Abstract—In wireless sensor networks (WSN), sensor nodes are densely deployed for environmental monitoring, the network runs under the cooperation between nodes. One of the most significant characteristics of WSN is the instability of wireless communication link and multi-hop transmission process, so that it is very tendentious to receive the distorted information of the source by the terminal node. To reconstruction the source of the original physical phenomenon is an important technical work. This paper proposed a method of WSN data distortion analysis based on spatial locations according to the most universal mode of omnidirectional Boolean sensing. Moreover, for extracting the data correlation in distortion function, a model of data correlation is also proposed. Both analysis and simulation results show the effectiveness of the the distortion function and correlation model, and by modifying the control parameter, the accuracy of the model is also be proved.

Index Terms—distortion analysis, data correlation parameter, spatial location, omnidirectional sensing

I. INTRODUCTION

Wireless sensor networks (WSN) is composed of lots of sensor nodes, these sensor nodes work coordinately to collect, transmit and process different kinds of physical phenomenon such as temperature, humidity and image information in the monitoring area. One of the most significant technical characteristics is that the network runs under the cooperation between nodes, and with thousands of sensor nodes, the monitoring area is covered broadly on space. And in usual scenarios WSN data is transmitted by multi-hop routing relay. For this situation, the wireless communication link and multi-hop transmission process are not instable, so that it is very tendentious to receive the distorted information of the source by the terminal node. To reconstruction the source of the original physical phenomenon is an important technical work, so it is necessary to analyze distortion of receive information. There is an important parameter, data correlation, in the distortion analysis; it reflects the relationship of different sensor nodes based on spatial locations. This paper proposed a method of WSN data distortion analyses based on spatial locations; meanwhile, we propose the model of data correlation for calculate the distortion according to the most universal mode of omnidirectional Boolean sensing.

In addition, the observation random data are highly correlated in space because of the dense deployment. It is unavoidable that there are much redundant data within the network, the sensor readings which collected by the nodes that are very close to each other on space has big correlation and repetition. And closer on space, higher on degree of the correlation and repetition. The redundancy of sensor collected data will reduce the network throughput, and bring extra consumption on network resource and node energy consumption. Data compression on the relay node within WSN or other processing method will effectively solve the data redundant problem. The data correlation calculation method proposed in this paper also works in the else methods of data processing.

For the issue of WSN correlated data collection, [1-3] consider it as spatio-temporal correlated processes. [1] has shown that an optimal number of nodes exists for gathering data in a spatio-temporally correlated field. [2] presents an analysis framework for estimating spatio-temporal distortion associated with data-gathering algorithms. However, for the data correlation of nodes readings, the analysis is separately independent from spatial and temporal aspect. So we discuss data distortion only on the spatial layer.

Explicit expressions for the spatial distortion in one- and two-dimensional grid scenarios are written in [1], for one-dimensional they consider the networks with $N$ nodes placed on a line of fixed length, and for two-dimensional they consider a square area, on which $N^2$ nodes are uniformly placed on a square grid. Based on [1], [2] improves the two-dimensional as a wheel network topology. Nevertheless, in the usual WSN, nodes are not deployed such regularly, the network topology is quite accordant with particular application. The network topology is stochastic deployment, and the most universal sensing mode is omnidirectional sensing as we assumed in this paper.

Extraction of the data correlation is not only working for distortion analysis, it also be used in the other network protocol design and algorithm. Based on the spatial dimensional they consider a square area, on which $N^2$ nodes are uniformly placed on a square grid. Based on [1], [2] improves the two-dimensional as a wheel network topology. Nevertheless, in the usual WSN, nodes are not deployed such regularly, the network topology is quite accordant with particular application. The network topology is stochastic deployment, and the most universal sensing mode is omnidirectional sensing as we assumed in this paper.

Extraction of the data correlation is not only working for distortion analysis, it also be used in the other network protocol design and algorithm. Based on the spatial
correlation of data, the WSN parameter estimation to random-field and network solutions for MAC Layer and Transport Layer are proposed in [3-4]. It takes advantage of correlation characteristic of spatial information to eliminate network redundancy. And source coding algorithms in WSN are proposed in [5-6]. They seek the optimum rate to compress redundant information, reduce intranet traffic of the network. [7-12] research the clustering method for WSN based on spatial correlation between nodes. All above research considers the effect that spatial distance takes on the correlation of sensor data between nodes. However, there is not a rational model which considers with the real network conditions of WSN. Because of the discrepancy on implementation condition and network configuration, there are many different fitting methods of modeling to extract the data correlation for sensor collected data. So a new model for data correlation is proposed in this paper, it is based on spatial location and is applicable for computing the data correlation between sensor nodes under omnidirectional Boolean sensing mode.

II. ARCHITECTURE FOR WSN

A. The Network Model

While there is widespread agreement in the WSN network frame that the nodes include sensor nodes and sink nodes. Information sensed by sensor nodes will aggregate and be processed at the sink nodes, then transmitted to the high level users. The nodes deployment of WSN is shown as Fig.1, the elliptical area represents the event area which is necessary to known by the sink. The gray node represents sink node, and the white nodes represent sensor nodes, the dashed circles represent valid sensing areas of sensors.

For contrasting, the other topologies are shown in Fig.2(a) and Fig.2(b). As we introduced in section I, [1] considers the networks for two-dimensional as a square area, and [2] considers the two-dimensional as a wheel network topology. On square area, \( N^2 \) nodes are uniformly placed; and on wheel topology, the sensing field is a plate area, sensor nodes are deployed on \( k \) concentric rings, with \( n \) nodes on each ring.

In the follow sections, we supposed that the WSN has characters as

\( a) \) All the sensor nodes in the network are isomorphic, which means that all the sensor nodes have the equal ability of information sensing, transmitting and processing.

\( b) \) All the sensor nodes are modeled as omnidirectional Boolean sensing, which means that all the nodes in the network have a fixed sensing radius, the sensing area is valid within a circle centered by the node’s spatial position, and the sensors have equal reading ability to arbitrary position within the circle, while information outside the circle is not able to be sensed [13].

\( c) \) Sensor nodes do not move any more if they are deployed in the network, so we can know the specific spatial location information of each node, and the distance between it and its neighbors can also be acquired.

B. The System Model

Let \( D \) denote the event area of WSN, \( S = \{s_1, s_2, \cdots\} \), where the subscript denotes the spatial location of the node, denotes the node’s spatial location,
$S \subset D$. $Z$ denotes the original information samples in event area, $\hat{Z}$ is the observation data consisted of all the sensor node’s observation results. Every sensor readings can be represented as function of spatial locations, $Z(s_i)$. $s_i$ denotes the information of single node location.

For every sensor node, the sensor reading is a random variable, each sensor observes the noisy version of a physical phenomenon, so $D$ is a random field. Sink is interested with the highest accuracy in the combination about the random field which includes all the variables. The combination is of multiple point sources where the sink is interested in reconstructing the signal in multiple locations or over an event area.

![System Model](image)

<table>
<thead>
<tr>
<th>Z</th>
<th>Observation</th>
<th>Multi-hop Transmission</th>
<th>$\hat{Z}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Z(s_i)</td>
<td>$\hat{Z}(s_i)$</td>
<td>$\hat{Z}(s_j)$</td>
<td>$\hat{Z}$</td>
</tr>
</tbody>
</table>

The model for the information gathering system of $N$ sensor nodes in an event area is illustrated in Fig. 3.

The original information samples in event area, $Z$, can be denoted as

$$Z(N) = \{Z(s_1), Z(s_2), \cdots, Z(s_N)\}$$

The sink is interested in estimating the event source, according to the observations of all the sensor nodes in the event area. Each sensor node observes $\hat{Z}(s_i)$, the noisy version of the event information $Z(s_i)$,

$$\hat{Z}(s_i) = Z(s_i) + N(s_i)$$

where $N(s_i)$ is the observation noise caused by the sense capability of nodes, and here we assume that $N(s_i)$ is a sequence of Gaussian random variables of zero mean and variance $\sigma_N^2$, which means $N(s_i) \sim N(0, \sigma_N^2)$. We further assume that the noise each sensor node encounters is independent of each other.

The estimation of the source, the combination of all the observations in event area, is received and reconstructed by the sink as

$$\hat{Z} = \{\hat{Z}(s_1), \hat{Z}(s_2), \cdots, \hat{Z}(s_N)\}$$

### III. Distortion Analysis Method

#### A. Data distortion

As illustrated previously, the source of information is a random field. The physical phenomenon is modeled as joint Gaussian random variables at each observation point as

$$E\{Z(s_i)\} = 0, i = 1, 2, \cdots, N$$

$$\text{var}\{Z(s_i)\} = \sigma_i^2, i = 1, 2, \cdots, N$$

The sink is interested in reconstructing the source $Z$ according to a distortion constraint

$$D = E\left[d(Z, \hat{Z})\right]$$

The event source can simply be computed by taking the average of all the event information received at the sink. Assume that $N$ packets are all received by the sink, where $N$ is the total number of sensor nodes in the event area. For simplifying the expression, let $Z_i$ instead of $Z(s_i)$, then the estimate is given as

$$\hat{Z}(N) = \frac{1}{N} \sum_{i=1}^{N} Z_i$$

Use the mean-squared error as the distortion metric, so the distortion estimated the event is given as

$$D(N) = E\left[ (Z - \hat{Z})^2 \right]$$

Using (1) and (2), the distortion function $D(N)$ is found to be

$$D(N) = E\left( Z^2 + \frac{1}{N^2} \left( \sum_{i=1}^{N} \hat{Z}_i \right)^2 - 2Z \cdot \frac{1}{N} \sum_{i=1}^{N} \hat{Z}_i \right)$$

$$= \sigma_s^2 \left( \frac{2N-1}{N} \right) \sigma_s^4 + \frac{\sigma_s^6}{N(\sigma_s^2 + \sigma_N^2)} \sum_{j=1}^{N} \sum_{i=1}^{N} \rho_{ij}$$

where $\rho_{ij}$ represents the correlation coefficients between nodes $i$ and $j$.

#### B. Data correlation based on spatial location

Hence, in the WSN, the correlation of different sensor nodes can be described by their readings’ association character which is covariance between variables in combination $Z$, and

$$\text{cov}\{Z_i, Z_j\} = \sqrt{DZ_i \cdot DZ_j} \cdot \rho_{ij}$$
where correlation coefficients $\rho_{ij}$ denotes the physical correlation caused by different special locations of various sensor readings.

Taking the spatial location of sensor node as independent variable, $K_\rho(|s_i - s_j|)$ is a function of spatial location, and it decreases monotonically with distance $d = |s_i - s_j|$, with limiting values of 1 at $d = 0$ and of 0 at $d = +\infty$. So $\rho_{ij} = K_\rho(|s_i - s_j|)$, $\theta = (\theta_1, \theta_2, \cdots)$ are control parameters of the correlation model, through changing which value, the model computing results can be modified.

The common correlation models based on spatial location are introduced in [14-15], the most conventional models are:
- Power exponential:
  $$K_\rho(d) = e^{-(d/\theta_1)^{\theta_2}}, \quad \theta_1 > 0, \theta_2 \in (0, 2];$$
- Rational quadratic
  $$K_\rho(d) = (1 + (d/\theta_1)^{\theta_2}), \quad \theta_1 > 0, \theta_2 > 0;$$
- Spherical:
  $$K_\rho(d) = \begin{cases} 1 - \frac{3}{2} \cdot \frac{d}{\theta_1} + \frac{1}{2} \left( \frac{d}{\theta_1} \right)^3 & \text{if } 0 \leq d \leq \theta_1, \\ 0 & \text{if } d > \theta_1 \end{cases}, \quad \theta_1 > 0;$$

These models are applicable for different network conditions and not suitable for the special omnidirectional sensing WSN info collection mode. In section IV, we propose a correlation model for the omnidirectional Boolean mode, and we call the model as OD Model for short.

IV. CORRELATION MODEL OF SENSOR READINGS

A. Explanation of Symbols

We use geometry manner to set up the correlation model. As shown in Fig. 4, in the monitoring areas $D$, the meanings of symbols explained as follows:
- $\bar{B}_i$ denotes the round region with center $s_i$ and radius $r$;
- $A_i = \text{Area } \bar{B}_i$ denotes the area of $\bar{B}_i$;
- $\bar{B}_i^j$ denotes the region which is demarcated by the perpendicular bisector of $s_i s_j$, and next to $s_i$ but belongs to $\bar{B}_i$;
- $A_i^j = \text{Area } \bar{B}_i^j$ denotes the area of $\bar{B}_i^j$;
- $A_i^j$ and $A_j^i$ are control parameters of the correlation model, through changing which value, the model computing results can be modified.
- $B$ denotes all the round region distributed in $D$;
- $\bar{B}$ denotes the area of $\bar{B}$;
- $d$ is the distance between $s_i$ and $s_j$;
- $o$ is the middle point of $s_i s_j$;
- $p_1$ and $p_2$ are the intersection points $s_i s_j$ and its perpendicular bisector intersect with the borderline of $B_i$;
- $x$ is the distance between $o$ and $p_1$, and $x = r - d/2$;
- $y$ is the distance between $o$ and $p_2$, and $y = \sqrt{r^2 - d^2/4}$;
- $\alpha$ is the central angle corresponding to $p_1 p_2$, and $\alpha = \arcsin y/r = \arcsin \sqrt{1 - d^2/4r^2}$;
- $A_\alpha$ denotes the area of the sectoral region with central angle $\alpha$ in $B_i$;
- $A_{p_1 p_2}$ denotes the area of the region surrounded by $p_1 p_2$ and $p_1 p_2$, as the shadow area in Fig.4.c

B. The Correlation Model

If $d < 2r$, $B_i$ overlaps with $B_j$, define the correlation as

$$K_\rho(d) \triangleq \frac{A_i^j + A_j^i}{A}$$

From Fig. 4, it is able to compute that

$$A_\alpha = \frac{1}{2} r^2 \cdot \alpha$$

$$A_{p_1 p_2} = A_\alpha - \frac{1}{2} r \cdot y = \frac{1}{2} r (r \cdot \alpha - \sqrt{r^2 - d^2/4})$$
\[ A_i^j = 2A_{pi+p_2} + xy = r^2 \cdot \alpha - \frac{d}{2} \sqrt{r^2 - \frac{d^2}{4}} \]

Therefore, (4) is transformed to

\[ K_\theta(d) = \frac{A_i^j}{A_i - A_i^j} \]

\[ r^2 \cdot \arcsin \left[ 1 - \frac{d^2}{4r^2} \right] - \frac{d}{2} \sqrt{r^2 - \frac{d^2}{4}} \]

\[ r^2 (\pi - \arcsin \left[ 1 - \frac{d^2}{4r^2} \right]) + \frac{d}{2} \sqrt{r^2 - \frac{d^2}{4}} \]

Let \( \theta = 2r \) (5) is simplified as

\[ K_\theta(d) = \frac{\theta^2 \cdot \arcsin \left[ 1 - \frac{d^2}{\theta^2} \right] - \sqrt{\theta^2 - d^2}}{\theta^2 (\pi - \arcsin \left[ 1 - \frac{d^2}{\theta^2} \right]) + \sqrt{\theta^2 - d^2}} \]

Consequently, the correlation model is rewritten as

\[ K_\theta(d) = \begin{cases} 
\frac{\theta^2 \cdot \arcsin \left[ 1 - \frac{d^2}{\theta^2} \right] - \sqrt{\theta^2 - d^2}}{\theta^2 \cdot \arcsin \left[ 1 - \frac{d^2}{\theta^2} \right] + \sqrt{\theta^2 - d^2}}; & 0 \leq d \leq \theta \\
0; & d > \theta 
\end{cases} \]  

C. Likelihood of Model Parameters

For better analyzing the likelihood of model parameters and without loss of generality, we assume that the WSN monitoring area \( D \) is a Gaussian random field, and the sensor readings set \( Z = \{Z(s_1), Z(s_2), \ldots, Z(s_N)\} \) follows the gauss distribution, \( E\{Z(s)\} = \mu \), \( \text{var}\{Z(s)\} = \sigma^2 \).

\[ E\{Z(s)\} = \sum_{j=1}^p \beta_j f_j(s) = \beta' f(s) \]

where, \( \beta = (\beta_1, \ldots, \beta_p)' \) are unknown regression parameters, \( f_j(s) = (f_{1j}(s), \ldots, f_{pj}(s))' \) are known location dependent covariates. Based on the observation results \( Z(s) \), the likelihood of model parameters \( (\beta, \sigma^2, \theta) \) is given by

\[ L(\beta, \sigma^2, \theta; z) = \frac{1}{(2\pi\sigma^2)^\frac{N}{2}} |\Sigma_\theta|^{-\frac{1}{2}} \exp \left\{ -\frac{1}{2\sigma^2} (Z - X\beta)' \Sigma_\theta^{-1} (Z - X\beta) \right\} \]

Where, \( X \) is known \( n \times p \) matrix, \( X_{ij} = f_j(s_i) \); \( \Sigma_\theta \) is \( n \times n \) matrix defined by

\[ \Sigma_{\theta,ij} = K_\theta \left( \|s_i - s_j\| \right) \].

V. EXPERIMENT AND SIMULATION

We adopt Matlab to carry through scene modeling and simulation of model performance. Firstly, the model effectiveness for node under simulative work surroundings is verified, and performance is analyzed based on model control parameters. Then, for the universal WSN application scenario, the sensor readings correlation result under omnidirectional Boolean sensing mode is given through OD Model.

A. Model Performance Analysis

Suppose the sensing radius is 4.5m which is limited by power of the sensor nodes. In the monitoring range of WSN, the occurrence of the event uses the equiprobable random distribution.

Fig. 5 compares the results for computing data correlation, and using different models including the OD Model proposed in this article and other models of Power exponential, Rational quadratic and Spherical. From the Fig. 5 we can figure out that when the node distance \( d \) varies from 1 to 12m, the value for each model will decrease from 1 gradually. The result of Spherical model is much closer to the OD Model proposed in this article.

Because of the threshold, the value for these two models are 0 when \( d = 2r \), which is accorded with the restriction condition of Boolean sensing mode. The simulation result also shows after comparing with the simulated data, the result of OD Model is very close to the simulated actual data, this proves that this model is more efficient than the other models.

To continue detailed simulation, we focus on the performance of control parameter and accuracy of the OD Model under the simulated condition in figure 2. The result of Fig. 6(a) shows that the value of control parameter \( \theta \) affects the accuracy of OD Model significantly, and deviation of the value between \( \theta \) and \( 2r \) is inversely proportional to the accuracy of calculation result. Consequently, to get satisfactory calculation accuracy, the control parameter must according to the network situation. Fig. 6(b) makes a contrast for error of OD Model with various deviation degree of control parameter and accuracy of the OD Model, less than 0.01 can be arrived.

B. WSN topology Simulation

We design several scenario simulations for universal WSN application.

Scenario I: In the 100×100m square area, 200 nodes are distributed by total random way, the topology is shown as Fig.7.
Scenario II: In the 100×100m square area, 200 nodes are distributed by Salama random way, the topology is shown as Fig. 8.

Scenario III: Thirty sensor nodes are distributed with the way of Salama random topology in a 50×50 square area. The sensing radius is 4.5m, and the control parameter is set as 9m. The network topology is shown in the Fig. 9; the asterisks represent node positions, and the numbers beside asterisks represent node labels. Every two nodes are connected by a solid line when the data correlation is greater than zero, and the distance between the two nodes is shown in the middle of the line.
C. Model Application Simulation

We give a group result of distance and data correlation calculated by OD Model as an example, which is shown in the Table I. calculated with the scenario in Fig. 9 by the order of node labels.

<table>
<thead>
<tr>
<th>Node label</th>
<th>Node distance</th>
<th>Correlation result</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1, 4)</td>
<td>7.2428</td>
<td>0.0529</td>
</tr>
<tr>
<td>(1, 6)</td>
<td>8.7109</td>
<td>0.0035</td>
</tr>
<tr>
<td>(2, 6)</td>
<td>8.6229</td>
<td>0.0051</td>
</tr>
<tr>
<td>(3, 7)</td>
<td>7.0335</td>
<td>0.0630</td>
</tr>
<tr>
<td>(4, 8)</td>
<td>7.5133</td>
<td>0.0409</td>
</tr>
<tr>
<td>(5, 9)</td>
<td>4.8809</td>
<td>0.2085</td>
</tr>
<tr>
<td>(7, 10)</td>
<td>8.3126</td>
<td>0.0127</td>
</tr>
<tr>
<td>(8, 10)</td>
<td>8.9218</td>
<td>4.8617e-004</td>
</tr>
<tr>
<td>(9, 11)</td>
<td>7.9962</td>
<td>0.0225</td>
</tr>
<tr>
<td>(9, 12)</td>
<td>4.6262</td>
<td>0.2312</td>
</tr>
<tr>
<td>(9, 13)</td>
<td>6.3257</td>
<td>0.1023</td>
</tr>
<tr>
<td>(11, 13)</td>
<td>5.9641</td>
<td>0.1254</td>
</tr>
<tr>
<td>(11, 18)</td>
<td>8.9235</td>
<td>4.6978e-004</td>
</tr>
<tr>
<td>(12, 17)</td>
<td>8.6389</td>
<td>0.0048</td>
</tr>
<tr>
<td>(13, 15)</td>
<td>7.0341</td>
<td>0.0630</td>
</tr>
<tr>
<td>(13, 18)</td>
<td>6.7369</td>
<td>0.0785</td>
</tr>
<tr>
<td>(14, 17)</td>
<td>8.8982</td>
<td>7.2095e-004</td>
</tr>
<tr>
<td>(15, 16)</td>
<td>6.7593</td>
<td>0.0772</td>
</tr>
<tr>
<td>(16, 19)</td>
<td>7.8696</td>
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</tr>
<tr>
<td>(19, 21)</td>
<td>7.0364</td>
<td>0.0628</td>
</tr>
<tr>
<td>(20, 24)</td>
<td>5.9592</td>
<td>0.1258</td>
</tr>
<tr>
<td>(22, 24)</td>
<td>5.8051</td>
<td>0.1363</td>
</tr>
<tr>
<td>(23, 26)</td>
<td>7.7828</td>
<td>0.0301</td>
</tr>
<tr>
<td>(25, 29)</td>
<td>6.1063</td>
<td>0.1161</td>
</tr>
<tr>
<td>(26, 28)</td>
<td>5.2555</td>
<td>0.1773</td>
</tr>
</tbody>
</table>

To performed a case study using the distortion function (3), simulations were done for a fixed topology with 1000 trials for each number of nodes. Event area is selected randomly among the 30 nodes for each trial, and the distortion function is calculated by 1 to 30 nodes of event area according to the locations of these nodes. The average distortion calculated from these simulations and the distribution of the distortion for each number of event area nodes is shown in Fig. 10.

We use the OD model with $\theta = 5, 9, 15, 20$ in (7), as shown in Fig. 10, with increasing $\theta$, the total event distortion $D(N)$ decreases. Because of the increasing of $\theta$, the valid sensing area of sensor is enlarged, and the highly redundant data sent by the sensor nodes are close to each other, the total distortion decreases. However, in the actual applications, $\theta$ can not be infinitely increased due to the sensing ability and power of sensor nodes.

VI. CONCLUSIONS

According to the most universal mode of omnidirectional Boolean sensing, this paper proposed a WSN data distortion analysis method and a data correlation model based on spatial locations. The correlation model has advantages of low computed complexity and flexibility of adjustable control parameter. The simulation results show that in the random node distribution scenarios, the model is effective and up to the standard of accuracy. Moreover, by using the model, a distortion case study is performed. In conclusion, the data correlation model proposed in this paper is competent for extracting the sensor readings correlation, and it is not only working for distortion analysis, it also can be helped for providing correlation parameters to other researches in WSN such as protocol design, routing planning, and data compression.

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