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Retraction

Retracted: Data Mining-Based Tracking Method for Multisource Target Data of Heterogeneous Networks

Wireless Communications and Mobile Computing

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] C. Li, "Data Mining-Based Tracking Method for Multisource Target Data of Heterogeneous Networks," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1642925, 8 pages, 2022.

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Research Article

Data Mining-Based Tracking Method for Multisource Target Data of Heterogeneous Networks

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In order to solve the problem that the target is easily lost in the process of multisource target data fusion tracking, a multisource target data fusion tracking method based on data mining is proposed. Multisource target data fusion tracking belongs to location level fusion. Firstly, a hybrid heterogeneous network fusion model is established, and then, data features are extracted, and a fusion source big data acquisition algorithm is designed based on compressed sensing to complete data preprocessing to reduce the amount of data acquisition. Based on data mining association multisource fusion target, get the relationship between each measurement and target, and build multisource target data fusion tracking model to ensure the stable state of fusion results. It shows that the proposed method can save the tracking time and improve the tracking accuracy compared with the methods based on NNDA and PDA, which is more conducive to the real-time tracking of multisource targets.

1. Introduction

With the rapid development of modern computer technology and detection and perception technology, the level of modern war has been continuously improved, and the world military changes with each passing day. In the new generation of combat system, the battlefield has gradually expanded to the complex space composed of land, sea, air, space, and electromagnetism. Only relying on single source information cannot adapt to the expanding scope of operations and increasingly complex battlefield environment and cannot meet the operational needs at this stage. Therefore, it is necessary to comprehensively optimize the multisource information, conduct real-time target reconnaissance, obtain target state estimation, effectively distinguish target attributes, and analyze behavior intention, situation assessment, and prediction information [1]. In the modern battlefield, various forms of information expression, huge amounts of information, and complex processing relations have greatly exceeded the scope of human brain's comprehensive information processing ability. For this reason, a new subject data fusion technology appeared in the 1970s, which developed rapidly and was widely used in important fields. It should

be pointed out that there are many terms to describe the concept of data fusion, such as information fusion and sensor fusion. In fact, these concepts are closely related. Most people think that data fusion is mainly for the formal expression of all kinds of available information data. When the sensor detection data is taken as the information to be fused, data fusion is also called sensor fusion [2]. The most important feature of multisource data fusion technology is that it overcomes the limitations of a single data source. By using the original measurements obtained by multiple homogeneous or heterogeneous sensors, multilevel effective fusion is carried out. After filtering out the interference information, the comprehensive judgment of the target is formed, and then, any single sensor cannot obtain more accurate, reliable, and effective information. In addition to the above characteristics, it also has good fault-tolerant performance and stable performance, high credibility of the conclusion, improved the reliability of the system, improved the detection performance, and so on.

Multisource target data fusion tracking method is an effective supplement to global satellite navigation system. Multisource fusion tracking technology uses a variety of positioning sources to achieve positioning service.

Multisource fusion positioning is based on multisource information fusion technology, which is different from the traditional single navigation source. In the multisource fusion tracking system, the positioning information from different fusion sources is reorganized and optimized by some optimization rules. Multisource fusion tracking can make full use of the positioning information of multiple positioning sources, so it can greatly improve the positioning accuracy and improve the reliability and robustness of the tracking system [3]. In the multitarget tracking environment, the measurement of the detected target is affected by clutter or noise and there is uncertainty, so the data association is needed. Data association is widely used in target tracking. In the process of association, it is necessary to determine the corresponding relationship between the measurement and the real target. When the tracking target increases, the corresponding association will become more and more complex [4]. If the association is wrong, the accuracy of the next tracking or fusion results will be greatly affected. Using data mining technology can fully mine the association relationship of multisource targets. Therefore, this paper proposes a heterogeneous network multisource target data fusion tracking method based on data mining to promote the continuous development of multisource data fusion technology to meet the needs of various application fields.

2. Multisource Target Data Fusion Tracking Method Based on Data Mining in Heterogeneous Network

2.1. Building Heterogeneous Network Convergence Structure. Data fusion is a comprehensive analysis and processing technology for multisource information. According to the output of fusion, data fusion is divided into three levels. The first is the position estimation and identity recognition, the second is situation assessment, and the third is threat estimation. According to the levels, data fusion can be divided into five levels, including detection, location, attribute, situation assessment, and threat estimation [5]. This paper mainly studies the fusion and tracking of multisource target data, which belongs to the fusion of location level. The fusion of position level focuses on fusion of the state estimation results of targets by processing the observation reports and tracks of each sensor. It can be divided into two aspects: time dimension and spatial dimension integration. It is mainly used in target tracking. It is in the middle layer of the fusion hierarchy model, and it is also the most widely used layer. According to the signal processing process, the structure can be divided into centralized, distributed, mixed, and multilevel [6]. The hybrid data fusion system combines the advantages of distributed structure and centralized structure, which is mainly accomplished by adding circuit breaker and selecting merging module on the basis of distributed structure. Based on the hybrid structure, this paper establishes a heterogeneous network fusion model, as shown in Figure 1.

As shown in Figure 1, the information of all fusion sources is collected by sensors and then transmitted to the fusion center through wireless transmission network. Each local node first needs to process and reconstruct the observed data to obtain the state information of the target, namely, the trajectory information, and then send it to the node. The center obtains the final target state estimation and track information by associating and processing multiple sets of target tracks [7]. The network transmission of data is the link between fusion center and sensing point. In the process of wireless transmission, there will be network transmission delay and network packet loss. Network transmission delay refers to the time interval between communication packets entering Ethernet and leaving Ethernet. The network transmission delay can be expressed as shown in

$$\tau = \tau_1 + \tau_2 + \Delta\tau. \tag{1}$$

In formula (1), τ represents the total delay of heterogeneous network; τ_1, τ_2, and $\Delta\tau$ represent the delay caused by network congestion, network jitter, and other factors, respectively. Packet loss rate (PLR) is used to evaluate network packet loss. In order to overcome the contingency caused by single round trip time, this paper calculates PLR based on time weight, as shown in

$$p = \frac{\sum_{n=1}^{n} s_n \cdot (t/t_0)}{\sum_{n=0}^{n} s_n}. \tag{2}$$

In formula (2), p represents PLR; s_n is the total package number of transmission; n is the total number of single round trip time; t and t_0 are packet loss time and total time. When the amount of fusion source data becomes larger, the network transmission delay and network packet loss problems are more serious [8]. In order to overcome the above problems, a multisource fusion positioning data preprocessing method is proposed to reduce the amount of fusion source data collection, so as to reduce the network transmission pressure. Multisource fusion tracking data preprocessing includes two parts, which are data feature extraction and fusion source big data acquisition algorithm based on compressed sensing.

2.2. Design Fusion Source Big Data Acquisition Algorithm. The purpose of data feature extraction is to extract the big data from fusion source. The basic method is to filter the data according to certain rules according to the characteristics of each fusion source information. In the network-based fusion location architecture, each target is regarded as a perception point [9]. Each sensor can sense 8 kinds of fusion source sensor data, which are WiFi fingerprint, acceleration sensor, gravity sensor, magnetic sensor, barometer, odometer, visual sensor, and satellite positioning. The information vector representation defining a perception point perception is shown in

$$A = [W, C, G, M, B, O, V, S]. \tag{3}$$

In formula (3), A represents the perceptual information vector; $W, C, G, M, B, O, V,$ and S are the sensor data of the above eight fusion sources, respectively. In some specific
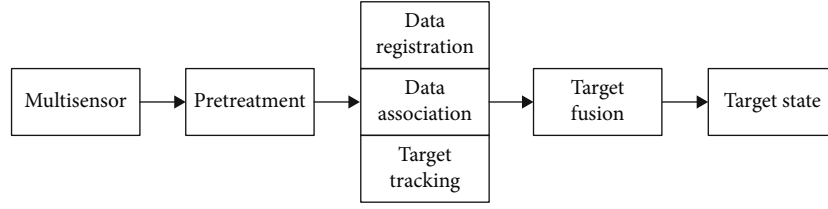
Figure 1: Heterogeneous network integration model.

scenarios, some of the location information in the eight kinds of location sources are unusable or meaningless. For example, when the sensing point is in the indoor scene, because the positioning satellite is blocked, the satellite positioning system cannot work normally. Another example is that when the barometer collects the same value twice or does not change much, the collected value of the later time is meaningless and can be omitted [10]. The collection and transmission of useless location information will lead to waste of network transmission resources. To solve the problems, in the multisource fusion tracking data feature extraction method, the feature extraction weight matrix is designed to refine the fusion source data and reduce the unnecessary waste of resources. The weight matrix of feature extraction is defined as, as shown in

$$
\varpi = \begin{bmatrix} \varpi_W & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \varpi_C & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \varpi_G & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \varpi_M & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \varpi_B & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \varpi_O & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \varpi_V & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \varpi_S \end{bmatrix}. \quad (4)
$$

In formula (4), ϖ represents the weight matrix; ϖ_W, ϖ_C, ϖ_G, ϖ_M, ϖ_B, ϖ_O, ϖ_V, and ϖ_S represent the weight factors of eight fusion source sensor data. According to the characteristics of different fusion sources, the weight factors in the positioning weight matrix are shown in Table 1.

After the above data feature extraction, the fusion source data is preliminarily screened. In order to further reduce the amount of data acquisition, an algorithm based on compressed sensing is proposed. In the algorithm of fusion source based on compressed sensing, only part of the original data of fusion source is collected and sent to the fusion center, and the original information is recovered by reconstruction algorithm in the fusion center [11]. This can greatly reduce the amount of fusion source information collection, so as to improve the efficiency of heterogeneous network transmission. In the heterogeneous network fusion structure, it is assumed that each sensing point can sense up to eight kinds of fusion source tracking information, and the sensing points are selected to measure the sampling information. The first key point of compressed sensing

information reconstruction is the choice of measurement matrix, which is PCI matrix. PCI measurement matrix can be expressed as

$$
\varphi = \begin{cases} 1, 1 \le x \le 8a, & 1 < y < 8b, \\ 0, & \text{otherwise.} \end{cases} \quad (5)
$$

In formula (5), φ represents PCI measurement matrix; x and y represent matrix elements; a and b represent all sensing points and the number of selected sensing points. Using PCI measurement matrix to realize compressed sensing can greatly reduce the computational complexity [12]. The measurement vector is first transferred to the fusion center, where the original information vector is obtained by reconstruction algorithm [13]. In this paper, discrete cosine transform (DCT) is selected as the basis matrix, and the basis pursuit algorithm is used to solve the reconstruction vector. After determining the measurement matrix, base matrix, and reconstruction algorithm, in the fusion center, the original information can be accurately reconstructed through the measurement information.

2.3. Multisource Fusion Target Association Based on Data Mining. Data mining is used to associate multisource fusion targets to determine the corresponding relationship between reconstructed information and real targets. From the process of data mining, it can be divided into three stages. First, data filtering is carried out. This stage is to select and filter all the measurements input by the sensor according to the actual situation or requirements and eliminate the information data that does not meet the condition rules, which has been completed in the data preprocessing above. Then, the incidence matrix is calculated. Incidence matrix can quantitatively describe the similarity degree between a measurement pair or a measurement target pair, including data association measurement standard, logic principle, and similarity calculation method, which is the key step of data association [14]. Generally, a similarity measurement method is selected according to the actual application situation to calculate the correlation degree for each measurement falling into the correlation gate. According to the correlation degree between measurement and target, the corresponding correlation matrix is established. Finally, the appropriate assignment strategy is selected to update the status. According to the data mining process, the specific steps of association process are given, as shown in Figure 2.

Correlation gate can be described as follows: the predicted position of the tracked target is set as the center,

TABLE 1: Weight factors.

Weight factor	Weight	Judging conditions	Weight factor	Weight	Judging conditions
ω_W	1	Get WiFi fingerprint information	ω_B	1	Difference between two measured values ≥ 0.5
	0	WiFi fingerprint information not obtained		0	Difference between two measured values < 0.5
ω_C	1	Difference between two measured values ≥ 0.5	ω_O	1	Get odometer positioning information
	0	Difference between two measured values < 0.5		0	Odometer positioning information not obtained
ω_G	1	Difference between two measured values ≥ 10^{-4}	ω_V	1	Get visual fingerprint information
	0	Difference between two measured values < 10^{-4}		0	No visual fingerprint information was obtained
ω_M	1	Difference between two measured values ≥ 10	ω_S	1	Number of visible stars ≥ 4
	0	Difference between two measured values < 10		0	Number of visible stars < 4

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┌─────────────────────┐      ┌─────────────────────┐
│ Known measurement   │ ───▶ │ Find alternative    │
│ behavior database   │      │ measurements in     │
│                     │      │ the database        │
└─────────────────────┘      └─────────────────────┘
                                        │
                                        ▼
┌─────────────────────┐      ┌─────────────────────┐
│ Prior measurement   │ ───▶ │ Calibration         │
│ behavior database   │      │ alternative         │
│                     │      │ measurements to     │
│                     │      │ observation time    │
└─────────────────────┘      └─────────────────────┘
                                        │
                                        ▼
┌─────────────────────┐      ┌─────────────────────┐
│ Sensor feature      │ ───▶ │ Calculate the       │
│ database            │      │ predicted position  │
│                     │      │ of alternative      │
│                     │      │ target measurement  │
└─────────────────────┘      └─────────────────────┘
                                        │
                                        ▼
                             ┌─────────────────────┐
                             │ Threshold filtering │
                             └─────────────────────┘
                                        │
                                        ▼
                             ┌─────────────────────┐
                             │ Calculation of      │
                             │ incidence matrix    │
                             └─────────────────────┘
                                        │
                                        ▼
                             ┌─────────────────────┐
                             │ Allocation strategy │
                             └─────────────────────┘
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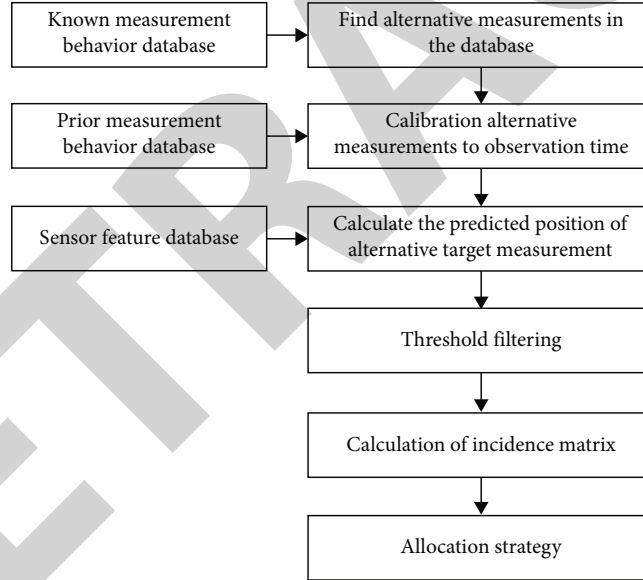
FIGURE 2: Specific steps of data mining.

which can determine the closed area where the target may measure. It is a filtering threshold to judge whether the measurement is from the target candidate echo. Generally, the measurement or echo falling into the correlation gate is called candidate echo [15]. The size of the closed area (correlation gate) can be determined by the probability of receiving the echo correctly. At the same time, the area size is also related to the observation error of the sensor, the motion state of the current target, and the tracking environment. In order to solve the problem of multitarget tracking, the joint probability of confirmation matrix is added to determine the correlation degree. Firstly, the association hypothesis between measurements and multiple targets is established, and the fusion value of effective measurements

in the association gate is calculated by taking the association probability as the weight to update the target state. The expression for defining the confirmation matrix is as follows:

$$Q_{ij} = \begin{cases} 0, & z_j \notin \Omega, \\ 1, & z_i \in \Omega. \end{cases} \tag{6}$$

In formula (6), Q_{ij} represents the confirmation matrix; i means measurement; j represents the goal; z means effective measurement; Ω represents the associated area. The relationship between the confirmation matrix and the correlation area is shown in Figure 3.
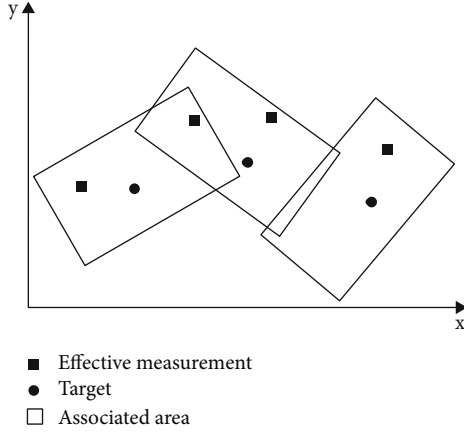
FIGURE 3: Relationship between confirmation matrix and correlation area.

Figure 3 shows the confirmation matrix and the formation of interconnected events. In the figure, the number of targets is 3 and the number of effective echoes is 4. The measurement exists in the intersection area of two related regions, which indicates that the measurement may come from two targets. The key of joint probabilistic data association is to calculate the probability of correlation between the target measurements detected in the correlation gate and various real targets, that is, joint association events and joint association probability. Without considering the indiscernibility, there is a unique source for the measurement. That is to say, every effective measurement that does not come from one of the targets must come from clutter. There is no case that the measurement comes from two targets or both targets and clutter. For a set target, at most, one real measurement corresponding to the target is generated [16]. In other words, if the set target is matched with multiple measurements at the same time, only one of the corresponding relationships holds. For each row in the confirmation matrix, only one 1 is selected and regarded as the unique nonzero element of the corresponding row in the interconnection matrix. For each column of the confirmation matrix (the first column is not included), there can only be one nonzero element in the remaining columns. The state estimation of target measurement is obtained by Kalman filter. If there is no measured value from the target, the detected echo value is used to update the target state, and the estimated value of the target is equal. The relationship between each measurement and target is obtained, which can be used in the subsequent multitarget fusion tracking model.

2.4. Construction of Multisource Target Data Fusion Tracking Model. Stable fusion result is the premise of building tracking model. Through the above multisource target association results, stable fusion results can be obtained. Based on this, a multisource target data fusion tracking model is constructed to ensure that the target state fusion results come from the real tracking target as the first principle. The purpose of the tracking model is to realize the tracking under the condition of unmanned switching. According

to the type of each sensor and the actual tracking environment, the priority of each sensor data should be set. Generally, the visible light sensor with higher accuracy has higher priority. Then, according to the change of data, the validity and stability of each priority data are analyzed [17]. Finally, on the basis of correctly tracking the target, the photoelectric tracking system selects the optimal sensor data for tracking. In the later analysis, the priority level of each sensor is used to represent the sensor. At the same time, the miss distance corresponding to the selected sensor is sent to the servo system for target tracking. When the data of miss distance of current sensor selection is in great error and there is a risk of losing target, it is necessary to switch to the sensor data of sub priority in time. The target miss data of the subsuperior sensor is used to track to ensure the tracking is normal [18–20]. After the current sensor data is stable, the measured data of the sensor can be reused for tracking to ensure the optimal tracking effect. Once the sensor tracking system is disturbed and the data is unstable, the corresponding data error will increase and the fusion coefficient will decrease. After the error accumulates to a certain extent, its weight coefficient will less than a certain threshold [21–23]. If at a certain sampling point, the tracking data fusion weight of the currently selected sensor is less than the threshold, the switching condition is satisfied. At each sampling time, the corresponding weight of each sensor's state is

$$\gamma = \frac{1/\delta^2}{\sum_1^u 1/\delta^2}. \tag{7}$$

In formula (7), γ represents the fusion corresponding weight; δ is the estimation of error covariance; u is the number of sensors. In the switching state, the credibility of sensor data has been reduced. If the miss distance of the sensor continues to be transmitted to the server, the tracking may be unstable or even the target may be lost. Therefore, it is necessary to select another sensors' data to transmit to the servo, that is, to do a switching action between the two sensor's data. In order to ensure that the fusion results can always maintain a stable state and accurately judge the credibility of each sensor data, the real error and real coefficient are used to represent the real change of each sensor data [24, 25]. Assuming that the sensor currently used is the sensor with the first priority, the processing process can be divided into three cases according to whether the data processing results of the current sampling point and the first U sampling points meet the switching conditions, as shown in Table 2.

In the third case, the replacement formula can be expressed as follows:

$$\chi'(\theta) = \frac{\chi\theta}{\theta - 1}. \tag{8}$$

In formula (8), χ and χ', respectively, represent the target state vectors corresponding to the sensors before and after replacement; θ is the least square curve fitting coefficient. The replaced target state vector and other sensor data

TABLE 2: Classification of treatment results.

Number	Condition	Explain	Handle
1	The sensor does not meet the switching condition at the current sampling time	The sensor data is still stable	Without any operation, the sensor data can be used for tracking
2	The data of the current sampling time and the first U sampling points meet the switching conditions	The sensor cannot get the target status data normally	Switch action is needed to select the next priority sensor data for tracking
3	At the current sampling time, the sensor meets the switching condition, but the first U sampling points do not meet the switching condition	The sensor has an extreme point	The target state vector corresponding to the sensor is replaced by its least square curve fitting result

TABLE 3: Initial state of target.

Target serial number	Location (m)		Speed (m/s)	
	x	y	v_x	v_y
1	1000	200	40	42
2	1000	500	42	44
3	1000	1000	44	46
4	1000	1500	46	48
5	1000	2000	48	50
6	1000	2500	50	50
7	1000	3000	51	51
8	1000	3500	50	50
9	1000	4000	51	51
10	1000	4500	50	50

TABLE 4: Target tracking time (s).

Target number	Method of this paper	NNDA	PDA
1	0.314	0.514	0.534
2	0.362	0.946	0.786
3	0.425	1.572	1.104
4	0.478	2.251	2.143
5	0.536	3.825	3.766
6	0.592	6.568	6.228
7	0.663	8.422	9.601
8	0.732	11.633	12.313
9	0.791	15.881	14.844
10	0.854	28.252	29.576

are sent to the fusion system again, and the calculation error and coefficient are obtained by recalculation. Finally, a stable fusion result is obtained.

3. Simulation Experiment and Result Analysis

3.1. Experimental Preparation. This simulation experiment mainly tests the target tracking effect of the heterogeneous network multisource target data fusion tracking method in the presence of clutter density interference. In the experiment, the clutter density is set as 4, and 100 Monte Carlo simulations are carried out. The initial state of setting multiple targets is shown in Table 3.

The sampling period is 1 s, the sampling time is 100, the detection probability is 1, the probability of correct measurement falling into the gate is 99%, and the correlation threshold is 9.18. Based on the above experimental conditions, the target tracking effect is tested.

3.2. Experimental Result. In order to verify the feasibility of the heterogeneous network multisource target data fusion tracking method proposed in this paper in multitarget environment, different tracking methods are simulated and compared in terms of tracking time and tracking accuracy. The two comparison methods are based on nearest neighbor data association (NNDA) and probabilistic data association (PDA). NNDA calculates the distance between the candidate echo and the predicted position of the target, selects the measurement that falls in the correlation gate, finds out the measurement that is closest to the predicted point of the tracked target, and selects it as the correct measurement to update the state of the target. PDA correlates all the determined measurements in the correlation gate, obtains the probability of each measurement from the actual source, and then updates the state. The comparison results of tracking time are shown in Table 4.

It can be concluded from Table 4 that the time of the three methods is obviously compared when the number of targets increases. Taking the number of targets as 10 as an example, the tracking time of this method is 0.854 s, which is 27.398 s and 28.722 s less than the two comparison methods. The tracking time based on NNDA and PDA shows an exponential growth trend, while the tracking time of this method is almost stable within one second with the increase of the number of targets. The above results show that the proposed method has obvious advantages in tracking time. The tracking accuracy is further compared, and the average mean square error (RMSE) is used to measure the accuracy error. The comparison results are shown in Figure 4.

According to the comparison results in Figure 4, the RMSE of the proposed method is smaller than that of the target data fusion tracking methods based on NNDA and PDA. Taking the number of targets as 10 as an example, the RMSE of this method is 18.92% under the same target data, which is 14.76% and 8.63% less than the two comparison methods. Based on the above results, the method proposed in this paper can realize multisource target data fusion tracking, save tracking time, and improve tracking
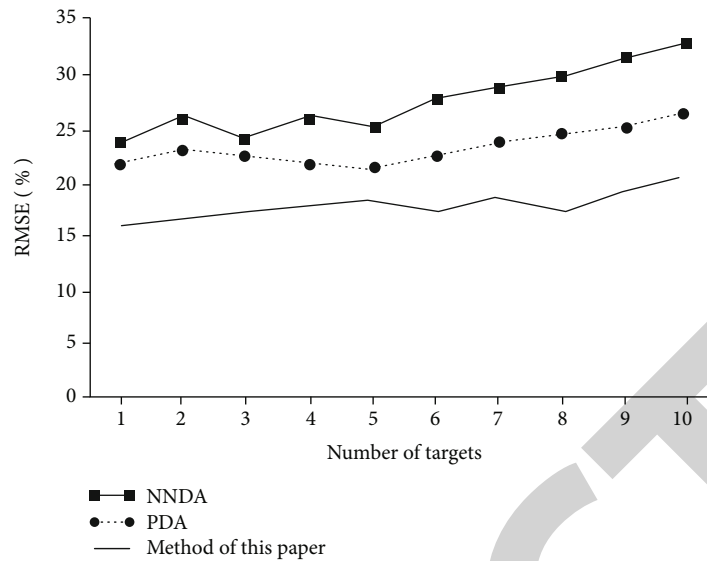
FIGURE 4: RMSE comparison.

accuracy and is more conducive to real-time tracking of multisource targets, which has a good engineering application prospect.

4. Conclusion

In this paper, based on data fusion and data mining, a heterogeneous network multisource target data fusion tracking method is proposed. The experimental results show that the method can save tracking time and improve tracking accuracy and can achieve real-time tracking of multisource targets. For the research of multisource fusion localization algorithm, we need to discuss more universal fusion localization algorithm and consider the joint use of multiple fusion localization algorithms for different localization scenarios. The data fusion algorithm assumes that each sensor is in a stable tracking state at the initial stage and does not consider the situation that the tracking data of a certain sensor will have a large error at the initial stage of tracking. In the next step, we need to add the initial state prediction of each sensor's data. First, we can get the credibility of the data according to the data changes of each sensor and decide whether to add the tracking data of the sensor to the fusion system.

Data Availability

Data is available on request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Acknowledgments

References

[1] L. Yu, C. H. E. N. Richeng, and J. I. N. Tao, "Research on multi-source heterogeneous data fusion technology for complex information system," *China Measurement Testing Technology*, vol. 46, no. 7, pp. 1–7, 2020, 23.

[2] L. Wen-long and H. Yang, "Improved simulation research of dynamic data fusion algorithm," *Computer Simulation*, vol. 37, no. 4, pp. 294–297, 2020.

[3] S. A. Jesudurai and A. Senthilkumar, "An improved energy efficient cluster head selection protocol using the double cluster heads and data fusion methods for IoT applications," *Cognitive systems research*, vol. 57, pp. 101–106, 2019.

[4] H. Guo and X. Li, "Multisource target data fusion tracking method for heterogeneous network based on data mining," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 9291319, 10 pages, 2022.

[5] A. Paulino, L. Guimaraes, and E. H. Shiguemori, "Assessment of noise impact on hybrid adaptive computational intelligence multisensor data fusion applied to real-time UAV autonomous navigation," *IEEE Latin America Transactions*, vol. 18, no. 2, pp. 295–302, 2020.

[6] M. B. Alazzam, F. Alassery, and A. Almulihi, "A novel smart healthcare monitoring system using machine learning and the Internet of Things," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 5078799, 7 pages, 2021.

[7] J. Muesing, N. Ahmed, L. Burks, M. Iuzzolino, and D. A. Szafir, "Fully Bayesian human–machine data fusion for robust online dynamic target characterization," *Journal of Aerospace Information Systems*, vol. 18, no. 2, pp. 26–49, 2021.

[8] D. Oliveira, L. Martins, A. Mora, C. Damásio, and R. A. Ribeiro, "Data fusion approach for eucalyptus trees identification," *International Journal of Remote Sensing*, vol. 42, no. 11, pp. 4087–4109, 2021.

[9] J. I. Zhen-yan, P. I. Huai-yu, and Y. A. O. Wei-na, "A hybrid recommendation model based on fusion of multi-source heterogeneous data," *Journal of Beijing University of Posts and Telecommunications*, vol. 42, no. 1, pp. 132–138, 2019.

[10] A. Mzu, C. Mmhb, B. Aa, and D. Cs, "A body sensor data fusion and deep recurrent neural network-based behavior recognition approach for robust healthcare," *Information Fusion*, vol. 55, pp. 105–115, 2020.

[11] T. R. Gonçalves, L. N. Rosa, A. S. Torquato et al., "Assessment of Brazilian monovarietal olive oil in two different package systems by using data fusion and chemometrics," *Food Analytical Methods*, vol. 13, no. 1, pp. 86–96, 2020.

[12] R. Wang, M. B. Alazzam, F. Alassery, A. Almulihi, and M. White, "Innovative research of trajectory prediction algorithm based on deep learning in car network collision detection and early warning system," *Mobile information systems*, vol. 2021, Article ID 3773688, 2021.

[13] L. I. Khudonogova and S. V. Muravyov, "Interval data fusion with preference aggregation for balancing measurement accuracy and energy consumption in WSN," *Wireless Personal Communications*, vol. 118, no. 4, pp. 2399–2421, 2021.

[14] E. M. Villa, I. M. Pinto, and L. Troiano, "Triangular norms for gravitational wave data fusion," *IEEE Transactions on Fuzzy Systems*, vol. 28, no. 3, pp. 534–543, 2020.

[15] G. Maier, F. Pfaff, M. Wagner et al., "Real-time multitarget tracking for sensor-based sorting," *Journal of Real-Time Image Processing*, vol. 16, no. 6, pp. 2261–2272, 2019.

[16] T. Li, F. De la Prieta Pintado, J. M. Corchado, and J. Bajo, "Multi-source homogeneous data clustering for multi-target detection from cluttered background with misdetection," *Applied Soft Computing*, vol. 60, pp. 436–446, 2017.

[17] M. Nazari and S. Pashazadeh, "Real-time adaptive fuzzy density clustering for multi-target data association," *Intelligent Data Analysis*, vol. 25, no. 1, pp. 5–19, 2021.

[18] A. Osojnik, P. Panov, and D. Eroski, "Incremental predictive clustering trees for online semi-supervised multi-target regression," *Machine Learning*, vol. 109, no. 11, pp. 2121–2139, 2020.

[19] M. Petkovi, D. Kocev, and S. Deroski, "Feature ranking for multi-target regression," *Machine Learning*, vol. 109, no. 6, pp. 1179–1204, 2020.

[20] M. B. Alazzam, F. Alassery, and A. Almulihi, "Development of a mobile application for interaction between patients and doctors in rural populations," *Mobile Information Systems*, vol. 2021, Article ID 5006151, 8 pages, 2021.

[21] B. Y. Jung, D. Ham, U. S. Suh, W. S. Ra, and D. H. Kim, "Predicted line-of-sight coordinate approach to target tracking for airborne AESA radars," *Transactions of the Korean Institute of Electrical Engineers*, vol. 69, no. 6, pp. 914–923, 2020.

[22] Q. I. A. N. Xiao-yan, Z. H. A. N. G. Dai-hao, and Z. H. A. N. G. Yan-lin, "Deep visual object tracking by multi-feature fusion," *Science Technology and Engineering*, vol. 19, no. 7, pp. 139–147, 2019.

[23] R. Radhakrishnan, S. Bhaumik, and N. K. Tomar, "Gaussian sum shifted Rayleigh filter for underwater bearings-only target tracking problems," *IEEE Journal of Oceanic Engineering*, vol. 44, no. 2, pp. 492–501, 2019.

[24] C. Xing, L. Zhan-wu, and X.-d. Hu, "Research on radar/infrared data fusion target tracking algorithm in cluttering," *Journal of Chinese Computer Systems*, vol. 40, no. 8, pp. 1794–1798, 2019.

[25] L. M. Kavitha, R. S. Koteswara, and S. Kodukula, "Three-dimensional submarine-to-submarine passive target tracking in the presence of non-Gaussian noises," *International Journal of e-Collaboration*, vol. 17, no. 3, pp. 1–24, 2021.