

Retraction

Retracted: Real-Time Collection of Training Distance of Long-Distance Runners Based on Wireless Sensor Network

Security and Communication Networks

Received 26 December 2023; Accepted 26 December 2023; Published 29 December 2023

Copyright © 2023 Security and Communication Networks. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] X. Li, “Real-Time Collection of Training Distance of Long-Distance Runners Based on Wireless Sensor Network,” *Security and Communication Networks*, vol. 2021, Article ID 9992239, 11 pages, 2021.

Research Article

Real-Time Collection of Training Distance of Long-Distance Runners Based on Wireless Sensor Network

Xin Li 

Physical Education Department, Qiqihar Medical University, Qiqihar 161000, China

Correspondence should be addressed to Xin Li; guanjingjing@qmu.edu.cn

Received 5 April 2021; Revised 23 April 2021; Accepted 8 May 2021; Published 21 May 2021

Academic Editor: Chi-Hua Chen

Copyright © 2021 Xin Li. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The real-time and accurate collection of long-distance runners' training distance can provide real-time scientific basis for long-distance runners' physical training. Therefore, the real-time collection method of long-distance runners' training distance based on wireless sensor network is studied in this paper. In this model, the position tracking algorithm of long-distance runners based on wireless sensor network is introduced to collect the training distance of long-distance runners. When collecting the training distance, the energy balanced clustering routing algorithm based on energy and location is used to optimize and balance the energy consumption distribution of nodes and prolong the network life cycle, so that the training distance of long-distance runners can be collected in real time. Through the test, in the straight line and curve training path, this method has significant accuracy in collecting the training distance of single and multiple long-distance runners and can collect the training distance of long-distance runners in real time, which has significant application value.

1. Introduction

The rapid development of information technology has had an unprecedented impact on modern competitive sports. The use of information technology to assist athletes in scientific training has become an important symbol of modern competitive sports [1]. In traditional sports training methods, coaches are mainly responsible for observing and recording athletes' sports data and judging the rationality of sports technology by experience. This kind of qualitative analysis method has some shortcomings, such as strong subjectivity, large error, and ease of being disturbed. The combination of information technology with traditional training methods, experience, and historical training data can timely and effectively obtain the quantitative parameters of athletes' movement, which can be statistically processed by computer, providing theoretical basis for accurate analysis of sports technology [2]. It is found that the topology of a data communication network plays a role as an important factor in its security robustness against attack. In such networks, by changing the topology, the security robustness against intentional attack that aims at bringing

down network nodes may vary. This bringing down is a kind of destruction and interruption threat that attacks the availability of the network (i.e., attack on network resources and links).

In recent years, with the rapid development of embedded technology, electronic circuit technology, sensor technology, and wireless communication capabilities, the rapid development of wireless sensor network (WSN) has been promoted. Wireless sensor network (WSN) is a comprehensive measurement and control network, which involves automation control, computer, communication, and artificial intelligence. Because of its high practicability, it widely exists in people's life, and wireless sensor network has developed into an information technology after the Internet, which greatly affects the way of human life.

The scale of wireless sensor network is larger than the Internet, and it contains more cross technology. It realizes the connection of the physical world, the computer world, and human society. The application prospect of wireless sensor network is extremely broad, and it will further go into human daily life. Wireless sensor network is a wireless self-organizing network composed of a large number of cheap

sensor nodes. Each sensor node is composed of computing unit, storage unit, sensor unit, and wireless communication unit. Its task is to use sensors to monitor the surrounding environment, collect relevant data, and then send the data to the sink node by using multihop routing through the wireless transceiver device and then transmit the data to the user through the sink node, so as to achieve the goal of monitoring. It integrates computing technology, communication technology, and sensor technology. It can monitor, sense, and collect the information of various environments or monitoring objects in real time through various integrated microsensors. The information is transmitted wirelessly and sent to the user terminal in the form of self-organizing multihop network, so as to realize the connection of the physical world, the computer world, and the ternary world of human society [3]. These architectures profit from important wireless communication technologies such as IEEE 802.15.3 and IEEE 802.15.4 for Wireless Personal Area Network (WPAN), IEEE 802.11g and 802.11n for Wireless Local Area Network (WLAN), and High Speed Downlink Packet Access (HSDPA) and Long-Term Evolution (LTE) for Wireless Wide Area Network (WWAN). In order to enhance application performance, the routing strategies discovering the best path to the destination, the energy-saving methods maximizing the life of sensors, and security protocols guarantying our privacy are the most important techniques used in WSNs.

However, there are many difficult issues of wireless sensor network as follows:

- (1) Node miniaturization: It is an important research direction to design sensor nodes with microvolume and long life by using current microelectric mechanical and microwireless communication technology. The dust sensor node developed by Berkeley University reduces the size of the sensor to one cubic millimeter, so that the sensor particles can be suspended in the air.
- (2) Looking for system energy-saving strategy: When wireless sensor networks are applied in special occasions, the power supply cannot be replaced, so the problem of power consumption is very important. At present, great achievements have been made on the low-power problem of nodes at home and abroad. Some low-power wireless sensor network protocols are proposed, which will make greater progress in the future.
- (3) Low cost: Because the number of sensor network nodes is very large, often thousands, in order to make the sensor network practical, the price of each node should be controlled below \$1, but now the cost of each sensor node is about \$80. If we can effectively reduce the cost of nodes, it will greatly promote the development of sensor networks.
- (4) Security and anti-interference problems of sensor networks: Like ordinary networks, sensor networks are also facing the test of security, that is, how to use less energy and less computation to complete data encryption, identity authentication, and so on. It is

also an important research topic to complete the task reliably in the case of destruction or interference.

The distance of athletes in the sports field is one of the important indexes to evaluate their physical fitness. In the past, the distance measurement of long-distance runners under the condition of training mostly uses the visual method, which has large error and low credibility. Therefore, this paper proposes a training distance measurement method for long-distance runner based on wireless sensor network through another data acquisition method, namely, the application of wireless sensor network, so as to realize the connection of the physical world, the computer world, and the ternary world of human society.

The contribution of our method can be described as follows:

- (1) The position tracking algorithm is induced to collect the training distance of long-distance runners.
- (2) The energy balanced clustering routing algorithm based on energy and location is used to optimize and balance the energy consumption distribution of nodes.
- (3) In the straight line and curve training path, this method has significant accuracy in collecting the training distance of single and multiple long-distance runners.

This paper is divided into 4 sections. Section 2 discusses how we build the wireless sensor networks. Section 3 describes the experimental results. Section 4 concludes this paper with contributions, limitations, and future works.

2. Real-Time Collection Method of Training Distance for Long-Distance Runners Based on Wireless Sensor Network

2.1. Training Scene Model of Long-Distance Runners Based on Wireless Sensor. The training scene model of long-distance runners based on wireless sensor consists of roadside nodes (nodes with known location), athlete movement nodes, and Sink nodes (Sink node in wireless sensor network is mainly responsible for the connection between sensor network and external network and can be regarded as gateway node). The structure of the model is shown in Figure 1. As shown in Figure 1, the square box represents the player who is tested, and the circles are sensors located in many areas to obtain the information of the players.

- (1) The roadside node is powered by battery, which has high working intensity and weak storage and processing capacity. After simple data fusion processing, the data is sent to Sink node, and the warning, replacement task, and other information from Sink node are received and processed.
- (2) The athlete movement node is a kind of wireless sensor microtransmitter placed on the back of the athlete.
- (3) Sink node has the characteristics of large storage capacity and strong computing power. The specific

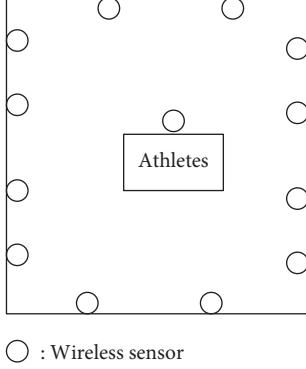


FIGURE 1: Training scene model of long-distance runners based on wireless sensor.

function is to collect the information from the roadside nodes, fuse the data and then transmit it to the roadside nodes within the management and control scope of the monitoring center, and receive various control commands from the monitoring center [4, 5].

2.2. Location Tracking Algorithm of Long-Distance Runners Based on Wireless Sensor Network. Wireless sensor network (WSN) is a kind of distributed sensor network. Its terminals are sensors that can sense and check the outside world. Sensors in WSN are communicated through wireless mode, so the network settings are flexible, the location of devices can be changed at any time, and they can also connect with the Internet in wired or wireless mode, forming a multihop self-organizing network through wireless communication [6]. Based on the distance measurement of the sensor itself, the distance between the sensors and the distance measurement of other sensors collected, combined with the dynamic distance model for nonlinear filtering, the distance and distance change rate between the sensor and the long-distance runner are estimated, and the training distance is collected.

2.2.1. Estimation of Distance and Its Rate of Change. Considering the relative motion between wireless sensor and long-distance runner, the state variables of dynamic distance model are as follows:

$$X = [d, \dot{d}, \theta], \quad (1)$$

where $d = [d_{12}, d_{13}, d_{14}, d_{1t}, d_{23}, d_{24}, d_{2t}, d_{34}, d_{3t}, d_{4t}]$ means the training distance vector of long-distance runners; $\dot{d} = [\dot{d}_{12}, \dot{d}_{13}, \dot{d}_{14}, \dot{d}_{1t}, \dot{d}_{23}, \dot{d}_{24}, \dot{d}_{2t}, \dot{d}_{34}, \dot{d}_{3t}, \dot{d}_{4t}]$ means the training distance change rate of long-distance runners; $\theta = [\cos \theta_1, \cos \theta_2, \cos \theta_3, \cos \theta_4, \cos \theta_5, \cos \theta_6, \cos \theta_7, \cos \theta_8]$ means the angle cosine value vector.

The dynamic distance model of long-distance runners is as follows:

$$X = f(X) + \Omega w, \quad (2)$$

where $f(X)$ is the nonlinear state transfer function (here, we use Gaussian function transfer); Ω is the disturbance gain matrix; $w = [\dot{d}_{12}, \dot{d}_{13}, \dot{d}_{14}, \dot{d}_{1t}, \dot{d}_{23}, \dot{d}_{24}, \dot{d}_{2t}, \dot{d}_{34}, \dot{d}_{3t}, \dot{d}_{4t}]$ is the disturbance vector, which is caused by the unknown change of the second derivative of the distance. Considering the ranging information and angle cosine value in practical application, the state vector of the model in (2) should meet the following physical constraints:

$$\begin{cases} d = X_i \geq 0, & i \in 1, 2, \dots, 10, \\ -1 \leq |\theta| = |X_i| \leq 1, & i \in 1, 2, \dots, 8. \end{cases} \quad (3)$$

According to the distance measurement and the distance information between sensors, each sensor $i \in S$ uses the distance information to form the measurement equation as follows:

$$Z = HX + \gamma, \quad (4)$$

where Z is the measurement vector of training distance of long-distance runners; H is the measurement matrix of training distance of long-distance runners; γ is the measurement error vector of training distance of long-distance runners.

By using the discretization method and sampling equations (2) and (4) at the time interval δ , the dynamic distance model transfer equation X_k and the corresponding measurement equation Z at the k -th sampling time in the discrete-time model are obtained.

$$\begin{cases} X_k = f(X_{k-1}), \\ Z = H_k X_k + \gamma_k, \end{cases} \quad (5)$$

where H_k and γ_k are the distance measurement matrix and the distance measurement error vector at the k -th sampling time. Because the state transfer function $F(X_{k-1})$ of training distance of long-distance runners is a nonlinear function with state constraints, the state estimation of dynamic distance model should be obtained by nonlinear filtering method. Here, the state estimation of dynamic distance model can be obtained directly by using UKF filtering algorithm based on uncorrelated transformation and projection.

$$\hat{X}_k = \begin{bmatrix} \hat{d}_k \\ \dot{\hat{d}}_k \\ \hat{\theta}_k \end{bmatrix}, \quad (6)$$

where \hat{d}_k is the training distance vector of long-distance runners at the k -th sampling time; $\dot{\hat{d}}_k$ is the training distance change rate of long-distance runners at the k -th sampling time; $\hat{\theta}_k$ is the angle cosine value vector of long-distance runners at the sampling time k .

2.2.2. Estimation of Target Location. According to the weighted multidimensional scaling method, the relative position matrix $P_{st,k}$ of long-distance runners is constructed.

$$P_{st,k} = P_{s,k} - P_{t,k} = [p_{1,k} - p_{t,k} \ p_{2,k} - p_{t,k} \ p_{3,k} - p_{t,k} \ p_{4,k} - p_{t,k}], \quad (7)$$

where $P_{s,k} = [p_{1,k} \ p_{2,k} \ p_{3,k} \ p_{4,k}]$ is the matrix of the real position of the wireless sensor; $p_{t,k}$ is the distance matrix of detection.

Based on the above position matrix, the scalar product matrix is constructed.

$$B_k = \begin{bmatrix} B_{k,11} & B_{k,12} & B_{k,13} & B_{k,14} \\ B_{k,21} & B_{k,22} & B_{k,23} & B_{k,24} \\ B_{k,31} & B_{k,32} & B_{k,33} & B_{k,34} \\ B_{k,41} & B_{k,42} & B_{k,43} & B_{k,44} \end{bmatrix}, \quad (8)$$

where the distance between wireless sensor i and long-distance runner j is $d_{ij}^k = \sqrt{(p_{i,k} - p_{j,k})^T (p_{i,k} - p_{j,k})}$, $p_{i,k}$ and $p_{j,k}$ are the relative position matrix of wireless sensor i and long-distance runner j , and T is transpose. Since the wireless sensor cannot obtain the true distance to the long-distance runner, the estimated distance \tilde{d}_{ij}^k between the sensor and the long-distance runner can only be obtained through the state estimation result of the dynamic distance model, and then it can get the estimated value A_k of the scalar product matrix B_k by importing d_{ij}^k into

$$A_k = \frac{\tilde{d}_{ij}^{2k}}{2}. \quad (9)$$

In addition, the following A_k matrix is defined:

$$A_k = [A_{k,1} \ A_{k,2}], \quad (10)$$

where $A_{k,1}$ is the first column of A_k and $A_{k,2}$ is composed of other columns.

Using multidimensional scaling method, it can get the initial position estimation $\hat{p}_{t0,k}$ of long-distance runners as follows:

$$\hat{p}_{t0,k} = -\left(\begin{smallmatrix} k,1 \\ A \end{smallmatrix}\right)^{-1} \left(\begin{smallmatrix} k,1 \\ A \end{smallmatrix}\right) A_{k,2}. \quad (11)$$

The above calculation does not use the weighting matrix, but in practice, whitening the residual vector M through the weighting matrix can further improve the training distance positioning accuracy of long-distance runners. Therefore, the weight matrix is calculated as follows:

$$W = M^{-T} Q^{-1} M^{-1}, \quad (12)$$

where Q is the covariance of distance estimation between wireless sensor and long-distance runner. The estimated position of the long-distance runners at time k is as follows:

$$\hat{p}_{t,k} = -\left(\begin{smallmatrix} k,1 \\ A \end{smallmatrix}\right)^{-1} \left(\begin{smallmatrix} k,1 \\ A \end{smallmatrix}\right) W A_{k,2}. \quad (13)$$

2.2.3. Estimation of Target Velocity. Combined with the position matrix, the relative speed matrix $V_{st,k}$ of long-distance runners is constructed as follows:

$$V_{st,k} = [v_{1,k} - v_{t,k} \ v_{2,k} - v_{t,k} \ v_{3,k} - v_{t,k} \ v_{4,k} - v_{t,k}], \quad (14)$$

where $v_{t,k}$ is the relative velocity vector.

The first derivative E_k of the matrix with respect to time is calculated as follows:

$$E_k = \begin{bmatrix} E_{k,11} & E_{k,12} & E_{k,13} & E_{k,14} \\ E_{k,21} & E_{k,22} & E_{k,23} & E_{k,24} \\ E_{k,31} & E_{k,32} & E_{k,33} & E_{k,34} \\ E_{k,41} & E_{k,42} & E_{k,34} & E_{k,44} \end{bmatrix}. \quad (15)$$

The calculation equation of distance change rate between wireless sensor i and long-distance runner j is as follows:

$$D_k = \begin{bmatrix} D_{k,11} & D_{k,12} & D_{k,13} & D_{k,14} \\ D_{k,21} & D_{k,22} & D_{k,23} & D_{k,24} \\ D_{k,31} & D_{k,32} & D_{k,33} & D_{k,34} \\ D_{k,41} & D_{k,42} & D_{k,34} & D_{k,44} \end{bmatrix}. \quad (16)$$

According to the symmetry of the matrix E_k and the penalty property of the matrix, the following equation can be deduced:

$$\begin{bmatrix} D_{k,11} \\ D_{k,12} \\ D_{k,13} \\ D_{k,14} \\ D_{k,22} \\ D_{k,23} \\ D_{k,24} \\ D_{k,33} \\ D_{k,34} \\ D_{k,44} \end{bmatrix} = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 2 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 2 \end{bmatrix} \underbrace{v_{t,k}}_{U_k}. \quad (17)$$

The training distance state estimation \hat{X}_k of the long-distance runners is obtained.

$$\hat{X}_k = [\hat{P}_{t,k}, \hat{V}_{t,k}], \quad (18)$$

where $\hat{P}_{t,k}$ and $\hat{V}_{t,k}$ are the relative position and speed of long-distance runners in turn.

2.3. Energy Balanced Clustering Routing Algorithm Based on Energy and Location. At present, the routing protocol of wireless sensor network can be divided into two kinds: plane routing protocol and layered routing protocol. In plane routing protocol, all network nodes are equal in status, and there is no difference in level. Routing is generated by local operation and information feedback between each other [7–9]. Typical plane routing algorithms include directed diffusion protocol and SAR.

The biggest disadvantages of plane routing are no management node in the network; lack of optimal management of communication resources; complex self-organizing cooperative work algorithm; slow response to network dynamic changes, etc.

Typical layered routing protocols include LEACH, TEEN, PEGASIS, and HEED. LEACH is the first layered routing algorithm in wireless sensor networks, and it is also a representative layered routing protocol. Its idea has led to the emergence of many layered routing protocols [6]. After the concept of LEACH clustering protocol is put forward, the energy saving property and network lifetime of network nodes have been greatly improved. However, the application of LEACH protocol in the training distance collection of long-distance runners has its own limitations that cannot be ignored [10]. On the basis of the LEACH protocol, this paper introduces an energy balanced clustering routing algorithm based on energy and location, which fully considers the energy and location factors of nodes in the cluster head election mechanism, avoids the nodes with low residual energy and poor geographical location from being selected as the cluster head node, effectively balances the energy consumption distribution of nodes, prolongs the network life cycle, and optimizes the training distance of long-distance runners from the collection efficiency, so as to realize real-time collection of long-distance athletes' training distance [11–13].

2.3.1. Selection of Cluster Head Node. Before clustering, Sink node calculates the maximum distance D_{\max} and minimum distance D_{\min} of all roadside nodes and broadcasts the whole network. Before each round of cluster reconstruction, all the roadside nodes send their own residual energy E_{current} and the collected training distance parameters to the cluster head node selected from the previous round. The cluster head node simply fuses the received data and sends its own E_{current} to the Sink node. After receiving the data, the Sink node transmits the useful data to the gateway and calculates the average residual energy E_{avg} of the whole network and sends to the whole network. After receiving the cluster head election command, each node compares E_{current} and E_{avg} and can participate in the cluster head election only if $E_{\text{current}} > E_{\text{avg}}$. The improved cluster head selection threshold is as follows:

$$T(n) = \begin{cases} \frac{p}{[1 - p(r \bmod 1/p)]} \left(\frac{E_{\text{avg}}}{E_{\text{current}}} + \frac{D_{\max} - d}{D_{\max} - D_{\min}} \right), \\ 0, \end{cases} \quad (19)$$

where p is the proportion of cluster heads in all nodes in WSN; r is the current round r ; n is a node; the node set that has not been selected before round r is G ; the symbol mod is the modulus operator; the maximum distance between all roadside nodes and Sink nodes is D_{\max} , and the minimum is D_{\min} ; d is the distance from the roadside node participating in cluster head selection to Sink node.

2.3.2. Routing Establishment within and between Clusters.

After the cluster head node is selected, the cluster head node broadcasts the selected cluster head message to the whole network. The message contains its own geographical location information, identity, and CDMA spread spectrum code. Other roadside nodes determine which cluster to join according to the strength of the signal received by the cluster head broadcast message and send the request to join the cluster [14]. After receiving the cluster request, the cluster head adds the roadside node to its own routing table and then allocates a time slice for each roadside node in the cluster and notifies all nodes in the cluster [15–17]. After receiving the broadcast message from other cluster heads, the cluster head node finds its own forward cluster head node according to its own location information. The specific judgment methods are as follows:

- (1) The cluster head node calculates the distance from Sink node.

$$D(\text{this}, \text{sink}) = \sqrt{(t_x - s_x)^2 + (t_y - s_y)^2}, \quad (20)$$

where t_x and t_y , s_x , and s_y are the abscissa and ordinate of the cluster head node "cluster_i" and Sink node "Sink," respectively.

- (2) Other cluster heads calculate the distance between themselves and Sink nodes.

$$D(\text{cluster}_i, \text{sink}) = \sqrt{(c_x - s_x)^2 + (c_y - s_y)^2}, \quad (21)$$

where c_x and c_y , s_x , and s_y are the abscissa and ordinate of cluster head node cluster_i and Sink node "Sink," respectively.

- (3) Select the cluster head node with $D(\text{this}, \text{sink}) > D(\text{cluster}_i, \text{sink})$ and calculate the distance between the cluster head node and itself.

$$D(\text{cluster}_i, \text{this}) = \sqrt{(c_x - t_x)^2 + (c_y - t_y)^2}. \quad (22)$$

- (4) If no other node satisfies $D(\text{this}, \text{sink}) > D(\text{cluster}_i, \text{sink})$, the next hop of current node is Sink node; otherwise, the minimum value $D_{\min}(\text{cluster}_i, \text{this})$ is selected from $D(\text{cluster}_i, \text{this})$. If $D_{\min}(\text{cluster}_i, \text{this}) < D(\text{this}, \text{sink})$, the node corresponding to $D_{\min}(\text{cluster}_i, \text{this})$ is the next hop cluster head of current cluster head node.

In this way, selecting the next hop cluster head can ensure that each cluster head can send the training distance data of long-distance runners with low energy consumption; according to the energy model of sending data between cluster head nodes given above, the cluster head node can send the training distance data of long-distance runners to the nearest cluster head node and forward it, which can

ensure that each cluster head node sends out the training distance data of long-distance runners with the lowest energy consumption [18].

2.3.3. Next Round of Cluster Reconstruction. After the establishment of intracluster and intercluster routes, Sink nodes send transmission instructions to the whole network and enter the current round of transmission stage of long-distance runners' training distance data. All the roadside nodes will transmit the collected training distance data and E_{current} to the cluster head node in their own time slice, and the nodes will enter the sleep state in the rest time slice; the cluster head node will send the training distance data to the next hop cluster head node and finally to the Sink node.

Before the next round of communication, Sink node collects the training distance data of long-distance runners, recalculates E_{avg} of the current network nodes, and sets a dynamic threshold $E_{\min} = (E_{\text{avg}}/2)$. Sink node compares the energy of cluster head node with E_{\min} . If $E_{\min} < E_{\text{current}}$, the current cluster structure will remain unchanged. Otherwise, it will enter the next round of reselection; that is, the node with the highest residual energy in the current cluster will be selected as the cluster head node. Sink nodes broadcast the new cluster head nodes to the whole network, while the nodes in the cluster update their own routes in time, and the cluster head nodes update their next hop nodes in time [19].

For each cluster reconstruction, Sink node adds cluster-round to 1. When $\text{cluster-round} > n \cdot p \cdot 25\%$, Sink node broadcasts to the whole network, reselects the general election in the whole network according to the cluster head selection mechanism, and then updates the intracluster and intercluster routes. Otherwise, it only reselects the cluster head in the cluster, publishes the new cluster head, and updates the intracluster and intercluster routes.

In the last three years, many methods are proposed to handle the problem of information collection for the long-run distance players; here, we introduced three outstanding methods such as GNNA [20], RNNNA [21], and CNNA [22], which can be used to solve the related works taking different kinds of network structures. GNNA is a graph-based network that builds connections between different risk nodes. And RNNNA uses a specific loss structure to keep the similarity of real and predicted crafts design. CNNA is the basic model that needs more computation consuming to obtain the desiring performances. However, these methods have their disadvantages, respectively. GNNA is too slow, RNNNA is so complicated, and CNNA also needs more spaces.

In this paper we utilize the entropy loss function to build the model for our research problems. It can be defined as follows: $\text{loss}(x, y) = \sum_{i=1}^n -p_i \log(1 - p_i)$, where x and y are represented as the real arts and crafts' score and difficulty and y means the predicted score and difficulty of our proposal. p_i means the probability of them when they are similar. The bigger the value of the loss, the worse our proposal performed. And our proposal is used to train a model that fits the real and predicted arts and crafts, so that the machine can assist the arts and crafts designed. And

compared with the three methods, our proposal can deal with the problems easily and we also need a smaller computation space to build our model. However, our model may obtain a relative lower accuracy than others sometimes which may lead to unstable prediction.

3. Related Work

In recent years, Internet of Things (IoT) has had great popularity in different aspects of modern life and a huge amount of IoT services are emerging. In the IoT area, user devices generate a large amount of data that can be used to improve the user experience of the intelligence system. However, the extensive users' data processing from the IoT device brings some privacy problems [23]. As the IoT devices can be deeply involved in users' private data, the data generated by them will contain privacy-sensitive information [24]. To tackle the privacy challenges and encourage clients to proactively participate in IoT services, federated learning enables training a deep learning model across different participants in a collaborative manner. It provides the privacy of clients to keep their original data training on their own devices, while jointly learning a global model by sharing only local parameters with the server.

However, several recent works have shown that the privacy in federated learning is insufficient for protecting the local training data from gradient-based reconstruction attacks [25]. The wide malicious devices in IoT make it vulnerable to these types of attacks based on shared parameters. The first type of attack is GAN-based attacks. Hitaj and Perez-Cruz proposed a GAN-based attack against collaborative deep learning on a malicious client, which infers sensitive information from another client successfully. Based on this work, an improved GAN with a multitask discriminator was proposed to enable a malicious server to discriminate category, reality, and client identity of input samples simultaneously [26]. Another type of gradient-based reconstruction attacks is Deep Leakage from Gradients (DLG), which was proposed by Zhu et al. to reveal the training data from gradients. The main idea of DLG is to generate dummy data and labels via matching the dummy gradients to the shared gradients. It has been used in many following works to perform the privacy leakage attacks on federated learning. The GAN-based attack uses GAN to generate pictures that look similar to the training images, while DLG aims at revealing the complete training data from gradients. These two types of attacks both utilize gradient to reconstruction [27].

4. Results

In order to test the effect of the proposed method on training distance collection of long-distance runners, its application effect is tested in MATLAB simulation software. In the MATLAB simulation software, it is assumed that the long-distance runner moves in the two-dimensional plane, and the initial position is (100100) m. Using the wireless sensor as the measuring device, the acquisition period is 2 s, the

communication range of the wireless sensor is 40, and the observation distance is 20 m.

4.1. Acquisition Effect of Single-Target Training Distance

4.1.1. Mean Square Error. The collection target of the proposed method is set as a single long-distance runner, and the training path of the athlete is straight line and curve, respectively. Under this condition, the collection effect of the single long-distance runner's training distance is tested. The acquisition effect is mainly described by mean square error (RMSE).

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{k=1}^n (x_k - \hat{x}_k)^2}, \quad (23)$$

where x_k and \hat{x}_k are the actual value and the collected value of the training distance of the long-distance runners at time k , respectively.

The acquisition effect of the proposed method for single target training distance is shown in Figures 2 and 3.

According to the analysis of Figures 2 and 3, when the athlete's training path is straight line and curve, respectively, after collecting the training distance of a single long-distance runner, the mean square error is less than 0.04, and the mean square error is very small, which proves that the method in this paper has high accuracy in collecting the training distance of a single athlete.

4.1.2. Real-Time Acquisition. In order to test the real-time acquisition of the training distance of a single athlete, when the athlete's training path is a straight line class and a curve class, whether the method can accurately collect the athlete's training distance with the change of the athlete's training distance is tested. The results are shown in Tables 1 and 2.

According to the analysis of Tables 1 and 2, when the athlete's training path is straight line and curve, respectively, with the change of time, the proposed method can collect the training position in real time and realize the real-time detection of training distance, and the detection result has no deviation. It can be proved that the proposed method has high real-time performance for acquisition of single target training distance.

4.2. Training Distance Acquisition Effect of Multiple Targets

4.2.1. Mean Square Error. In order to test the collection effect of the proposed method on multitar get training distance, the number of long-distance runners to be collected by this method is set in MATLAB simulation software as 5, 10, 15, and 20 in turn. The collection accuracy of this method on multitar get training distance is shown in Figures 4 and 5.

According to the analysis of Figures 4 and 5, when the numbers of athletes are 5, 10, 15, and 20 in turn, and the athletes' training paths are straight line and curve, respectively. After collecting the training distance of straight line and curve training paths, the mean square error is less than

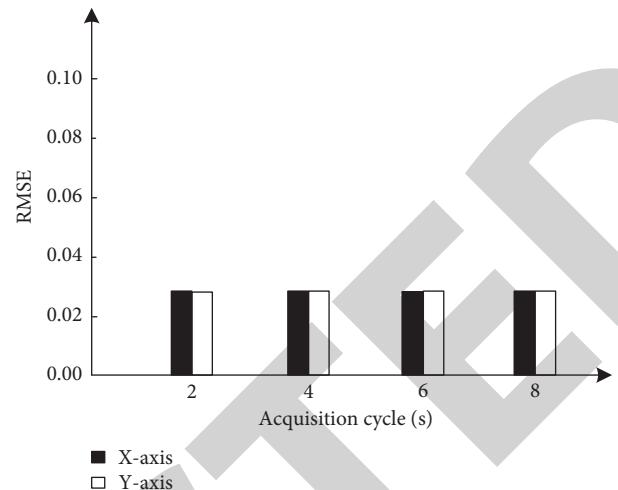


FIGURE 2: Training distance acquisition accuracy of linear training path.

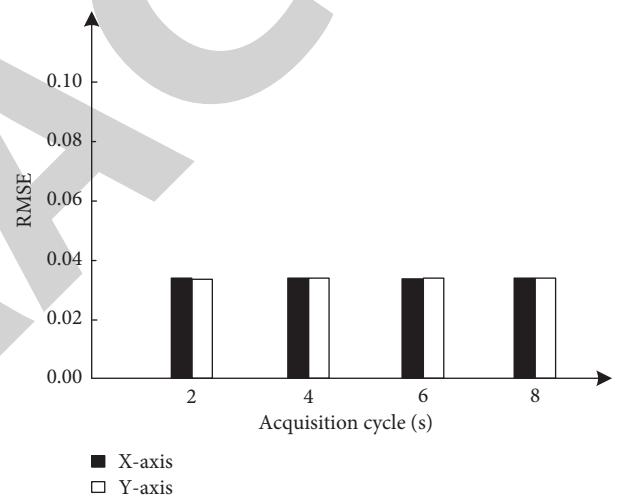


FIGURE 3: Training distance acquisition accuracy of curve training path.

0.04, and the mean square error is very small, which proves that the method in this paper has high accuracy in collecting the training distance of multiple targets.

4.2.2. Real-Time Acquisition. When multiple athletes' training paths are straight line and curve, respectively, whether the proposed method can accurately collect multiple athletes' training distance with the change of athletes' training distance is tested. The real-time acquisition performance is reflected by the mean square error of the acquisition results, and the results are shown in Tables 3 and 4.

According to the analysis of Tables 3 and 4, when multiple athletes' training paths are linear, with the change of time, the mean square errors of the training distance of 5, 10, 15, and 20 athletes collected by the proposed method are 0.01, 0.02, 0.03, and 0.04, respectively. After collecting the training distance of 15 and 20 athletes, the mean square errors of the results are 0.02, 0.03, 0.04, and 0.05,

TABLE 1: Real-time acquisition of training distance for linear training path.

Time	Coordinates of actual training position of athletes (m)	In this paper, the method is used to collect the results (m)
8:10	(100,100)	(100,100)
8:20	(200,200)	(200,200)
8:30	(300,300)	(300,300)
8:40	(400,400)	(400,400)
8:50	(500,500)	(500,500)
9:00	(600,600)	(600,600)
9:10	(650,650)	(650,650)
9:20	(700,700)	(700,700)
9:30	(750,750)	(750,750)
9:40	(800,800)	(800,800)

TABLE 2: Real-time acquisition of training distance for curve training path.

Time	Coordinates of actual training position of athletes (m)	In this paper, the method is used to collect the results (m)
8:10	(100,100)	(100,100)
8:20	(150,100)	(150,100)
8:30	(200,250)	(200,250)
8:40	(300,350)	(300,350)
8:50	(400,450)	(400,450)
9:00	(550,650)	(550,650)
9:10	(750,750)	(750,750)
9:20	(800,860)	(800,860)
9:30	(950,1000)	(950,1000)
9:40	(1100,1200)	(1100,1200)

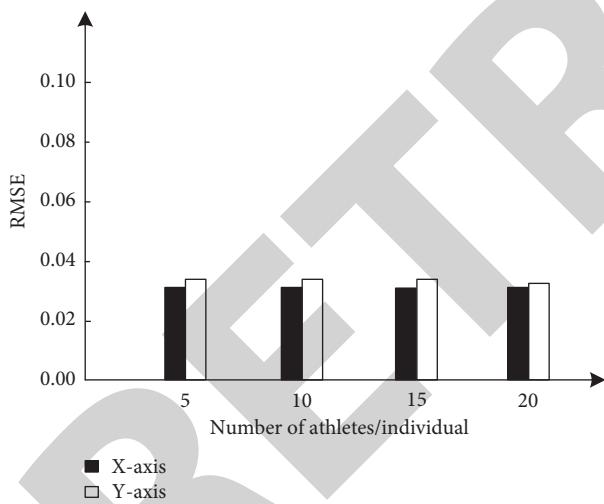


FIGURE 4: Training distance acquisition accuracy of linear training path.

respectively. The mean square error is very small, which indicates that the method in this paper can accurately collect the training distance of long-distance runners in real time with the change of time.

4.3. In-Depth Test of Application Performance of the Proposed Method. The importance of energy balanced clustering routing algorithm based on energy and location is tested. When the wireless sensor network is used to collect the training distance of long-distance runners, the mean square error and real-time performance of long-distance runners'

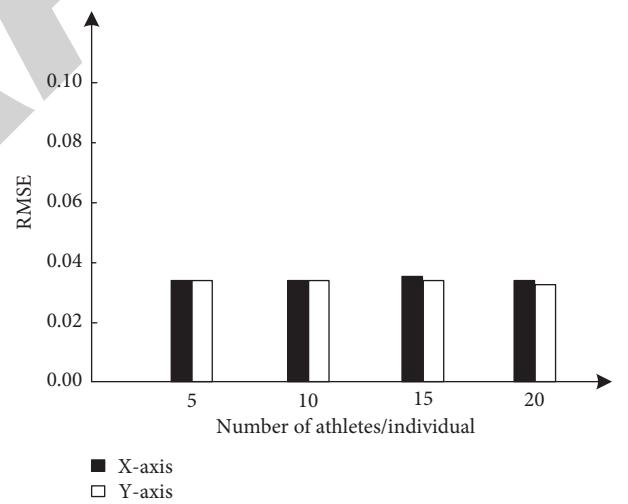


FIGURE 5: Training distance acquisition accuracy of curve training path.

training distance collection are tested before and after using the energy and location-based energy balanced clustering routing algorithm. The results are shown in Figure 6 and Table 5.

As shown in Figure 6, when the athletes' training paths are straight line and curve, respectively, under multiple tests, before and after using the energy balances clustering routing algorithm based on energy and location, the mean square error of the training distance collection results of long-distance runners is quite different, so that the mean square error before use is greater than 0.08, and the mean square error after use is less than 0.04. The use of energy balanced

TABLE 3: Real-time acquisition of training distance for linear training path.

Time	5 athletes	10 athletes	15 athletes	20 athletes
8:10	0.01	0.02	0.03	0.03
8:20	0.01	0.02	0.03	0.03
8:30	0.01	0.02	0.03	0.03
8:40	0.01	0.02	0.03	0.03
8:50	0.01	0.02	0.03	0.03
9:00	0.01	0.02	0.03	0.03
9:10	0.01	0.02	0.03	0.03
9:20	0.01	0.02	0.03	0.03
9:30	0.01	0.02	0.03	0.03
9:40	0.01	0.02	0.03	0.03
Mean value	0.01	0.02	0.03	0.03

TABLE 4: Real-time acquisition of training distance for curve training path.

Time	5 athletes	10 athletes	15 athletes	20 athletes
8:10	0.02	0.03	0.03	0.03
8:20	0.02	0.03	0.03	0.03
8:30	0.02	0.03	0.03	0.03
8:40	0.02	0.03	0.03	0.03
8:50	0.02	0.03	0.03	0.03
9:00	0.02	0.03	0.03	0.03
9:10	0.02	0.03	0.03	0.03
9:20	0.02	0.03	0.03	0.03
9:30	0.02	0.03	0.03	0.03
9:40	0.02	0.03	0.03	0.03
Mean value	0.02	0.03	0.03	0.03

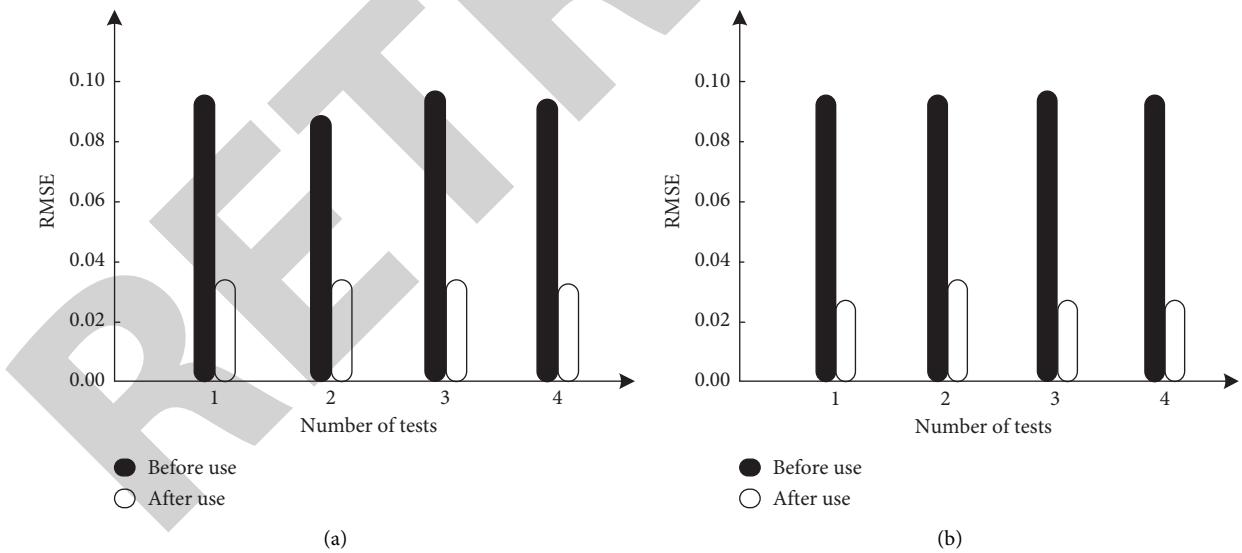


FIGURE 6: Application effect test of energy balanced clustering routing algorithm based on energy and location. (a) Training distance acquisition accuracy of linear training path. (b) Training distance acquisition accuracy of curve training path.

clustering routing algorithm based on energy and location can improve the accuracy of athletes' training distance collection.

As shown in Table 5, before and after using the energy balanced clustering routing algorithm based on energy and location, the real-time performance of training distance

collection for long-distance runners is quite different. When the athletes' training paths are straight line and curve, respectively, with the change of time, the mean square error of the collection results before use is 0.07 and 0.09, respectively, and the mean square error of the collection results before use is 0.02 and 0.02, respectively. Therefore, the use of energy

TABLE 5: Real-time test results of energy balanced clustering routing algorithm based on energy and location before and after use.

Time	Before use		After use	
	Line class	Curve class	Line class	Curve class
8:10	0.08	0.08	0.02	0.02
8:20	0.07	0.09	0.02	0.02
8:30	0.07	0.09	0.02	0.02
8:40	0.08	0.09	0.02	0.02
8:50	0.07	0.09	0.02	0.02
9:00	0.07	0.09	0.02	0.02
9:10	0.08	0.09	0.02	0.02
9:20	0.07	0.09	0.02	0.02
9:30	0.07	0.09	0.02	0.02
9:40	0.08	0.09	0.02	0.02
Mean value	0.07	0.09	0.02	0.02

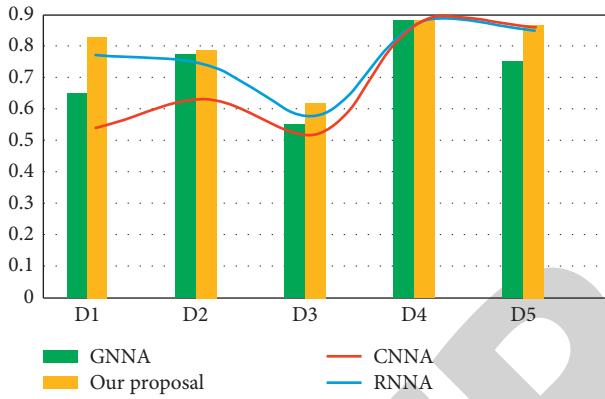


FIGURE 7: The F1-score of our proposal and other methods.

balanced clustering routing algorithm based on energy and location can improve the real-time collection of athletes' training distance.

In order to investigate the effectiveness of our proposal and other methods, here we take F1-score into account to assess the experiment results, which can be defined as follows: $f1\text{-score} = (2 * \text{precise} * \text{recall}) / (\text{precise} + \text{recall})$, $\text{precise} = (\text{TP}/(\text{TP} + \text{FP}))$, $\text{recall} = (\text{TP}/(\text{TP} + \text{FN}))$. And we also compared three methods proposed in the last three years such as GNNA, RNNA, and CNNA with our proposal to investigate the effectiveness of our methods. And all these methods are introduced in Section 2. The results can be shown in Figure 7. As shown in Figure 7, the yellow bar represents our proposal and on all datasets we can see that our proposal is better than others except D4, where all methods obtain the same results. It indicated that our proposal can perform better than the other three methods.

5. Conclusion

Wireless network sensor technology has created a lot of fun for people's life, and it also plays a certain role in promoting the effective and timely transmission of information. People increasingly rely on wireless sensor network technology to bring comfort and convenience to their lives. Wireless network sensor technology has attracted more and more

attention from all walks of life. In this paper, a real-time acquisition method of training distance for long-distance runners based on wireless sensor network is proposed, and its application value is verified in the experiment. We have established a good wireless sensor network to collect data such as distance and energy consumption of long-distance runners, and we used this to guide and analyze the training of athletes. However, due to the data security and latency caused by network bandwidth in wireless sensor networks, the energy consumption and configuration of sensor devices will bring challenges to subsequent data collection. In our experiment, we lost data of a few sensors because of the instability of Internet communication. In the future, we will shift the focus of our work to wireless sensing. The optimization of the network comes up, such as how to efficiently cover the devices and how to reduce the communication delay of different devices. Although our method has achieved good accuracy at present, it is still unable to achieve considerable accuracy in the face of complex environment, and the training time of the model is long. In the future, we will further optimize our model to improve the training speed of the model while ensuring the accuracy.

Data Availability

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

Conflicts of Interest

The author declares no conflicts of interest.

Acknowledgments

The study was supported by "2016 Humanities and Social Sciences Research Project" of the Education Department of Heilongjiang Province (Grant no. 2016-KYYWF-0898).

References

- [1] J. Qi and G. P. Liu, "Design and implementation of an indoor localization system based on wireless sensor networks and ultrasonic," *Kongzhi Yu Juece/Control and Decision*, vol. 33, no. 8, pp. 1391–1398, 2018.
- [2] Z. Sheng, C. Mahapatra, and V. C. M. Leung, "Energy efficient cooperative computing in mobile wireless sensor networks," *IEEE Transactions on Cloud Computing*, vol. 6, no. 99, pp. 114–126, 2018.
- [3] J. Singh and V. Mansotra, "Prospect convenient steadfast procedure in wireless sensor network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 9, no. 3, pp. 613–615, 2018.
- [4] C.-H. Chen, "A cell probe-based method for vehicle speed estimation," *IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences*, vol. E103.A-A, no. 1, pp. 265–267, 2020.
- [5] V. U. Rani and K. S. Sundaram, "Dirichlet distribution based trust model for malicious node detection in wireless sensor network," *Journal of Engineering and Applied Sciences*, vol. 14, no. 12, pp. 4191–4199, 2019.

- [6] A. Steingass, T. Thiasiriphet, and J. Samson, "Modeling distance measurement equipment (DME) signals interfering an airborne GNSS receiver," *Navigation*, vol. 65, no. 2, pp. 221–230, 2018.
- [7] R. A. Setyawan, R. Sunoko, and M. A. Choiron, "Implementation of stereo vision semi-global block matching methods for distance measurement," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 12, no. 2, pp. 585–591, 2018.
- [8] K.-W. Cho and C.-H. Oh, "Data transmission distance actual measurement according to receiver height for LPWA-based IoT application," *International Journal of Control and Automation*, vol. 11, no. 7, pp. 139–148, 2018.
- [9] S. Abd-Elkhalig, M. Faied, R. Aboul Seoud, and A. Gody, "Distance and error measurement for wireless sensor network system localization using RSSI measurement," *The International Conference on Electrical Engineering*, vol. 11, no. 11, pp. 1–14, 2018.
- [10] N. Wili, H. Hintz, A. Vanas, A. Godt, and G. Jeschke, "Distance measurement between trityl radicals by pulse dressed electron paramagnetic resonance with phase modulation," *Magnetic Resonance*, vol. 1, no. 1, pp. 75–87, 2020.
- [11] Y.-K. Kim, J.-T. Kim, K.-J. Ko et al., "Performance improvement of distance measurement type adherence detector consistings of dual system, verified by field application test results," *Journal of the Korean Society for Railway*, vol. 23, no. 5, pp. 431–439, 2020.
- [12] V. D. Soni, A. N. Soni, and K. Pothuganti, "Student body temperature and physical distance management device in the classroom using 3D stereoscopic distance measurement," *International Journal of Innovative Research in Science Engineering and Technology*, vol. 9, no. 9, pp. 9294–9299, 2020.
- [13] A. Layek, T. Chung, and E. N. Huh, "Remote distance measurement from a single image by automatic detection and perspective correction," *KSII Transactions on Internet and Information Systems*, vol. 13, no. 8, pp. 3981–4004, 2019.
- [14] B. Bastien, L. Chassagne, and H. Guan, "Simultaneous visible light communication and distance measurement based on the automotive lighting," *IEEE Transactions on Intelligent Vehicles*, vol. 4, no. 4, pp. 532–547, 2019.
- [15] N. Dey, A. S. Ashour, F. Shi, S. J. Fong, and R. Simon Sherratt, "Developing residential wireless sensor networks for ECG healthcare monitoring," *IEEE Transactions on Consumer Electronics*, vol. 63, no. 4, pp. 442–449, 2018.
- [16] X. J. Jiang and J. Y. Sun, "Simulation of outlier tracking method in wireless sensor network dataset," *Computer Simulation*, vol. 35, no. 1, pp. 265–268, 2018.
- [17] P. S. Mann and S. Singh, "Improved metaheuristic-based energy-efficient clustering protocol with optimal base station location in wireless sensor networks," *Soft Computing*, vol. 23, no. 3, pp. 1021–1037, 2019.
- [18] P. S. Lorenz, "New path centrality based on operator calculus approach for wireless sensor network deployment," *IEEE Transactions on Emerging Topics in Computing*, vol. 7, no. 1, pp. 162–173, 2019.
- [19] R. Jyothi and N. G. Cholli, "A secure data aggregation technique for wireless sensor networks using iterative filtering," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 11, no. 1, pp. 284–293, 2018.
- [20] W. Wang and M. Zhang, "Self-Adaptive gathering for energy-efficient data stream in heterogeneous wireless sensor networks based on deep learning," *IEEE Wireless Communications*, vol. 27, no. 5, pp. 74–79, 2020.
- [21] J. Zhang and D. Tao, "Empowering Things with intelligence: a survey of the progress, challenges, and opportunities in artificial intelligence of Things," *IEEE Internet of Things Journal*, vol. 8, no. 10, pp. 7789–7817, 2021.
- [22] M. S. Hossain and G. Muhammad, "An audio-visual emotion recognition system using deep learning fusion for a cognitive wireless framework," *IEEE Wireless Communications*, vol. 26, no. 3, pp. 62–68, 2019.
- [23] K. Praveen, A. Tarachand, and C. Sekhar, "Machine learning algorithms for wireless sensor networks: a survey," *Information Fusion*, vol. 49, pp. 1–25, 2019.
- [24] W. Cheng, W. Ou, X. Yin, W. Yan, D. Liu, and C. Liu, "A privacy-protection model for patients," *Security and Communication Networks*, vol. 2020, Article ID 6647562, 12 pages, 2020.
- [25] Y. Zhou, X. Chen, and M. Chen, "Privacy-preserving multidimensional data aggregation scheme for smart grid," *Security and Communication Networks*, vol. 2020, Article ID 8845959, 14 pages, 2020.
- [26] Y. Li, Y. Li, H. Xu, and S. Ren, "An adaptive communication-efficient federated learning to resist gradient-based reconstruction attacks," *Security and Communication Networks*, vol. 2021, Article ID 9919030, 16 pages, 2021.
- [27] P. Singh and N. Mittal, "An efficient localization approach to locate sensor nodes in 3D wireless sensor networks using adaptive flower pollination algorithm," *Wireless Networks*, vol. 27, no. 8, 2021.