the traditional multi-radar detection system, each radar independently completes the target detection task, lacks a unified collaborated control system. Only a small number of target points and track information are shared inefficiently, and it is difficult to meet the needs of future collaborative detection. ii) As an important part of multi-radar coordination, data fusion still has many problems to be solved urgently. Firstly, the effective information obtained by feature-level data fusion is less and the fusion speed is slow. Secondly, the signal-level data fusion lacks a unified signal format for a complex system composed of multiple radars with different systems, different frequency bands, and different polarization modes.

In this paper, we proposed a multi-radar collaborative networking method based on the Temporal Graph Convolutional Network (T-GCN). Our purpose is to improve the collaborative detection capabilities of future radar systems to deal with the increasingly severe electrical interference environment and the increasing threats of various targets. Through the development of a networked, collaborated, and information-based multi-radar collaborated detection system, multiple radars are optimally configured and have complementary capabilities to achieve comprehensive, three-dimensional, and multi-level collaborative network detection. The radar network can continuously track and detect small targets, low-altitude targets, high-speed and high-maneuvering targets in a broader and more flexible working manner.

We learn from the decentralized concept of distributed computation to eliminate the dependence of the radar network on the collaborative control center, increase the speed of information transmission...
and processing. Aiming at the problem that it is difficult to define a unified signal format for multiple radars in the network, we try to introduce the concept of edge computing to solve the programmability issues.

The main contributions of this article are as follows: i) We proposed a distributed multi-radari networking method. ii) Our radar network can realize signal-level information processing, accelerated information processing speed. iii) We do not need data fusion, solved the programmability issues.

2. Related work

2.1. Radar network
Since the 1980s, the research field of multi-radar collaborative detection has mostly focused on the basis of fusion judgment. With the support of the U.S. Naval Laboratory, researchers at MIT proposed to apply Bayesian criteria to data-level fusion detection, and then obtain a local optimal decision. P.K.Varshney and Z.Chair applied data fusion to the multi-radar Bayes detection problem based on the binary hypothesis testing problem, and then came up with an optimal data-level fusion detection method[1]. R. Niu proposed a new fusion rule Counting Rule by assuming that the detection probability of the node radar is equal to the false alarm probability[2]. In [3], in order to solve the problem that the detection performance of sensor networks is easily affected by the environment, a multi-sensor cooperative target detection algorithm based on adaptive iterative threshold is proposed. With the improvement of computer communication bandwidth, computer memory, and data processing capabilities, more observation information is allowed to be transmitted to the fusion center for processing. Researchers at the University of Rhode Island in the United States, with the support of the United States Air Force Rome Laboratory, conducted research on the signal-level fusion detection method of original echo signal fusion and its key problems. The signal-level fusion detection is mostly carried out under the condition that the echoes are independent of each other. Fishler gives the conditions for the independence of the nodal radar receiving echo[4-5]. I. Y. Hoballah proposed distributed Bayesian signal detection in [6]. In terms of single-platform with multi-radar integrated collaboration, multi-functional phased array radar is the core for integrated radar design. The most typical is Integrated Topside project, supported by U.S. Navy. Through unified resource management, status control, signal processing, data processing, and signal display, the project realized signal-level collaboration of single-platform with multi-radar[7]. The core of the InTop is to develop a modular and open architecture that can adapt to changes in technology and naval combat requirements[8-9]. Under the InTop architecture, the radar function system can support one or more narrow/wide beams of any specified in-band frequency, can generate, receive and process multi-frequency complex waveforms, and can simultaneously scan and track multiple targets for alert and precision track[10-13].

2.2. Graph Convolutional Network
At first, we sort out the differences and connections between Graph Embedding, Graph Neural Network and Graph Convolutional Network.

Graph Embedding[14-18] belongs to the category of representing learning, which usually has two levels of meaning. First, nodes in the graph are represented as low-dimensional, real-valued, and dense vector forms, so that the obtained vector form can have the ability of representation and reasoning in the vector space, and such vectors can be used in specific tasks. For example, the node representation obtained by the user social network is the representation vector of each user, which is then used for node classification. Second, entire graph is represented as a low-dimensional, real-valued, dense vector form, which is used to classify the entire graph structure. There are three methods of graph embedding: matrix factorization, Deepwalk, and Graph Neural Network.

Graph Neural Network is a general term for the models applied by neural networks on graphs. According to different classification methods and adopted technologies, GNN can be divided into different types[19]. At present, GCN, GAT and GraphLSTM[20-22] are more effective.
Graph Convolutional Network is a type of neural network that uses graph convolution. GCN has developed to many versions based on the simplest graph convolution improvement, and its status in the field of graph network is just like the status of convolution operation in image processing. The following characteristics are defined for the graph: a graph define as a pair $G = (V, E)$ with $N$ nodes $v_i \in V$, edges $(v_i, v_j) \in E$, each node $i$ has feature $x_i$, $X_{N \times D}$ is a matrix of node feature vectors $x_i$, $N$ is the number of the nodes, $D$ represents the feature dimension of each node, also called the dimension of the feature vector. Therefore, any graph convolutional layer can be written as such a nonlinear function:

$$H^{l+1} = f(H^l, A)$$

$H^0 = X$ is the first layer input, $x \in R^{N \times D}$, $A$ is adjacency matrix, Different models are selected for different problems. The difference lies in the implementation of the function $f$.

3. Our work

Our key idea is to abstract the radar network as an unweighted graph. We extract the interconnections between radars and the features of radars and normalize them, which are used to construct adjacency matrix and feature matrix. Then input them into T-GCN to train the model as show in Fig. 1.

3.1. Embedding

To deal with the differences between multiple radars, we need to carry out a unified formal description and functional encapsulation of the multi-radar collaborative detection system resources, and map specific system physical resources to logical resources. Therefore, we learn from the process of embedding for words in natural language processing to obtain word vectors, and abstract the radar physical resources into feature vectors. To ensure that the multiple physical resources of different radars can be represented by a unified feature vector, we set the dimension of the feature vector to be large enough to make the different features discrete from each other and retain as much information as possible. The feature matrix of the radar is $X_{N \times D}$, $x_i$ is the i-th feature of the radar, $N$ is the dimension of the feature vector. We use Continuous Bag of Words Model, which is word2vec[23] way, to embed radar feature as show in Fig. 2.
Figure 2. CBOW is a kind of word2vec.

Assuming that the CBOW model takes $k$ words before and after the target word $w_t$, that means the size of the window is $k$, then the CBOW model predicts as

$$p(w_t | w_{t-k}, w_{t-(k-1)}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+(k-1)}, w_{t+k})$$

(2)

The weight matrix from the input layer to the hidden layer is $W$, and the vector of the hidden layer is $h$, then:

$$h = \frac{1}{k} \sum_{i=1}^{k-1} (w_i^T \cdot x_{t-i} + w_i^T \cdot x_{t+i})$$

(3)

The weight matrix from the hidden layer to the output layer is $U_{d \times 1}$, and the vector of the output layer is $y_{d \times 1}$, then:

$$y = \text{softmax}(U^T \cdot h)$$

(4)

And loss function:

$$L = \prod_{t=1}^{V} p(w_t | w_{t-k}, w_{t-(k-1)}, \ldots, w_{t-1}, w_{t+1}, \ldots, w_{t+(k-1)}, w_{t+k})$$

(5)

3.2. Temporal Graph Convolutional Network

In this section, we elaborate on the algorithm framework and algorithm implementation. To capture the space and time dependencies at the same time, we adopt the Temporal Graph Convolutional Network proposed by Zhao, L. in [24]. This model combines graph convolutional network (GCN) and gated recursive unit (GRU). GCN is used to learn complex topological structures to capture spatial dependencies, and GRU is used to learn the dynamic changes of radar networks to capture temporal dependencies. In this research, the goal of the multi-radar network is to predict the radar feature in a certain period of time based on the historical detection information in the network. In our method, the radar feature is a general concept which can be center frequency, bandwidth, beamforming, or sampling rate.

Definition 1: radar network $G$. We use an unweight graph $G = (V, E)$ to describe the topological structure of the radar network, and we treat each radar as a node, where $V$ is a set of radar nodes, $V = \{v_1, v_2, \ldots, v_N\}$, $N$ is the number of the nodes, and $E$ is a set of edges, $(v_i, v_j) \in E$. The adjacency matrix $A$ is used to represent the connection between radars, $A \in \mathbb{R}^{N \times N}$. The adjacency matrix contains only elements of 0 and 1. The element is 0 means there is no link between two radars and 1 denotes there is a link. Because the radars are connected to each other, the collaborative control system is no longer needed. This is an end-to-end learning process, and there is no need to consider data fusion.

Definition 2: feature matrix $X^{N \times D}$. We regard the radar feature on the radar network as the attribute features of the node in the network, expressed as $X \in \mathbb{R}^{N \times D}$, where $N$ is the number of the nodes, $D$
represents the feature dimension of each node and $X_t \in \mathbb{R}^{N \times d}$ is used to represent the bandwidth on each radar at time $i$. Again, the node attribute features can be any radar feature such as center frequency, bandwidth, beamforming, or sampling rate.

Thus, the problem of spatio-temporal radar forecasting can be considered as learning the mapping function $f$ on the premise of radar network topology $G$ and feature matrix $X$ and then calculating the radar feature in the next $T$ moments, as shown in equation 6:

$$[X_{t+1}, \ldots, X_{t+T}] = f(G; (X_{t-n}, \ldots, X_{t-1}, X_t))$$  \hspace{1cm} (6)

where $n$ is the length of historical time series and $T$ is the length of the time series needed to be predicted.

![Graph Convolution Network and Gated Recurrent Unit model](image)

**Figure 3.** Overview. We take the historical radar feature as input and obtain the final prediction result through the Graph Convolution Network and the Gated Recurrent Unit model.

Now, we describe how to use the T-GCN model to realize the radar forecasting task based on the radar network. Specifically, the T-GCN model consists of two parts: the GCN and the GRU. As shown in Figure 3, we first use the historical $n$ time series data as input and the GCN is used to capture topological structure of radar network for obtaining the spatial features. Second, the obtained time series with spatial features are input into the GRU model and the dynamic change is obtained by information transmission between the units, to capture temporal features. Finally, we get results through the fully connected layer.

Given an adjacency matrix $A$ and the feature matrix $X$, the GCN model constructs a filter in the Fourier domain. The filter, acting on the nodes of a graph, captures spatial features between the nodes by its first-order neighborhood, then the GCN model can be built by stacking multiple convolutional layers, which can be expressed as equation 7:

$$H^{(l+1)} = \sigma \left( \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} \theta^{(l)} \right)$$  \hspace{1cm} (7)

where $\tilde{A} = A + I_N$ is the matrix with added self-connections, $I_N$ is the identity matrix, $\tilde{D}$ is the degree matrix, $\tilde{D} = \sum_j \tilde{A}_{ij}$, $H^{(l)}$ is the output of $l$ layer, $\theta^{(l)}$ contains the parameters of that layer, and $\sigma(\cdot)$ represents the sigmoid function for a nonlinear model.
We use the 2-layer GCN model to obtain spatial dependence[20], which can be expressed as equation 8:

\[ f(X, A) = \sigma(\hat{A})ReLU(\hat{A}XW_0)W_1 \]  

(8)

where \( \hat{A} = \hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}} \) denotes pre-processing step, \( W_0 \in \mathbb{R}^{P \times H} \) represents the weight matrix from input to hidden layer, \( P \) is the length of feature matrix, and \( H \) is the number of hidden unit, \( W_1 \in \mathbb{R}^{H \times T} \) represents the weight matrix from hidden to output layer. \( f(X, A) \in \mathbb{R}^{N \times T} \) represents the output with the prediction length \( T \), and \( ReLU() \), standing for REctified Linear Unit, which is a frequently used activation layer in modern deep neural networks.

Then, we combine graph convolution process \( f(X, A) \) which defined in equation 8, with GRU. \( f(X, A) \) represents the point-wise multiplication. W and b represent the weights and biases in the training process.

\[ u_t = \sigma(W_u[f(A, X_t), h_{t-1}]) + b_u \]  

(9)

\[ r_t = \sigma(W_r[f(A, X_t), h_{t-1}]) + b_r \]  

(10)

\[ c_t = tanh(W_c[f(A, X_t), (r_t \ast h_{t-1})] + b_c \]  

(11)

\[ h_t = r_t \ast h_{t-1} + (1 - u_t) \ast c_t \]  

(12)

In the training process, the goal is to minimize the error between the real radar feature and the predicted value. \( Y_t \) is the real value and \( \hat{Y}_t \) is the predicted one. The first term is used to minimize the error between the real radar feature and the prediction. The second term \( L_{reg} \) is the L2 regularization term that helps to avoid an overfitting problem and \( \lambda \) is a hyperparameter.

\[ loss = ||Y_t - \hat{Y}_t|| + \lambda L_{reg} \]  

(13)

4. Conclusions

The Multi-radar collaborative networking method based on T-GCN can deal with complex spatial dependence and temporal dynamics in radar network. On one hand, we use GCN to capture the topological structure of the radar network for obtaining the spatial dependence. On the other hand, the GRU is used to capture the dynamic variation of radar feature in the network for obtaining the temporal dependence and eventually for realizing radar collaboration tasks.

References

[1] Chair,Z., & Varshney,P.Optimal Data Fusion in Multiple Sensor Detection Systems[J].Ieee Transactions on Aerospace and Electronic Systems,1986(1):98-101.

[2] North,D.O.An Analysis of the Factors Which Determine Signal/noise Discrimination in Pulsed-carrier Systems[J].Proceedings of the Ieee,1963,51(7):1016-1027.

[3] Li,T., Sun,Y., & Yu,J.A Cooperative Target Detection Algorithm Based on Distributed Sensor Networks[C]/2017 Ieee 3rd Information Technology and Mechatronics Engineering Conference (itoec):Ieee,2017:32-36.

[4] Fishler,E., Haimovich,A., Blum,R.S., Cimini,L.J., Chizhik,D. et al. .Spatial Diversity in Radars—models and Detection Performance[J].Ieee Transactions on Signal Processing,2006,54(3):823-838.

[5] Fishler,E., Haimovich,A., Blum,R., Chizhik,D., Cimini,L. et al. .Mimo Radar: an Idea Whose Time Has Come[C]/Proceedings of the 2004 Ieee Radar Conference (ieee Cat. No. 04ch37509):Ieee,2004:71-78.

[6] Hoballah,I.Y., & Varshney,P.K.Distributed Bayesian Signal Detection[J].Ieee Transactions on Information Theory,1989,35(5):995-1000.

[7] Henry,M., Iacovelli,M., & Thacher,J.Ddg 1000 Engineering Control System (ecs)[C]/Asne Intelligent Ship Viii Symposium:Citeseer,2009:12-26.

[8] Tavik,G., Alter,J., Evans,J., Patel,D., Thomas,N. et al. .Integrated Topside (intop ) Joint Navy-industry Open Architecture Study[R]:Naval Research Lab Washington Dc,2010.

[9] Kemkemian,S., Le roy-rameix,I., Mallegol,S., Perpère,B., & Renard,C.Wideband and Very Wideband Thin Structural Tiles for Airborne Active Antennas[C]/2013 7th European
Conference on Antennas and Propagation (eucap):IEEE,2013:2744-2747.

[10] Van rossum,W., De wit,J., Otten,M., & Huizing,A.Smrf Architecture Concepts[J].IEEE Aerospace and Electronic Systems Magazine,2011,26(5):12-17.

[11] Hurley,S., & Khan,M.I.Netted Radar: Network Communications Design and Optimisation[J].Ad Hoc Networks,2011,9(5):736-751.

[12] Blunt,S.D., Yatham,P., & Stiles,J.Intrapulse Radar-embedded Communications[J].IEEE Transactions on Aerospace and Electronic Systems,2010,46(3):1185-1200.

[13] Infante,L., De luca,A., & Teglia,M.Low-profile Ultra-wide Band Antenna Array Element Suitable for Wide Scan Angle and Modular Subarray Architecture[C]/2010 IEEE International Symposium on Phased Array Systems and Technology:IEEE,2010:157-163.

[14] Goyal,P., & Ferrara,E.Graph Embedding Techniques, Applications, and Performance: a Survey[J].Knowledge-based Systems,2018,151:78-94.

[15] Cui,P., Wang,X., Pei,J., & Zhu,W.A Survey on Network Embedding[J].IEEE Transactions on Knowledge and Data Engineering,2018,31(5):833-852.

[16] Cai,H., Zheng,V.W., & Chang,K.C.A Comprehensive Survey of Graph Embedding: Problems, Techniques, and Applications[J].IEEE Transactions on Knowledge and Data Engineering,2018,30(9):1616-1637.

[17] Zhang,D., Yin,J., Zhu,X., & Zhang,C.Network Representation Learning: a Survey[J].IEEE Transactions on Big Data,2018,6(1):3-28.

[18] Hamilton,W.L., Ying,R., & Leskovec,J.Representation Learning on Graphs: Methods and Applications[J].Arxiv Preprint Arxiv:1706.05584,2017.

[19] Zhou,J., Cui,G., Zhang,Z., Yang,C., Liu,Z. et al. .Graph Neural Networks: a Review of Methods and Applications[J].Arxiv Preprint Arxiv:1812.08434,2018.

[20] Kipf,T.N., & Welling,M.Semi-supervised Classification with Graph Convolutional Networks[J].Arxiv Preprint Arxiv:1609.02907,2016.

[21] Liang,X., Shen,X., Feng,J., Lin,L., & Yan,S.Semantic Object Parsing with Graph Lstm[C]/European Conference on Computer Vision:Springer,2016:125-143.

[22] Veličković,P., Cucurull,G., Casanova,A., Romero,A., Lio,P. et al. .Graph Attention Networks[J].Arxiv Preprint Arxiv:1710.10903,2017.

[23] Goldberg,Y., & Levy,O.Word2vec Explained: Deriving Mikolov Et Al.'s Negative-sampling Word-embedding Method[J].Arxiv Preprint Arxiv:1402.3722,2014.

[24] Zhao,L., Song,Y., Zhang,C., Liu,Y., Wang,P. et al. .T-gen: a Temporal Graph Convolutional Network for Traffic Prediction[J].IEEE Transactions on Intelligent Transportation Systems,2019,21(9):3848-3858.