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Distributed Clustering Method Based on Spatial Information

XIN DONG[1], YAN LIANG[1], AND JIE WANG[2]
[1]Computer Engineering College, Chengdu Technological University, Chengdu 611730, China
[2]Southwest Institute of Electronic Equipment, Chengdu 610036, China

Corresponding author: Jie Wang (wangjie16@cetc.com.cn)

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ABSTRACT Radar pulse deinterleaving is the core part of electronic reconnaissance system, which is responsible for sorting out the pulses coming from different emitters. In the process of signal deinterleaving, parameter clustering is an important method. The features for clustering are mainly derived from pulse parameters emitted by the radiation source transmitter. When the multiple target signals are seriously mixed in a complex environment, the clustering accuracy decreases. To solve this problem, a distributed clustering method based on spatial information is proposed. First, a multi-node distributed system is built, one of the nodes is taken as the central node, and the pulse information transmitted by other nodes through the link is received. All pulses at the central node are jointly clustered according to the three parameters of radio frequency (RF), pulse width (PW) and time of arrival (TOA), forming an associated pulse description word (APDW). Then, the associated pulse is spatially marked based on its spatial information within the range of the target area of interest. Finally, the associated pulse is re-clustered using the marked information and pulse parameters to achieve effective target separation. The simulation results show that the method can overcome the influence of parameter agility and make full use of the spatial information of the target to improve the accuracy of pulse clustering.

INDEX TERMS Clustering, distribution, radar emitter, signal deinterleaving, spatial information.

I. INTRODUCTION

Radar radiation source signal deinterleaving is the process of separating multiple radiation source pulses that are interleaved in the time-frequency space domain, such that pulses belonging to the same radiation source are clustered and pulses that do not belong to the same radiation source are separated. It is not only an important processing link in the electronic reconnaissance system, but also the basis and premise for realizing the identification, positioning and interference guidance of radar radiation sources [1].

To realize the effective sorting of radiation source pulses, it is necessary to find the gatherable features from the same radiation source and the separable features among different radiation sources. All of these features should have strong stability and universality.

The radiation source characteristics that can be used by the single-platform electronic reconnaissance system include RF, PW, and modulation of pulse (MOP), etc [2], [3]. It primarily uses the signal parameters emitted by the radiation source transmitter. When faced with a radiation source signal with variable parameters, it is likely-to that one radiation source is separated into multiple classes. This ''increasing batch'' phenomenon brings a lot of troubles to subsequent identification and localization [4]. Therefore, it is necessary to obtain more stable signal characteristics.

Although the signal parameters emitted by the radiation source can easily change or even change rapidly during the working process, the spatial position of the radiation source cannot change rapidly, but only slowly or remains unchanged. Therefore, the spatial information of the radiation source can be used to achieve the aggregation of the same radiation source and the separation of different radiation sources.

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With the development of ''informatization, networking and intelligence'' technology, distributed electronic reconnaissance systems composed of multiple reconnaissance processing nodes have increasingly become a development trend in this field. In particular, the distributed electronic warfare system represented by an unmanned aerial vehicle (UAV) swarm will be a typical distributed electronic warfare system in the future [5].

A distributed electronic reconnaissance system can extract the spatial information of the target owing to its multi-node distribution characteristics. Therefore, this study proposes distributed clustering method based on spatial information to improve the accuracy of clustering when facing multiple changing targets which have complex and variable parameters. This method can overcome the influence of target signal parameter agility, and make full use of the spatial information of radar targets to improve the ability of pulse clustering. The main objectives of this study are as follows:

(1) A new pulse description model is introduced. An APDW can be formed which can unify the description of radar pulse reception in electromagnetic environments under distributed conditions.
(2) Spatial information is extracted. The spatial features of each pulse can be obtained from the relative spatial relationships between multiple nodes and targets. The received pulse can be spatially marked based on the library of time differences between the target and each node within the range of interest.
(3) A clustering method based on spatial information is proposed. The associated pulse is clustered using marked information and pulse parameters to achieve effective separation of radar targets, which can improve the accuracy of pulses clustering.

The remainder of this paper is organized as follows. Section II introduces some works related to the clustering method. Section III presents the pulse description model under distributed conditions. Section IV introduces distributed clustering algorithm, including algorithm principle and algorithm flow. Section V verifies the reliability and accuracy of the new algorithm by simulation experiments. In addition, a comparative analysis is introduced. Finally, Section IV concludes the paper.

II. RELATED WORK

From a mathematical point of view, the sorting of radiation source pulse signals uses multi-dimensional features to separate the pulses, and divide them into multiple different clusters according to the attributes of the radiation source.

Radiation source pulse signal deinterleaving methods mainly include two categories: one is a deinterleaving method derived from the pulse repetition interval (PRI) information deinterleaving method for time series parameters, and the other is derived from pattern recognition theory using multiple non-temporal parameters for joint processing.

Signal deinterleaving methods based on PRI information include the cumulative difference histogram method [6], sequence difference histogram method [7]–[9], and PRI transform method [10]–[12]. This type of method has a good effect in a simple electromagnetic environment where the pulse repetition interval of the radiation source is fixed, the number of series parameters is simple and the number of radiation sources is small. However, it has poor adaptability to situations where the pulse repetition interval is complex and the number of targets in the environment is large.

From the perspective of pattern recognition, signal deinterleaving is a typical unsupervised clustering problem. The basic idea of clustering is the process of separating objects with different attributes and merging them with the same attributes. These combined features form clusters.

Clustering techniques have been in several fields. In [13] the authors proposed an energy-efficient clustering method for optical wireless sensor networks that fused the Firefly algorithm and hierarchical maximum likelihood (HML) technology, overcoming some shortcomings of the simple Firefly algorithm. In [14] the authors proposed a deep neural network-based clustering method for the security of data information for industrial internet of things (IIoT) applications. This method used deep learning to enhance the security of the physical layer under different channel state conditions.

The characteristics of radiation source signals in the electronic reconnaissance system can be divided into two categories: the characteristics associated with the transmitted signal, such as RF, PW and MOP, and the characteristics associated with the spatial position of the transmitter, such as the direction of angle (DOA) and target location. Location information can also be characterized by the difference in the time of arrival (DTOA) and the difference in radio frequency (DRF) between the target and each node [15], [16].

At present, the clustering of radar radiation source pulses is mainly derived from a single detection platform (node) that receives the radiation source pulses in the environment for processing. The use of multi-parameter clustering methods such as carrier frequency and pulse width solved the problem of complex pulse repetition interval changes to a certain extent [17]–[21]. Reference [22] also proposed a pulse sequence retrieval algorithm based on the idea of clustering. The separation of the mixed pulsed flow was completed. Reference [23] introduced a novel clustering method derived from complex networks, using a limited penetrable visibility graph (LPVG) to construct the network, and using the label propagation algorithm (LPA) and density peak clustering (DPC) to divide the network to ensure that the pulse signals from the same radiation source belong to the same cluster. Reference [24] combined with fuzzy rough set theory, proposed a feature extraction and feature selection method for radar signal pulse clustering, and obtained an optimal feature subset. Reference [25] proposed a two-step clustering method to realize the separation of unknown radar signals, applied the first-step clustering output as a feature to the second-step clustering process, and obtained a good separation effect.

The RF and PW of the radiation source signal often change depending on the task adjustment. When the carrier frequency and pulse width parameters are complexly changed, the probability of increasing-batch for one target will increase. The clustering method using intra-pulse features [26], [27] had strong adaptability to targets with complex and variable conventional parameters and relatively stable intra-pulse features, but the extraction of intra-pulse features required a large amount of computation. Real-time extraction of all pulse intra-pulse features in a dense environment is difficult, the accuracy of intra-pulse feature extraction needed to be improved, and the application effect was not good.

At present, a typical clustering method requires prior information in the process of using it. For example, the K-means method [28] and fuzzy clustering method [29] generally need to know the number of classification clusters in advance, which is more difficult to obtain.

To overcome these problems, this study proposes a distributed clustering method. This method obtains relatively stable features of radiation sources by exploiting the relative spatial position information between multiple nodes and targets in a distributed detection system. Spatial feature combined with signal features can ensure better sorting accuracy.

III. PULSE DESCRIPTION MODEL UNDER DISTRIBUTED CONDITIONS

A typical distributed electronic reconnaissance system is constructed, in which the number of nodes is N, and the number of targets of radar radiation sources in the environment is M, as shown in Figure 1. The pulses emitted by the M targets are arranged in chronological order in the time domain to form a continuous interleaved pulse sequence stream, as shown in Figure 2, where each radiation source emits pulse signals using the TOA, RF, and PW three-dimensional parameter representation.

In a distributed system environment, the pulse signal emitted by the target of a radar radiation source may be received by one or multiple nodes. In this study, the comprehensive performance of the detection of the same pulse at different nodes is defined as an APDW, as shown in Equation (1):

$$APDW_i = \begin{bmatrix} PDW_{i1} \\ PDW_{i2} \\ \cdots \\ PDW_{iN} \end{bmatrix} = \begin{bmatrix} TOA_{i1} & RF_{i1} & PW_{i1} \\ TOA_{i2} & RF_{i2} & PW_{i2} \\ \cdots & \cdots & \cdots \\ TOA_{iN} & RF_{iN} & PW_{iN} \end{bmatrix} \quad (1)$$

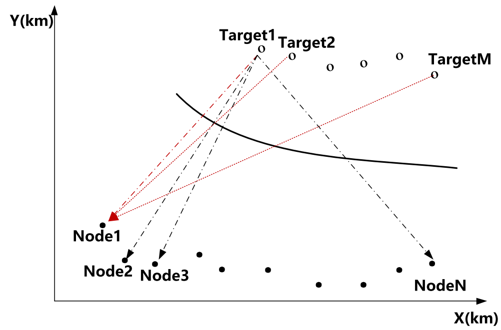


FIGURE 1. Schematic diagram of multi-node distributed reception of multi-target signals.

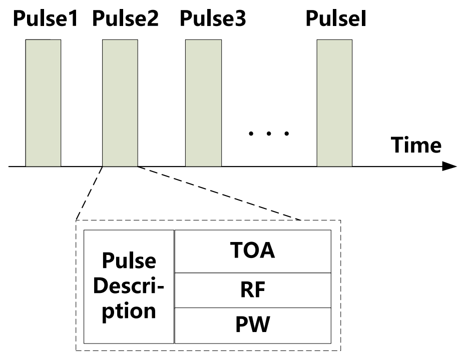


FIGURE 2. Description of target pulse parameters.

where $APDW_i$ represents the ith APDW, $i = 1, 2, 3, \ldots, I$, and all radiation source pulses have total I associated pulses; PDW_{i1} indicates that the first node receives the ith pulse, other nodes, etc.

In a distributed system, a pulse emitted by a radar radiation source may be received by some nodes but not by other nodes. If the nth node does not receive the ith pulse, PDW_{in} is set to 0. For example, Equation (2) describes the fifth joint pulse. The expression $PDW_{52} = 0$ indicates that the second node did not receive the 5th pulse signal.

$$APDW_5 = \begin{bmatrix} PDW_{51} \\ 0 \\ \cdots \\ PDW_{5N} \end{bmatrix} = \begin{bmatrix} TOA_{51} & RF_{51} & PW_{51} \\ 0 & 0 & 0 \\ \cdots & \cdots & \cdots \\ TOA_{5N} & RF_{5N} & PW_{5N} \end{bmatrix} \quad (2)$$

According to the associated pulse description defined by Equations (1) and (2), the receiving results of the same pulse arriving at different nodes under distributed conditions can be described uniformly, and the parameters of the same pulse received by different nodes can also be correlated and analyzed to mine spatial information, which is convenient for subsequent parameter clustering.

IV. DISTRIBUTED CLUSTERING ALGORITHM

A. ALGORITHM'S PRINCIPLE

In a distributed system consisting of N nodes, a central node is arbitrarily selected in advance. For simplicity, this study selects node 1 as the central node.

The purpose of parameter clustering is to realize pulse aggregation of the same radar radiation source target and pulse separation of different targets. Therefore, it is necessary to fully utilize of the similar characteristics between different pulses of the same target. The target signal parameters will change with the change in the combat mission, and the spatial position information of the target is more stable and reliable than the signal parameters. However, obtaining the target position information in the passive positioning system requires a complex calculation process [30], which increases the complexity of the system. The time information of the target arriving at different nodes indirectly implies the spatial position of the target. Therefore, the time information of the arriving node can be used to characterize the spatial position characteristics of the target without the need for a positioning solution.

Set the time for the ith associated pulse from an unknown radar radiation source to reach the nth in the interest space range as t_{in}, and the time difference between the n_1 node and the n_2 node as $r_{in_1n_2}$, namely:

$$r_{in_1n_2} = t_{in_1} - t_{in_2} \tag{3}$$

Then the target arrival time difference matrix under distributed conditions R_i can be defined as:

$$R_i = \begin{bmatrix} r_{i11} & r_{i12} & \cdots & r_{i1N} \\ r_{i21} & r_{i22} & \cdots & r_{i2N} \\ \cdots & \cdots & \cdots & \cdots \\ r_{iN1} & r_{iN2} & \cdots & r_{iNN} \end{bmatrix} \tag{4}$$

Based on the range of the space of interest, the distributed system can dynamically construct the time difference matrix of potential targets according to its own system architecture and node distribution to form a dynamic time difference library. If the number of potential targets is K, the kth potential target time difference matrix is defined as:

$$R_k = \begin{bmatrix} r_{k11} & r_{k12} & \cdots & r_{k1N} \\ r_{k21} & r_{k22} & \cdots & r_{k2N} \\ \cdots & \cdots & \cdots & \cdots \\ r_{kN1} & r_{kN2} & \cdots & r_{kNN} \end{bmatrix} \tag{5}$$

where r_{knq} represents the time difference between the nth node and qth node receiving signal from the kth target. In the clustering process, N nodes independently detect the waveform of the radiation source of interest in the electromagnetic environment according to standard time, detect and measure to form their own pulse description word (PDW), and then send their respective PDWs through the link. The pulse parameter data is transmitted to the central node, which performs joint pulse clustering derived from the spatial information and combined with the parameter information to complete the separation of the radiation source signals.

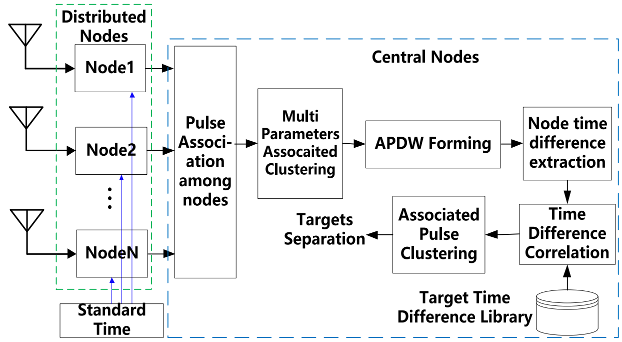


FIGURE 3. Block diagram of distributed pulse clustering.

The similarity between the ith joint pulse received by the distributed system and the kth potential target of the time difference library d_{ik} is expressed by the Frobenius norm [31], as shown in Equation (6).

$$d_{ik} = \|R_i - R_k\|_F = \left(\sum_{n=1}^{N} \sum_{q=1}^{N} \left| r_{inq} - r_{knq} \right|^2 \right)^{1/2} \tag{6}$$

where $i = 1, 2, 3, \ldots, I$ represents all the received joint pulses; $k = 1, 2, 3, \ldots, K$ represents all potential targets in the time difference library; n and q represent the node serial numbers respectively.

The Frobenius norm represents the Euclidean distance between the two matrices R_i and R_k. The smaller the value, the closer the two matrices are. If the ith pulse comes from the kth potential target, the Frobenius norm between the two is close to 0 (under certain measurement error conditions), which indicates the highest similarity, and the target number k is marked as the joint pulse i at this time. In the actual calculation, a certain similarity threshold can be set. Exceeding the similarity threshold indicates that the pulse belongs to the corresponding target.

A block diagram of the working principle of the distributed pulse clustering proposed by this method is shown in Figure 3. In the figure, pulse fusion between nodes sorts the pulses of all nodes according to the arrival time; multi-parameter joint clustering uses parameters such as carrier frequency, pulse width and pulse arrival time to achieve unsupervised clustering; joint pulse formation associates the information of N nodes from the same pulse according to the clustering results; the node time difference extraction is used to extract the corresponding time difference for each joint pulse; the time difference association associates each joint pulse with the time difference library based on the time difference information, finds the distance in the library the closest target serial number and the serial number is marked to the joint pulse; and joint pulse clustering uses the marking information combined with the signal parameters to realize the clustering of the joint pulse, and finally completes the target separation.

TABLE 1. Targets' parameter table (case 1).

Target ID	RF Type	RF(MHz)	PW(μ s)	PRI Type	PRI(μ s)	Pulse Num	Target Position(km)
1	Fixed	1100	1	Stagger	1000~1110	942	(1,80)
2	Agile	1400~1600	3	Coded	1000~1300	862	(3,70)
3	Agile	2850~3150	5	Jitter	1000~1300	867	(6,60)
4	Fixed	2000	7	Slider	1000~1300	874	(10,65)
5	Agile	3350~3650	9	Jitter	1000~1300	873	(15,80)

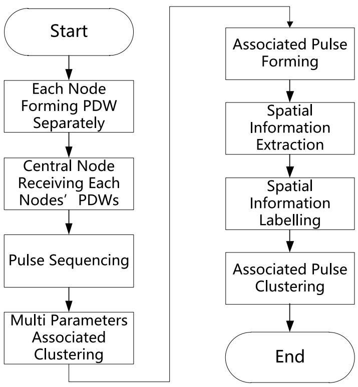


FIGURE 4. Distributed Pulse Clustering Flowchart.

B. ALGORITHM PROCEDURE

For a complex electromagnetic environment with multiple targets, the distributed pulse clustering process for target separation based on a distributed electronic reconnaissance system composed of N nodes is shown in Figure 4.

Step 1: Each node of the distributed system autonomously receives the radiation source signal of the electromagnetic environment, measures the pulse parameters, and forms a pulse description word under the unified standard time, which includes three-dimensional parameter information, such as pulse arrival time, pulse frequency, and pulse width.

Step 2: Take one of the nodes as the central node and receive the pulse description word information transmitted by the other nodes through the link.

Step 3: Sort the pulse parameters of all nodes according to the arrival time at the central node.

Step 4: Jointly cluster the sorted pulses according to the three parameters of pulse frequency, pulse width and pulse arrival time to form a joint pulse description. Each joint pulse is composed of the same pulse from the same radiation source at different nodes. The pulse parameters are then combined.

Step 5: Extract the spatial information of the node time difference based on each joint pulse. First, find the pulse with the smallest node number among the pulses actually received in the joint pulse, then derived from the arrival time of the pulse, calculate the time difference of the arrival times of the pulses received by other nodes, and use Equation (4) to form the time difference matrix of the joint pulse.

Step 6: Based on the potential target time difference library, each joint pulse is marked with spatial information. Each joint pulse time difference matrix is associated with each potential target time difference matrix in the target time difference library, and Equation (6) is used to mark the target sequence number with the highest similarity in the library to the joint pulse.

Step 7: Perform joint clustering on the marked joint pulses using the marking information combined with pulse parameters, to gather joint pulses belonging to the same radiation source into a cluster, and separate joint pulses of different radiation sources to complete all pulse clustering.

V. SIMULATION AND ANALYSIS OF EXPERIMENT RESULTS

A. SIMULATION SCENE SETTING

To verify the spatial position relationship between the receiving node and the target in the distributed system, it is necessary to construct the spatial position coordinates of each node and target. For the sake of simplicity and without loss of generality, this study designs a two-dimensional plane simulation scene that is set as follows: a distributed system with 10 nodes is constructed, and the position coordinates of the nodes are (0, 0), (2000, 200), (4000, 300), (6000, −200), (8000, 500), (10000, −200), (12000, 100), (14000, −300), (16000, 0), and (18000, 200) (unit: m), where node 1 is the central processing node. Assuming that there are 5 targets of interest in the environment, the target position coordinates are (1, 80), (3, 70), (6, 60), (10, 65), and (15, 80) (unit: km).

There are three situations for determining the relationship between target signal parameters of different radar radiation sources. Case 1: The target signal parameters are clearly distinguishable; Case 2: Most of the target signal parameters are distinguishable; and Case 3: The target signal parameters are distinguishable. The signal parameters are listed in Tables 1, 2, and 3.

Considering the actual situation, there is a certain deviation in the receiver measurement of the target signal parameters of the radar radiation source. In this study, the parameter measurement errors are set as normal distribution random errors, in which the root mean square error of frequency is 0.5MHz, the root mean square error of arrival time and pulse width is 0.05μs, and the root mean square error of angle is 2.5°. The algorithm used in this study does not require the measurement of the target angle. The angle information is primarily used

TABLE 2. Targets' parameter table (case 2).

Target ID	RF Type	RF(MHz）	PW(μ s)	PRI Type	PRI(μ s)	Pulse Num	Target Position(km)
1	Fixed	1100	1	Stagger	1000~1110	942	(1,80)
2	Agile	1400~1600	3	Coded	1000~1300	862	(3,70)
3	Agile	2800~3200	5	Jitter	1000~1300	867	(6,60)
4	Fixed	2000	3	Slider	1000~1300	874	(10,65)
5	Agile	3250~3750	5	Jitter	1000~1300	873	(15,80)

TABLE 3. Targets' parameter table (case 3).

Target ID	RF Type	RF(MHz）	PW(μ s)	PRI Type	PRI(μ s)	Pulse Num	Target Position(km)
1	Fixed	1300	1	Stagger	1000~1110	942	(1,80)
2	Agile	1250~1750	1	Coded	1000~1300	862	(3,70)
3	Agile	1400~1800	1	Jitter	1000~1300	867	(6,60)
4	Fixed	3000	2	Slider	1000~1300	874	(10,65)
5	Agile	2850~3150	2	Jitter	1000~1300	873	(15,80)

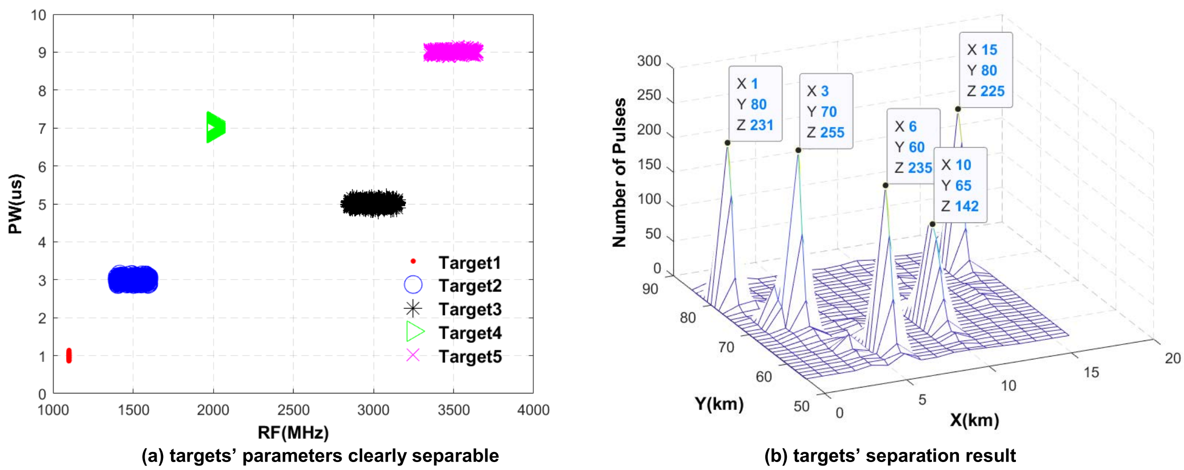


FIGURE 5. Targets' parameter distribution and clustering result (case 1).

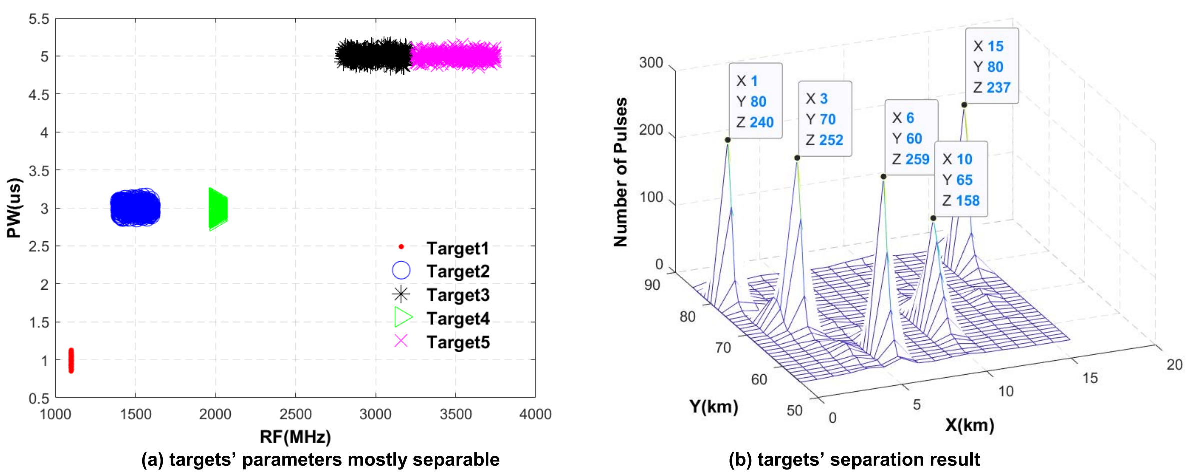
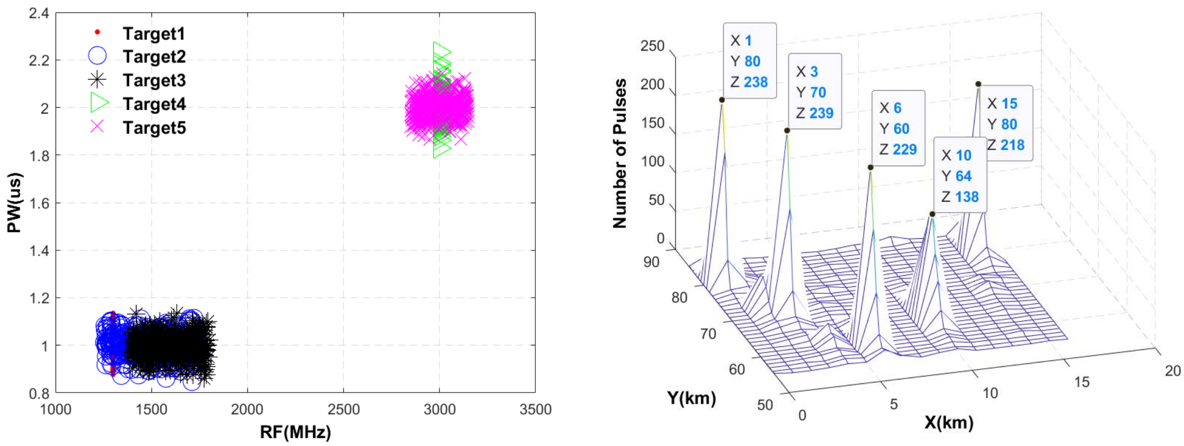


FIGURE 6. Targets' parameter distribution and clustering result (case 2).



(a) targets' parameters basically separable (b) targets' separation result

FIGURE 7. Targets' parameter distribution and clustering result (case 3).

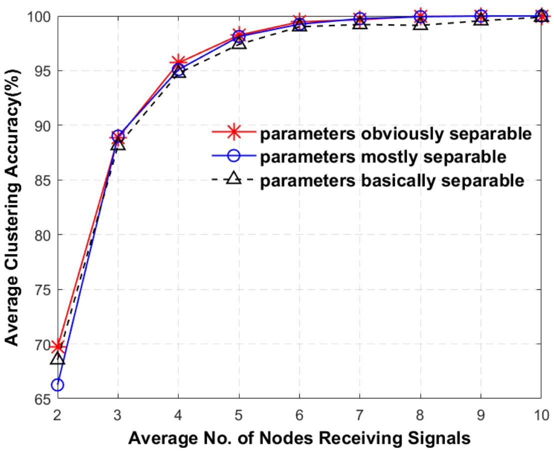


FIGURE 8. relationship between average correct rate and average number of nodes.

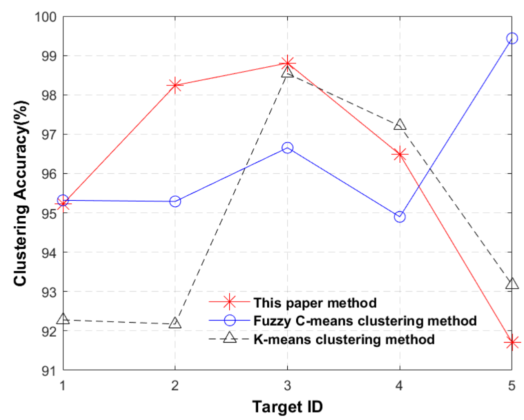


FIGURE 9. Correct rate of clustering by different algorithms (case 1).

for comparison with other common clustering algorithms, and other algorithms require the angle information to be set.

The simulation time is 1s, and the statistical results of 100 Monte Carlo simulations are used to analyze the effectiveness of the algorithm and clustering accuracy.

B. ANALYSIS OF ALGORITHM VALIDITY

The analysis of the algorithm validity is mainly used to judge whether the algorithm in this study can effectively separate the target of interest in three different situations. In the three simulation situations, the spatial three-dimensional results of the separation target of the algorithm in this study are shown in Figures 5, 6, and 7.

In all three cases, the algorithm in this study can ensure that the pulses form an obvious clustering effect in the spatial position, and can form 5 obvious peaks, which correspond to the actual spatial position of the target, and efficient separation of objects of interest can be achieved by peak search. The algorithm in this study mainly uses the spatial information of the target, which is basically not affected by the change in the parameters of the target transmitted signal, and the spatial information of the target cannot change rapidly relative to the parameter information, which shows the effectiveness of the algorithm.

In practical applications, owing to the directional transmission of the target signal and the scattered characteristics of space receiving nodes, it is impossible for every node to receive the pulse signal transmitted by the target at the same time. Therefore, the difference in the number of receiving nodes affects clustering performance. Figure 8 depicts the variation in the average correct rate with the average number of nodes under different receiving conditions. The average number of receiving nodes refers to the average number of nodes that a target signal can simultaneously receive. With an increase in the number of receiving nodes, the average correct rate of clustering also increases accordingly. When

TABLE 4. Correct rate of clustering of targets T1~T5 by different algorithms (%) (case 1).

	T1	T2	T3	T4	T5	Mean
Method in Study	95.2	98.2	98.8	96.5	91.7	96.1
Fuzzy C-Means Clustering	92.3	92.2	98.5	97.2	93.2	94.7
K-means clustering	95.3	95.3	96.7	94.9	99.4	96.3

TABLE 5. Correct rate of clustering of targets T1~T5 by different algorithms (%) (case 2).

	T1	T2	T3	T4	T5	Mean
Method in Study	95.2	98.3	98.8	96.6	91.5	96.1
Fuzzy C-Means Clustering	96.6	91.5	89.1	95.6	89.7	92.5
K-means clustering	99.1	95.3	93.2	93.5	93.0	94.8

the number of nodes exceeds 3, the average correct rate can reach more than 90%. As long as the average number of nodes reaches 3 or more, the algorithm in this study can obtain better clustering performance, and this condition is relatively easy to satisfy in practice, which further demonstrates that the algorithm has good engineering application value.

C. CLUSTERING ACCURACY COMPARISON

As mentioned above, there are many methods for clustering the target parameters of radar radiation sources, K-means clustering and fuzzy clustering methods are more typical in the open literature. Two typical methods, K-means clustering and model C-means clustering, and the method in this study are selected to compare and analyze the clustering accuracy in the same scene. The first two typical methods assume that information on the number of clusters 5 has been obtained by other methods.

The correct rate of a certain target clustering is defined as follows:

$$\text{correct rate of a certain target clustering} = \frac{\text{correct clustering pulses num of a certain target}}{\text{all pulses num of a certain target}} \times 100\% \quad (7)$$

The average clustering accuracy is the mean of all target clustering accuracy.

Under the condition of Case 1, the clustering accuracy rates of the three methods for the five targets T1~T5 can reach more than 90%, and the average accuracy rate is more than 94%, all of which exhibit good clustering performance. The performance of the method in this study is comparable to that of the fuzzy C-means clustering method, and slightly better than the K-means clustering method, as shown in Table 4 and Figure 9.

TABLE 6. Correct rate of clustering of targets T1~T5 by different algorithms (%) (case 3).

	T1	T2	T3	T4	T5	Mean
Method in Study	94.8	97.6	98.5	95.8	91.1	95.6
Fuzzy C-Means Clustering	65.1	58.1	69.0	71.5	72.0	67.1
K-means clustering	63.1	57.5	69.6	72.6	71.7	66.9

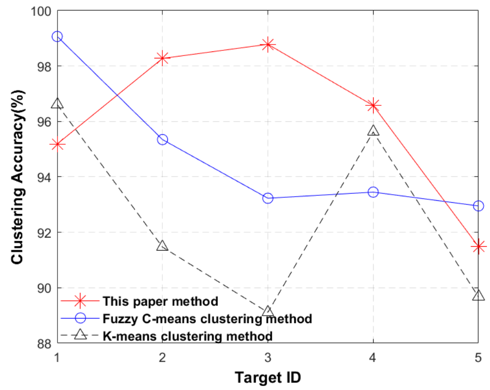


FIGURE 10. Correct rate of clustering by different algorithms (case 2).

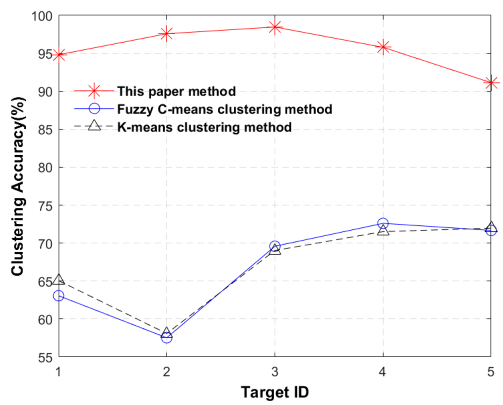


FIGURE 11. Correct rate of clustering by different algorithms (case 3).

Under the condition of Case 2, the overall clustering performance of the three methods is comparable to that of Case 1, and the clustering accuracy rate of the five targets from T1 to T5 can still exceed 90%. However, compared with case 1, the average clustering accuracy of the three methods has declined to a certain extent, and the fuzzy C-means clustering and K-means clustering methods have dropped even more, with a performance drop approximately 2%, while the performance of the method in this study the drop is less than 0.1%. Compared with the fuzzy C-means clustering and K-means clustering methods, the method in this study is less sensitive to change in target parameters, as shown in Table 5 and Figure 10.

Under the conditions of Case 3, the average clustering accuracy rate of the fuzzy C-means clustering and K-means clustering method both dropped to below 70%, and the performance dropped by more than 25%, while the average clustering accuracy of the method in this study was still above 95%, and the performance decreased by no more than 1%. This shows that the clustering performance of the fuzzy C-means clustering and K-means clustering methods decreases rapidly in the case of serious parameter overlap, whereas the method in this study still maintains a good clustering performance. This is because the method in this study mainly uses the target spatial information to achieve pulse clustering, so it is not sensitive to change in the target parameters and has strong anti-aliasing ability of target parameters, as shown in Table 6 and Figure 11.

VI. CONCLUSION

This study proposes a distributed clustering method based on spatial information. A description model of the joint pulse under distributed reception conditions was established. Then, the steps of the method were listed. Finally, a typical scenario was set up and Monte Carlo simulation verification was performed. The simulation results proved that the proposed method can still achieve a clustering accuracy of more than 90% compared to the typical single-node clustering method when the radar radiation source signal parameters overlap significantly.

This method makes use of the facts that the target spatial position of the radar radiation source can only change slowly or remain unchanged, whereas the signal parameters can change rapidly. It can not only adapt to the situation of RF agility, but also adapt to the situation of PRI multi-level stagger, coded, jitter, slider and so on. In addition, this is in line with the development trends of future distributed systems. In the future, studies on the associated pulse feature extraction and real-time target separation may be conducted.

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XIN DONG was born in Chongqing, China, in 1979. She received the B.S. and M.S. degrees in information engineering from the University of Electronic Science and Technology of China, Chengdu, in 2001 and 2004, respectively.

From 2004 to 2005, she was an Algorithm Engineer at the Southwest Institute of Electronic Equipment, Chengdu. From 2005 to 2016, she was a Senior Software Engineer at Motorola Solutions, Chengdu. Since 2016, she has been an Associate Professor at the Computer Engineering College, Chengdu Technological University, Chengdu. She is the author of two books with more than 20 articles. She holds nine patents. Her research interests include machine learning, data analysis, and software AI testing.

Prof. Dong has been a member of the China Computer Federation, since 2016, and the Expert Group of the Chinese Software Testing Qualifications Board, since 2020.

YAN LIANG was born in Gansu, China, in 1986. She received the B.S. degree in software engineering from the Wuhan University of Technology, Wuhan, China, in 2008, and the M.S. degree in computer application technology from Central China Normal University, Wuhan, in 2011.

From 2011 to 2017, she was a Software Engineer at Zhuhai Xuji Electric Company Ltd., Zhuhai. Since 2017, she has been a Lecturer at the Computer Engineering College, Chengdu Technological University, Chengdu. She is the author of two books and about ten articles. She holds six patents. Her research interests include deep reinforcement learning, intelligent computing, and spatial indexing technology.

Ms. Liang has been a member of the China Computer Federation, since 2018.

JIE WANG was born in Hubei, China, in 1976. He received the B.S., M.S., and Ph.D. degrees in communication and information engineering from Harbin Engineering University, Harbin, in 1999, 2001, and 2004, respectively.

From 2004 to 2007, he was an Algorithm Engineer at the Southwest Institute of Electronic Equipment, Chengdu, where he was a Senior System Engineer, from 2008 to 2018, and has been a Professor, since 2019. He is the author of two books with more than 20 articles. He holds five patents. His research interests include data mining and data processing.