Energy-Efficient Data Acquisition in Wireless Sensor Networks through Spatial Correlation

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***Abstract* - The application of Wireless Sensor Networks (WSNs) is restrained by their often-limited lifetime. A sensor node's lifetime is fundamentally linked to the volume of data that it senses, processes and reports. Spatial correlation between sensor nodes is an inherent phenomenon to WSNs, induced by redundant nodes which report duplicated information. In this paper, we report on the design of a distributed sampling scheme referred to as the 'Virtual Sampling Scheme（VSS）'. VSS is formed from two components: an algorithm for forming virtual clusters and a distributed sampling method. VSS primarily utilizes redundancy of sensor nodes to get only a subset to sense the environment at any one time. Sensor nodes that are not sensing the environment are in a low-power sleep state, thus conserving energy. Furthermore, VSS balances the energy consumption amongst nodes by using a round robin method.**

Index Terms - Virtual cluster; wireless sensor networks; spatial correlation.

I. INTRODUCTION

Wireless Sensor Networks (WSNs) consist of multiple sensor nodes [1] deployed over an area for monitoring some phenomena or tracking targets. In target tracking WSNs, sensor nodes cooperate to acquire the signal of the spatially and temporally dynamic target. Generally, a sensor node is powered by a local battery which has a limited energy budget. There is a contradiction for a sensor node that it should have a sufficient lifetime to finish the application task, while recharging the battery can be difficult, costly and even impossible in a hostile environment. Although a sensor node can be powered by energy harvesting technology [2], the energy obtained from the external environment is dependent on the environmental conditions and is rarely continuous.

Energy conservation is an important research field for WSNs. Anastasi et al. classified the majority of energy conservation techniques into duty cycled and data-driven approaches [3]. Communication protocols, such as S-MAC [4], commonly adopt a duty cycled approach. When communication is not required, a sensor node switches into a low-power sleep state to reduce the energy consumption. Recent research has shown that some types of sensors can consume more energy than the communication process [5]. Data-driven approaches to conserve energy can eliminate unnecessary sensing by adjusting the sample frequency and reducing the number of sensor nodes which participate in sensing. Methods of energy conservation often aim to put more sensor nodes into a sleep state, but tracking applications usually require a certain number of sensor nodes to be activate in order to sufficiently sample the target signal.

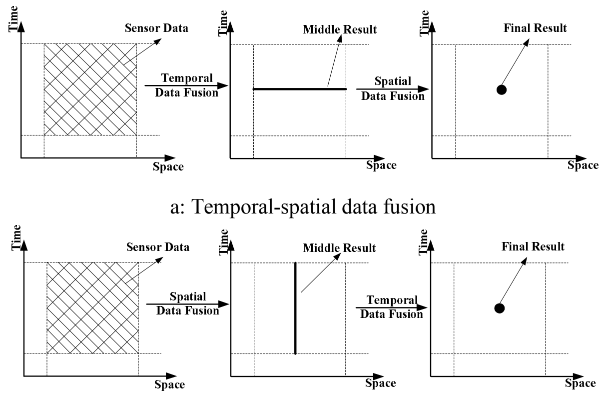
Generally, sensor nodes are densely deployed. Therefore sensor data from adjacent nodes will be highly redundant. Consecutive samples from the same node are also likely to exhibit temporal correlation. Vuran et al. analyzed the spatial and temporal correlation of WSNs [6]. Reducing redundant data can conserve a node's energy. Redundant information is not useful to data fusion, but sensing, processing and communication of the information can consume extra unnecessary energy.

Eliminating the acquisition of redundant data will have a significant effect on nodes in a WSN. The energy consumed on data acquisition and on communication will be both reduced. Without redundant data, the data processing is expedited in the microcontroller and a lower data rate will be created. So the occupation of the wireless channel and the probability of inducing congestion will be lower. As a result, the lifetime of WSNs is prolonged, and the QoS is increased.

In this paper, we investigate the energy conservation and balance (i.e. the distribution of energy throughout the nodes in the network) of WSNs. We present a novel scheme, referred to as Virtual Sampling Scheme (VSS), to fulfill distributed data acquirement in WSNs. VSS is based on virtual clusters (VCs), which represent a set of adjacent nodes. We design an algorithm to form VCs, which derives the VCs by using a spatial correlation model before nodes start to sample the target signal. The algorithm operates without calculating a complex distortion function as required by other reported research. The computation required in our algorithm is also lighter. We present a round robin sampling scheme as the second part of VSS, which balances the energy consumption of each sensor node in a VC. Therefore VSS assures the accuracy in signal estimation. The VSS algorithm is simulated to evaluate the fusion accuracy and energy consumption.

II. RELATED WORK

In a WSN, multiple sensor nodes often sample a signal at the same time. The node to fuse the sensor data from nodes may get more consecutive sensor data in a fusion periods. Two different methods can be used for data fusion, as Figure 1 shows:



a: Temporal-spatial data fusion

b: Spatial-temporal data fusion

Figure 1. Model of data fusion

The model showed in Figure 1a first takes the sensor data from each node and first fuses it in the temporal field. Then the middle results from all of nodes are fused to derive the final result. Figure 1b shows a similar model, but where the sensor data are first fused in the spatial field.

Whichever model is used, the key is how many nodes are selected, and how long is spent to obtain the final result. From the perspective of spatial correlation, it may be unnecessary for all nodes to participate in data acquisition. It has been shown that the accuracy of fusion depends on the number of nodes, the spatial correlation amongst nodes, and the spatial correlation between nodes and the source [6].

A number of papers have reported algorithms for data acquisition based on spatial correlation. Vuran and Akyildiz exploited spatial correlation on medium access control [7].They presented a theoretical framework under a distortion constraint. In the theoretical framework, they obtained a minimum node set, and every node in the set acted as representative node. To realize this framework, the CC-MAC protocol was developed which can regulate node to access medium. CC-MAC includes two parts, N-MAC and E-MAC, where E-MAC filters out the correlation in sensor records.

Willett et al. presented an adaptive sampling scheme, called ‘Backcasting’ [8]. The main idea of this scheme is that nodes deployed with sufficient density do not have to sense the same field simultaneously. A hierarchical approach of estimation and communication is proposed in their scheme. In the first phase, called preview, a small subset of the sensor nodes transmit their information to a fusion center, providing an initial estimation of the environment being sensed. In the second phase, called refinement, the fusion center activates additional sensors by ‘Backcasting’ an activation message.

Gedik et al. described an adaptive sampling approach to data collection, called ASAP [9]. ASAP consists of three main mechanisms. Firstly, nodes with close sensor readings are assigned to the same sub-cluster. Secondly, based on spatial correlation between nodes in one sub-cluster, one or more nodes are selected as samplers. The samplers sense the environment and transmit their data to the base station. Finally, adaptive data collection and model-based prediction are designed to minimize the number of messages used to extract data from the network.

In the above three papers, although the methods employed are different, all authors aim to get a subset of sensor nodes to participate in sampling process. Because of the existence of spatial correlation among adjacent nodes in a field, a subset of sensor nodes can represent the network to sense the environment. This paper presents an algorithm which utilizes spatial correlation, operates with a lower computational load (not requiring a complex distortion function), and balances the energy consumption of the network's nodes.

III. Network Architecture and System Model

A. Networks architecture

WSNs may have a flat or hierarchical architecture. A hierarchical WSN consists of clusters of nodes, where each cluster has a cluster head (CH) responsible for communicating with other clusters. In this paper, a hierarchical WSN with N sensor nodes is considered. Nodes $n_1, n_2 ... n_N$ are stationary in a set G .Node n_i ($i = 1, 2, \cdots N$) is at location $s_i(x_i, y_i)$. All sensor nodes are divided into M clusters, every CH is resource-rich nodes which can perform data aggregation as presented in [10]. Let C_j ($j = 1, 2, \cdots M$) denote the j^{th} cluster. The CH of C_j is ch_j and the number of nodes (including ch_j) in C_j is M_j , defined by equation (1).

$$\sum_{j=1}^{M} M_j = N$$
$$C_j = \{n_i, ch_j \mid n_i \in G, i = 1, 2 \cdots M_j - 1\} \qquad (1)$$

B. Spatial correlation model

Spatial correlation between two nodes is decided by the distance between them. Berger et al. discussed four spatial correlation models [10]. The power exponential model is often used in applications, and defined in equation (2).

$$K(d_{ij}) = e^{-d_{ij}/\theta_1}, \theta_1 > 0 \qquad (2)$$

Where d_{ij} is the distance between node n_i and node n_j, calculated as equation (3).

$$d_{ij} = \|s_i - s_j\| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (3)$$

At each observation point, the signals, from the source signal which is modeled as Gaussian random variables, are joint Gaussian random variable [6]. The noise is modeled as independent and identically distributed Gaussian random variables. Sensor data, combining signal with noise, can be obtained using equation (4).

$$X_i = S_i + N_i \qquad (4)$$

Where $S_i \sim (0, \sigma_S^2)$ and $N_i \sim (0, \sigma_N^2)$ .The covariance of sensor data of nodes n_i and n_j is given by equation (5).

$$
\begin{aligned}
&Cov(X_i, X_j) = Cov(S_i + N_i, S_j + N_j) \\
&= E(S_i S_j) + E(S_i N_j) + E(N_i S_j) + E(N_i N_j) \\
&= E(S_i S_j) = \sigma_s^2 e^{-d_{ij}/\theta_1}
\end{aligned}
\tag{5}
$$

If d_{ij} is small enough, $Cov(X_i, X_j)$ will be relatively large. X_i and X_j are highly redundant, nodes n_i and n_j do not need to join the sensing process together.

IV. Virtual Sampling Scheme

A. Definition of virtual cluster

Definition: A node set (called VC_{ij}) which has M_{ij} nodes is called a 'Virtual Cluster' of cluster C_i , if the following conditions are satisfied.

1) If $n_k \in VC_{ij}$,then: $n_k \in C_i, k = 1, 2, \cdots M_{ij}$
2) If $n_k, n_l \in VC_{ij}, k, l = 1, 2, \cdots M_{ij}$,then $\|s_k - s_l\| \le d_{\min}$

Where $d_{\min}$ is a distance threshold. A VC should have a head (VCH) which implements a scheduling function. Assume that the VC number in C_i is K_i , the VCH of VC_{ij} is vch_{ij} .

$$
\begin{aligned}
&VC_{ij} = \left\{ n_l, vch_{ij}, d_{\min} \mid n_l \in C_i, l = 1 \cdots M_{ij} - 1 \right\} \\
&\sum_{j=1}^{K_i} M_{ij} = M_i, \quad i = 1, 2 \cdots M, \quad j = 1, 2 \cdots K_i
\end{aligned}
\tag{6}
$$

Figure 2 presents the relationship between cluster and VCs.

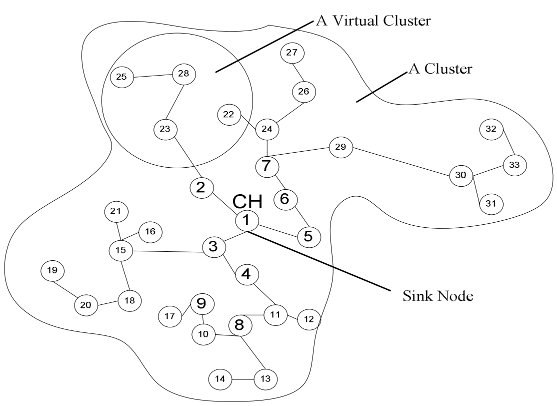


Figure 2. Cluster and virtual cluster

Note that a VC is meaningful when sensor nodes take part in sampling a signal. It does not affect the communication architecture of the network.

B. Forming a virtual cluster

A VC is a set of nodes with a VCH and a distance threshold. In order to form a VC, we should set a VCH, derive $d_{\min}$ and find nodes with the limitation $\|s_k - s_l\| \le d_{\min}$. A VC can be any shape in topology, and can be thought of as a circle whose center is VCH and radius is $d_{\min}/2$. All nodes belonging to the VC are in the circle and satisfy $\|s_k - s_l\| \le d_{\min}$. It is enough that only one sensor node in this VC performs sampling function at a time, other nodes can enter into sleep state.

Figure 3 shows an example of VCs, where nodes 1, 8, 15, 23, 26 and 30 are VCHs. The values r and d denote the communication radius of CH and circle radius of VCs, respectively.

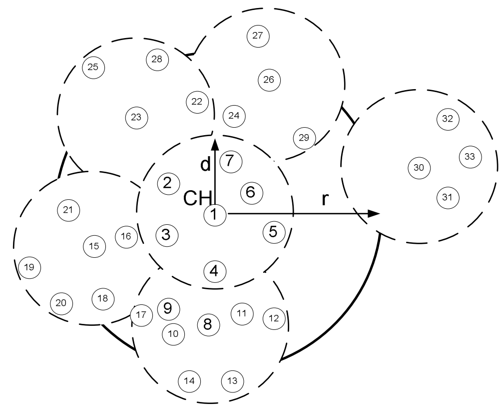


Figure 3. Virtual clusters

The process of forming VCs starts from the CH. After the cluster is constructed, the process can begin. CH sets distance threshold and sends it to other nodes

Assumption 1: Every node in G has an exclusive identification (ID) number. Some clustering algorithms are based on the node's ID number [11], so the assumption is easy to satisfy.

Assumption 2: Every node can calculate the distance to other nodes. Guoqiang Mao et al. presented some method about how to calculate the distance between nodes [12].

Assumption 3: The expected distance threshold is shorter than the communication radius of a node, as shown in Figure 3. The assumption can ensure the correlation amongst nodes is relatively high.

If a node in the cluster C_i , assume that it is n_k , wants to form a VC, it should broadcast a message with the expected distance value d and its ID. Node n_k will become a VCH after it broadcasts the message. Node n_l , which is still not in a VC, will be at one of three possible states after n_k broadcasts its message. The three possible states are as follows.

State1: $S1 \rightarrow \|s_k - s_l\| \le d$

State2: $S2 \rightarrow \|s_k - s_l\| \le r, \|s_k - s_l\| > d$

State3: $S3 \rightarrow \left\| s_k - s_l \right\| > r$

If node n_l receives the broadcast message, it calculates the distance $\left\| s_k - s_l \right\|$ and compares it with d. Node n_l will join the VC if it is in state S1 after comparison. It will reply to n_k with its ID. If node n_l is in state S2, it will set a timer T_1 with random time once it receives the broadcast message. Before T_1 expires, n_l should keep listening to a new message. If it can change to state S1, it will send a reply message and join the VC that the VCH is the node which sends the broadcast message. When T_1 expires, n_l sends a broadcast message to claim a new VC. Node n_l will be a VCH.

Initially, all nodes are in state S3, every node sets a timer T_2 with random time, which should be longer than T_1. Before T_2 expires, a node should listen to a broadcast message and change state to S1 or S2. When timer T_2 of a node expires, the node can not receive a broadcast message, and it does not know value d. E.g., In Figure 2, although node 30 is close to node 29, but node 29 can not broadcast a claiming message after it joins a VC, so node 30 can not receive any broadcast message. Once T_2 expires, node 30 broadcasts an enquiring message with its ID. Node 29 will receive the enquiring message and send a reply with value d. After receiving the value d, node 30 broadcasts a message to claim a new VC. Figure 4 presents the states relationship. In Figure 4, state S5 means that the node has been a member of one VC. S4 is a middle state. In S4, a node will send a broadcast message to become a VCH after it receives a reply for its enquiry.

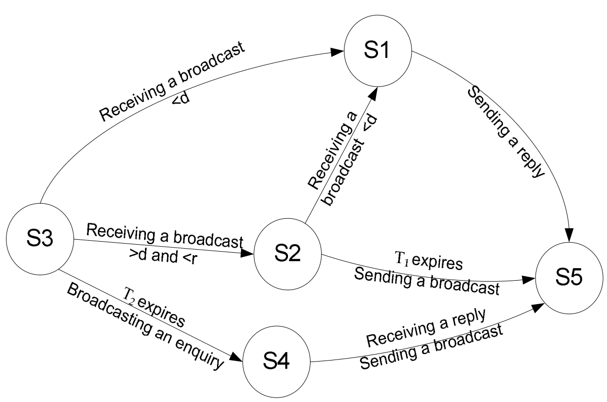


Figure 4. States relationship in one node

When a VC has been formed, the VCH should maintain a ID table. Every node in a VC will receive some parameters from their VCH, and this VCH should report its ID to the CH. Each VCH will receive some parameters from a CH and sends these parameters to each node, such as the sample frequency.

There is no central node to control the forming process, it is distributed. The CH will be the first node to broadcast message. Note that a node in state S5 will not reply to any broadcast message from other nodes to claim a new VC. Figure 5 describes the algorithm running at a node.

Variable:
BMC: Broadcast Message to Claim a virtual cluster;
BME: Broadcast Message to Enquire a distance;
RMJ: Reply Message to Join a virtual cluster;
RMA: Reply Message to Answer the enquiry;
ED: Expecting Distance;
RD: Real Distance between two nodes;
R: Communication radius.
Initialization:
Set timer $\boldsymbol{T_2}$.
Label1: Listening
If receive a BMC
If timer T_2 *is running*
Stop timer T_2.
Extract ED and VCH ID from the message.
Calculate RD.
If RD<ED
Stop Timer T_1;
Send a RMJ, Join the virtual cluster.
Else RD<R
Set timer T_1.
Go to label 1.
Timer $\boldsymbol{T_1}$ ***expires:***
Initialize $M_{ij}=0$;
Send a BMC, Become a new VCH.
Label2: Listening
If receive a RMJ
Extract node ID from the message and store it;
$M_{ij} = M_{ij} + 1$.
Go to Label2.
Timer $\boldsymbol{T_2}$ ***expires:***
Initialize $M_{ij}=0$;
Send a BME.
Label3: Listening
If receive a RMA
Extract ED from the message and store it;
Send a BMC, become a new VCH.
If receive a RMJ
Extract node id from the message and store it;
$M_{ij} = M_{ij} + 1$.
Go to Label3.

Figure 5. Forming algorithm

C. Distributed round robin sampling in a virtual cluster

In a VC, all nodes are equal. Every node can perform sampling function as the representative of the VC. We can set a node to sample the signal while other nodes can work in sleep state. But sampling node will consume its energy more quickly than others. We adopt a distributed round robin sampling scheme to balance energy amongst sensor nodes.

While forming a VC, the VCH receives the reply from other nodes with their ID, and knows the total number of nodes and their ID. Assume that the ID table is $\left\{ id_1, id_2, \cdots id_{M_{ij}} \right\}$ of VC_{ij}, ordered from small to large. Every ID has an index in the table, $Index(id_k) = k$. The round robin scheme requires all nodes in the VC to synchronize with vch_{ij}. Because there are only limited nodes in a VC, the reference broadcast synchronization method [13] can be used. The distributed sampling process has two steps: allocation and start, both steps are scheduled by vch_{ij}.

Allocation: vch_{ij} allocates sample time for all nodes. The round robin period is $T = M_{ij} / f_{\min}$. The id_k node samples the source signal at time:

$$t_0 + \frac{k}{f_{\min}} + T \times m, \quad (m = 1, 2, \cdots) \tag{7}$$

Where t_0 is the start time to sample, $f_{\min}$ is the expected sample rate. In this step, vch_{ij} sends parameters T, k and $f_{\min}$ to every node in the same VC.

Start: This step starts the sampling process. vch_{ij} sends a start command with starting time t_0, every node start to sample according to equation (7).

Figure 6 shows the sampling and sleeping period of nodes.

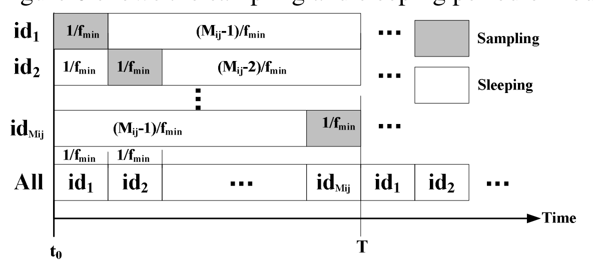


Figure 6. Sampling schedeme

We use the same method discussed in [6] to fuse the data and analyze the tracking error. Minimum mean square error estimation is used to estimate the event S_i signal. The estimation, Z_i, is:

$$Z_i = \frac{E(S_i X_i)}{E(X_i^2)} X_i = \frac{\sigma_S^2}{\sigma_S^2 + \sigma_N^2} X_i = \frac{\sigma_S^2}{\sigma_S^2 + \sigma_N^2}(S_i + N_i) \tag{8}$$

The estimation of S, also the fusion result, is:

$$\bar{S} = \frac{1}{K}\sum_{i=1}^{K} Z_i = \frac{\sigma_S^2}{K(\sigma_S^2 + \sigma_N^2)}\sum_{i=1}^{K} X_i = \frac{\sigma_S^2}{K(\sigma_S^2 + \sigma_N^2)}\sum_{i=1}^{K}(S_i + N_i) \tag{9}$$

The distortion between the source and the fusion result is:

$$\begin{aligned} D = E[(S - \bar{S})^2] &= \sigma_S^2 + \frac{\sigma_S^4}{K(\sigma_S^2 + \sigma_N^2)} \\ &- \frac{2\sigma_S^4}{K(\sigma_S^2 + \sigma_N^2)}\sum_{i=1}^{K}\rho_{s,i} + \frac{\sigma_S^6}{K^2(\sigma_S^2 + \sigma_N^2)^2}\sum_{i=1}^{K}\sum_{j \neq i}\rho_{i,j} \end{aligned} \tag{10}$$

Where $\rho_{s,i}$ is the spatial correlation coefficient between source and nodes n_i, $\rho_{i,j}$ is the spatial correlation coefficient between nodes n_i and n_j.

D. Analysis of energy conservation

In every T interval, a node is active for $1/f_{\min}$ time to sample the signal. Assume that the consuming power of sensing unit of a sensor node in active mode and sleep state is P_A and P_S, respectively. The energy consumption of a node is:

$$E_N = P_A \times \frac{1}{f_{\min}} + P_s \times (T - \frac{1}{f_{\min}}) = \frac{1}{f_{\min}} \times \left[P_A + P_s \times (M_{ij} - 1) \right] \tag{11}$$

If the round robin sampling scheme is not adopted, a node should be active in the whole T interval, the conservation of energy of a node is:

$$1 - \frac{E_N}{P_A \times T} = (1 - \frac{1}{M_{ij}}) \times (1 - \frac{P_S}{P_A}) \approx 1 - \frac{1}{M_{ij}} \tag{12}$$

Only a node is active in a VC within $1/f_{\min}$ interval, the VC will consume energy:

$$E_V = P_A \times \frac{1}{f_{\min}} + P_S \times (M_{ij} - 1) \times \frac{1}{f_{\min}} \tag{13}$$

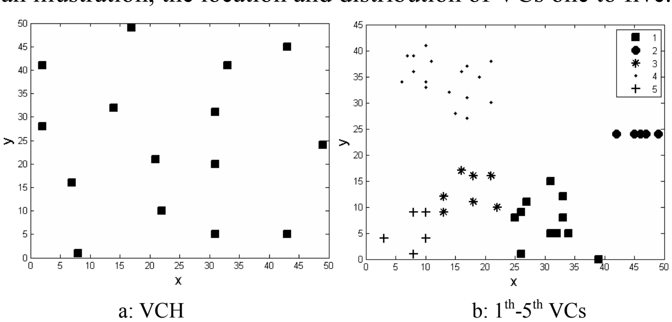
If the round robin scheme is used, the ratio of which a VC conserves energy is:

$$1 - \frac{E_V}{P_A \times M_{ij} \times \frac{1}{f_{\min}}} = (1 - \frac{1}{M_{ij}}) \times (1 - \frac{P_S}{P_A}) \approx 1 - \frac{1}{M_{ij}} \tag{14}$$

From equations (12) and (14), we can conclude that a node conserves energy as the same level as the VC which the node belongs to. The ratio of energy conservation is only related with the number of nodes in the VC. The number of nodes is larger, the energy conservation is more.

V. Simulation Results

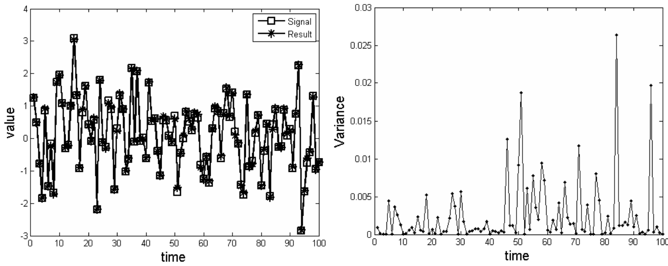
The simulation environment has 100 nodes and covers a $50 \times 50\,\mathrm{m}^2$ area. Each node is randomly deployed in this area. The radius of a VC is set as 10m. The result of simulation shows fifteen VCs are formed if the algorithm illustrated in Figure 5 is used. Figure 7 illustrates the fifteen VCHs and, as an illustration, the location and distribution of VCs one to five.



a: VCH b: 1^{th}-5^{th} VCs

Figure 7. Distribution of VCH and VCs

There is only one source signal in the simulation. The signal is a Gaussian random variable with expectation and variance of (0,1). The noises at each observed location are joint Gaussian random variables with expectations and variances of (0, 0.01). By using the fusion method given in equation (9),Figure 8 shows the fusion result and the variance of the fusion result at a fusion node. The number of samples is 100.

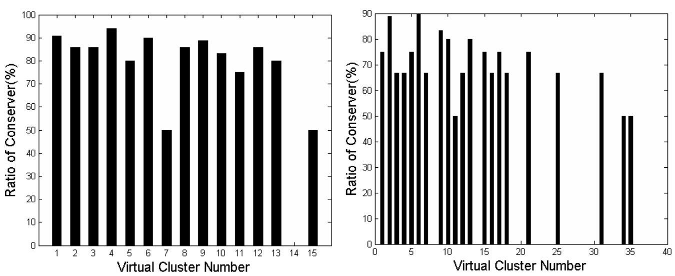


a: Fusion result b: Variance

Figure 8. Fusion result and variance

At each sample time, each VC has a node to sample the signal. Hence, fifteen sensor data are fused in every sample period. Because the number of nodes in each VC is not equal, the combination of nodes to sample the signal is different. According to equation (10), although the number of nodes which join the fusion process is the same, the distortion is different. This is illustrated in Figure 8b. A few points in Figure 8b show a greater variance, but in most cases, although only a subset of the nodes take part in the sampling process at any one time, the fusion result is improved.

In Figure 9, the energy conservation of the VCs is shown. The ratio of energy conservation of a VC is calculated as equation (14) shows. In order to compare different VCs, we set the radius of the VC as 5m and 10m, respectively.



a: Radius=10m b: Radius=5m

Figure 9. Ratio of energy conservation

The ratio of energy conservation is proportional to the number of nodes in a VC. As the radius of a VC increases, the number of nodes inside the VC also increases, and hence permits better energy conservation (as each node spends more of its time in a sleep state).Figure 9a shows the largest ratio is 95%, while the largest ratio is 90% in Figure 9b. Some VCs, such as VC14 in Figure 9a, has only one node, the node will continue to sample the signal and can not conserve energy according to VSS. Because the spatial correlation model is related to the radius, careful consideration should be taken in the selection of the radius. A larger radius can give better energy conservation, though may result in worse fusion. As proved in section III, each node in the VC consumes the same amount of energy. Therefore, Figure 9 is also showing the energy conservation of the individual nodes.

VI. CONCLUSION

Based on spatial correlation among adjacent sensor nodes, this paper presents a distributed virtual sampling scheme, referred to as VSS. VSS is a novel method to acquire data in a WSN. In order to realize VSS, we design a round robin sampling scheme and an algorithm to form the VCs. Through analysis and simulation, it is proved that VSS can conserve node's energy while also providing a better fusion result. By VSS, each node in a VC consumes the same amount of energy, hence balancing energy consumption.

VSS can reduce redundant sensor data to conserve energy, while retaining the meaningful information. However, if a VC has few nodes, the nodes in this VC will consume energy at a faster rate. This raises a significant challenge, and we are currently investigating refinements to VSS to balance the energy between different VCs. Furthermore, while VSS should ensure the accuracy of the fusion result, our simulation results have shown that, in a small number of cases, VSS can give a worse result. By combining the spatial correlation with the number of nodes, we aim to find the optimal node set to get a better fusion result while keeping a high efficiency of energy conservation.

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