Hindawi
Mobile Information Systems
Volume 2022, Article ID 7872741, 13 pages
https://doi.org/10.1155/2022/7872741

Research Article

Construction of International Education Talents Training Mechanism Based on Data Fusion Algorithm

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Received 28 April 2022; Revised 6 June 2022; Accepted 24 June 2022; Published 11 July 2022

Academic Editor: Liming Chen

With the increasing trend of economic globalization and the continuous evolution of economic forms, the role of science and technology in promoting the development of human civilization has become more and more obvious. With the improvement of comprehensive national strength, the knowledge economy has brought new opportunities and challenges. With the increasing internationalization of higher education, it has not only driven the economic exchanges between countries but also led to the exchange of educational resources among transnational countries. However, China's international education talent cultivation started late, with poor teaching awareness, imperfect discipline construction, and low quality of international education talents. A series of problems have seriously hindered the establishment of the talent training mechanism. In order to establish a reasonable and perfect talent training mechanism, optimize the international education talent training mechanism, make the international education talent training mechanism keep up with the development trend of science, technology, and education in the contemporary world, promote the internationalization of international education talent training, and strengthen the exchange of educational resources among countries. This paper uses various algorithms of fusion algorithms to accurately calculate the talent data. The algorithm results show that the optimized grouped quadratic combined Kalman filter has a shorter running time than the traditional Kalman filter, which decreased about 20%. The S-LEACH algorithm outperforms the traditional algorithm in the simulation results of the number of surviving nodes, relative energy consumption, and data transmission. In response to the national strategy of rejuvenating the country through science and education, cultivating international talents and building a modern talent training mechanism are particularly important.

1. Introduction

Since the 1980s, the number of multinational companies in the world has been increasing year by year at an average annual growth rate of 29%. With the continuous expansion of these multinational organizations, the demand for international education talents has also increased. However, in terms of international talent education, China's training mechanism started relatively late, with little emphasis in the early stage, resulting in mixed data and information in the later stage of international talent education. The quality of teaching could not keep up, and the shortcomings of discipline construction appeared, which seriously hindered the cultivation progress and effects of international talents in China. Data fusion algorithm is an information processing algorithm that mainly collects and stores data information through computer and finally distributes and transmits data through sensors. In the process of building a talent training mechanism, it can not only improve the speed of data calculation, but also improve the calculation accuracy, as well as provide technical support for the construction of an international education talent training mechanism. Build the international education talent training mechanism under the data fusion algorithm, use science and technology to improve China's international talent training and education level, break the traditional rigid mode and institutional constraints, open the door to the world, integrate with the world education, and enhance the strength of China's international education talents in the international competition.

Based on the data fusion method, this paper cites the basic algorithms of data fusion algorithms such as Bayesian decision algorithm, Kalman filter algorithm, grouped quadratic joint Kalman filter information fusion algorithm, LEACH routing algorithm, and S-LEACH routing algorithm. Both the aspects of data calculation and network life have been improved, which is conducive to improving system performance and allowing the international education talent training mechanism in order to form a clear hierarchical positioning system under the fusion algorithm. In the process of building a talent training mechanism, the improvement of these algorithms can effectively improve the measurement accuracy of data and shorten the measurement cycle and data analysis capabilities. Through data analysis, a clearer training plan will be formulated. The training objectives will also be clarified, and the school-running model will be diversified and open.

As the application of data integration becomes more and more extensive, more and more research is being done on fusion data. In order to improve the network survival time, H Wang combined the optimal BP network, the genetic algorithm, and the particle swarm algorithm and proposed the GAPSOBP data improvement algorithm. In GAPSOBP, wireless sensors are like neurons in a neural network. The data collected by the sensor is output through the BP network and then combined with the cluster path to mix additional data, thus reducing the amount of data sent to the base station or sink. The simulation results show that the GAPSOBP algorithm is higher than the LEACH and PSOBP algorithms in terms of power consumption and grid life [1]. In order to solve the experimental problem that the model on which the assimilation system was based was discretized on a spatial grid with a horizontal dimension of tens of kilometers and there might be tens or hundreds of measurements in the future, N Zoppetti developed a new data fusion method, namely, a full data fusion algorithm for combining a set of retrieved products in a single product. In this paper, they use the full data integration method for ozone profile measurements to simulate thermal infrared and ultraviolet groups in real-world scenarios. The combined product is then compared to the input area. The comparison shows that the output of the data mix has the lowest total error and the highest data content [2]. Through in-depth research and analysis of dance motion enhancement algorithms in wearable sensor networks, Li Y selected the advanced Kalman filter algorithm and the quaternary method. A sensor measurement system based on manual measurement was proposed. The algorithm is a legendary optimization algorithm, which divides each iteration into one step of optimal and maximum probability and finds the best value completion. The values of each gesture and practice are introduced in the training algorithm model for the detection and differentiation of control data, the monitoring of its recognition accuracy, and the continuous improvement of the model to achieve accurate recognition of controls and human behaviors, thus evaluating its training of the model [3]. In order to improve the reliability of wireless sensor network (WSN) monitoring system and prolong the service life of monitoring system, an adaptive prediction weighted data fusion (AFWDF) algorithm based on clustering is proposed by Yu X. AFWDF establishes a prediction model based on the time correlation of data. The source node extracts feature values and eliminates outliers by comparing predicted values with measured values. The cluster head recovers the monitoring value and calculates the reliability and weight of the monitoring value to fuse it. Through performance analysis and simulation, it is concluded that AFWDF algorithm has high reliability. In the simulation environment, the network life cycle is about 15% higher than SAEMDA and BPNDA [4].

The development of China's international talent education mechanism started relatively late. Rakhmonov pointed out through the report that it was necessary to strengthen the connection between higher education institutions and the labor market by improving the quality of higher education institutions and cultivating high-quality talents. The report also noted that the relationship between the higher education system and production and labor markets has not been fully developed. During the independence period, the dynamics of higher education institutions and student numbers were analyzed. He studied the strategy of action and the implementation of the tasks set forth in the Decree of the President of the Republic of Uzbekistan and the resolution of higher education institutions on improving the quality of education, as well as the principles of the Bolon model on improving the quality of education [5]. Zhang surveyed Chinese HR managers' perceptions of the value of different talent development practices, with a particular focus on MBAs. This qualitative study involved 16 interviews with Chinese human resource managers. A five-dimensional human capital model was employed to guide the assessment of perception. The findings suggested that MBAs were believed to increase the value of all five human capital dimensions of the human capital model used in the study. Both national and institutional culture were believed to influence the implementation of talent development and the perceived value of an MBA by HR managers [6]. Zheng outlined "embedded" international talent training, a practice in Hebei province's two-way opening of higher education to cultivate talents with understanding of international law, mastery of economic management expertise in a globalized context, cross-cultural competence, and strong innovative international management. They could be familiar with international business activities and rules and could work in enterprises and institutions. While building cultural self-confidence, it was a practice to introduce high-quality educational resources from abroad [7]. The above literature is mainly about the knowledge of data fusion and international talent education, which is instructive for the following research.

This paper mainly uses data fusion algorithm to build a perfect international education talent training mechanism with technical support. This article analyzes and compares four basic data fusion algorithms including Kalman filter algorithm, grouped quadratic joint Kalman filter information fusion algorithm, LEACH routing algorithm, and S-LEACH routing algorithm. It is found that the running time of the grouped quadratic joint Kalman filter information fusion algorithm is increased by 20% compared with the traditional Kalman filter algorithm, and the S-LEACH algorithm is superior over traditional algorithms in terms of the number of surviving nodes, relative energy consumption, and data transmission.

2. Construction of International Education Talents Training Mechanism Based on Data Fusion Algorithm

2.1. Data Fusion Concept. The basic idea of data fusion is to collect and store target information in a certain order by means of computer technology, electronic communication technology, etc. Then the data information is analyzed, parsed, and comprehensively processed from multiple levels or angles through relevant criteria, and then the information such as the state and characteristics of the target can be grasped and the decision-making related to the target can be made.

According to the different levels of fusion, in data fusion, there are generally three levels of fusion, which are data layer fusion, feature layer fusion, and decision layer fusion [8]. These three levels of fusion are represented from low level to high level. As shown in Figure 1, it is a hierarchical model diagram of data fusion.

2.1.1. Data Layer Fusion. Data fusion firstly obtains the fusion for the information channels in the sensor. According to the data information obtained after fusion, the system extracts the feature vector, and then the system performs the process of data identification and transmission [4]. There is no problem of data loss in data fusion, and such results are the most accurate. Sensors must meet the conditions of the same type. If multiple sensors are heterogeneous, data can only be fused at a higher layer. If the data traffic is large, the bandwidth and processing capacity of the system are very high.

2.1.2. Feature Layer Fusion. Feature layer fusion, as the name implies, is to classify according to the feature model of the data and extract the features to form different types of feature data vectors. Then it uses pattern recognition to process, which requires less bandwidth of the system than data layer fusion. However, due to the inaccurate problem of extracting features, in extreme cases, the opposite fusion results will be produced.

2.1.3. Decision Level Fusion. After the feature layer is completed, the decision layer fusion is to integrate the features of multiple sensors. The main advantage of feature fusion is that it combines a variety of features for calculation with high accuracy.

2.2. Multisensor. As the most basic facility of information fusion, multisensor can use different dimensions of sensor information data combined with computer technology to measure and analyze, and it can also collect data information according to time sequence [9]. Through the optimization of various information and feature extraction, more valuable information can be extracted. According to the level of data flow, it can be divided into data layer, feature layer, and decision layer. Each layer has its own function, and finally they will form a complete system that depends on each other and cooperates with each other. After each sensor identifies the target, the results of multiple sensors are integrated. According to the synergistic and complementary relationship between the comparative data, the expected data fusion result is finally achieved. The main purpose of using information fusion technology to establish a talent training mechanism is to obtain more effective information and to integrate and analyze the information received by multiple sensors, which can effectively solve the unilateral problem of information collection from a single sensor. The establishment of a multisensor information fusion model for the talent training mechanism is of great significance for improving the talent training mechanism.

2.3. Bayesian Decision Algorithm. Bayesian decision algorithm is a frequently used data fusion algorithm for parameter estimation [10]. Using the knowledge of probability and statistics for classification, a value is given. Then a measurement evidence fusion is added to the algorithm to estimate and update the data, which is a kind of data fusion algorithm.

Using R1, R2, R3, etc. to represent n assumptions that do not contain enumerables, the Bayesian formula is in the form as the following formula:

$$T\left(R_i|H\right) = \frac{T\left(H|R\right)T\left(R_i\right)}{\sum_{j=1}^{n} T\left(H|R_j\right)T\left(R_j\right)}, \tag{1}$$

$$\sum_{i}^{n} T\left(R_i\right) = \sum_{i}^{n} T\left(H \mid R_i\right)T\left(R_i\right) = \sum_{i}^{n} T\left(H, R_i\right) = T(H). \tag{2}$$

The Bayesian inference method was first used to determine inference, and its important advantage is that it is based on axioms and has a strong theoretical data foundation that can be intuitively understood [11]. Bayesian decision-making provides a feasible method for data fusion, which is used for multisensor high-level information fusion in a static environment. According to the probability principle of sensor information combined with Bayesian decision-making, the conditional probability is used to represent the uncertainty of different measurements. When the target of the sensor tends to be consistent, it can be directly used for data fusion. But in most cases, multisensor data is constantly changing, and even the range of changes will be very large. Therefore, it is not optimal in most cases.

Its main disadvantages include the following:

(1) The probability distributions required for Bayesian decision-making must be independent, which becomes particularly difficult in systems that contain

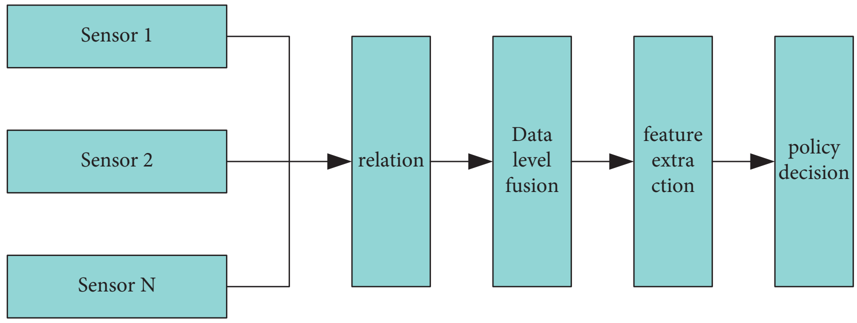

Figure 1: Hierarchical model of data fusion.

multiple sources of linked information. Sometimes it may be even impossible.

(2) The acquisition of the conditional probability of prior knowledge and the acquisition of prior probability are difficult. The results of the obtained probability are inconsistent, resulting in large workload and low efficiency, which is not desirable for large-scale system calculation.

(3) Updating the rule base is computationally expensive, because when the system needs to increase or decrease a rule, all the probabilities must be recalculated to ensure the correlation and consistency of the system, which is not desirable for large systems.

(4) The Bayesian method must be used on the same level of recognition framework. If in the data fusion, it is impossible to use the Bayesian method to fuse the data collected at different levels. Because the prior probability is known in advance, and the prior probability of high-level evidence cannot be assigned in advance, it will lead to fusion errors of different layers [12].

2.4. Kalman Filter Algorithm. It is a powerful tool for solving state space model estimation and prediction. It does not need to rely on huge historical data and is implemented by recursive method based on the minimum mean square error. This algorithm is mainly a multidimensional and nonstationary processing process. It is often used in the establishment of various mechanisms [13]. Kalman filter algorithm is a data fusion algorithm for dealing with linear system noise. The realization method is to obtain the fusion estimated value after a series of linear combinations of the estimated values of sensor nodes in the network.

Kalman filtering is widely used in discrete control systems, so the following analysis is based on this system. The system is actually a linear stochastic differential equation as the following formula:

$$W(h) = \mathrm{RW}(h-1) + \mathrm{YU}(h) + P(k). \tag{3}$$

The measured values of the system are expressed as the following formula:

$$F(h) = \mathrm{EW}(h) + V(h). \tag{4}$$

In formula (4), the control variable $U(h)$ corresponds to time h, the others are various parameters in the system, and each parameter forms a matrix in the model. In the Kalman filter system, if the measured value is not large or the number of measurements is only one, then E is 1. If the matrix of the system is multidimensional, then this parameter represents a matrix E at that time. $W(h)$ represents the noise in the measurement process. According to the above formula, it can be known that if the process noise satisfies the Gaussian white noise, the co-square error of these white noises can be measured.

In the Kalman filter system, the measurement error estimation that satisfies white Gaussian noise can be divided into five steps. Firstly, the following formula is obtained:

$$W(h|h-1) = \mathrm{RW}(h-1|h-1) + YU(h). \tag{5}$$

In formula (5), $W(h|h-1)$ represents the result obtained by the system at the top level. $\mathrm{RW}(h-1|h-1)$ is the optimal result selected from the results obtained by the system, and $YU(h)$ represents the control amount. If there is no control amount in the system, this parameter is generally set to 0 by default.

The system forecast results are recalculated to obtain the latest system results. When the covariance of the predicted value is not updated, M is used to represent the covariance. The calculation formula of the covariance is as followsa:

$$M(h|h-1) = \mathrm{RM}(h-1|h-1)R + Q. \tag{6}$$

According to the observed results above, the measured value of the system in the current state can be calculated. Combined with the above results, the optimal estimated value $W(h|h)$ in the current state can be obtained as follows:

$$W(h|h) = W(h|h-1) + \mathrm{Kg}(h)(F(h) - \mathrm{EW}(h|h-1)). \tag{7}$$

In formula (7), Kg represents the Kalman gain, and the formula can be obtained:

$$\mathrm{Kg}(h) = P(h|h-1)E|(\mathrm{EP}(h|h-1)E + A). \tag{8}$$

Now, the optimal estimated value of h in the current state of the system is obtained. In order to keep the calculation of the system going, knowing that there is no next measurement value in the system calculation, the covariance calculation will be used after iterative update. The calculation formula is as follows:

$$P(h|h) = (L - \mathrm{Kg}(h)E)P(h|h-1). \quad (9)$$

The above is the basic principle and basic formula of Kalman filter. Kalman filtering is well suited for solving the inertial feature problem associated with filtering. For example, the possible position of the object is predicted by detecting the current position of the object in real time at the next moment. For moving objects with changing positions, assuming that the next position is the current position, there is a deviation between the predicted value and the actual value. The Kalman filter can estimate the deviation, so it is suitable for real-time measurement of the target position for tracking. The target is constantly moving, so the data of the two states before and after the moving target have motion characteristics, and the Kalman filter is used to solve the abovementioned motion prediction problem [14]. Meanwhile, Kalman has higher requirements on the change model of the prediction object and the distribution model of noise, and the filtering results can directly reflect the quality of the model. Since the Kalman filter is very easy to diverge, it is generally used for data fusion at low levels. At the same time, the Kalman filter process is a process of continuously updating the current state for recursion, so it is no longer necessary to save all the states that have occurred in advance and then perform calculations, which does not require high system requirements and has good real-time performance [15]. When there is a lot of redundancy in the sensor combination information, the dimension of the observation matrix will become huge, and the calculation amount of the filter will soar. Adding sensors increases the complexity and probability of failure of the system, and when a system failure cannot be detected, it can quickly contaminate the entire system.

2.5. Grouped Quadratic Joint Kalman Filtering Information Fusion Algorithm. According to the optimal criterion of information fusion and the three fusion structures improved above: centralized structure, distributed structure, and hybrid structure, all have their own scope of application, advantages, and disadvantages. To address the problem that Kalman centralized data processing causes excessive computation and that erroneous data from a single sensor can rapidly contaminate the entire system, a data fusion algorithm based on joint Kalman filtering is used to improve the computational speed and scalability of the system [16]. The grouping here does not mean that there is no relationship with each other but another interpretation of distribution. It is used to specify the structure of the local filter, which indicates that the components are distributed into the local filter in groups. Figure 2 shows the basic structure of grouped quadratic fusion.

In recent years, joint Kalman filtering has been applied to various traffic and navigation information systems. It is widely praised in practical production applications. Among them, the joint filtering model has made significant improvements to the algorithm under the premise of the original distributed state fusion. The joint Kalman filter model not only requires a small amount of computation, but also has outstanding performance in terms of flexibility and reliability. Now it has become a new generation of general-purpose filtering models. Decentralized filtering is the basis of the joint filter, and the joint Kalman provides data from the local filter, so as to achieve the reliability of the data. The local filter must include an information distribution process. During this process, the dynamic information of the main filter is proportionally distributed among the local filters.

2.6. LEACH Routing Algorithm. The LEACH algorithm is a cluster-based protocol algorithm, which randomly selects the balanced nodes within the network to carry energy according to logical division and finally achieves an energy-saving routing algorithm within the system [17]. The LEACH algorithm uses multiple rounds of operation in its work. During each round, the nodes in the network complete the work of electing cluster heads in the aggregation area. After the cluster head election is successful, the message will be transmitted to other nodes, and other noncluster head nodes choose which cluster to join according to their own conditions (such as signal strength, etc.). Since the energy consumption of the cluster head is larger than that of the noncluster head nodes, the LEACH algorithm has to reelect the cluster head after each round to achieve the purpose of balancing the energy. To ensure that the collected data is accurate enough, it is required that the nodes in the network can be evenly distributed, and the energy and structure of the nodes must be consistent. The phenomena of node heterogeneity cannot exist. It is done in order to make the data compatible during aggregation and fusion without generating errors. When deploying nodes within the network, it needs to be ensured that the energy value of each node is sufficient along with other nodes for information transmission, so that the system can carry out the next operation of electing the cluster head. It also needs to be ensured that the cluster head and the noncluster head can keep in touch with each other. The protocol is simple and its implementation is easy. The protocol adopts the node random election cluster head strategy. The cluster head is adaptively generated, and the whole network load is balanced, reducing network energy consumption. The cluster-based protocol structure allows the cluster head node to fuse the information of the nodes in the cluster. The generated data packets are sent to the sink node uniformly, which avoids the energy loss caused by the large-scale transmission of multiple single nodes. Even when the node energy is exhausted due to uneven load or environmental factors, a timely response mechanism can be made. Figure 3 is the flowchart of the LEACH routing algorithm.

2.6.1. Cluster Head Election Policy and Data Transmission.

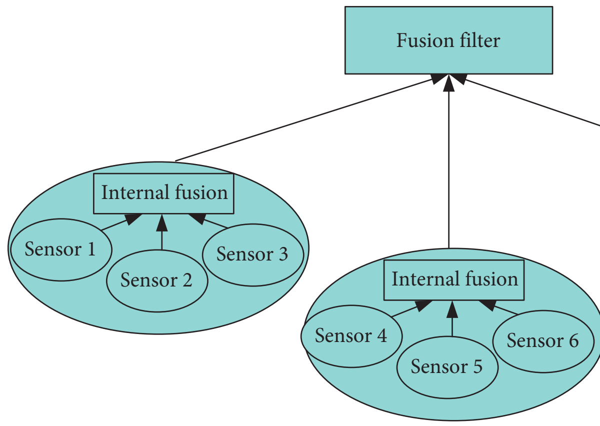

Figure 2: Basic structure of grouped secondary fusion.

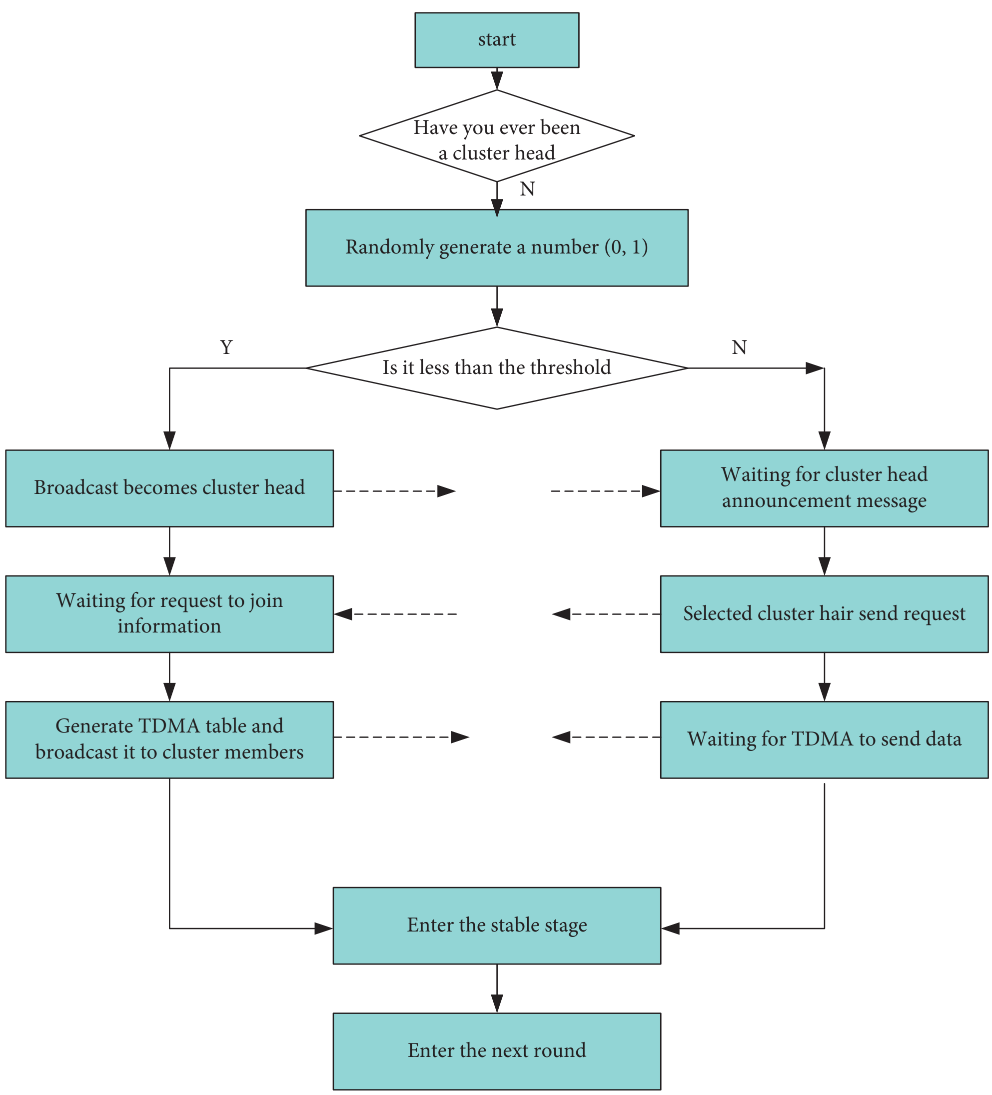

Figure 3: LEACH routing algorithm process.

The election of the clusters is conducted in a random manner. Before the election continues, a threshold is first set so that the random data generated by the node is between 0 and 1. Then, the threshold for the election is as follows:

$$U(s)=\left\{\begin{array}{cc}\dfrac{T}{1-T\times[r\bmod(1/T)]}, & s\in G\\ \\ 0 & \end{array}\right\}. \tag{10}$$

In formula (10), T is the probability of being elected as the cluster head node, and G is the set of nodes that have not been elected as the cluster head; r represents the current election round number. In this link, the nodes are elected until the last unelected node becomes the cluster head, which means that this link ends. As can be seen from the structure diagram, the way that the LEACH algorithm collects the information of the cluster is mainly the TDMA mechanism. This mechanism integrates the collected information by the cluster head in the node and then transmits it to the information gathering point by the cluster head. After the transmission of the nodes in the cluster is determined by the TDMA timing message, the nodes in the cluster start to transmit data in their own transmission time slots, and the transmission adopts a simple single-hop mode. After a round of transmission, the cluster head compresses and summarizes the received node data into a new transmission signal.

2.6.2. Communication Energy Model. Since each point in the LEACH algorithm has a consistent energy value, it is assumed that all nodes in the network have the same initial energy value and limited energy. The energy consumption per unit distance is the same, and there is only one sink node in the network. Its location is fixed, and then the energy of the first part of the level in the sensor can be expressed as follows:

$$\begin{aligned}D_{\mathrm{Tn}}(l,h)&=\mathrm{lD_{elec}}+l\beta h^{r}\\&=\left\{\begin{array}{l}\mathrm{lD_{elec}}+l\times\beta_{\mathrm{mp}}\times h^{4},h\geq h_0\\ \mathrm{lD_{elec}}+l\times\beta_{\mathrm{fs}}\times h^{2},h<h_0\end{array}\right\}.\end{aligned} \tag{11}$$

During the signal transmission process, the energy of the node will be weakened with the transmission. There are two attenuation paths: multipath attenuation and free space attenuation. The attenuation path becomes the threshold distance. The calculation formula of the threshold distance is as follows:

$$h_0=\sqrt{\frac{\lambda_{\mathrm{fs}}}{\lambda_{\mathrm{mp}}}}. \tag{12}$$

The energy consumption of the second part level is expressed as follows:

$$D_{\mathrm{Qn}}(l,h)=\mathrm{lD_{elec}}. \tag{13}$$

In summary, the energy consumed in the system is as follows:

$$D_T(l,h)=D_{\mathrm{Tn}}(l,h)+D_{\mathrm{Rn}}(l,h)=2\,\mathrm{lD_{elec}}+l\beta h^{r}. \tag{14}$$

Although the LEACH routing algorithm has many advantages, it also has disadvantages such as ignoring the remaining energy, repeated collection of information, etc., which lead to rapid consumption of energy consumption between nodes. In this way, internal nodes often die prematurely, and network life is also impaired [18]. Long-distance transmission is not considered. The algorithm is only suitable for small-scale networks. When the distance is short, the single-hop transmission method can still exert its advantages. But when the transmission distance is long, the single-hop transmission method will consume a lot of energy of the cluster head.

2.7. S-LEACH Routing Algorithm. Aiming at the shortcomings of LEACH routing algorithm, an improved and optimized algorithm, S-LEACH routing algorithm, is proposed in this paper. In the S-LEACH algorithm, the remaining energy of the node, the location of the node, and the density of the node are the factors that are mainly considered in the election of the cluster head. The specific election process is as follows.

(1) The remaining energy ratio of the node is recalculated as follows:

$$\frac{D_i(r)}{D_{ic}}. \tag{15}$$

D_{ic} represents the remaining energy of node i in the r^{th} round of cluster head election and the initial energy at the beginning of the node. The ratio of the first two is proportional to the remaining energy. The larger the ratio is, the higher the probability of becoming a cluster head will be.

(2) The formula for calculating the distance between the node and the sink point is as follows:

$$h(i)=\sqrt{(m_i-m_0)^2+(n_i-n_0)^2}. \tag{16}$$

In formula (16), (m_i-m_0) represents the node coordinates of node i in the internal network, and (n_i-n_0) represents the coordinates of the convergence point. In the cluster head election, the node closest to the sink is the most likely to become the cluster head.

Relative density calculation of nodes is as formula:

$$\partial(x)=\frac{\mathrm{Nei}(x)}{(1/P)-1}. \tag{17}$$

Relative density refers to the relative density of nodes within the range of the specified radius R, which is the ratio of the number of adjacent nodes to the number of adjacent nodes in the standard cluster.

In formula (17), P represents the proportion of cluster heads in all nodes, and the number of adjacent nodes between each cluster head is represented by $(1/P)-1$. The formula for calculating the radius H is as formula:

$$H=\sqrt{\frac{Q}{\pi\times F\times P}}. \tag{18}$$

In formula (18), Q represents the coverage area of the sensor, and F is the total number of nodes existing in the network range.

After the cluster head election in LEACH is optimized, a new threshold can be obtained. The calculation formula is as follows:

$$U(s) = \left\{ \begin{matrix} \dfrac{T}{1 - T \times [r\bmod(1/t)]} \times E, s \in G \\ \\ 0 \end{matrix} \right\}. \tag{19}$$

In formula (19), E is the impact factor of the threshold. Its calculation formula is as follows:

$$E = e_1 \frac{E_i(r)}{E_{ic}(r)} + e_2 \frac{h_{avg}}{h(i)} + e_3 \frac{\mathrm{Nei}(x)}{(1/p) - 1}. \tag{20}$$

According to these formulas, the optimized algorithm can achieve the optimal cluster head election. According to the new threshold formula, nodes which are with high residual energy, close to the sink node, and of relatively high density will make the threshold larger, thus making it more likely to be elected as the cluster head [19].

2.8. Talent Training Mechanism Fusion Algorithm Architecture. According to the different fusion architectures, the talent training mechanism is divided into the following three architecture modes, namely, centralized fusion, distributed fusion, and hybrid fusion structure [20].

2.8.1. Centralized Fusion Structure. The processing center of the centralized fusion structure can use all the original measurement sensor values without data loss, so the fusion result is theoretically optimal. The centralized structure is generally used in small systems. In large systems, the above two problems will cause the fusion structure to fail to meet the requirements, as shown in Figure 4.

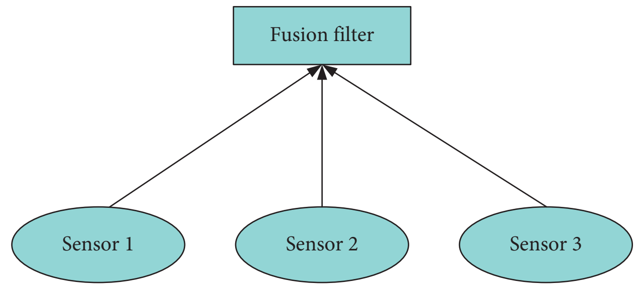

Figure 4: Centralized fusion structure.

Centralized Kalman filtering also has irreparable shortcomings. In the multisensor information system, there will be some problems, such as poor performance and real-time performance. If the number of sensors becomes large, it will lead to a very large amount of calculation, which will seriously affect the real-time performance and performance of the sensor system [21]. Its fault tolerance is poor. Since the centralized Kalman filter processes all the data uniformly, if the data of a certain sensor is polluted due to device damage or other factors such as environmental changes, it is even considered that the data is polluted. This contamination data is diffused into the observations and states of all other normal sensors. This will lead to a decrease in the correctness of the entire system data.

2.8.2. Distributed Fusion Structure. In the distributed fusion structure, each local sensor (ellipse node in the figure) has its own processor, which performs preprocessing before sending the data to the processing center, as shown in Figure 5. Since each sensor has its own processor, the corresponding filtering estimation results can be obtained. Finally, the processing center obtains the global estimation result. Compared with the centralized structure, the results obtained by distributed fusion are usually suboptimal [22]. However, this fusion method has the characteristics of low communication bandwidth requirements, strong system vitality, and relatively easy implementation.

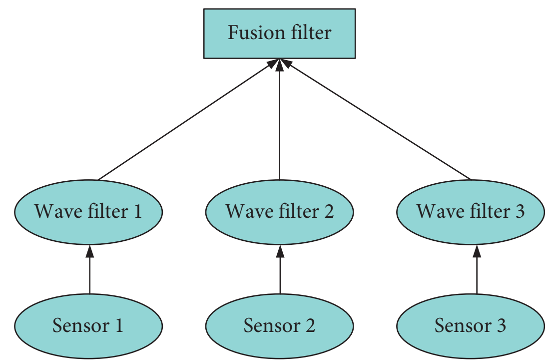

Figure 5: Distributed fusion structure.

The distributed structure also has the problem that the centralized structure can be improved due to the large amount of computation. However, after local processing, the information that may affect the final fusion result is lost because it needs to be compressed and refined and then transmitted to the fusion filter, which will eventually lead to the fusion result being suboptimal. It is unacceptable in large application systems to have a corresponding processor for each sensor. It will cause the cost to rise in a straight line, and it will also have a long-term impact on future maintenance. However, due to the improved performance, it has great application value in some simple systems that do not require high fusion accuracy and are relatively simple.

2.8.3. Hybrid Fusion Structure. The hybrid fusion structure is a hybrid of the two fusion structures described above. The part obtained by the fusion center is the original measurement value directly given by the sensor, and the remaining part is the intermediate data processed by the remaining local nodes, as shown in Figure 6. Since this structure combines the characteristics of both centralized and distributed fusion structures, the advantages and disadvantages are dealt with between the two. At the same time, this structure provides merit for the fusion of

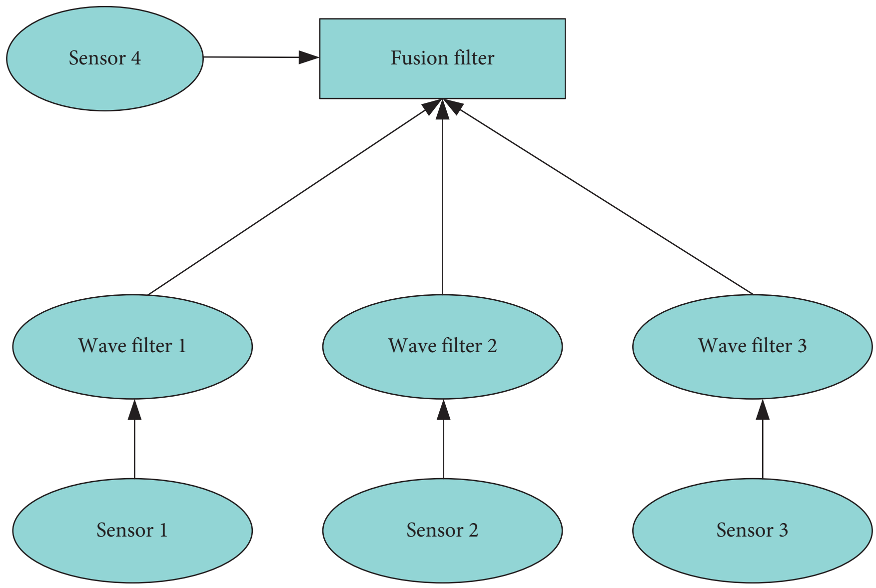

Figure 6: Hybrid fusion structure.

multiprocessing, multiplatform, and heterogeneous sensor information [23].

The hybrid structure combines the advantages of the centralized and distributed structure described above and reasonably avoids the disadvantages of the centralized structure, which has a large amount of computation. It is difficult to process in heterogeneous systems, and the distributed structure fusion structure is suboptimal. Not only can the heterogeneous system be handled calmly, but also the measurement data of the direct sensor can produce a relatively better fusion structure compared to the centralized structure. However, the hybrid structure design is more complicated. In large-scale application systems, changes to some sensors will lead to major changes in the entire fusion processing system, so its scalability and reliability are not high.

Considering the configurability and scalability, as well as the optimization and improvement of the algorithm, the processing flow of the whole system is as follows: After the system starts, it first reads the configuration file and encapsulates the data necessary for the database connection as a CProperty entity object. Then the data is handed over to the joint Kalman filter package class. Then the whole process starts. Connected to the database through CProperty, three local filters and each pre- and postprocessor are initialized. Then data can be read. If there is no data, it will exit directly. Otherwise, the data will be encapsulated into entity objects according to the weight value and handed over to the preprocessor for processing. If the processing does not pass, it will continue to read the next piece of data directly. If not, each data part of the entity object is handed over to three local filters, respectively. The local filter first obtains the local state estimate by generating the predicted state and then adds the covariance matrix of the three local filters to obtain

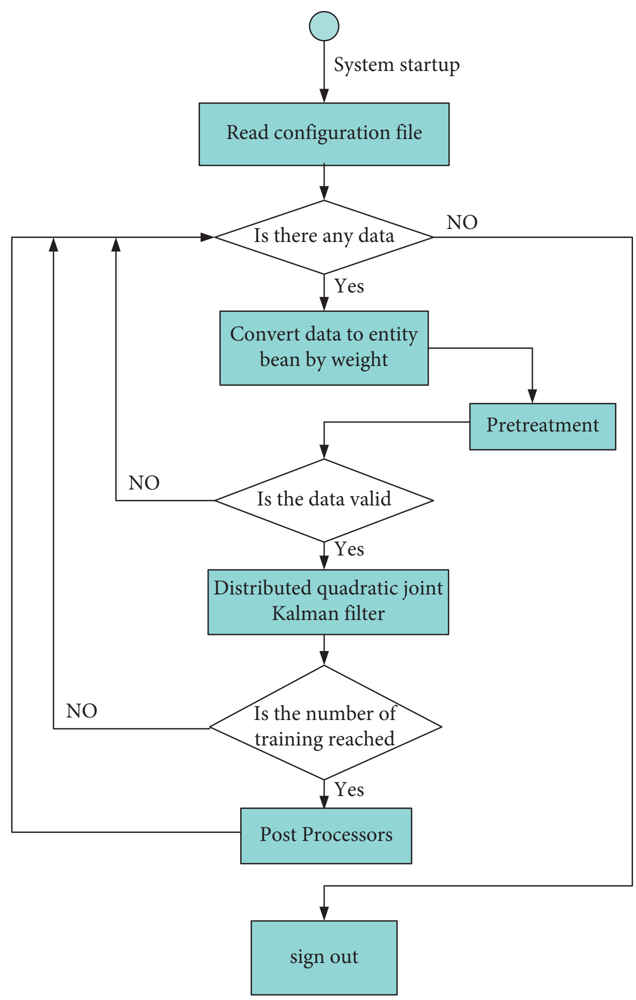

Figure 7: Overall flowchart of the fusion system.

Table 1: Performance comparison table of two fusion algorithms.

Hardware environment	Win-XP sp3+Intel Corei3 3.5 GHz + 4G memory			
Contrast scene (run 50 respectively) time (average)	Standard joint Kalman filter		Grouping quadratic joint Kalman filter	
	242 records	484 records	242 records	484 records
Overhead (MS)	1	1	1	1
Filtering overhead (MS)	164.9	310.7	129.44	265.3
After overhead (MS)	17.97	30.18	20.43	28.56
Total time cost	183.87	441.88	150.87	294.86

the global covariance. After adding the local state estimates of the three filters, the global estimate is obtained by left-multiplying the global covariance device. The global covariance is scaled down by 1/3, and the local filter is updated with the measured value of the solid object. Then whether the number of training data is reached will be determined. If the number of training records is not reached, the next record in the database will be read directly. It is responsible for handing over the results to the postprocessor for processing, generally writing to a database or file. Figure 7 shows the overall flowchart of the data fusion system.

3. Experiment on the Construction of International Education Talent Training Mechanism Based on Data Fusion Algorithm

3.1. Applicability of Kalman Filter Algorithm in International Education Talents Training Mechanism. In this paper, the construction information of the international talent education mechanism is studied, and the data sources of talent education information are combined to compare the efficiency of the grouped quadratic joint Kalman filter and the original standard joint Kalman filter. In this experiment, the time overhead of preprocessing, filtering, and postprocessing of the two algorithms was calculated at the same time to reduce the measurement error. Table 1 shows some results obtained by comparing the operation time.

It can be seen from Table 1 that the two filtering algorithms occupy a small proportion of time in preprocessing and postprocessing and have little impact on the overall performance. One of the time-consuming items is the loss of filtering. In the experiment, the filtering script was repeatedly executed 50 times. Then the average filtering time was calculated, and the time of each scene was added to obtain the final average filtering duration. The experimental results show that the total cost of the original standard Kalman filter is 341.88 in 484 records when the average is obtained after running 50 scenarios. The running time of the grouped quadratic joint Kalman filter in the same record is 294.86, which is 72.02 less than the running time of the standard Kalman filter. The running time of the grouped quadratic joint Kalman filter is reduced by about 20% compared with the standard Kalman filter, and the operational efficiency of the system is improved by about 20% after optimization and improvement. If the grouped quadratic combined Kalman filter is applied to the actual construction of the international education talent training mechanism, it can effectively not only improve the measurement accuracy of data, but also shorten the measurement period, as well as improve the system's data analysis capabilities more significantly.

3.2. Network Simulation and Performance Analysis of LEACH Algorithm and S-LEACH Algorithm. In order to verify whether the LEACH algorithm and the S-LEACH algorithm have better performance in the process of establishing the international talent education mechanism, this paper compares the S-LEACH algorithm with the traditional LEACH algorithm, using the MATLAB tool. The simulation results are calculated. Then the simulation parameter settings in s-leach algorithm can be obtained, as shown in Table 2.

It can be seen from Figure 8 that the number of surviving nodes of the LEACH algorithm is lower than that of the S-LEACH algorithm. In the experiment, the initial number of nodes of the two algorithms remained the same, and the LEACH algorithm ran out of energy when it ran to about 460 rounds. However, the nodes of the S-LEACH algorithm all died after 820 rounds. It can be seen from the experimental data that S-LEACH algorithm can effectively prolong the life cycle of the network.

From the simulation results in Figure 9, it can be seen that the energy loss curve in the traditional LEACH algorithm was more complex and extreme, indicating that the energy suddenly disappears in a short time or reached a certain time. At about 300 rounds, the energy consumption reached its peak; however, under the optimized S-LEACH algorithm, the consumption curve was relatively regular and flat. It can be seen from the figure that the curve of energy consumption changed regularly with the change of cycle, and the decline was also slow. It reached its peak value after more than 700 rounds. Therefore, S-LEACH algorithm can reduce the speed of energy consumption in the system, save cluster head energy, ensure cluster head vitality, and improve network life.

From the comparative analysis of the data transmission of the two algorithms, it can be seen in Figure 10 that the traditional LEACH algorithm was also weaker than the S-LEACH algorithm data transmission in terms of data transmission. The capacity curve of LEACH data transmission was flat. Even if the number of rounds reached 1000, the amount of transmitted data was still below 0.5 bit. The S-LEACH data transmission curve rose steadily. The maximum transmission effect was between 3 and 3.5 bit, and the transmission capacity was strong. It also can be seen that

Table 2: Setting of simulation parameters in S-LEACH algorithm.

Parameter name	Parameter	Size	Company
Network size	S	$200 * 200$	m^2
Sink node coordinates		(100,100)	
Total number of nodes	N	100	
Node initial energy	D_0	0.5	J
Communication radius	r	20	m
Wireless signal energy consumption	D_{elec}	50	$nJ\ bit$
Power amplifier	β_{amp}	10	$pJ/(bit.m^{-2})$
Power amplifier	β_{mp}	0.0013	$pJ/(bit.m^{-4})$
Reference distance	h_0	87	m
Single sample signal	k	4000	bit
The energy consumed by the fusion of the	D_l	5	$nJ/bit/signal$

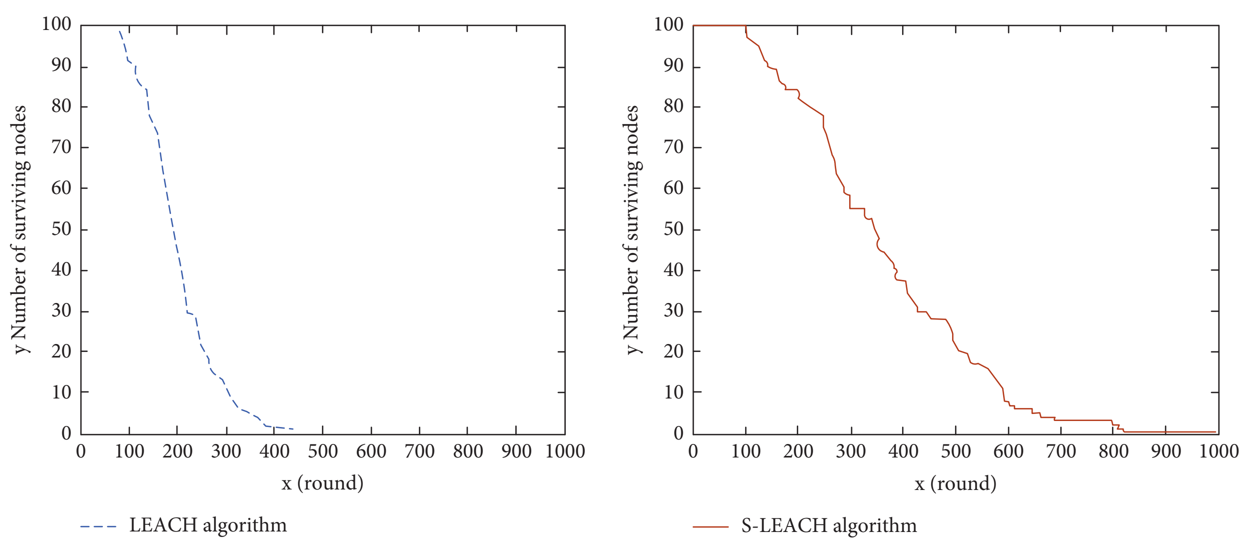

Figure 8: Comparison of the number of surviving nodes with time.

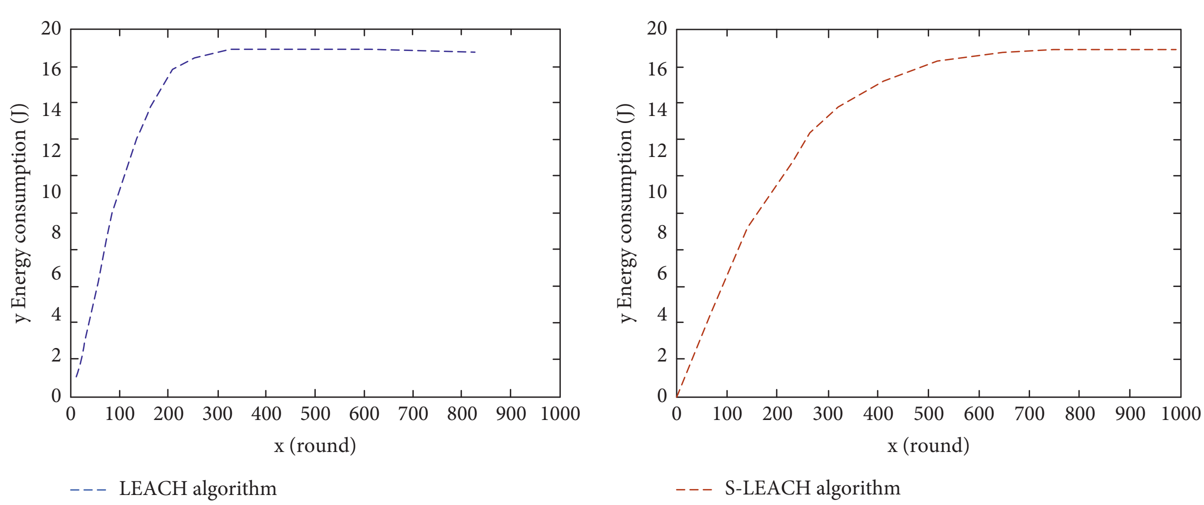

Figure 9: Comparison and analysis of network energy consumption of two algorithms.

S-LEACH has strong transmission capability. Therefore, the S-LEACH algorithm is obviously superior to the traditional LEACH algorithm in terms of the number of surviving nodes, relative energy consumption, and data transmission.

4. Discussion

This paper analyzes the data fusion algorithm to build a perfect international education talent training mechanism.

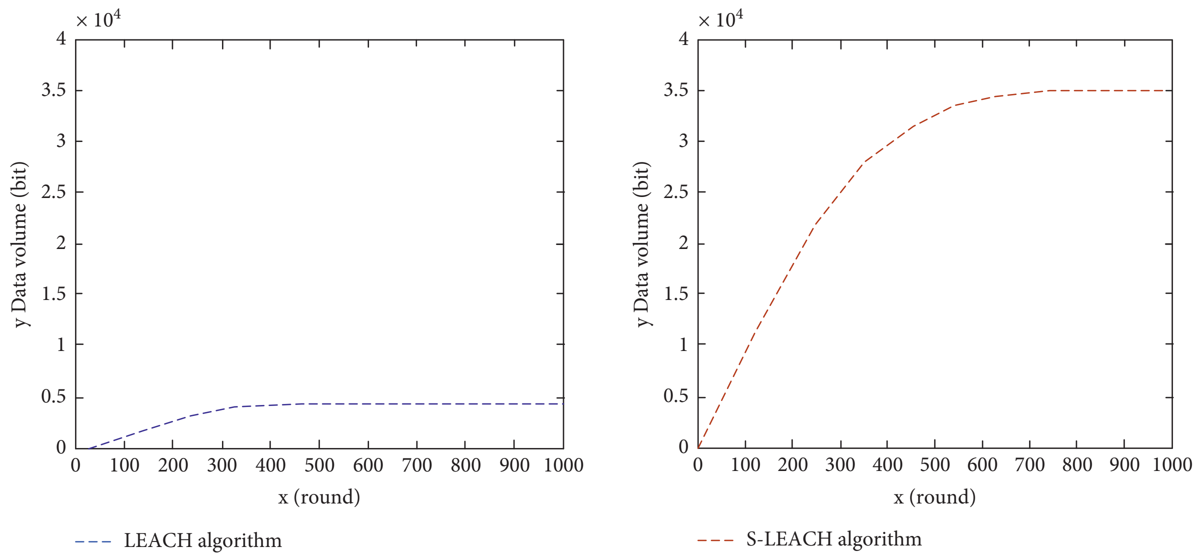

Figure 10: Comparison and analysis of data transmission between two algorithms.

According to the shortcomings found in the traditional fusion algorithm, the optimized data fusion algorithm is derived, and the Kalman filter algorithm, the grouped quadratic joint Kalman filter information fusion algorithm, the LEACH routing algorithm, and the S-LEACH routing algorithm are used to test the system performance of the international education personnel training mechanism. The comparison between the system's running time, node survival number, relative energy consumption, and data transmission speed is verified through tests. It is found that the improved algorithm is more beneficial to the overall operation of the system and improves efficiency.

5. Conclusions

This paper focuses on the role of Kalman filter algorithm, grouped quadratic joint Kalman filter information fusion algorithm, LEACH routing algorithm, and S-LEACH routing algorithm to build the international education personnel training mechanism. The article first talks about the concept and basic structure of fusion algorithm, such as sensors, so that people have a preliminary understanding of data fusion. Then, the basic algorithm of data fusion is described in detail. The benefits of these algorithms for building an international education talent training mechanism and how to build a perfect talent training mechanism are discussed. In the experiment part of the article, the applicability of data fusion algorithm in the international education talent training mechanism is explored through Kalman filter algorithm and grouping quadratic joint Kalman filter. The experiment shows that the operation efficiency of the system is improved by 20% under grouping quadratic joint Kalman filter. By comparing the network simulation and performance of LEACH algorithm and s-leach algorithm, it is found that s-leach algorithm can effectively prolong the network life cycle and improve the network life. Finally, it is found that the grouped quadratic joint Kalman filtering information fusion algorithm and the S-LEACH routing algorithm are superior to other algorithms in terms of performance and data transmission. Although the article proposes some data fusion algorithms that are beneficial to the construction of a talent training mechanism, the actual operation of data algorithms in the mechanism remains to be considered [24–26].

Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflicts of Interest

The author states that this article has no conflicts of interest.

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