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Research Article

Medical Social Security System Considering Multisensor Data Fusion and Online Analysis

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At present, multi-sensor data fusion technology has been applied in many fields, and we have to understand the algorithm principle of multisensor data fusion technology, master the basic theory of multisensor data fusion technology, and analyze the application field of multisensor data fusion technology. The technical challenges of its application area should be understood. The discussion on its development direction has promoted the wide application of multisensor data fusion technology. By improving the query planning, query interpretation, and cache query optimization mechanism of different data organization models, a scalable and efficient distributed hybrid online analytical processing system is designed and implemented. With the opening of the medical system reform, the construction of the medical security system will be continuously improved. The in-depth reform of the medical security system will affect the medical treatment of more than one billion people, involving thousands of households, and it is a great cause for the welfare of the people. In this paper, exploration and research are carried out, combined with the basic algorithm and typical application of data fusion, and the construction of urban residents' medical insurance is studied. The experimental results show that the Cavani index of medical expenses generally shows a downward trend in urban and rural areas, and the urban area has decreased from −0.1916 in 2012 to −0.2995 in 2020. This paper focuses on the in-depth study of the development process, actual situation, and existing problems of the social medical insurance system for urban residents, compares the development models of urban medical insurance in other places, and tries to put forward valuable and constructive countermeasures for the medical insurance system for urban residents.

1. Introduction

Medical insurance is an important part of the social security system and plays an important role in social and economic life: first, the security function. The protection function of medical insurance is mainly reflected in the protection of medical expenses. The social medical insurance system is an important project that cares about the health of the people. As an important part of the social security system, it is not only a profound social change, but also a worldwide problem. Interest is a major event related to the national economy and people's livelihood. Therefore, in the process of promoting the reform of the social security system, it is necessary to deal with complex data forms at multiple levels. The huge amount of data and the requirements for real-time and accurate data processing results exceed the human ability to comprehensively process information. The goal of data fusion technology is to reduce the amount of data and integrate all kinds of data and give real-time and accurate results. Therefore, multisensor data fusion and classical signal processing have become the best choices. These information abstraction levels include the data layer (pixel-level), the feature layer, and the decision layer. The corresponding data fusion platform mainly includes data level, feature level, and decision-level fusion platform. The data fusion platform mainly includes HIS methods. Transform, PCA transform, wavelet transform, and weighted average mainly apply multisource image complex, image analysis, and understanding. Data-level fusion refers to the fusion algorithm at any abstract level that requires matching accuracy to one pixel between sensor data for fusion; feature-level fusion refers to the raw data provided from each sensor.

The main methods of the feature fusion are weighted average method, Bayesian estimation method, DS evidence inference method, cluster analysis method, information drop method, voting method, and neural network method. It is mainly used in the fusion system in the field of multisensor target tracking. It mainly implements parameter correlation and state vector estimation. Decision-level fusion means that each sensor data source is transformed and an independent identity estimate is obtained before the fusion. The information is combined with the attribute decision results of the respective sensors according to certain criteria and the credibility of the decision, and finally an overall consistent decision is obtained.

There are also many studies on data fusion, online analysis, and medical social security system. The multiresolution and the multisensor fusion between optical data obtained at 20 cm resolution and long wave (thermal) infrared hyperspectral data obtained at 1 m resolution is considered by Liao [1]. Sun et al. compared the classification accuracy of PLS-DA, Simca, SVM, and ANN. They improved the classification model using data fusion strategy [2]. Yokoya proposed various technologies to solve the problem of data fusion, including component replacement (CS), multi-resolution analysis (MRA), spectral decomposition, and Bayesian probability [3]. Ghamisi proposed a new framework for fusing hyperspectral and light detection and ranging derived rasterized data using extinction profile (EP) and depth learning [4]. Chen proposed a deep learning framework based on the convolutional neural network (CNN) and the naive Bayesian data fusion scheme called NB-CNN, which is used to analyze a single video frame for crack detection [5]. Tao integrated dead reckoning sensors. Then he expressed the problem of data fusion as sequential filtering. He proposed reduced order state space modeling for observation problems to provide an easy-to-implement real-time system [6]. Lin examined three indicators of economic welfare: social security income, social security welfare level, and poverty. They enjoyed relatively high social security benefits and a low poverty level [7]. Imrohoroglu A studied the impact of China's social security reform in the model of bilateral altruism and the pure life cycle model. The results show that the quantitative impact of social security reform, especially on capital accumulation and output, is very different in the two models [8]. Sean et al. investigated whether the conclusions of the small public under study and review would affect observers' support for changing social security plans. Survey respondents in primary treatment conditions were exposed to the findings of the deliberative citizens group on the proposed social security reform [9]. In Geiger view, social security disability assessment should directly assess the claimant's working ability, rather than relying on functional agents. However, there is little academic discussion on how to conduct such an assessment [10]. Nielsen showed that when rational agents have inconsistent expectations of their future wealth and productivity or their return on investment, there is no need for bounded rational assumptions to explain social security and other mandatory pension plans [11, 12]. Seaton A believed that the strategies used by medical professionals to counteract these anxieties help to promote public acceptance of forms of care consistent with social democratic community values [13, 14]. These methods provide some references for our research, but due to the short time and the small sample size of the relevant research, the research has not been recognized by the public.

This article aims to understand the current major medical needs and their perceptions of existing medical security services through the analysis of the current situation of social medical security and interviews with different medical social security subjects. Use multisensor data fusion to analyze the current status of the social medical security system and the problems and challenges it faces, and then complete the description of the target for each sensor, group the description data of all sensors, and use a specific data fusion algorithm for analysis. The multiple sensor data of each target are assembled to obtain the consistent description and interpretation of the target, and the research results of the current social medical insurance system are obtained. In-depth research on resampling, denoising, feature extraction, and high-level data fusion of the original data of the medical security system is carried out, the advantages and disadvantages of the main methods are compared, and the appropriate data preprocessing and the fusion in different environments are analyzed. In order to solve the above problems, this paper integrates ROLAP for real-time data processing and MOLAP for offline processing of historical data and conducts research on the corresponding query planning process, so as to more efficiently support OLAP queries and business decisions with different requirements. After analyzing the query requirements of users' data at different scale levels, the factors that affect multidimensional query are studied. This factor is mainly manifested in the characteristics of the data organization model and the query cache optimization strategy. On the basis of this research, a complete set of query optimization schemes for different scale levels of data to meet the needs of multiple query is proposed.

2. Data Fusion Model and Basic Algorithm

The data fusion model in this paper is developed from the general model of three-tier data fusion. Its components include three parts of JDL data fusion model: target condition estimation, location estimation, and threat estimation. The multisensor data fusion studied is as follows: firstly, collect sign data from multiple sensors in the body area network and preprocess it, then extract the eigenvalues of these sign data to obtain feature vectors, and then associate each feature vector according to the same target, and finally use it. The fusion method synthesizes these vectors to obtain the evaluation value of the medical security data. The data fusion level is divided into three levels from low to high: pixel-level fusion, feature-level fusion, and decision-level fusion. In addition, it also includes data preprocessing, feedback and information correction. That is, the data fusion model in this paper usually consists of five parts. Among them, data preprocessing is zero level data fusion, target state estimation, position estimation, and threat estimation are first level, second level, and third level fusion, respectively, and information feedback and correction are finally fourth level fusion. Figure 1 is the schematic diagram of the data fusion model in this paper [15].

2.1. Multi Target Tracking. One of the purposes of target tracking is to give the track of each target in a period of time. For this purpose, the target tracking system must first be able to find the target and establish the initial track of the target. With the passage of time, it continuously reconnoiters and updates the track of the target, so as to obtain the track of the target in a period of time. The characteristic of multitarget tracking is that there are multiple targets to be tracked; that is, there are multiple target tracks to be established and updated, or whether the two should be related together, which is also the data association problem that this paper focuses on, as shown in Figure 2.

According to the Newton Gauss iterative method, the function of the Hessel matrix is to modify the gradient of criterion function and obtain more accurate descent direction to achieve faster convergence. Since the negative direction of the gradient represents the falling direction of the criterion function, in order to make the estimation of the target value converge, it requires that Hessel must be positive definite in each iteration. In practical application, this condition cannot be guaranteed. Therefore, people usually modify the Hessel matrix in various ways to ensure its positive characterization, as shown in Table 1.

2.2. Multisensor Track Fusion. In this experiment, there are many different types of signal sensors. These sensors communicate directly with the SINK node through the Zigbee protocol and also form a small sensor network. The use of other sensors is also similar. Simulation results show that the EML algorithm can better estimate the real position of the target and the deviation of the sensor system. Even after the introduction of noise, it can maintain high accuracy and high anti-noise performance. However, because the maximum likelihood algorithm in three-dimensional coordinate system needs more iterations and the iterative efficiency of MATLAB is very low, it is a test for the real-time performance of the system. And the target altitude measured in IFF can be directly equivalent to the z-axis value in the three-dimensional coordinate system. The mutual positions of the sensors and the conversion of their measured values can also be obtained directly by translation and rotation. However, when the distance between sensors and targets is large, because the Earth is an ellipsoid, the rectangular three-dimensional coordinate system is not so accurate. In particular, the altitude of the target requires a very complex conversion to be expressed as the pitch angle of the target. Therefore, the distortion of the large-scale target position model by a three-dimensional rectangular coordinate system will cause great deviation to the expression of target spatial position.

The distributed fusion system of IFF and the radar system is shown in Figure 3. Both IFF and the radar systems need filter tracking, which is called local filtering. Therefore, it requires less communication overhead, and the central computer hardly needs to store mixed information in the fusion process. It is fast but not as fast as a centralized fusion system, which needs to filter and track all sensors.

With the widespread use and development of data warehouses, the concept of multidimensional analysis for multidimensional data organization models has gradually developed. Multidimensional analysis tools: Online analytical processing systems have become an important part of building data warehouses. The data warehouse can transform and model all the data used for transaction processing and organizational management of the enterprise and analyze and display from various angles through a MDX multidimensional query and OLAP operations. It is assumed that in a three-dimensional coordinate system of a sensor system, five targets moving in a uniform straight line are tracked to generate the track of target motion. Clutter is evenly distributed in the detection cycle. The target state information with clutter is shown in Figure 4.

The simulation experiment includes two parts. It is equipped with two sensors to receive target measurement data, and the period of receiving data is 0.1 s. After obtaining the sampled data, the multitarget tracking algorithm based on FCM and the multitarget tracking algorithm based on FCSs proposed in this paper are used to process the target measurement data and obtain the track of each target. The experimental data analysis software is designed based on the Bluetooth function of Android mobile phones. Google also provides a rich programming interface for developers to use the Bluetooth function, considering measurement noise contained in the data received by the sensor in the actual situation; the experiment first generates the real track of the target, then adds Gaussian noise with zero mean value to the real track, and sets its variance as 100 m. Gaussian noise is usually thought of as an additive structure, and speckle noise of image noise is usually modeled as a multiplicative structure. If the signal denoising work is not conducted well, it will bring a greater amount of calculation to the subsequent data fusion work, and even make the decision based on the data fusion result lose its due meaning and value. For simplicity, it does not consider the coordinate transformation and time calibration in the process of target, and the obtained target position is located in the rectangular coordinate system. It is equipped with two parallel targets moving at a uniform speed. The initial position of target 1 is (100020008000), and the initial position of target 2 is (100022008000), with the unit of M. The initial velocity of both is (300, 0, 0), and the unit is m/s. The whole process lasted for 10 s and 100 groups of data were obtained. In order to facilitate the simulation and drawing of target tracks, the heights of the two targets remain unchanged. In addition, it can be seen that the two targets move at a uniform speed along the x-axis direction. It can be seen from Figure 5 that the tracking performance of the three algorithms is relatively close, but the tracking performance of the insensitive Kalman filter algorithm and the particle filter algorithm is better than that of the extended Kalman filter algorithm, but because the extended Kalman filter algorithm uses linearization processing to complete the nonlinear filter estimation,

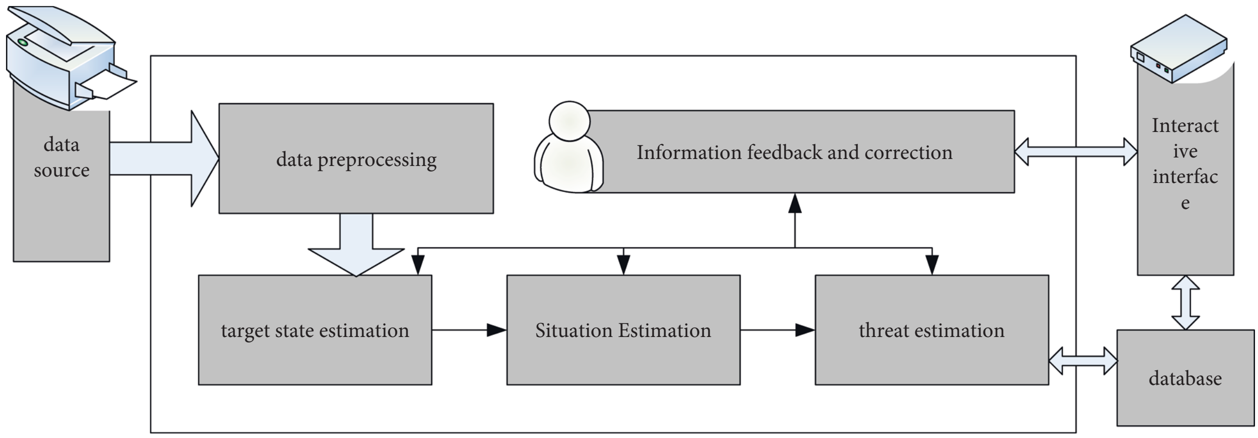

Figure 1: Basic model of the data fusion.

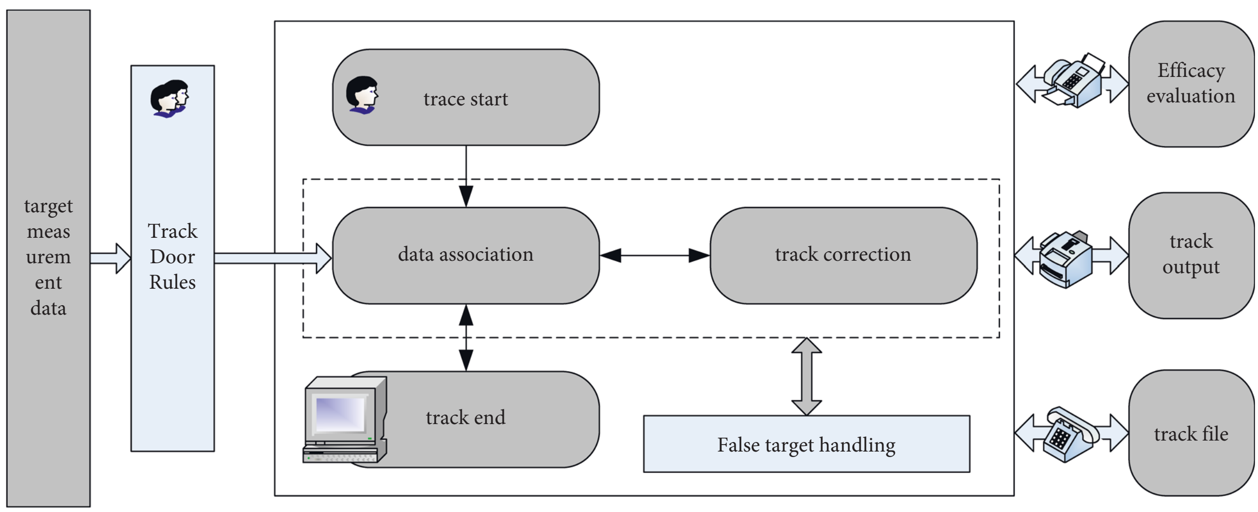

Figure 2: Basic block diagram of multitarget tracking.

Table 1: Bias values for multisensor systems.

	IFF system bias estimation			Radar system bias estimation		
	rf	of	hf	rd	Od	nd
$N = 10$	−2.3565	0.0192	0.3641	−2.5132	0.0145	0.0371
$N = 20$	−2.3132	0.0186	0.3841	−2.4654	0.0151	0.0386
$N = 30$	−2.6331	0.0187	0.3563	−2.3163	0.0168	0.0375
$N = 40$	−2.5161	0.0186	0.3623	−2.1643	0.0159	0.0368
$N = 50$	−2.1235	0.0185	0.3845	−2.2471	0.0166	0.0359
$N = 60$	−2.7856	0.0180	0.4456	−2.1645	0.0165	0.0353
$N = 70$	−2.5456	0.0175	0.4574	−2.0863	0.0161	0.0355
$N = 80$	−1.9312	0.0185	0.4456	−2.0465	0.0178	0.0346
$N = 90$	−2.5132	0.0180	0.4212	−2.0546	0.0172	0.0342
$N = 100$	−2.5145	0.0181	0.4321	−2.0123	0.0163	0.0340

the insensitive Kalman algorithm and particle filter are algorithms that use to determine the probability density distribution of the sample approximation state. Therefore, it is necessary to choose the appropriate filtering algorithm according to the actual engineering situation. It is better to use the extended Kalman filtering algorithm for the system without considering non-Gaussian and nonlinear strength. It has the same algorithm structure as the linear Kalman filter in terms of filter algorithm. The difference lies in the different system models of the two. The system of the linear Kalman filter is itself a linear system, and the system of the extended Kalman filter is itself a nonlinear system. For the general nonlinear Gaussian model, the insensitive Kalman filtering algorithm is suitable, and in the complex nonlinear non-Gaussian environment, the particle algorithm will be the optimal choice. After analyzing the files, we came to the conclusion: in actual situations, the proportion of false data information caused by various external factors is indeed very high, which also shows the necessity of eliminating false data, so as to improve the decision-making of data fusion correctness of the results.

Figure 6 shows the results of the multitarget tracking algorithm based on FCM. The smooth horizontal line represents the real track of two targets, and the curve represents the target track calculated by the algorithm. It can be seen from the figure that the tracking accuracy of the algorithm in this paper is higher than that of the multitarget tracking algorithm based on FCM, which shows that the

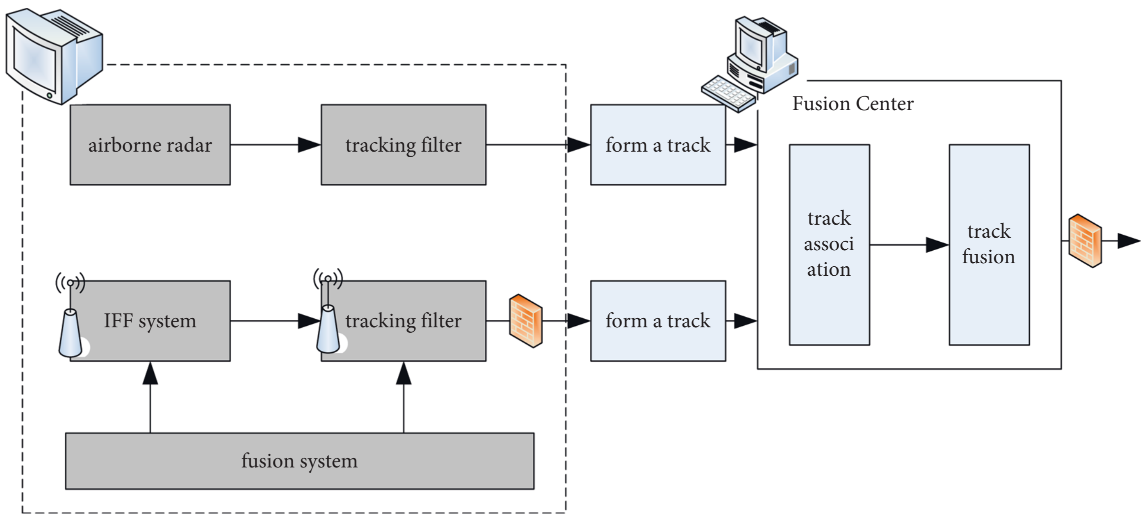

Figure 3: Distributed fusion system.

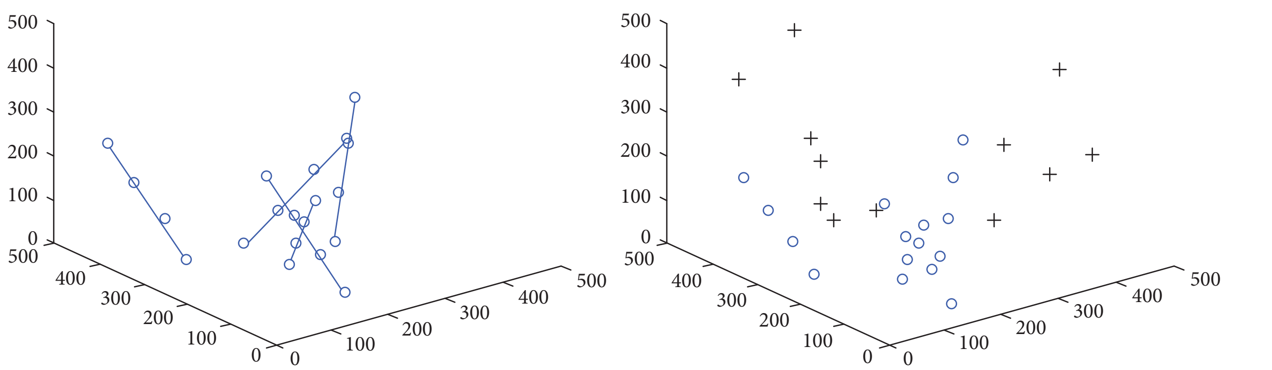

Figure 4: Target state infographic with clutter.

FCSSB-MTT algorithm proposed in this paper is effective and feasible.

3. GCDS-TR Algorithm

According to the number of our platforms and the number of enemy targets, 500 groups of reconnaissance data are selected for testing, and the time consumption analysis of the algorithm is shown in Table 2:

3.1. Selection and Implementation of the Multisensor Data Fusion Algorithm. Data registration should be done before the multisensor data fusion. Registration includes temporal registration and spatial registration. Time registration is to convert the data detected by different types of sensors from the asynchronous state to the synchronous state. The fusion tracking of the sensors in the article is carried out on the basis only time registration is required. The performance standard of the least squares algorithm is that the sum of the squares of the variance of the measured values is the smallest, the data of the sensor with a small period is fitted to the time point of the sensor with a large period, and the obtained virtual measured value is compared with the measured value of the sensor with a large period. The fusion algorithm, which can reduce the sensor data in small cycles, reduces the amount of fused data, is simple to operate and has high alignment accuracy. However, in the field of signal processing, the phenomenon of signal oversampling, undersampling, and signal loss often occurs, which requires resampling of the signal. The first case can be handled by downsampling, and the latter two by interpolation.

$$\begin{aligned} z_i &= z + (i-n)T \cdot z + v_i \, (i = 1, 2, \ldots, n), \\ Z_n &= W_n U + V_n, \\ \operatorname{cov}(V_n) &= E\left[V_n V_n^T\right] = \operatorname{diag}\left\{\sigma_r^2, \sigma_r^2, \ldots, \sigma_r^2\right\}. \end{aligned} \tag{1}$$

The defined set function $(1\text{–}N)$ t is also the basic reliability allocation. Its measurement noise variance is

$$\begin{aligned} Wn &= \begin{bmatrix} 1 & 1 & \ldots & 1 \\ (1-n)T & (2-n)T & \ldots & (n-n)T \end{bmatrix}^T, \\ J &= V_n^T V_n = \left[Z_n - W_n \widehat{U}\right] T \left[Z_n - W_n \widehat{U}\right], \\ \frac{\partial J}{\partial U} &= -2\left(W_n^T Z_n - W_n^T W_n U\right) = 0. \end{aligned} \tag{2}$$

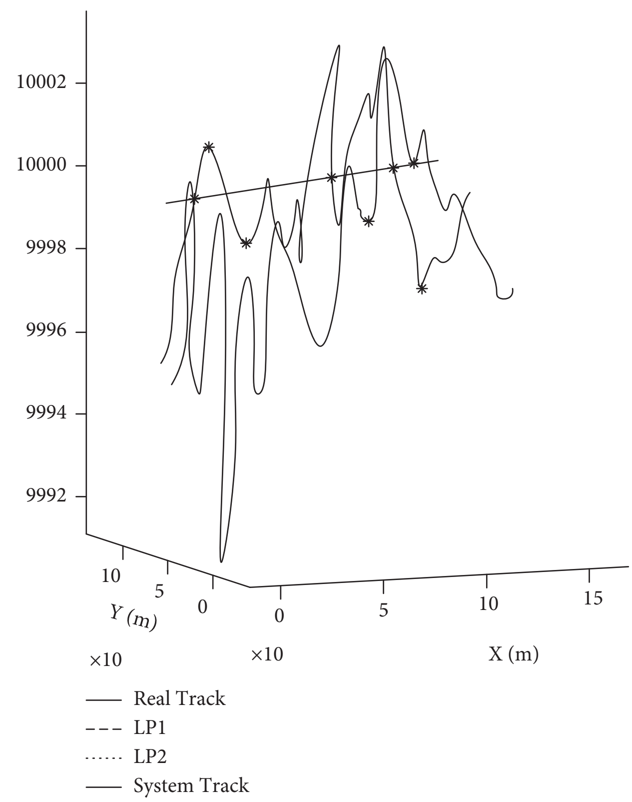

Figure 5: Local track vs system track.

Given $u \subseteq Z$, if $C1 = C2$ exists, then $n + 1 = \mathrm{w}n$ is a part of the basic trusted number assigned to C, so the exact basic trusted number assigned to C can be obtained, as shown in the following formula. The corresponding covariance estimate is

$$
\begin{aligned}
U &= \left[\widehat{Z}_n, \widehat{\dot{Z}}\right] = \left(W_n^T W_n\right)^{-1} W_n Z_n,\\
R_{\widehat{U}} &= \left(W_n^T W_n\right) - 1 \cdot \sigma_r^2,\\
\operatorname{var}\left(z_n\right) &= \frac{2\sigma_r^2 (2n+1)}{n(n+1)},\\
c_1 &= \frac{2}{n},\\
c_2 &= \frac{6}{[n(n+1)]}.
\end{aligned}
\tag{3}
$$

The sine of the pitch angle can be obtained from the previous formula:

$$
\begin{aligned}
x_s &= (C + H_s)\cos L_s \cos \lambda_s,\\
y_s &= (C + H_s)\cos L_s \sin \lambda_s.
\end{aligned}
\tag{4}
$$

Therefore, it is necessary to remove the trust number assigned to the empty set and multiply the remaining basic trust number by a coefficient, so that the total basic trust distribution is consistent with the two conditions in its definition.

$$
\begin{aligned}
z_s &= \left[C\left(1 - e^2\right) + H_s\right]\sin L_s,\\
C &= \frac{Eq}{\left(1 - e^2 \sin^2 L_s\right)^{1/2}}.
\end{aligned}
\tag{5}
$$

The measured data of the radar is converted into local rectangular coordinates from target oblique range, azimuth, and pitch angle.

$$
\begin{aligned}
x_d &= r_d \sin \theta_d \cos \eta_d,\\
y_d &= r_d \cos \theta_d \cos \eta_d,\\
z_d &= r_d \sin \eta_d.
\end{aligned}
\tag{6}
$$

If R is divided into R $(1 < R < n)$, an I can be used × Matrix R to represent the division, similarity measure between eigenvalues:

$$
\begin{aligned}
R_i &= \left[r_1, r_2, \ldots, r_n\right],\\
\Delta i &= \left[\delta_1, \delta_2, \ldots, \delta_n\right], \quad i = 1, 2.
\end{aligned}
\tag{7}
$$

Another important concept in the c-means clustering algorithm is clustering prototype vector D. Clustering prototype vector D is the object representative in the class C object set. There are R clustering prototypes in D, and like objects, it has R characteristic attributes. The sum of squares of the distances from each clustering prototype to each object in D is the smallest, even if the formula is

$$
\begin{aligned}
d_{ij} &= \left\{\left\|R_i - R_j\right\|\right\} i \neq j,\\
d_{ij} &= \left\{\left\|\Delta_i\right\|\right\} i = j.
\end{aligned}
\tag{8}
$$

The basic reliability distribution obtained from multiple batches of evidence is calculated one by one using the above formula, and the calculation result is independent of the calculation order. The similarity measures between are

$$
\begin{aligned}
uij &= \frac{\left(1/d_{ij}\right)^{2/(m-1)}}{\left[\sum_{s=1}^{c}\left(1/d_{sj}\right)^{2/(m-1)}\right]} \forall i, \quad j = 1, 2,\\
Dg &= \begin{cases} 1, & u_{12} > u_{22},\\ 0, & u_{12} < u_{22}. \end{cases}
\end{aligned}
\tag{9}
$$

After the data registration is completed, the optimal weighted average algorithm is used to fuse the data. When the weighted average method is used to fuse data measured by multiple sensors, the choice of weights has a great influence on the fusion accuracy, after which the best accuracy is achieved.

4. Experimental Analysis and Results

In the experiment, we selected a social medical system in a certain place for research and analyzed the data by traditional methods, multisensor data fusion, and online analysis of data. Real-time monitoring of various signals of the social security system will generate a huge amount of data, and

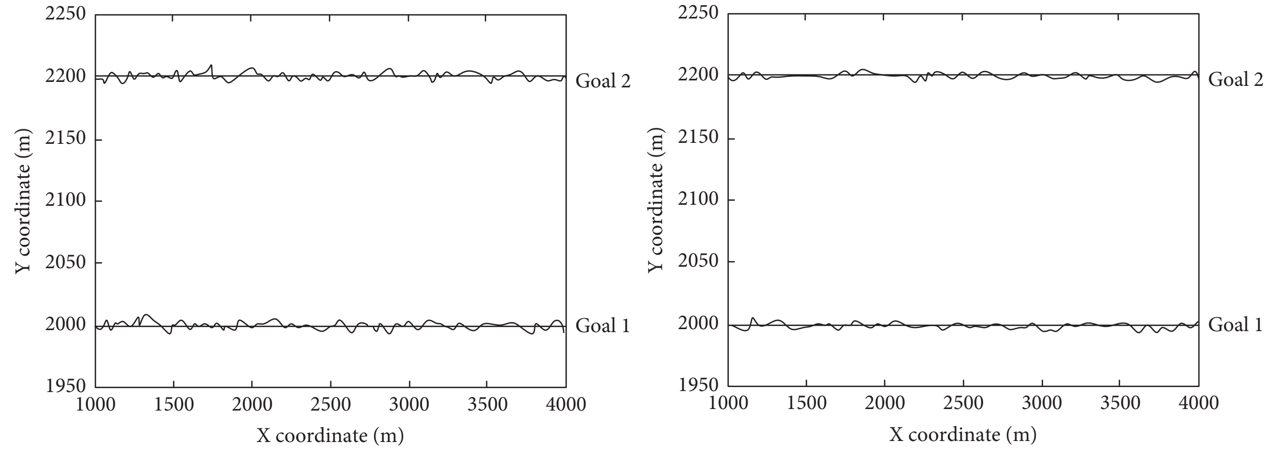

Figure 6: Track output of the FCSS-based multitarget tracking algorithm.

Table 2: Target recognition algorithm consumption time (ms) based on grey relational analysis and D-S evidence theory.

	Number of enemy targets	1	3	4	5	6	7
Number of our platforms	3	2.81	16.52	26.32	39.12	53.15	68.63
	4	3.53	22.32	39.23	54.26	73.54	95.63
	5	4.58	29.26	47.65	69.63	95.36	123.62
	6	5.56	36.26	59.32	86.62	117.62	152.32
	7	6.65	43.61	70.26	102.32	140.62	182.32
	8	8.52	50.23	82.62	120.69	163.12	215.32

these raw data formats are also different. After denoising the source data, it is necessary to perform feature extraction operations to reduce data redundancy, improve data reliability, and facilitate subsequent data fusion processing.

We have counted the data from 2015 to 2020, and the statistical results show that the city's medical pension almost doubles every year, medical expenses increase significantly, and then increase rapidly year by year. At the same time, the medical aid system developed rapidly, with the number of recipients nearly doubling the following year, as shown in Table 3 and Figure 7.

With the improvement of the treatment level, the funding level of various social insurances in medical equivalent has increased, especially the traditional methods and the different funding levels of the multisensor data fusion. Increasing financial investment plays an important role in narrowing the income gap and improving income distribution. Table 4 and Figure 8 show that personal income and the use of primary health insurance and rural cooperative medical care are increasing. The growth rate of personal wages and financial expenses of rural health workers are higher than that of employee medical insurance, which is of great help to income distribution.

In the heterogeneous multi-sensor fusion tracking system, the root mean square error of the distance of the target after the sensor fusion is smaller than that of the traditional method, and the error is about 20% smaller. About 10%, the error of the same pitch angle is also 10% smaller. This shows that the multisensor data fusion can achieve accurate calculation, and the fusion tracking effect of the target is significantly improved due to any single sensor, as shown in Figure 9.

Due to the large gap between community medical insurance, different insurance funds seek balance in principle, and the financial situation of each insurance company is not the same. In fact, the difference in the funding level is a reflection of the difference in community medical insurance benefits. Under the current organizational structure, the basic medical insurance for employees is jointly paid by the employer and employees. The national average is about 8%; the new rural cooperative medical system and basic medical insurance funds for urban residents are raised according to a certain amount, and family or individual contributions are linked to government financial subsidies. According to the fixed price in 2010, the online analysis calculation in 2020 is 1331.61 yuan per person, and the multisensor data fusion algorithm calculation cost is 126.24 yuan, an increase of 10 times. It is true that the computational efficiency of the ordinary method is indeed lower than that of the multisensor data fusion algorithm, but the cost of seeing a doctor is not low. Under the same treatment plan, hospitals and pharmacies charge prices that do not differentiate between urban and rural residents, giving equal treatment to all and charging the same fees. In fact, the cost of medical treatment for rural residents in the city is often higher than that of urban residents. Due to the low level of rural medical care, it is often necessary to go to the urban area for treatment, which includes the cost of travel and accommodation. Compared with residents who can easily travel to and from the city, rural medical expenses are usually higher than those of urban residents. What is more noteworthy is that the per capita fund level rises and narrows the gap not quickly. Table 5 and Figure 10 show that the per capita income of the

Table 3: Medical assistance for urban and rural residents.

Years	Funding to participate in cooperative medical care	Subtotal
2015	654.9	854.5
2016	1317.1	1556.2
2017	2531.3	2869.3
2018	3456.4	4125.3
2019	4026.1	4765.1
2020	4626.4	5635.6

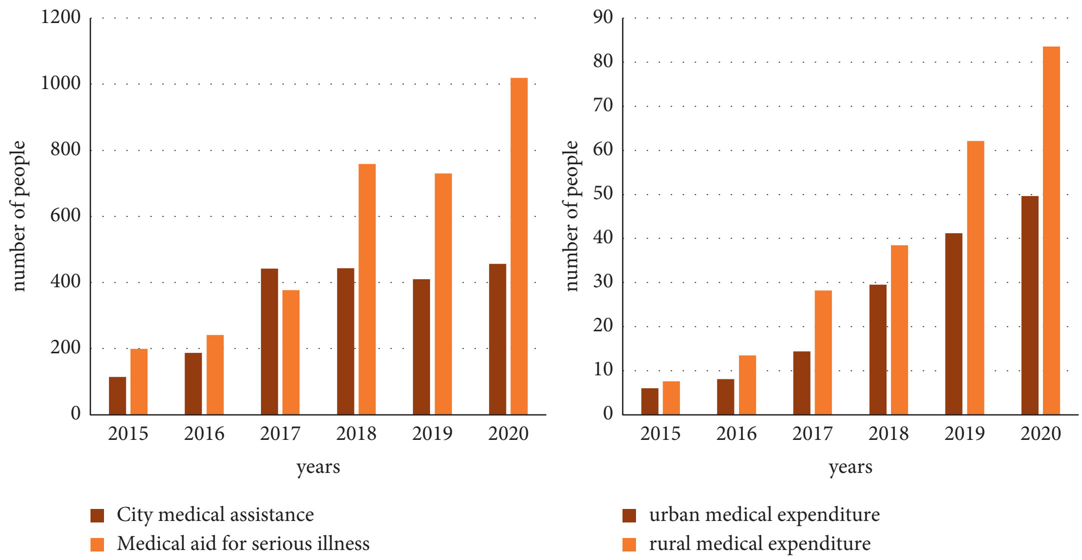

Figure 7: Comparison of urban and rural assistance.

Table 4: Per capita fund income and expenditure of basic medical insurance for employees.

	Fund income per capita			Fund spending per capita		
	The impact of changes in the consumer price of urban residents has not been deducted	After deducting the impact of changes in the consumer price of urban residents	Growth rate of per capita fund income	The impact of changes in the consumer price of urban residents has not been deducted	After deducting the impact of changes in the consumer price of urban residents	Growth rate of fund expenditure per capita
2010	448.45	448.45	-	328.65	326.35	-
2011	526.26	522.62	16.56%	332.65	332.65	1.24
2012	645.26	652.36	23.23%	465.65	423.65	31.56
2013	816.25	807.65	24.65%	599.65	593.65	36.36
2014	919.64	795.62	8.65%	639.36	642.32	11.65
2015	1026.62	953.62	8.65%	782.33	732.56	10.65
2016	1110.26	1026.65	7.62%	821.35	742.35	2.32
2017	1223.15	1080.35	5.65%	861.56	752.35	1.65
2018	1443.21	1165.62	10.26%	1065.56	836.65	10.65
2019	1556.15	1320.35	8.65%	1192.35	1006.65	19.65
2020	1596.65	1335.62	2.32%	1325.56	1103.65	10.64

new rural cooperative medical care is lower than the basic income of employee medical insurance. The level of employee medical insurance started late and the starting point was low. Before 2019, the per capita income of rural medical cooperatives was not as high as that of the basic income of employee medical insurance. Even if the per capita income growth of the new rural cooperative medical system in 2020 is smaller than the basic medical insurance for employees, it is uncertain whether this trend can continue. The multi-sensor data fusion in the experiment is as follows: firstly, we collect the sign data from multiple sensors in the body area network and preprocess it, then extract the eigenvalues of these sign data to obtain the feature vector, and then associate each feature vector according to the same target, and

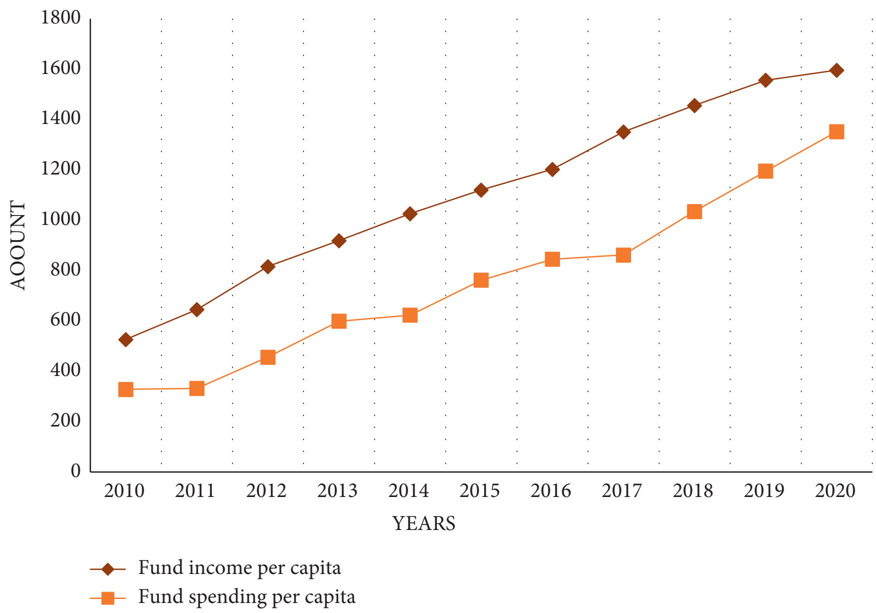

Figure 8: Employee medical income and expenditure.

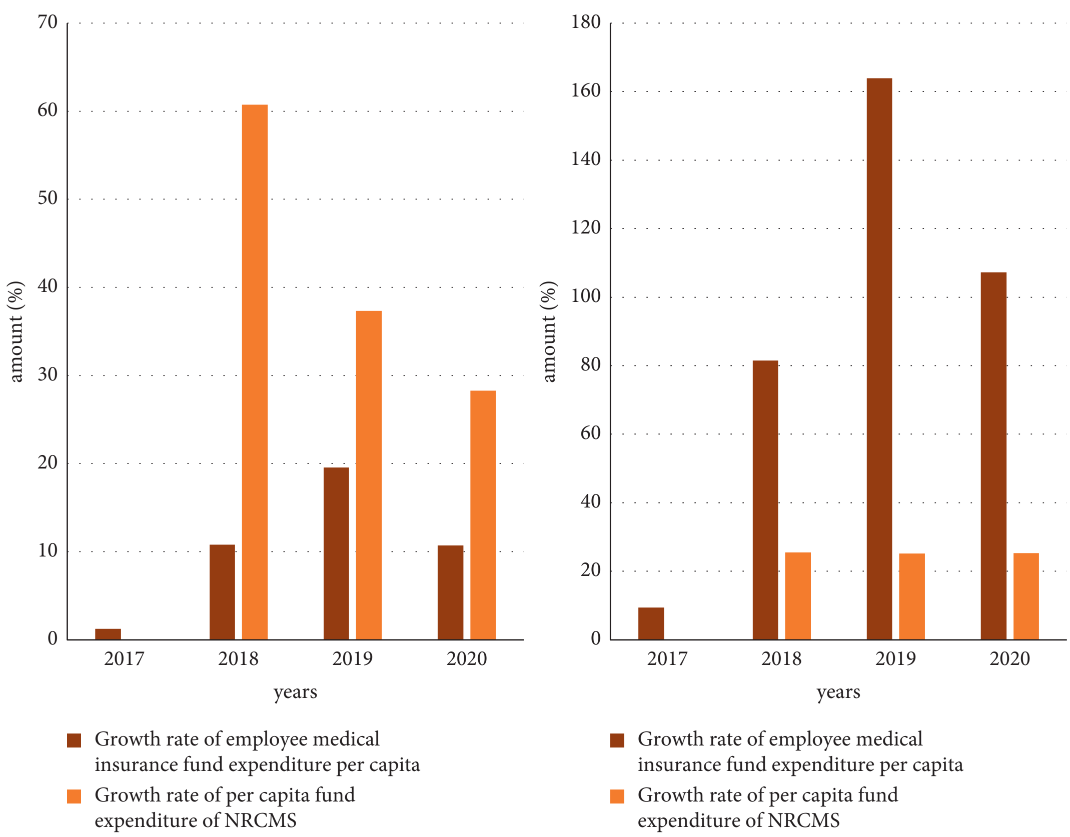

Figure 9: Comparison of per capita fund expenditure growth between employee basic medical insurance and new rural cooperative medical care.

then finally use it. The fusion method synthesizes these vectors and obtains the situation level evaluation value of the human health state.

Based on the distributed data fusion processing structure model, different data models of the heterogeneous multisensor data fusion for the social medical security system are

Table 5: Comparison of per capita fund income growth between employee basic medical insurance and new rural cooperative medical care.

	Employee basic medical insurance			New rural cooperative medical care		
	Fund income per capita	Increment	Growth rate	Fund income per capita	Increment	Growth rate
2017	1080.65	57.65	5.23%	50.52	—	—
2018	1165.16	115.65	10.65%	75.65	26.56	55.65
2019	1302.56	106.56	8.65%	95.65	14.65	18.35
2020	1331.25	27.35	2.65%	126.65	34.65	38.65

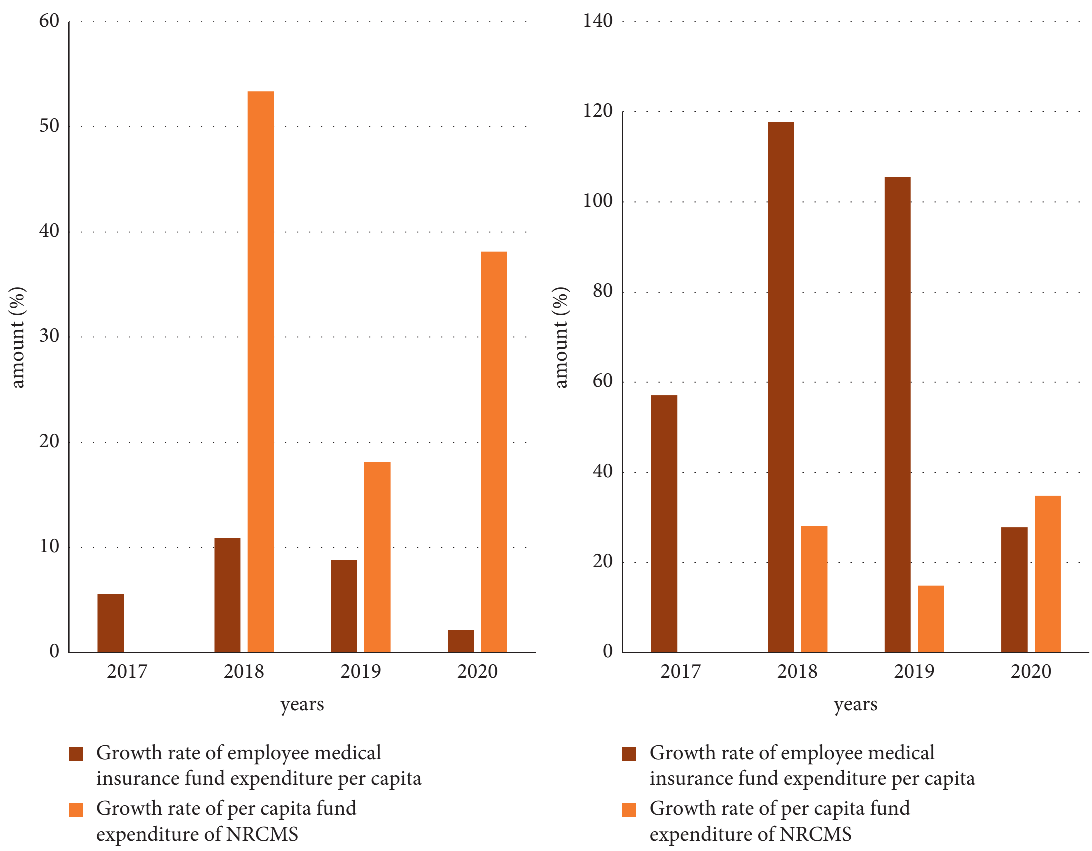

Figure 10: Comparison of per capita fund income growth between employee basic medical insurance and new rural cooperative medical care.

constructed. First, each sensor preprocesses the obtained target information data, and then performs filtering and estimation processing. Complete the combined processing of the respective different data, and then use a certain algorithm to judge the data association between the combined results and the data estimation results. If the data comes from the same target, perform data fusion processing, analyze the fusion results, and pay the new rural cooperative medical system. There is basically no problem with the insurance participation fee. The main problems today are mainly reflected in the high threshold line and the large proportion of self-inflicted expenses. Therefore, the relevant part can implement the policy of a double threshold and a double reimbursement ratio according to the analysis data of fusion results.

5. Discussion

On the basis of data fusion research, including the research on sensor and data association, data fusion algorithm, filter tracking algorithm, and a heterogeneous multisensor data fusion tracking system based on the distributed fusion is established, which is composed of radar, infrared sensor, and laser sensor. After establishing the measurement model, determining the target model and the observation model, selecting the appropriate data association and data fusion, and the filtering and tracking algorithm, the system detects the air target. The tracking effect error is better than that of a single sensor, so the reliability and effectiveness of the heterogeneous multisensor fusion tracking system are verified.

The development of science and technology is to improve people's quality of life, and theory as the cornerstone of science and technology is also based on this purpose. The study of data fusion theory, especially the multisensor data fusion theory under the body area network, is of great benefit to many fields, such as telemedicine. Due to the diversification of human sign data, the huge amount of data and the real-time and accurate requirements of data processing results exceed the human ability to comprehensively process information. The goal of data fusion technology is to reduce the amount of data, synthesize all kinds of data, and give real-time and accurate results. Although the theory of data fusion has been developed for decades, it has not yet reached a mature stage. At present, an effective generalized data fusion model has not been established, and there is no good solution for the robustness of the fusion system. The purpose of our research on the multi-physiological parameter data fusion theory under the body area network is to improve the efficiency of data transmission and improve the accuracy and reliability of data. Therefore, in this paper, the resampling, denoising, feature extraction and high-level data fusion, and other related algorithms of the original data are deeply studied, and the advantages and disadvantages of the main methods are compared, and the appropriate data preprocessing and fusion methods in different environments are analyzed.

With the continuous development of sensor technology and data fusion technology, the application of multisensor data fusion in the computationally complex medical system is more and more extensive, and the multisensor data fusion technology has also attracted the attention of scholars in the field. The problem of multi-sensor data fusion is studied to detect social medical security state information by location-level data fusion, and based on the distributed data fusion structure model, studies the multisensor data association method, data fusion method, and filter state estimation method, and on this basis establishes a multisensor data fusion tracking system composed of medical security, rural medical, and urban medical security, selects appropriate target models and observation models, and selects appropriate correlation, fusion, and filtering algorithms. The target is detected, and the effect of obtaining the precise position and state information of the target is finally achieved.

6. Conclusion

In essence, the establishment of a social medical insurance system is a public service and public goods provided to the people, so the experimental research and development of the social medical insurance system has become a general consensus in society. As one of the main technologies of social medical insurance, the multisensor data fusion method under the body area network becomes more and more important. In this context, this paper conducts a preliminary study on the multisensor data fusion method under the body area network. After researching the query planning process for OLAP with different data organization models, a scalable and efficient distributed hybrid online analytical processing system (HOLAP) is designed and implemented from the corresponding query interpretation, cache query optimization mechanism, etc. The system is designed to solve multidimensional queries of datasets of different scale levels and make efficient and reasonable query processing according to the realization modes of different multidimensional organizations. Based on the theory of data fusion, this paper combines signal processing technology, artificial intelligence method, and fuzzy reasoning method and initially realizes the fusion of multisensor data, and uses experimental data to obtain a series of results. The social medical insurance system is only an integral part of the three medical system reforms, namely, the reform of the drug circulation system, the reform of the medical and health system, and the reform of the medical insurance system. In order to realize the original intention of the design of the social medical insurance system, it is necessary to fundamentally improve the medical environment of the social population and control the cost of medical services. This paper perfects and improves the joint algorithm of multisensor data fusion and improves the shortcomings of the algorithm. Finally, this paper uses the data after feature extraction to verify the neural network algorithm, the fuzzy neural network algorithm, and the improved fuzzy neural network algorithm. Through the results to understand these problems encountered in the process of implementing the current policy, it leads to some thinking about the current medical social security system and explores the most suitable path for today's medical security. However, the denoising process of data is usually carried out in the node, and the energy of the node is limited, which requires the algorithm running in the node to be as simple and effective as possible. The denoising method and feature extraction method used in this paper require too many computing resources and should modify this method to work within a node.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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