# A novel spatial correlation model for wireless sensor network applications

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Dr.Rajeev K. Shakya
Adama Science and Technology University



Yatindra Singh
Indian Institute of Technology Kanpur

# A Novel Spatial Correlation Model for Wireless Sensor Network Applications

Rajeev K. Shakya, Yatindra Nath Singh, and Nishchal K. Verma
Department of Electrical Engineering, Indian Institute of Technology Kanpur
Email: {rajeevs,ynsingh,nishchal}@iitk.ac.in

***Abstract*—Wireless sensor networks (WSN) are densely deployed to promise the fine-grain monitoring in various applications. For example, it may be as high as 20 $nodes/m^3$ or more [1]. Due to high density of sensor nodes, spatially correlated information is observed and transmitted by surrounding sensor nodes once an interest of event detected. Thus, there exists spatial correlation among the sensor observations. The spatial correlation brings significant potential advantages along with collaborative nature of the WSN in energy-efficient design of communication protocols. This paper presents a novel spatial correlation model for wireless sensor networks. Based on sensor coverage model and location of sensor nodes, a spatial correlation function is derived to describe the correlation characteristics of measurements observed by sensor nodes. The case studies using correlation function are performed to study the correlation relationship between sensor nodes. Finally, based on case studies, their results, and discussions, a correlated cell construction algorithm is proposed and possible approaches are explored to exploit spatial correlation for efficient medium access and clustering protocols for WSN.**

***Index Terms*—spatial correlation, MAC protocol, Clustering protocol,Wireless Sensor Networks.**

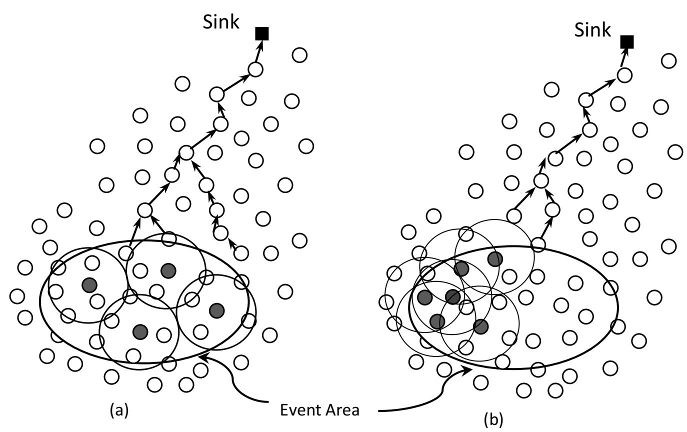


Fig. 1. Examples of reporting of event information in an event area for wireless sensor networks.

## I. Introduction

The recent developments of wireless sensor network (WSN) have enabled low cost, low power sensor nodes which are capable of sensing, processing and transmitting sensory data from sensing environment such as surveillance fields. These sensor nodes cooperatively monitor physical environmental conditions (for examples temperature, sound, pressure etc.) accurately in space and time to detect the events of interest. Since sensor nodes have limited battery power which gets depleted easily, the sensor nodes will die out in the network. The failure of nodes should not affect the overall performance of the network. However, It could be impossible to replace/change the battery, because sensor nodes may be deployed in remote locations and thus replacing the batteries could be costly or time-consuming. A significant amount of energy is consumed in transmission and reception and idle mode, while very low energy loss in sleep mode. Therefore, forcing the nodes into sleep mode whenever possible will be optimal solution to increase life-time of the network.

The primary function of a sensor network is to sample sensory information from its vicinity such as temperature, light etc., and send this information to the base station node. The base station node mostly forwards all the data wire-line or an independent wireless network to control center. The sensor nodes in such network operate as a collective structure which makes this network different than traditional ad-hoc networks. Due to high density of sensor nodes spatially correlated information is observed and transmitted by surrounding sensor nodes once an interest of event appeared in sensor field. Thus it may not be necessary that every sensor nodes should report its sensed data to the sink due to redundancy in data. For example, in Fig. 1(a), four black nodes denote active nodes inside event area, and big circle denotes the correlation region, in which sensor nodes have similar readings. We can see that these four sensor nodes are selected according to correlation region to cover whole event area. Hence observed information from these selected sensor nodes are sufficient to detect/estimate the event source at the sink. In addition, it is also noted here that redundant reports are minimized according to correlation characteristics among sensor nodes. For example, in Fig. 1(b) the six black nodes are insufficient to cover the entire event area and redundant information is also observed from these nodes at sink. The correlation in WSN and exploiting the correlation of sensory data have been studied by Vuran et al. [2], Scaglione and Servetto [3], Yoon and Shahabi [4], Guoqiang et al. [5] and so on.

In this paper, we study the correlation characteristics among sensor nodes for sensor network applications. Based on sensor coverage model and location of nodes, we propose a mathematical framework to drive correlation function for sensor

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network applications. More specifically, given a certain area of interest, suppose there are $N$ sensor nodes that can sense it. We will derive a correlation coefficients to describe the degree of correlation between $N$ sensor nodes. After getting the spatial correlation coefficient (i.e. correlation function), we study relationship between positions of nodes and correlation function. Intuitively, the spatial correlation between sensor nodes is directly related to the correlation characteristics of event information observed by these sensor nodes. If the sensor nodes are less correlated, they will provide more reliable information to the sink. An example is shown in Fig.1. Thus, some possible approaches are also discussed to exploit spatial correlation for efficient medium access and clustering protocols for WSN. Finally, the case studies are performed and a correlation set construction algorithm is proposed based on results and analysis.

The rest of the paper is organized as follows. Section II briefly states the problem to be studied. The spatial correlation function along with case studies is introduced in Section III. Finally the conclusion is presented in Section IV, followed by references.

## II. Problem Statement

In densely deployed WSN, many sensor nodes in an event area observe the event information and send this information to the sink. Due to physical properties related to sensed event, this information is highly correlated according to degree of correlation between sensor nodes based on location of sensor nodes. Fig. 1 gives the examples of such behavior. For a certain area of interest, suppose there are $N$ sensor nodes that can sense it, we denote them $N = \{n_1, n_2, n_3, ...\}$ with spatial coordinates, $\{s_1, s_2, s_3...\}$. There exists correlation among these nodes based on location, which can be exploited to increase the overall network performance.

## III. Proposed Correlation Model

In this section, we present a correlation model that derives the correlation function to describe the characteristics among sensor nodes for sensor network applications. It helps in determining the mutually correlated nodes based on spatial location in randomly deployed sensor networks. We first consider the sensor deploying model stating all assumptions in next section, before presenting the proposed correlation model. The performance evolution, discussions, and case studies are then performed to gain more insight using correlation model for the development of possible communication approaches for WSN.

### A. Sensor Deploying Model

Consider a sensor network application where large number of sensor nodes are deployed randomly over the surveillance region. An example of nodes deployment for WSN is shown in Fig. 2. The circle area indicates the event area; the dashed circle represents valid sensing area of the sensors; black node represents sink node; white nodes represent sensor nodes; and a random event is represented by star. Recall that wireless

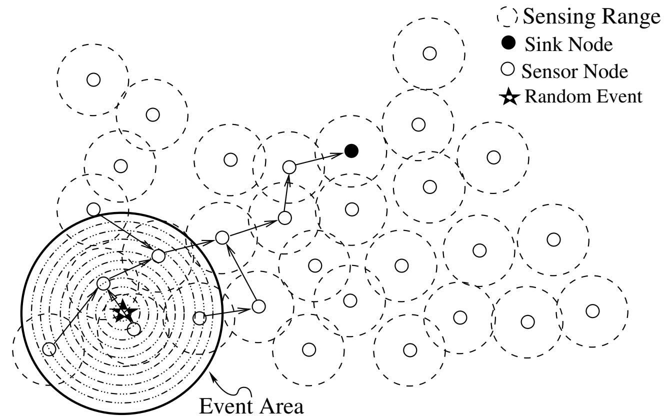


Fig. 2. The model architecture

sensor networks are characterized by their coverage range (i.e., sensing range for detecting the events) and transmitting range (for communicating with sensor nodes). The followings are a few reasonable assumptions. (i) All the sensor nodes are assumed to follow the boolean disk coverage Model, which means that sensor nodes have fixed sensing radius and sensing area is represented by a disk centered at the sensor node's spatial position. All the events within such a disk is sensed by the sensor node while no event outside the disk, is sensed. This sensing model is traditionally known as omni-directional sensing model [6]. (ii) Apart from sensing range, each sensor node has a communication range which is much larger than sensing range. (iii) The sink node is only interested in collective reports from all nodes of a detected event. (iv) There is no movement among sensor nodes after deployment, so the location information of each node is known and distance between its neighbors can also be acquired.

### B. The correlation Model

In this section, we derive a correlation function to describe the degree of correlation among sensor nodes in the event area. Since a boolean disk coverage model is considered with sensing range $r$ at location $s_i$, $s_j$, the fraction of common sensing area covered by two circular disks represents the correlation coefficient, denoted by $K_\theta\{||s_i - s_j||\}$ which is function of distance (i.e., $||s_i - s_j||$) between sensor node $n_i$ and $n_j$ as shown in Fig. 3. Here $\theta$ will be a control parameter discussed later.

It is noted that intuitively, the spatial correlation between sensor nodes is directly related to the correlation characteristics of event information observed by these sensor nodes in spatial domain [2].

To find the correlation coefficient among $N$ nodes in event area, assuming that $N$ nodes observe the event source $S$ in the event area. We then construct a mathematical model to compute the correlation with respect to event source $S$. The correlation between different sensor nodes can be described by their readings, which will be represented as a covariance function in set $Z$. From statistical properties, here $Z$ is

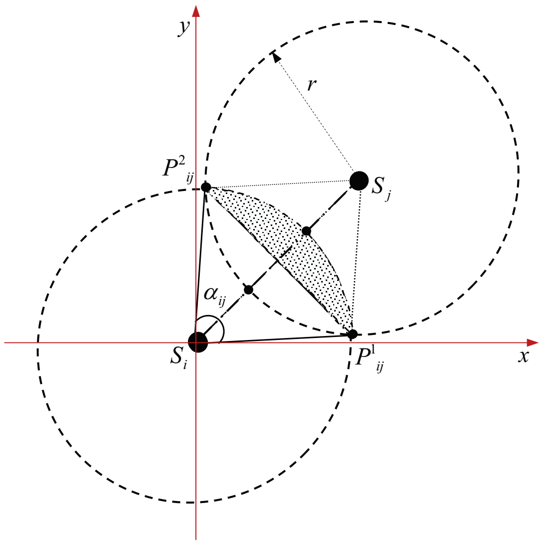


Fig. 3. The spatial circular correlation model

assumed to be a random matrix associated with measured readings of sensor nodes (i.e. correlation coefficients).

Consider event area $S$ is random field, total sensor nodes, $N = \{n_1, n_2, n_3, ...\}$ are within event area with spatial coordinates, $\{s_1, s_2, s_3 ...\}$. The data set $Z = \{z(n_1), z(n_2), z(n_3), ...\}$ contains the measured information from all the sensor nodes. The sink node will be responsible for collecting these readings to compute the correlation characteristics between sensor nodes.

Note that since event area is random variable, so $Z$ is also assumed to be random variable. We use the notations $z_i$,$z_j$ instead of $z(n_i)$, $z(n_i)$ for simplicity. The data set $Z$ is associated with covariance function $K_\theta(.)$, which is function of correlation coefficients between the sensor nodes. Now, we found from statistical properties:

$$corr\{z_i, z_j\} = \frac{cov\{z_i, z_j\}}{var\{z_i\}.var\{z_j\}} = K_\theta\{||s_i - s_j||\} \qquad (1)$$

where $K_\theta\{||s_i - s_j||\}$ denotes the correlation coefficient of sensor node $n_i$ and $n_j$. The $K_\theta\{||s_i - s_j||\}$ decreases monotonically with distance $d$ (i.e. $||s_i - s_j||$) between sensor node $n_i$ and $n_j$, located at $s_i$ and $s_j$ respectively.

*1) Symbols and notation used:* In this section, we use geometric notation to design a mathematical model using two sensor nodes with disk coverage of radius $r$. As shown in Fig. 3, the symbols used are as follows.

- $S_i$ denotes the sensing region of node $n_i$ that is a circular area with radius $r$ centered at $s_i$.
- Each sensor nodes pairs $n_i$ and $n_j$ have common sensing area with triple $(P^1_{ij}, P^2_{ij}, \alpha_{ij})$, where $(P^1_{ij}, P^2_{ij})$ indicates the two intersections between $s_i$ and $s_j$, and $\alpha$ denotes the effective angle.
- $d_{(i,j)}$ is the distance between nodes pairs located at $s_i$ and $s_j$.
- $L_{ij}$ is the chord length, denoted by length of connected line between two intersections given by $(P^1_{ij}, P^2_{ij})$, where $L_{ij} = 2.\sqrt{r^2 - d^2_{(i,j)}/4}$.
- $A$ is area of the circular region.
- $A^j_i$ is area of region surrounded by arc denoted by $\overset{\frown}{P^1_{ij}P^2_{ij}}$ for $S_i$ and chord denoted by $\overline{P^1_{ij}P^2_{ij}}$ (shown by shaded area).
- $A^i_j$ is area of region surrounded by arc denoted by $\overset{\frown}{P^1_{ij}P^2_{ij}}$ for $S_j$ and chord denoted by $\overline{P^1_{ij}P^2_{ij}}$.

*2) The correlation model:* If $d_{(i,j)} < 2r$, $S_i$ overlaps with $S_j$, then we define the correlation as

$$K_\theta(d_{(i,j)}) = \frac{A^j_i + A^i_j}{A} \qquad (2)$$

where $K_\theta(d_{(i,j)})$ is the decreasing function with distance $d$, following the limiting value of 1 at $d_{(i,j)} = 0$ and of 0 to $d_{(i,j)} \geq 2r$. The $A^j_i$ and $A^i_j$ are same due to symmetry as shown in Fig. 3.

$$A^j_i = \frac{r^2 \cos^{-1}(\frac{d_{(i,j)}}{2r})}{2} - \frac{L_{ij} d_{(i,j)}}{4} = A^i_j \qquad (3)$$

From Eq. (2), we get

$$K_\theta(d_{(i,j)}) = \frac{\cos^{-1}(\frac{d_{(i,j)}}{2r})}{\pi} - \frac{d_{(i,j)}}{2\pi r^2} s.\sqrt{(r^2 - \frac{d^2_{(i,j)}}{4})} \qquad (4)$$

Let $\theta$ be a control parameter, and $\theta = 2r$, Eq. (4) is simplified as

$$K_\theta(d_{(i,j)}) = \frac{\cos^{-1}(\frac{d_{(i,j)}}{\theta})}{\pi} - \frac{d_{(i,j)}}{\pi\theta^2}.\sqrt{(\theta^2 - d^2_{(i,j)})} \qquad (5)$$

We see that when $d_{(i,j)} = 2r$, the correlation model gives zero value. It means that there is no correlation between sensor nodes. So, we introduce a control parameter $\theta$ equal to $2r$, as a variable to control the correlation among nodes. Thus, the correlation model can be rewritten in general form as follow.

$$\begin{aligned} K_\theta(d) &= \tfrac{\cos^{-1}(\frac{d}{\theta})}{\pi} - \tfrac{d}{\pi\theta^2}.\sqrt{(\theta^2 - d^2)} \\ & \qquad\qquad \text{For } 0 \leq d \leq \theta; \\ &= 0 \qquad\qquad \text{For } d > \theta. \end{aligned} \qquad (6)$$

where $\theta = 2r$, and $d = ||s_i - s_j||$.

It is clearly seen from Eq. (6) that when covariance function $K_\theta(d)$ is 0, it means that there is no correlation between sensor node $n_i$ and $n_j$, located at distance $d$ to each other. If it is equal to 1, then sensor nodes are highly correlated.

### C. Discussion

In sensor network applications, as long as area of interest is specified, the correlation characteristics of sensory observations of nodes can be obtained as given in previous Section. The proposed correlation model can be used to design distributed source coding between sensor nodes as well data aggregation of sensor measurements in WSNs. The distributed source coding is a compression mechanism used

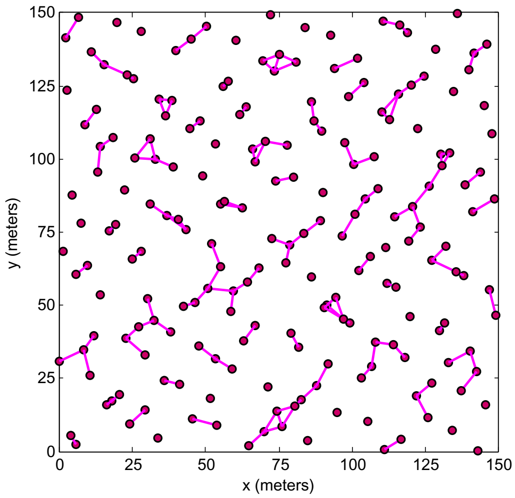


Fig. 4. Random distribution of 200 nodes with $\theta = 9$.

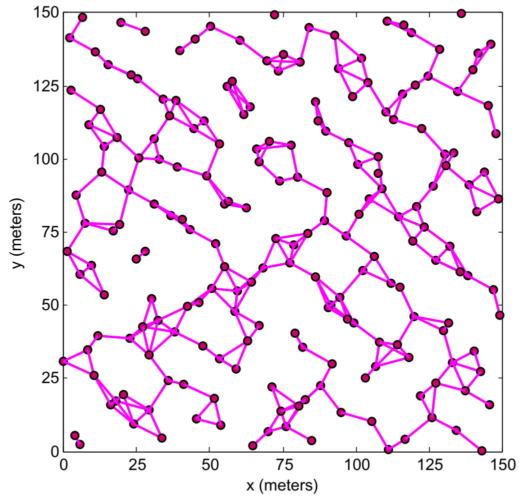


Fig. 5. Random distribution of 200 nodes with $\theta = 12$.

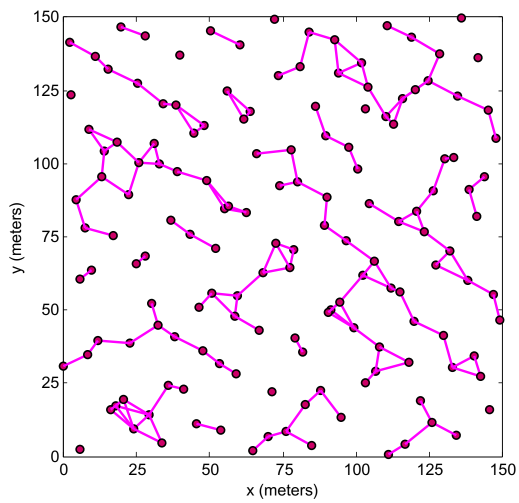


Fig. 6. Random distribution of 150 nodes with $\theta = 12$.

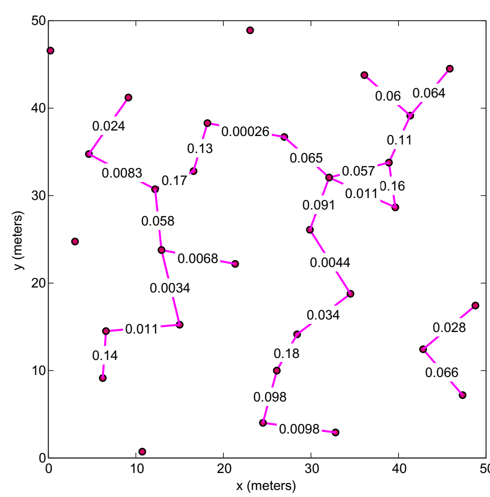


Fig. 7. Random distribution of 30 nodes with $\theta = 9$.

to reduce spatial correlation between sensor nodes. However, the proposed model is a general correlation model that can be applied to all sensor network applications, because the assumptions used in this model are common for WSNs. The sensor coverage model is the traditionally used sensing model for WSNs. Generally, sensor nodes are equipped with temperature, humidity, magnetic sensors etc. These sensors can sense in $360^\circ$ around the sensor node. So unit disk coverage model (also known as omni-directional sensing model) is valid for WSNs [6]. The proposed correlation model is different from common covariance models given in [7], because it considers the real network conditions of WSNs such as location of nodes, sensing range, and distance between them.

In addition, the proposed correlation model can help in design of energy-efficient communication protocols for WSNs. For example, the Vuran et al. [8] and Guoqiang et al. [5] have used different covariance functions [7] to determine the relationship between the locations of sensor nodes and event estimation reliability in order to design energy-efficient MAC protocol. We can apply our proposed correlation model to the work by Vuran et al. [8] and Guoqiang et al. [5] respectively. A comparative study with existing correlation models will be extensions of this work.

### *D. Case study for correlation function, $K_\theta(d)$*

We present the computation results using MATLAB for randomly distributed 200 and 150 nodes in 150x150m area (as shown in Figs. 4, 5, and 6) and for 30 nodes in 50x50m area (as shown in Fig. 7). The correlation relationship between nodes has been drawn by varying control parameter $\theta$. If the value of $K_\theta(d)$ between two nodes is greater then zero, then they are connected using a solid line. In Figs. 4 and 5, a node-pair with $K_\theta(d)$ equal to zero does not show any correlation (i.e. no connected line), because both the nodes are out of sensing range of each other. The distribution of 200 nodes with $\theta = 9$ (i.e. r = 4.5m) is shown with a few connected lines, it means less number of nodes are in correlation distance (see

Fig. 4). Given location of nodes, if we change the sensing range, more connected lines appear. It indicates more nodes are correlated with their neighboring nodes (see Fig. 5). When node density changes for given fixed sensing radius (i.e. $\theta$), correlation function between nodes is also changed due to change in location of nodes as shown in Fig. 6. In Fig. 7, we see the calculated correlation function value in the middle of the lines connected between two nodes. It is clearly seen from plots that according to sensing range and position of nodes, the nodes divide into groups like clusters such that the nodes in a cluster have spatial correlation given by correlation function, $K_\theta(d)$. In next subsection, this property is discussed in more details.

### *E. Partition of event sensing area in correlated cells*

From the results discussed in previous section, we can determine the number of nodes which falls under weak correlation or strong correlation according to sensing radius $r$ and location of sensor nodes. In other words, larger the overlapped area between nodes stronger is the correlation among them. So we define a correlation threshold $\xi$ for $0 < \xi \leq 1$ which follows two properties:

- If $K_\theta(d_{(i,j)}) \geq \xi$, the node $n_i$ and node $n_j$ are strongly correlated neighbor of each other.
- If $K_\theta(d_{(i,j)}) < \xi$, the node $n_i$ and node $n_j$ are weakly correlated neighbor of each other.

Both the above properties depend on sensing radius $r$ (i.e., $\theta$) and node density in event area.

From Eqs. (1) and (6), we can determine the correlation relationship between sensor nodes $n_i$ and $n_j$. If the sensor nodes are highly correlated in the spatial domain, then

$$corr\{z_i, z_j\} = K_\theta\{||s_i - s_j||\} \geq \xi \tag{7}$$

By using Eq (6),

$$\frac{\cos^{-1}(\frac{d_{(i,j)}}{\theta})}{\pi} - \frac{d_{(i,j)}}{\pi\theta^2}.\sqrt{(\theta^2 - d^2_{(i,j)})} \geq \xi \tag{8}$$

where $d_{(i,j)}$ is Euclidean distance between sensor node $n_i$ and $n_j$ which is given by

$$d^2_{(i,j)} = (x_i - x_j)^2 + (y_i - y_j)^2 \tag{9}$$

Comparing Eq. (9) with equation of a circle with radius $R$, as given

$$(x_i - x_j)^2 + (y_i - y_j)^2 = R^2 \tag{10}$$

Using Eqs. (8), (9) and (10), we can determine the radius $R$ as a circular correlation range of each sensor node $n_i$, where node $n_i$ is located in the center. Thus, we call it as correlation region, denoted by $R_{corr}$. Therefore, we get final expression by replacing $d_{(i,j)}$ to $R_{corr}$, as follow.

$$\xi = \frac{\cos^{-1}(\frac{R_{corr}}{\theta})}{\pi} - \frac{R_{corr}}{\pi\theta^2}.\sqrt{(\theta^2 - R^2_{corr})} \tag{11}$$

The Eq. (11) gives important relationship in terms of parameters $\theta$, $\xi$ and $R_{corr}$. It is found that strong correlated nodes are the nodes located within a circle with the radius of $R_{corr}$ of node $n_i$. Hence the value of $\xi$ controls the number of nodes which are within a correlation region.

**Algorithm 1** Correlated cell construction

**Input:** Graph G
**Output:** Set of cells in Graph G
$v$ = Set of all vertices in Graph G.
$C$ = Set of all cells
$R_{corr}$ = Radius of correlation region

**function:**
**for** each vertex $v$ in graph G **do**
  $Q := v$
  $S :=$ empty set
  **while** Q is not an empty set **do**
    $u := \text{argmax}\{dist[Q]\}$
    $S := S$ union $\{u\}$
    **for** each edge $(u, v)$ **do**
      **if** $dist(u, v) \leq R_{corr}$ **then**
        $S := S$ union $\{v\}$
      **end if**
      $Q := Q - \{v\}$
    **end for**
  **end while**
  Construct a new cell $C$
  $C := S$
  $v := v - \{C\}$
**end for**
**return** $C = \{C_1, C_2, ...\}$
**end function**

Based on results obtained using correlation function $K_\theta(d)$ and Eq. (11), Following discussions can be made.

**Remark 1.** If the neighboring node $n_j$ falls under the circular correlation region $R_{corr}$ of node $n_i$, node $n_j$ is in strong correlation range of node $n_i$.

**Remark 2.** If the neighboring node $n_j$ is outside the circular correlation region $R_{corr}$ of node $n_i$, node $n_j$ is in weak correlation range of node $n_i$.

**Remark 3.** For given parameters $\theta$, $\xi$ and the densely deployed WSN can be partitioned into disjoint and equal-sized hexagon cells with radius $R_{corr}$.

**Remark 4.** Since each cell formed by sensor nodes represents the highly correlated region, a significant amount of energy saving is possible by selecting only a single node from each cell to transmit sensed data due to redundancy.

**Remark 5.** The value of $\xi$ should be determined according to application requirements i.e., certain data resolution/reliability which is measure of how close the correlation is in measurements of sensor nodes. The strong spatial correlation allows a larger value of $\xi$.

Motivated by the above outcomes, we develop a dynamic clustering approach to exploit the spatial correlation in measurements with wireless sensor networks. Our solution is to dynamically group the nodes into a set of disjoint clusters such that nodes into a cluster have strong spatial correlation and hence, greater redundancy in measurements. Therefore, all the nodes in a cluster can be treated as equally, and only a small fraction of nodes (or at least one node) are required to be active for serving as the representatives to whole cluster. Without loss of event quality in measurements (i.e. reliability/Distortion), remaining node can sleep in a cluster. As illustrated in **Algorithm 1**, we model it as a graph $G$ such that each nodes denotes vertex in graph and distance between an edge $(u, v)$ is denoted by $dist(u, v)$. The basic idea is to find nodes (i.e. vertex) with radius $R_{corr}$ that cover more vertices which is not clustered. The output of this algorithm is a set of cells that cover all the vertices.

### *F. Discussion*

Results and analysis using proposed correlation model show that model identifies the degree of correlation in information observed by sensor nodes based on location of sensor nodes. By exploiting the spatial correlation, we can avoid the redundant information observed by nodes. The our proposed correlation model can do the best by partitioning the entire event area into correlated disjoint and equal-sized hexagons with radius $R_{corr}$. In this case, a clustering mechanism is responsible to exploit the spatial correlation in event area so that redundant transmissions from correlated neighbors can be suppressed more effectively. Exploiting the spatial correlation can be done into two phases using our proposed correlation model, as following. In first phase, each cluster-head run the procedure of **Algorithm 1** before execution of its dynamic clustering procedure. Hence cluster-head divides its clustered region into highly correlated regions according to application requirements in term of required reliability/distortion. Then in next phase, cluster-head will select only one member node in each correlation region to remain active during current round. After correlation-based selection, clustering protocol can execute its dynamic procedure on currently selected active member nodes. For example, best clustering protocol, LEACH [9] can perform the above operation before executing its dynamic clustering on selected active sensor nodes. Therefore, entire sensor field is represented by a subset of active sensor nodes which perform its task well. In each round, clustering protocol can repeat the above procedure dynamically, further by exploiting the spatial correlation according to immediate application requirements in term of reliability/distortion. More specifically, the cluster-head can run above procedure whenever there is need to change on the closeness among sensor nodes (by tuning $\theta$), required reliability/distortion (by tuning $\xi$), and active member nodes due to depletion of energy of active member node. Therefore network-lifetime can be improved dynamically using proposed correlation model.

## IV. Conclusion and Future work

In this paper, a mathematical framework is introduced to find accurate information about correlation characteristics between sensor nodes based on location. We showed via mathematical analysis, their results, and discussions that our proposed correlation model determines accurate correlation measure between sensor nodes based on sensing coverage. We found that the densely deployed WSN can be partitioned into non-overlapping correlation regions. Hence, a significant amount of energy saving can be possible by exploiting the spatial correlation. Based on mathematical framework, possible approaches are also discussed to design MAC and clustering protocols taking the advantage of spatial correlation between nodes. To design energy-efficient communication protocols for WSN, we conclude that the energy can be optimized further by the adjustment of the parameters, $\theta$ and $\xi$ using proposed correlation model.

In future, we will extend our work for two folds. On one hand, we will extend our work by comparing proposed correlation model with existing correlation models, for example, given by Vuran et al. [8] and Guoqiang et al. [5]. On the other hand, We will also use this model to guide the development of MAC and routing protocols and evaluate the efficiency in terms of energy, latency, and distortion.

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