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Security Detection Method for Clustering Wireless Sensor Networks Based on Markov Chain

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In order to improve the mining and intelligent analysis capability of the transmission information of clustered wireless sensor networks, a security detection method for transmission information of clustered wireless sensor networks based on Markov chain is proposed. This involves constructing a distributed sensing sequence sampling model of clustered wireless sensor network transmission information, reconstructing association rule feature quantities of clustered wireless sensor network transmission information obtained by sensing detection, establishing a Markov chain information mining model of clustered wireless sensor network transmission information, adopting a wireless sensor network information fusion tracking identification method, carrying out adaptive fusion and feature clustering of clustered wireless sensor network transmission information. Combined with the phase space reconstruction method, the discrete fusion processing of the transmission information of the clustered wireless sensor network is carried out, and the correlation spectrum feature extraction is carried out on the transmission information of the clustered wireless sensor network in the routing relay node, so that the safety detection of the transmission information of the clustered wireless sensor network is realized. The simulation results show that this method has higher accuracy, better security and a higher level of fusion for the transmission information detection of clustered wireless sensor networks as well as good security detection and feature analysis capabilities for clustered wireless sensor networks.

Keywords: Markov Chain; Clustering; Wireless Sensor Networks; Safety Inspection; Information Clustering.

1. INTRODUCTION

With the development of large data network sensing technology, sensor networks are adopted to collect and mine large data information, and distributed sensor detection methods are combined to carry out large data mining and safety detection, so as to improve the collection and characteristic analysis capability of physical information, build a clustered wireless sensor network transmission information safety detection model, and improve the effective data mining and safety detection capability (Zhou et al., 2018; Zhang et al., 2019; Zhang et al., 2012). In the process of data monitoring using wireless sensor networks, visual reconstruction and security detection and identification of transmission information of clustered wireless sensor networks should be carried out (Mao et al., 2016; Lin et al., 2016), and a security detection model of transmission information of clustered wireless sensor networks should be established. Combined with large data mining and information reconstruction methods, fusion detection and feature analysis of the transmission information of clustered wireless sensor networks should be carried out, so as to improve the detection and identification capability of transmission information of clustered wireless sensor networks (Zhou et al., 2014; Qi et al., 2014; Mohan et al., 2013). According to recent research, relevant security detection methods of transmission information of clustered wireless sensor networks have received great attention. A detection method of transmission information of clustered wireless sensor networks based on Markov chain is proposed. Firstly, a distributed sensing sequence sampling model of the transmission information of clustered wireless sensor networks is constructed (Sheeza et al., 2019; Gita and Pri, 2019; Moin et al., 2020). Adaptive fusion and feature clustering of transmission information of clustered

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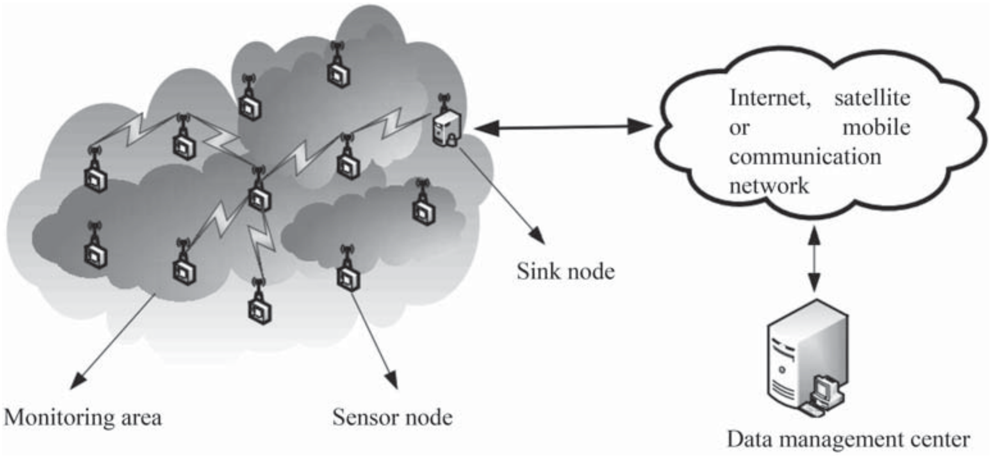

Figure 1 Wireless sensor network structure.

wireless sensor networks are then carried out (Kimmett et al., 2015; Zhao et al., 2018). Combined with the phase space reconstruction method, discrete fusion processing of transmission information of clustered wireless sensor networks is carried out to realize the detection of transmission information of clustered wireless sensor networks. Finally, simulation experiment analysis is carried out to obtain an effective conclusion.

2. BASIC DEFINITIONS

2.1 Concepts and Features

A Wireless Sensor Network (WSN) is a wireless network composed of a large number of sensor nodes in an ad-hoc multi-hop self-organizing form, which collects, processes and transmits the information of the perceived object in the monitoring area by collaboration, and finally sends the information to the user for analysis and decision-making (Li et al., 2018; Fan et al., 2018). Figure 1 is a schematic diagram of a typical wireless sensor network structure.

In this network, a large number of sensor nodes are randomly deployed in the monitoring area. These sensor nodes perceive and collect data on the surrounding environment of the monitoring area through one or more micro sensors they carry, transmit the collected data to the convergent (Sink) node in a multi-hop relay mode, and finally the convergent node transmits the collected data to the remote data management center by means of the Internet, satellite link or mobile communication network for processing and analysis.

The wireless sensor network is a data-centric network whose main purpose is to sense and collect the information of the perceived object in the monitoring area and process the information to transmit to the user terminal with as little energy consumption as possible. Therefore, processing the perceptual data and transmitting it in the most efficient manner is the core problem in the research of wireless sensor networks. However, the energy, communication, computing and storage resources of sensor nodes are very limited, thereforer the manner in which to save energy more effectively is the primary design goal considered by sensor networks. Unlike traditional ad-hoc networks, the main features of wireless sensor networks are:

(1) Large number of nodes, high deployment density: The number of nodes deployed in a wireless sensor network can reach tens of thousands, so there is a huge volume of data to be transmitted. The node density deployed in the network is high, and this can lead to a high level of redundancy in the data collected, especially in the examples of forest fire or environmental monitoring applications, so it is necessary to process the data to reduce duplication before transmission.

(2) Limited resources: The energy of the sensor node is generally provided by the battery and cannot be charged or replaced during use, therefore saving the battery energy in order to prolong the network life cycle is the primary design goal considered by the sensor network. In addition, the communication distance of the sensor node is short, with the general transmission range only being from tens to hundreds of meters, the node only being able to communicate with its neighbor nodes, and communication with other nodes that can only be forwarded through intermediate nodes, the design of efficient routing protocols to save node energy consumption is an important research content in wireless sensor networks. As the sensor node is limited by volume, power consumption and other factors, its computing power and storage capacity are also very limited. Therefore, the designed algorithm or protocol must be simple and the computational complexity must be low.

(3) Network topology dynamic: Due to the influence of surrounding environmental factors, the sensor network nodes are prone to fault or failure, which leads to the change of network topology, which requires the designed protocol or algorithm to be robust and adaptable to the change of topology in real time. Nodes may also be mobile and can move to other locations in the network at any time to work, which requires the network to have dynamic topology organization function.

(4) Data-centric: Unlike traditional wireless networks, wireless sensor networks are data-centric networks,

interested in indicators of observational data in the monitoring area of the network rather than in individual actual data. Therefore, in the transmission process, the data can be processed by aggregation, fusion or compression techniques.

2.2 Distributed Sensing Sequence Sampling Model

In order to realize the security detection of the transmission information of the clustered wireless sensor network, it is necessary to first construct a distributed sensing sequence sampling model of the transmission information of the clustered wireless sensor network, carry out information fusion and adaptive feature sampling on the transmission information of the clustered wireless sensor network obtained by sensing detection, and establish a Markov chain information mining model of the transmission information of the clustered wireless sensor network (Gu et al., 2012). The expression of the feature evaluation concept set of the optimized sampling of the transmission information of the clustered wireless sensor network is as follows:

$$p(y|\alpha, \theta) = \sum_{k=1}^{K} \alpha_k p_k \left(y|\mu_k, \sum\nolimits_k \right) \quad (1)$$

Combining this with the fuzzy association rule scheduling method, and mining the attribute association rule feature quantity of the information transmitted by the clustered wireless sensor network:

$$\max_{x_{a,b,d,p}} \sum_{a\in \mathrm{A}} \sum_{b\in \mathrm{B}} \sum_{d\in \mathrm{D}} \sum_{p\in \mathrm{P}} x_{a,b,d,p} V_p \quad (2)$$

$$\text{s.t.} \sum_{a\in \mathrm{A}} \sum_{d\in \mathrm{D}} \sum_{p\in \mathrm{P}} x_{a,b,d,p} R_p^{bw} \le K_b^{bw}(\mathrm{S}), b \in \mathrm{B} \quad (3)$$

Assuming the sensor node mi ∈ M, the characteristic fusion of the information transmitted by the clustered wireless sensor network is carried out, and a spatial distributed sampling model of the sensor node of the large data network is constructed (Guo et al., 2018; Lyu et al., 2016), wherein the sampling time sequence is $x(t), t = 0, 1, \cdots, n-1$, the two-dimensional sensing detection characteristic distribution model of the information transmitted by the given clustered wireless sensor network is $x_1, x_2, \cdots x_n \in C^m$ (m-dimensional complex space), and the distributed point set of the sensor node mi and other nodes within the sensing range v is $P_i = (p_{i1}, p_{i2}, \cdots p_{iD})$, wherein:

$$j \in N_i(k), N_i(k) = \{\|x_j(k) - x_i(k)\| < r_d(k)\} \quad (4)$$

By adopting a multi-element information fusion method, the optimal scheduling of the transmission information of the clustered wireless sensor network is carried out, a characteristic extraction model of the transmission information of the clustered wireless sensor network is constructed, fuzzy information identification is carried out according to the state characteristics of a sensing detection sequence, and the time window function of the transmission information detection of the clustered wireless sensor network is set, then:

$$R_2 = \{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}^T \quad (5)$$

When $R_2^T R_2 = \{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}\{X_{d+1}, X_{d+2}, \cdots X_{d+m}\}^T$, the window function $V = [V_1, V_2, \cdots, V_m] \in R^{m\times m}$ of the state space reorganization of the transmission information of the clustered wireless sensor network takes the minimum value. When $V \in R^{m\times m}, VV^T = I_M$, has a minimum value, at this time, the autocorrelation fusion method is adopted to obtain the data state characteristic quantity of the sensor node satisfying the sensing coverage condition. Assuming that the number of sensors in the B range is n, the fuzzy membership function of the transmission information of the clustered wireless sensor network is obtained as follows:

$$y(t) = \frac{1}{\pi} P \int \frac{x(\tau)}{t-\tau} d\tau = x(t) * \frac{1}{\pi t} \quad (6)$$

In the above formula, P is the correlation dimension of neighbor nodes connected to sink nodes, $x(t)$ is the characteristic distribution length of transmission information of the original clustered wireless sensor network, τ is the time delay of data acquisition, and in the sensing range of the sensor, a regional information fusion method is adopted to obtain that the spectrum z of transmission information of the clustered wireless sensor network obeys Gaussian distribution with parameter β_d, wherein:

$$\beta_d = (MPDist - d + 1)/MPDist, d \in [2, MPDist] \quad (7)$$

In which $adj(a, c)$ represents the feature vector of the reconstructed clustered wireless sensor network transmission information flow, and based on the above analysis, a distributed sensing sequence sampling model of the clustered wireless sensor network transmission information is constructed to carry out distributed sensing sequence sampling (Xiao et al., 2017).

2.3 Reconstruction of Feature Quantity of Association Rules

The sending State (T), receiving state (R), idle state (I), sleep state and nodes with the same work cycle length and wake-up time are set respectively. When a node wakes up, it can receive data, send data, or enter an idle state. When the node is dormant, it will not process, send or receive data and will remain dormant until the next work cycle starts again. After the node is re-awakened, it will start a new round of work cycles. The work cycle of the node is shown in Figure 2. It should be noted that when the workload is too large, the node may not be able to enter dormancy in a single cycle. At the beginning of a new cycle, it will continue to perform operations such as data receiving or sending.

When the node is in idle state, the packet of the child node can be received, the node then decides according to the set scheduling probability whether to send the packet or to remain in the idle state. When the node is scheduled to enter the

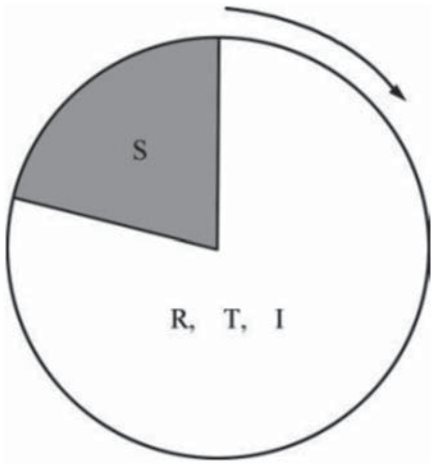

Figure 2 Node work cycle.

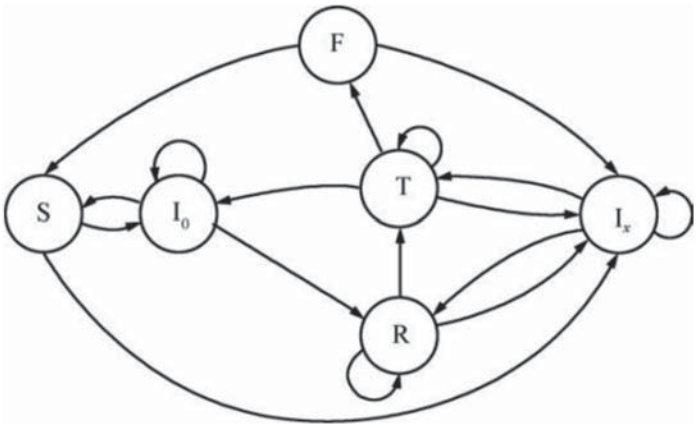

Figure 3 Transfer process of node working state.

sending state, it will return to the idle state after sending the packet. When the node is running, the node's state sequence will be a DTMC.

In Figure 3, S, T, R and F represent the states of hibernation, sending, receiving and sending failure, respectively. I_0 and I_x represent the free state of packet time and packet time in the FIFO queue, respectively.

The distributed sensing sequence sampling model of the clustered wireless sensor network transmission information is constructed above, association rule feature quantity reconstruction is carried out on the clustered wireless sensor network transmission information obtained by sensing detection, association rule feature quantity reconstruction is carried out on the clustered wireless sensor network transmission information obtained by sensing detection, clustering wireless sensor network transmission information detection and feature reconstruction are carried out (Moosavi et al., 2017), and the phase space fusion model of the clustered wireless sensor network transmission information in the sensing range of the sensor is as follows:

$$X = [s_1, s_2, \cdots s_K] = \begin{bmatrix} x_1 & x_2 & \cdots & x_K \\ x_{1+\tau} & x_{2+\tau} & \cdots & x_{K+\tau} \\ \cdots & \cdots & \cdots & \cdots \\ x_{1+(m-1)\tau} & x_{2+(m-1)\tau} & \cdots & x_{M+(m-1)\tau} \end{bmatrix} \tag{8}$$

Wherein, $K = N - (m - 1)\tau$, it is the embedded dimension of transmission information source integration of the clustered wireless sensor network represented by τ is the probability of sensor coverage, m is the dimension of feature sampling, $s_i = (x_i, x_{i+\tau}, \cdots, x_{i+(m-1)\tau})^T$ is the spatial distribution feature quantity of transmission information of the clustered wireless sensor network, and the associated feature detection analysis of transmission information of the clustered wireless sensor network is carried out by adopting the wireless sensor network information fusion tracking analysis method, and the quantitative learning function of transmission information of the clustered wireless sensor network is as follows:

$$\begin{cases} \min \sum\limits_{1 \le i \le K} \sum\limits_{e \subseteq k(e)} \frac{f(e(i))}{C(e,i)} \\ 0 \le f(e,i) \le C(e,i) \\ F = const \\ \sum\limits_{1 \le i \le K e \subseteq k(e)} \frac{f(e(i))}{C(e,i)} + \sum\limits_{e \subseteq k(e)} \frac{f(e'(i))}{C(e',i)} \le k(v) \end{cases} \tag{9}$$

Combined with the stochastic feature reconstruction method, dynamic information detection of transmission information in clustered wireless sensor networks is carried out (Zhang et al., 2017; Ghosh, 2017; Nematollahi et al., 2017), and the output load is obtained as follows:

$$Computition(n_j) = (E_{elec} + E_{DF})l\delta + E_{Tx(l,d_j)}$$
$$= (E_{elec} + E_{DF})l\delta + lE_{elec} + l\varepsilon_{fs}d_j^2$$
$$= [(E_{elec} + E_{DF})\delta + E_{elec} + \varepsilon_{fs}d_j^2]l \quad (10)$$

Adaptive fusion and feature clustering algorithms are adopted to detect the transmission information of clustered wireless sensor networks. Under the condition that the minimum number of sensor nodes N is randomly deployed, the comprehensive scheduling output of data detection is as follows:

$$\eta_k^w(\omega) = \mathrm{E}(T_k^w | T_k^w > \xi_k^w(\omega)), k \in R_w, w \in W \quad (11)$$

Among them, the error $\xi_k^w(\omega)$ of multi-queue scheduling of transmission information in clustered wireless sensor networks can be expressed as follows:

$$\xi_k^w(\omega) = \min\{\xi | \Pr(T_k^w \le \xi) \ge \omega\}$$
$$= \mathrm{E}(T_k^w) + \gamma_k^w(\omega)k \in R_w, w \in W \quad (12)$$

The sensing detection characteristic value of cluster wireless sensor network transmission information is extracted, and a sensing detection index set of clustering wireless sensor network transmission information detection output in a neighborhood space (t, f) is obtained as follows:

$$f(x) = \begin{cases} f(x), x \in Levf \\ a, x \in Levf \end{cases} \quad (13)$$

The sensor detection feature quantity of the information transmitted by the clustered wireless sensor network is extracted, and the correlation fusion detection method is adopted to obtain an information fusion model $\mathrm{E}(T_k^w - \xi_k^w(\omega) | T_k^w \ge \xi_k^w(\omega))$. According to the above analysis, the Markov chain information mining model of the information transmitted by the clustered wireless sensor network is established, and the sensor node data security detection is carried out by combining the large data mining method (Yang et al., 2018; Sun, 2017).

3. OPTIMIZATION OF DATA SECURITY DETECTION ALGORITHM FOR SENSOR NODES

3.1 Feature Extraction of Correlation Spectrum

Based on the above-mentioned construction of the distributed sensing sequence sampling model of the clustered wireless sensor network transmission information and the reconstruction of the association rule feature quantity of the clustered wireless sensor network transmission information obtained by sensing detection, the superior design of the clustered wireless sensor network transmission information detection method is carried out (Yu et al., 2017; Yang et al., 2018), and the clustered wireless sensor network transmission information detection method based on Markov chain is proposed. The aggregation node set s_h^w for information fusion of clustered wireless sensor networks can be expressed as:

$$s_h^w = \mathrm{E}\left[\min_{k \in R_w}\{\mathrm{H}_{h,k}^w\} | \boldsymbol{\eta}^w\right] = -\frac{1}{\theta}\ln\sum_{k \in R_w}\exp(-\theta\eta_{h,k}^w(\omega)),$$
$$w \in W, h \in H \quad (14)$$

According to the above analysis, the adaptive feedback adjustment method is combined to reconstruct the characteristics of the transmission information surface of the clustered wireless sensor network, and the optimal solution of the sparse table matrix of the transmission information of the clustered wireless sensor network is solved, namely:

$$\mathbf{W}_{opt} = \arg\min_{\mathbf{W}} \lambda \|(\mathbf{X} - \mathbf{DW})\mathbf{G}\|_F^2 \ s.t \|\mathbf{w}_i\|_0 \le k\forall i \quad (15)$$

Combined with the phase space reconstruction method, the discrete fusion processing of the transmission information of the clustered wireless sensor network is carried out, and the sensing data optimization detection of the large data network is also carried out (Osamy et al., 2018). Calculate the time taken by the sensor to sense the data and the transmission time of the data packet, and the output is:

$$\left.\begin{array}{l} \min\limits_{\alpha} \frac{1}{2}\sum\limits_{i=1}^{l}\sum\limits_{j=1}^{l} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum\limits_{j=1}^{l}\alpha_j \\ s.t. \quad \sum\limits_{j=1}^{l} y_j \alpha_j = 0 \\ \qquad 0 \le \alpha_j \le u(x_j)C, \qquad j = 1, 2, \ldots, l \end{array}\right\} \quad (16)$$

In the reconstructed phase space of the transmission information distribution of the clustered wireless sensor network, the principal component characteristic sampling method is adopted to schedule the association rule set of the transmission information of the clustered wireless sensor network, and the optimized sampling model is obtained as follows:

$$\mathbf{D}_{opt} = \lambda\mathbf{X}\mathbf{V}^{-1}\mathbf{W}^T(\mathbf{W}\mathbf{V}^{-1}\mathbf{W}^T)^{-1} \quad (17)$$

Setting the mean value of the transmission information fusion of the clustered wireless sensor network as t_a and the variance as ε_t^a, and expressing the dynamic distribution symbols of the transmission information of the clustered wireless sensor network as:

$$t_a = \mathrm{E}(T_a) = t_a^0 + \beta t_a^0\mathrm{E}((V_a)^n)\mathrm{E}(1/(C_a)^n), a \in A \quad (18)$$
$$\mathrm{E}((T_a)^2) = (t_a^0)^2 + 2\beta(t_a^0)^2\mathrm{E}((V_a)^n)\mathrm{E}(1/(C_a)^n) \quad (19)$$
$$+ (\beta t_a^0)^2\mathrm{E}((V_a)^{2n})\mathrm{E}(1/(C_a)^{2n}), a \in A$$
$$\varepsilon_t^a = \mathrm{Var}(T_a) = \mathrm{E}((T_a)^2) - (\mathrm{E}(T_a))^2, a \in A \quad (20)$$

In the surface distribution structure model of the transmission information of the clustered wireless sensor network, the sparse point expression method is adopted to analyze the correlation degree characteristics of the transmission information of the clustered wireless sensor network (Ha et al., 2017; Wang et al., 2018), the adaptive equalization control is carried out on the detection result of the transmission information of the clustered wireless sensor network, and the extraction output of the correlation spectrum characteristics in the whole life cycle is obtained as follows:

$$C_{T'}(f)Y_{T'}(f) = C_{T'}(f)\sum_{n} x\left(f - \frac{n}{T'}\right)e^{j2\pi\left(f\frac{n}{T'}\right)\tau_0} = C_{T'}(f)X(f)e^{j2\pi f\tau_0} \tag{21}$$

The optimal distribution outputs of the sensor node data security detection data are Q^w, V_a, F_k^w. Combined with the phase space reconstruction method, the discrete fusion processing of the clustered wireless sensor network transmission information is carried out to improve the data security detection capability.

3.2 Sensing Quantization Fusion Tracking Recognition and Safety Detection

Carrying out discrete fusion processing on the transmission information of the clustered wireless sensor network by combining a phase space reconstruction method to obtain the connection weight value of the wireless sensor network sensor node of the k layer; $x_i^{(k)}$ is an k data input ($i = 1, 2, \ldots, N_k$) of a clustering wireless sensor network transmission information fusion node of the k layer, $s_j^{(k)}$ and $y_j^{(k)}$ respectively represents the energy threshold value of the K-th sampling node of the layer in the wireless sensor network, and the statistical analysis model of the sampling node of the clustering wireless sensor network transmission information is obtained as follows:

$$x^{(k)} = [x_1^{(k)}, x_2^{(k)}, \ldots x_{N_{k-1}}^{(k)}]^T \tag{22}$$

$$s^{(k)} = [s_1^{(k)}, s_2^{(k)}, \ldots s_{N_k}^{(k)}]^T \tag{23}$$

$$y^{(k)} = [y_1^{(k)}, y_2^{(k)}, \ldots y_{N_k}^{(k)}]^T \tag{24}$$

Assuming that the distributed function of the sampled data of the wireless sensor network is f, the node mi is set to send data to the sink node, and correlation spectrum feature extraction is carried out on the clustered wireless sensor network transmission information in the routing relay node to realize the detection of the clustered wireless sensor network transmission information. The obtained fuzzy decision function is:

$$y_j^{(0)}(n) = s_j^{(0)}(n) = x_j^{(0)}(n) \tag{25}$$

In the hidden layer of the wireless sensor network, the optimized detection output of the clustered wireless sensor network transmission information in the L layer ($k = 1, \ldots, L$) is obtained as follows:

$$x_j^{(k)}(n) = y_j^{(k-1)}(n) \tag{26}$$

$$s_j^{(k)}(n) = \sum_{j=1}^{N_{k-1}} W_{ij}^{(k)}(n)x_j^{(k)}(n) \tag{27}$$

$$y_j^{(k)}(n) = f(s_j^{(k)}(n)) \tag{28}$$

According to the above model construction, correlation spectrum feature extraction is performed on the transmission information of the clustered wireless sensor network in the routing relay node to realize the detection of the transmission information of the clustered wireless sensor network (Qasim et al., 2018), and the implementation flow is shown in Figure 4.

4. SIMULATION EXPERIMENT AND RESULT ANALYSIS

4.1 Parameter Setting

In order to verify the application performance of this method in realizing the transmission information detection of clustered wireless sensor networks, simulation experiments were carried out with Matlab7. A WSN network was constructed with 200 nodes, random uniformly distributed in a square region with a side length of 2000m, with the sink node located in the center of the region (Lin et al., 2017; Wang et al., 2019). Each node periodically generates data and sends data to the Sink node. The communication distance of the node is uniformly set to 250m. Referring to the energy consumption of IRIS nodes in Crossbow, the state energy consumption model of the nodes was set as shown in Table 1.

Since the RAM capacity of the IRIS node is double that of MICAZ, the use of external memory is not considered in this paper. The energy consumption power value of the node in each state is calculated according to the measured current value of the IRIS node in t, r, i state and the current value of each component in the IRIS node manual when it is dormant. The energy consumption power is definied as 0.053 W when the node receives, 0.07 W when transmitting, 0.048 W when free, and 0.000033 W when dormant. The energy consumption of nodes for sensor sensing is not considered in this paper.

The network communication rate is set to 250 kbps, the application layer produces 100 bytes of data every 20 seconds, the node work cycle is 10 seconds, and the node data transfer phase is set to 60 seconds, followed by a schedule update. When the next data transfer phase begins after the scheduling update, the node wakes up and retransmits the data.

The setting system has the requirement of high reliability, and the data cannot be lost. Data transfer uses point-to-point data confirmation. When the node fails to send data, the packet should be retransmitted. The packet is sent sequentially in the FIFO queue, sending one packet successfully before sending the next. The experimental settings are shown in Table 2.

According to the above simulation environment and parameter setting, the transmission information of the clustered wireless sensor network is detected, a distributed sensing sequence sampling model of the transmission information of the clustered wireless sensor network is constructed, and a scatter diagram of data sampling is obtained as shown in Figure 5.

Taking the data in Figure 5 as input, a Markov chain information mining model for the transmission information of clustered wireless sensor networks is established. The adaptive fusion, feature clustering and data detection of the transmission information of clustered wireless sensor networks are carried out by using the information fusion

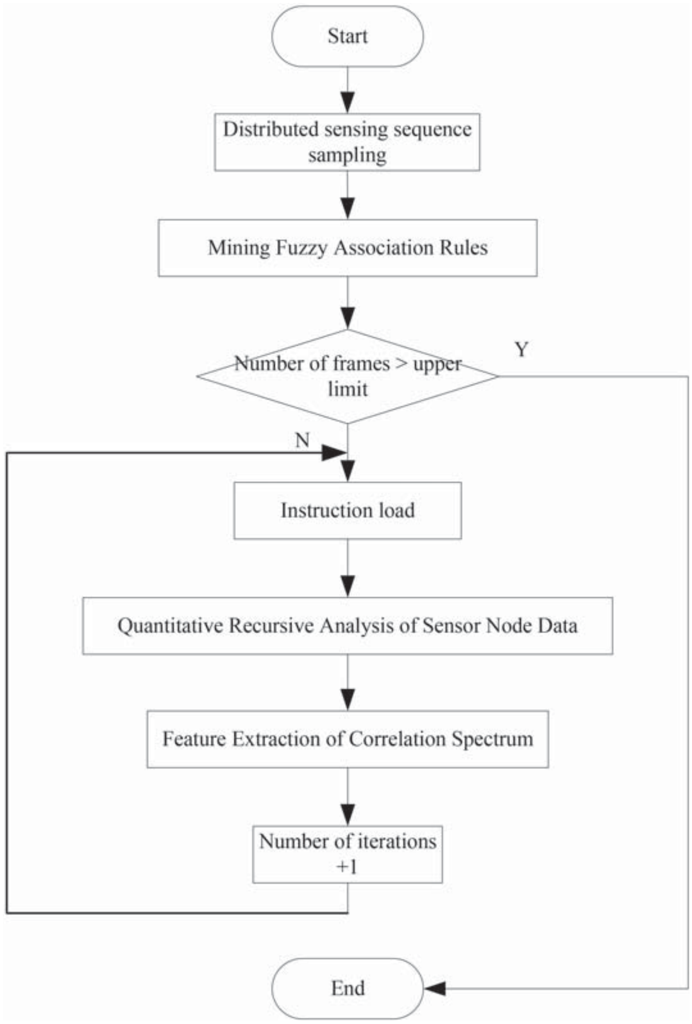

Figure 4 Implementation flow.

Table 1 Energy consumption model of node state.

Status	Processor	Sending and Receiving Module	External Memory
T	Activity	Transmit by radio	Dormancy
R	Activity	Receive	Dormancy
I	Idle	Receive	Dormancy
S	Dormancy	Dormancy	Dormancy

Table 2 Simulation parameters.

Parameter	Numerical Value	Unit
Number of nodes	200	\
Placement area	2000×2000	m^2
Haul up	250	m
Receiving energy consumption	0.053	W
Send energy consumption	0.06	W
Idle energy consumption	0.032	W
Dormant energy consumption	0.0000021	W
Traffic rate	253	Kbps
Work cycle	8	s
Update cycle	56	s
DL	231	byte
Data generation cycle	32	s

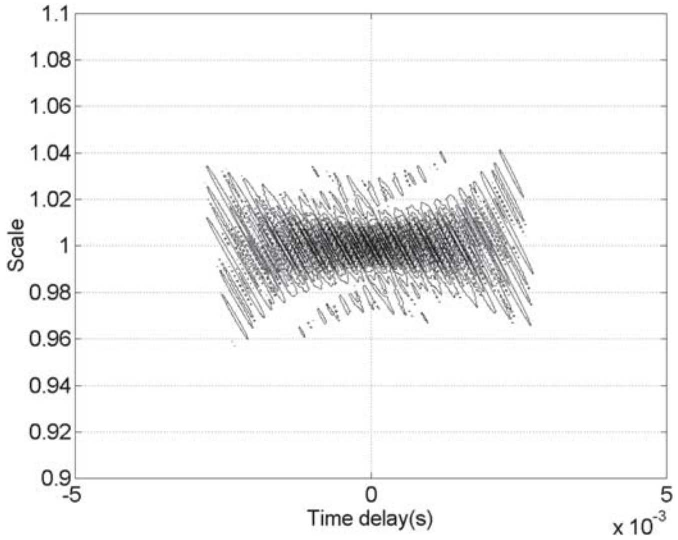

Figure 5 Scatter diagram of data sampling.

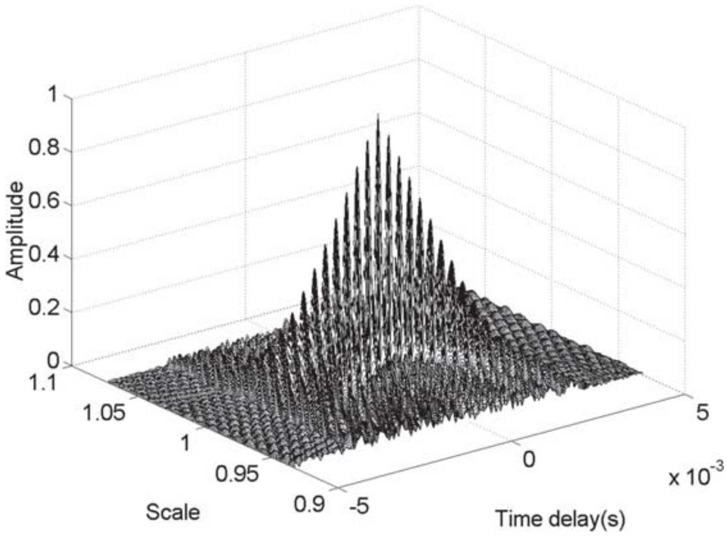

Figure 6 Data detection output.

tracking analysis method of wireless sensor networks, and the detection output is shown in Figure 6.

Analysis of Figure 6 shows that the peak output and beam output performance of the clustered wireless sensor network transmission information detection using this method are better than that of previous methods.

4.2 Compressibility Analysis of Segmented Smooth Area

The network model employed in this chapter is a random geometric network, which can be generated by the random and uniform deployment of n nodes in a square area of 1. Since the network topology of the stochastic geometric network is irregular, the eigenvectors of Tulapras are adopted as the orthogonal basis. Based on this setting, the approximate error of the reconstructed signal is estimated, and the result is shown in Figure 7.

From Figure 7, we observe that the reconstruction error decays exponentially with the value of k, which means that the Tulapras feature vector basis can good detection of related areas. Thus, compression sensing techniques can be used to approximate the reconstruction of the sensing region. At the same time, it can also be seen from the figure that the value of k does not increase with the increase of the number of network nodes n under the given reconstruction error. Figure 8 shows the error of signal reconstruction using different random projection numbers. It can be seen from the graph that the number of random projections required to reconstruct the original data is much smaller than the number of nodes in the network under the allowable reconstruction error.

4.3 Analysis of SNR Results of Different Methods

The accuracy of different methods for clustering wireless sensor network transmission information detection is tested. The results are shown in Tables 3–5.

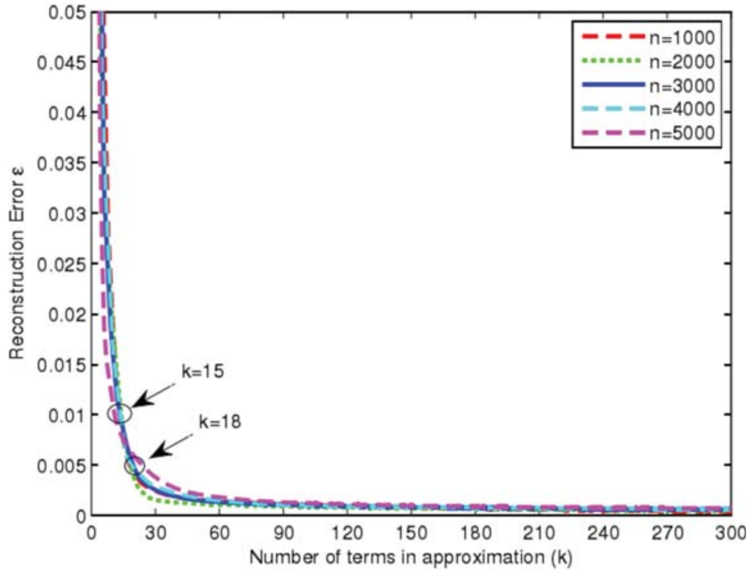

Figure 7 Approximate error of reconstructed signal in sensing region.

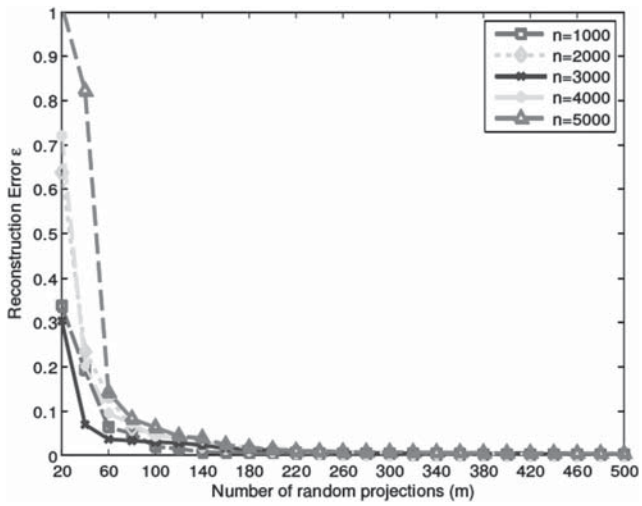

Figure 8 Approximate error of reconstructed signal under random projection.

Table 3 Method performance in this paper.

SNR/dB	Accuracy of Information Detection
−10	0.943
−8	0.966
−6	0.975
−4	0.992
−2	1

Table 4 Reference [4] method performance.

SNR/dB	Accuracy of Information Detection
−10	0.843
−8	0.865
−6	0.911
−4	0.924
−2	0.936

Table 5 Reference [5] method performance.

SNR/dB	Accuracy of Information Detection
−10	0.919
−8	0.926
−6	0.932
−4	0.965
−2	0.975

The comparison results are shown in Table 3–5. Analysis of Table 3–5 shows that the accuracy of the clustered wireless sensor network transmission information detection using this method is higher.

5. CONCLUSION

A security detection model for transmission information in clustered wireless sensor networks is constructed to improve the effective data mining and security detection capabilities. A detection method for transmission information in clustered wireless sensor networks based on Markov chains is proposed. The main contents of this paper are as follows:

(1) A distributed sensing sequence sampling model of clustered wireless sensor network transmission information is constructed, and association rule feature quantity reconstruction is carried out on the clustered wireless sensor network transmission information obtained by sensing detection.

(2) Adaptive fusion and feature clustering of the clustered wireless sensor network transmission information are carried out by adopting a wireless sensor network information fusion tracking analysis method.

(3) Association spectrum feature extraction is carried out on clustered wireless sensor network transmission information in routing relay nodes, and clustered wireless sensor network transmission information detection is realized.

Analysis shows that this method has high accuracy and good anti-interference performance in detecting the transmission information of clustered wireless sensor networks, and has good capability of detecting and analyzing the transmission information of clustered wireless sensor networks.

However, there are still some issues to be resolved that were not considered in this paper. In this paper, the network model was considered without packet loss in the application of compression sensing method in wireless sensor network data collection. However, the wireless sensor network is prone to packet loss due to the interference of the external environment. Although some measures can be taken, such as retransmission mechanism on the MAC layer, to solve the packet loss problem, in the future work, using the matrix filling method in the compression perception theory can be considered to solve the data loss problem when the signal is reconstructed and improve the quality of the signal reconstruction.

REFERENCES

1. Fan, C.L., Song, Y.F., Lei, L., et al. Evidence reasoning for temporal uncertain information based on relative reliability evaluation. *Expert Systems with Applications*, 2018, 113: 264–276.
2. Ghosh, N., Banerjee, I., Simon Sherratt, R. On-demand fuzzy clustering and ant-colony optimisation based mobile data collection in wireless sensor network. *Wireless Networks*, 2017, 16(8): 1–17.
3. Gita A., Pri H. (2019). Pre-Trip Decision on Value Co-Creation of Peer-To-Peer Accommodation Services. *Acta Informatica Malaysia*, 3(2):19–21.
4. Gu, Q., Yuan, L., Ning, B., et al. A novel classification algorithm for imbalanced datasets based on hybrid resampling strategy. *Computer Engineering and Science*, 2012, 34(10): 128–134.
5. Guo, H.P., Zhou, J., Wu, C.A., Fan, M. K-nearest neighbor classification method for class-imbalanced problem. *Journal of Computer Applications*, 2018, 38(4): 955–959.
6. Ha, T., Kim, J., Chung, J.M. He-mac: Harvest-then-transmit based modified EDCF mac protocol for wireless powered sensor networks. *IEEE Transactions on Wireless Communications*, 2017, 18(3): 456–461.
7. Kimmett, B., Srinivasan, V., Thomo, A. Fuzzy joins in MapReduce, an experimental study. *Proceedings of the VLDB Endowment*, 2015, 8(12): 1514–1517.
8. Li, A.N., Zhang, X., Zhang, B.Y., Liu, C.Y., Zhao, X.N. Research on performance evaluation method of public cloud storage system. *Journal of Computer Applications*, 2018, 37(5): 1229–1235.
9. Lin, C., Han, D., Deng, J., et al. P2S: A primary and passer-by scheduling algorithm for on-demand charging architecture in wireless rechargeable sensor networks. *IEEE Transactions on Vehicular Technology*, 2017, 17(12): 79–84.
10. Lin, J.M., Ban, W.J., Wang, J.Y., et al. Query optimization for distributed database based on parallel genetic algorithm and max-min ant system. *Journal of Computer Applications*, 2016, 36(3): 675–680.
11. Lyu, Y.X., Wang, C.Y., Wang, C., et al. Online classification algorithm for uncertain data stream in big data. *Journal of Northeastern University (Natural Science Edition)*, 2016, 37(9): 1245–1249.
12. Mao, W.T., Tian, Y.Y., Wang, J.W., et al. Granular extreme learning machine for sequential imbalanced data. *Control and Decision*, 2016, 31(12): 2147–2154.
13. Mohan, B., Govardhan, A. Online aggregation using MapReduce in MongoDB. *International Journal of Advanced Research in Computer Science and Software Engineering*, 2013, 3(9): 1157–1165.
14. Moin K., Ahthasham S., Arsal H., Muhammad A., Afia Z. (2020). A Review on Wi-Fi vs. Li-Fi Technology. *Information Management and Computer Science*, 3(1): 10–13.
15. Moosavi, H., Francis, M.B. A game-theoretic framework for robust optimal intrusion detection in wireless sensor networks. *IEEE Transactions on Information Forensics and Security*, 2017, 9(9): 1367–1379.

16. Nematollahi, P., Naghibzadeh, M., Abrishami, S., et al. Distributed clustering-task scheduling for wireless sensor networks using dynamic hyper round policy. *IEEE Transactions on Mobile Computing*, 2017, 17(3): 1–10.
17. Osamy, W., Salim, A., Khedr, A.M. An information entropy based-clustering algorithm for heterogeneous wireless sensor networks. *Wireless Networks*, 2018, 32(12): 37–43.
18. Qasim, T., Zia, M., Minhas, Q.A., et al. An ant colony optimization based approach for minimum cost coverage on 3-D grid in wireless sensor networks. *IEEE Communications Letters*, 2018, 14(5): 23–30.
19. Qi, C.Y., Li, Z.H., Zhang, X., et al. The research of cloud storage system performance evaluation. *Journal of Computer Research and Development*, 2014, 51(S1): 223–228.
20. Sheeza I., Ahthasham S., Raja A.W. (2019). Review Paper on Wearable Computing its Applications and Research Challenges. *Acta Electronica Malaysia*, 3(2): 37–40.
21. Sun, C.H. A time variant log-linear learning approach to the set K-COVER problem in wireless sensor networks. *IEEE Transactions on Cybernetics*, 2017, 40(14): 12–20.
22. Wang, Z.F., Zhang, H., Lu, T.T., et al. Cooperative RSS-based localization in wireless sensor networks using relative error estimation and semidefinite programming. *IEEE Transactions on Vehicular Technology*, 2018, 10(12): 17–22.
23. Wang, Z.H. Simulation of hybrid data efficient storage method for wireless sensor networks. *Computer Simulation*, 2019, 36(7): 23–30.
24. Xiao, K.J., Li, J., Yang, C.H. Exploiting correlation for confident sensing in fusion-based wireless sensor networks. *IEEE Transactions on Industrial Electronics*, 2017, 35(18): 44–56.
25. Yang, H., Zou, Y.J., Wang, Z.Y., et al. A hybrid method for short-term freeway travel time prediction based on wavelet neural network and Markov chain. *Canadian Journal of Civil Engineering*, 2018, 45(5): 45–52.
26. Yang, X., Chen, P.P., Gao, S.W., et al. CSI-based low-duty-cycle wireless multimedia sensor network for security monitoring. *Electronics Letters*, 2018, 54(5): 323–324.
27. Yu, T., Yusuke, K., Gento, M., et al. Design and implementation of lighting control system using battery-less wireless human detection sensor networks. *Ieice Transactions on Communications*, 2017, 100(6): 55–63.
28. Zhang, H.L., Li, X.F., Yang, S.B., Xu, J.Y., Li, H.Y., Wang, Q. Dual closed-loop fuzzy PID depth control for deep-sea self-holding intelligent buoy. *Information and control*, 2019, 48(2): 202–208, 216.
29. Zhang, W., Zhu, S.W., Tang, J., et al. A novel trust management scheme based on Dempster–Shafer evidence theory for malicious nodes detection in wireless sensor networks. *Journal of Supercomputing*, 2017, 74(3): 1–23.
30. Zhang, Y., Li, Z.R., Liu, X.D. Active learning SMOTE based imbalanced data classification. *Computer Applications and Software*, 2012, 29(3): 91–93.
31. Zhao, Q.Q., Huang, T.M. Multi-objective decision making based on entropy weighted-Vague sets. *Journal of Computer Applications*, 2018, 38(5): 1250–1253.
32. Zhou, X.P., Zhang, X.F., Zhao, X.N. Cloud storage performance evaluation research. *Computer Science*, 2014, 41(4): 190–194.
33. Zhou, Y.H., Zhang, H.L., Li, F.F., Qi, P. Local focus support vector machine algorithm. *Journal of Computer Applications*, 2018, 38(4): 945–948.