

A Critical Observation Collection Method for Sensor Networks Inspired by Behavioral Ecology

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Abstract—In this paper, inspirations from behavioral ecology are applied for mobile agent assisted data collection in a Wireless Sensor Networks (WSNs). With the help of the marginal value theorem based strategy (MVTs), each observation (A), which is gathered by a given sensor node, is considered as a marginal information source with a relative entropy $H(A)$. The mobile agent exploits the correlation and chooses the next sensor node to be visited, which is deemed that the information contribution of the contained observation is not smaller than a predefined threshold (TH). Therefore, understanding the correlation models can benefit the WSNs system from two aspects. On one hand, the resource consumption could be reduced during the acquisition process of the observation; on the other hand, the accuracy of the reconstructed field data is least compromised, due to relatively critical observations being collected by the mobile agent over a dynamically changing environmental. The resource consumption such as energy and bandwidth, is proportional to the number of visited sensors. With MVTs, the resource consumption is optimized through bypassing the sensors with relatively unimportant observations. Illustrated analytical and simulation results confirm the above achievements.

I. INTRODUCTION

Wireless sensor network (WSN) is a promising technology for enabling a variety of applications, such as data harvesting and monitoring. Regardless of their application domain, a majority of end users are interested in reconstructing an accurate enough data representation of the field with the use of collected observations from sensors. It is well known that the limitation of resources is the most critical problem in a WSN. According to literature [1], majority of the resources consumed by WSNs are for transmitting data within the WSN. By and large, typical traditional WSNs relay the sensor observations to a common node, known as a sink, via a tree structure. This inevitably involves huge amounts of data exchanging between sensor nodes, as well as many overheads to maintain the network structure.

To overcome these problems, in recent years, the concept of having a mobile assisted data collection agent in a WSN was first introduced in MULE [2]. This uses a mobile agent roaming inside a sensor field for dynamically collecting observations from sensors. Since then, different flavors of this concept have been proposed by researchers and engineers [3], [4]. Almost all such approaches collect observations from every sensor node in the WSN. Unfortunately, all of these methods overlook the correlation and redundancy of the

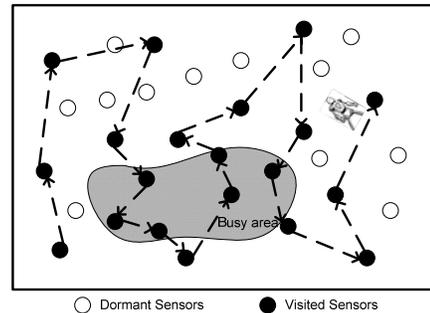


Figure 1. The working process of proposed sensor visiting strategy.

collected data. Therefore, in order to optimize the resource consumption of the WSN, it is essential to understand the correlation of data in order to minimize the redundancy, hence, the motivation for this work. The data collected from different areas of the sensor field have a tendency of showing various correlations. For example, in high correlated areas (i.e., a quiet area), the environmental data change relatively slowly along the spatial domain, while, in the low correlated areas (i.e., a busy area), the environmental data may exhibit sharp discontinuities along the spatial domain. Therefore the observation collecting rate in a quiet area could be much lower than in a busy area, where huge amount of information are concentrated. All resources consumed, such as energy and bandwidth, are proportional to the number of reporting sensors. Therefore, by considering even the basic spatial correlation, the entire system may experience a considerable saving of resources [5].

In this work, an ecologically inspired approach to optimize this problem in a dynamically changing environment is proposed. The marginal value theorem based strategy (MVTs) is applied for mobile agent assisted data collection in a WSN. In behavioral ecology, the marginal value theorem [6] defines the optimal time that an foraging animal remains in a patch to explore its food resources, so that the marginal value of the benefit is maximized. Hence, we argue that the marginal value theorem can be applied for gaining a relatively sufficient benefit by spending the minimal cost. A mobile agent equipped with MVTs visits different sensors to collect their observations, which are considered as marginal information sources with an entropy $H(A)$. By adaptively detecting the busy/quiet areas, the corresponding collecting rate in different areas are adjusted to only visit those critical sensors with

This work is partly supported by the Australian Research Council under the Discovery Project Scheme (DP1096276).

relatively critical observations. A critical observation (A) is defined as an observation of a random variable with a relative entropy $H(A|\lambda)$ not smaller than a predefined threshold (TH). The λ is the set of known observations, which are already collected by the data collecting agent. The critical sensors are deemed to contain critical observations to report. A high level view of the proposed framework is illustrated in Fig. 1. The potential advantages of our proposal are:

- The mobility pattern of the data collection agent is calculated from the current collected observations.
- The total resource consumption is reduced by ignoring some sensors. However, the overall visiting rate of sensor nodes in a busy area will be relatively higher for ensuring the accuracy.
- The time for the mobile agent to complete a round of data collection may be reduced via bypassing dormant sensors.

The remainder of this paper is organized as follows. Section II provides an overview on the related works and the state-of-the-art. Section III, outlines the system structure and assumptions, followed by the description of the marginal value theorem strategy under Section IV. Section V presents some examples and simulation results to demonstrate the correctness and efficiency of MVTS followed by the concluding remarks.

II. RELATED WORKS

The idea of exploiting mobility for data collection has recently received much attention. In [7], authors introduce multiple mobile base stations over a WSN. According to [7], this method evenly drains the energy from sensor nodes, thus increasing the lifetime of the WSN. Similarly a different flavor of mobile sink nodes are introduced in [8]. Although this approach solves the hot-spot problem caused by traditional multi-hop relay WSNs, due to the exchange of sink re-location updates, message relaying overheads remain high.

Therefore, in order to eliminate overheads associated with message relaying, Sushant et al have proposed an alternative approach known as data MULE [2]. This is one of pioneering works in the mobile assisted WSNs, where several randomly roaming data harvesting agents directly collect data from individual static sensors. However, the disadvantages of a random mobility model are high latency in data delivery and the high probability of losing observations due to sensors overflowing buffers. In light of improving this, interest is shifted towards using data collecting agents with controlled mobility. For instance, a mobile agent can be programmed with predefined trajectories [9]. Here, the trajectory of the mobile agent is designed to satisfy latency constraints while keeping the number of message relays minimized. Similarly, there are works on predefined scheduling algorithms proposed for data harvesting [3], [10]. In references [3] and [10], a Partitioning-Based Scheduling (PBS) algorithm is proposed to reduce the minimum required speed of a mobile agent to prevent data loss. However, all of the above mentioned works do not consider the spatial correlations of the environmental data, which is the essence of our work. By considering the correlation,

performance of resource consumption and latency of collection will be improved.

On the other hand, some works introduce mobile agents with controlled mobility where data aggregation techniques are embedded [11]. Here, normal sensors send their observations to local aggregation centers, which are accessed by the mobile agent. As a result, the latency of message delivery is reduced. There are also other approaches where stop-stations similar to cluster heads are visited for data collection in a WSN [12]. However, this type of approach requires each sensor node to transmit at least one packet to the aggregation center.

The motivation for developing a sophisticated collection strategy for a mobile agent is to balance the tradeoff between accuracy and resource consumption by exploiting the spatial correlation. The proposed MVTS is able to remove the information redundancy by not requiring every sensor to report their observations. The authors of [5] have developed a special media access control (CC-MAC) protocol for preventing every sensor node reporting their observations. However, the CC-MAC is used in traditional tree structure WSNs for applications like event detection. On the contrary, the proposed MVTS does not put any heavy load on weak sensors, and can be perfectly applied for field data reconstructing applications.

III. SYSTEM MODEL

This section presents the system model underlying the MVTS method, and describes the assumptions made within reasonable limits. The entire system consists of a relatively large number of sensor nodes and an intelligent mobile agent. Normal sensor nodes are densely deployed over the sensor field. Each sensor node has a limited power and processing capability. It is practically inconvenient and unfeasible to replace or recharge sensor nodes. The sensor nodes are assumed to be static and identical. The radio model of a sensor node works in a reactive way, which means that one sensor node passes its current observation to the intelligent mobile agent only when it is visited. For the energy saving purpose, the transmission range is assumed to be relatively small. It is also assumed that sensor nodes can communicate with the mobile agent when they are in close proximity. For the purpose of field data reconstruction, in each sampling round, the sensor nodes are responsible for reading the environment synchronously and storing the obtained values.

The mobile agent, which roams inside the sensor field for collecting observations from sensor nodes, is equipped with MVTS. It is assumed that the mobile agent is a robot or a vehicle with controlled motion. Therefore, it is also reasonable to assume that the mobile agent is able to record the locations of all sensor nodes. The mobile agent is relatively more powerful than a sensor node, which can easily be recharged. Once the mobile agent visits a specific sensor node, it collects and stores the observation from a visited sensor node. Furthermore, upon learning fresh information from a new observation, the mobile agent uses MVTS to exploit the

correlation model of the current located areas, and chooses the next sensor node to be visited.

The interested background environmental data from the sensor field are assumed to be correlated normal random variables, whereas the strength of correlation varies in different areas of the sensor field. In the highly correlated areas (quiet areas), the collected observations change relatively slowly along the spatial domain, while in the low correlated areas (busy areas), the environmental data may exhibit sharp discontinuities along the spatial domain. The locations of busy areas and quiet areas are dynamically changed and independent to each round of sampling. According to [13], the general correlation models in the nature can be summarized into four groups: *spherical*, *exponential*, *rational quadratic*, and *matérn*. All of these models show similar properties along the spatial domain. In order to keep the generality, we use the exponential model in this paper. This model is widely used in the literature, such as in [5], which can be represented as:

$$\text{corr}_{i,j} = \exp(-d_{i,j} / \theta) \quad (1)$$

where $d_{i,j}$ is the distance between two locations (i and j), and θ is the correlation factor, which controls the strength of the correlation. Higher θ values represent stronger correlation. The θ is various in different areas without being known by mobile agents. However, we assume that the highest value for all possible θ is known, which is used for constructing the basic information patches in the sensor field as described in next section.

Based on the correlation models, each new observation is considered to contain a marginal information entropy $H(A)$. The system is required that the mobile agent only collects observations over the threshold (TH) information level to reduce the resource consumption, while maintaining the required level of accuracy.

IV. MARGINAL VALUE THEOREM STRATEGY (MVTS)

Marginal value theorem studied under behavioral ecology defines the optimal foraging behavior of an animal for exploiting food resources distributed in patches [6]. The foraging animal uses the rate of gain to decide when to leave the patch and to start searching for a fresh one. In the case of mobile agent assisted WSNs, the sensor field can be divided into patches and each observation gathered by its sensor nodes contain certain amounts of information, which can be used to reconstruct the field data. Due to the spatial correlation and redundancy, the relative information gain after removing the redundancy in a patch can be mapped as the marginal value. The mobile agent that is equipped with the MVTS visits the sensor nodes and collects observations.

In order to apply the MVTS to a WSN, the information contained in an observation must be defined. As described in section III, the environmental data consist of correlated normal random variables. An observation can be represented as a sample of this normal random variable, $N(m, \sigma^2)$, where m is the mean value, and σ is the standard deviation.

According to the properties of normal distribution, the

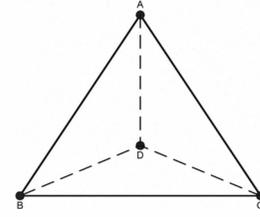


Figure 2. The specification of basic patch.

information entropy of an observation A can be represented as:

$$H(A) = 1/2 \times \ln(\sqrt{2\pi e\sigma^2}) \quad (2)$$

When σ is greater than zero, the $H(A)$ is a monotonically increasing function. It is required that the $H(A)$ contained in each collected observation is not less than TH . Hence, the minimal standard deviation of the collectable observations are

$$\sigma_{TH} = \sqrt{e^{4 \times TH - 1} / 2\pi} \quad (3)$$

A. Forming Basic Patches

The basic patches in the sensor field are formed by exploiting the basic spatial correlation model. The basic spatial correlation model is the strongest correlation that may exist in a sensor field. This is determined by the highest value of the correlation factor, θ_H , which is assumed to be known.

Because the correlation factor, θ , may change in different areas, the system can only exploit the correlation from one patch to another. The specifications of the patches can be arbitrary according to the usage of the WSN system. To keep the simplicity and generality, we adapt an equilateral triangle as the basic shape of an ideal theoretical patch, where the three vertices and the centroid of the triangle become the critical locations of a patch. This is illustrated in Fig. 2. Based on the requirements of the system, each observation should contribute information that is not less than TH . This means, in a basic patch with a basic correlation model, the marginal information gain from background data of A, B, C and D should not be less than TH ($\sigma \geq \sigma_{TH}$), and the marginal information gain from the background data from the remaining locations should smaller than TH ($\sigma < \sigma_{TH}$).

In Fig. 2, the standard deviation of data from D is the smallest, relative to A, B and C . This is since D is located at the centroid of the patch, which is surrounded by A, B and C . Hence, it shows the closest correlation to the other three. In the patch, D is the only one, which has same distances with A, B and C . If the standard deviation of D is equals to σ_{TH} , with the nonlinear change in the covariance matrix, the standard deviation of data from the rest of the locations in the patch are smaller than σ_{TH} . Hence, the smallest basic patch according to the basic correlation model is an equilateral triangle, in which the data from the centroid has a standard deviation equal to σ_{TH} .

Suppose, the data vector collected from A, B, C, D , is X , which contains correlated normal random variables,

$$X = [x_A, x_B, x_C, x_D] \quad (4)$$

the transpose of X can be calculated by

$$X' = \psi Z' \quad (5)$$

where Z is an independent standard normal random variables vector

$$Z = [z_1, z_2, z_3, z_4] \quad (6)$$

where z_i is a vector of samples of the standard normal random variable. The covariance matrix of z is

$$C_Z = E(Z'Z) = I_4 \quad (7)$$

where I_4 is a 4-by-4 identity matrix. According to the basic correlation model, we can derive the relationship between ψ and the covariance matrix of X as:

$$C_X = E(X'X) = E((\psi Z')(\psi Z')) = \psi C_Z \psi' = \psi \psi' \quad (8)$$

$$= \begin{bmatrix} 1 & e^{-\frac{d_{A,B}}{\theta_H}} & e^{-\frac{d_{A,C}}{\theta_H}} & e^{-\frac{d_{A,D}}{\theta_H}} \\ e^{-\frac{d_{B,A}}{\theta_H}} & 1 & e^{-\frac{d_{B,C}}{\theta_H}} & e^{-\frac{d_{B,D}}{\theta_H}} \\ e^{-\frac{d_{C,A}}{\theta_H}} & e^{-\frac{d_{C,B}}{\theta_H}} & 1 & e^{-\frac{d_{C,D}}{\theta_H}} \\ e^{-\frac{d_{D,A}}{\theta_H}} & e^{-\frac{d_{D,B}}{\theta_H}} & e^{-\frac{d_{D,C}}{\theta_H}} & 1 \end{bmatrix} \sigma^2$$

Equation (8) is the necessary and sufficient condition for generating correlated random variables. There are many solutions for ψ in equation (8). In order to form the basic patches, the Cholesky Decomposition is adopted to exploit the correlation. From the definition of Cholesky Decomposition, we have

$$C_X = LL' \quad (9)$$

where L is a lower triangle matrix with strictly positive diagonal entries, in which

$$l_{i,j} = \frac{1}{l_{j,j}} \left(C_{X_{i,j}} - \sum_{k=1}^{j-1} l_{i,k} l'_{j,k} \right) \quad \left. \vphantom{l_{i,j}} \right\} \text{for } i, j = 1, 2, 3, 4 \quad (10)$$

$$l_{i,i} = \sqrt{C_{X_{i,i}} - \sum_{k=1}^{i-1} l_{i,k}^2}$$

Substituting ψ in (5) with L , we have

$$X' = LZ' \quad (11)$$

Hence, one sample vector of X , $S_X = [s_{XA}, s_{XB}, s_{XC}, s_{XD}]$ can be represented by another sample vector, $S_Z = [s_{z1}, s_{z2}, s_{z3}, s_{z4}]$, of independent standard normal random variables. Suppose the samples of $[s_{XA}, s_{XB}, s_{XC}]$ are already known, we can solve,

$$s_{z1} = s_{XA} / l_{1,1}$$

$$s_{z2} = (s_{XB} - l_{2,1}s_{z1}) / l_{2,2}$$

$$s_{z3} = (s_{XC} - l_{3,1}s_{z1} - l_{3,2}s_{z2}) / l_{3,3}$$

Since z_4 is a standard normal random variable, with mean equals to 0 and standard deviation equals to 1, we can say that when the back ground environmental observations from A, B, C are $[s_{XA}, s_{XB}, s_{XC}]$, the observation from D is a normal random variable with mean equals to

$$m_D [s_{XA}, s_{XB}, s_{XC}] = l_{4,1}s_{z1} + l_{4,2}s_{z2} + l_{4,3}s_{z3} \quad (12)$$

and the standard deviation equals to

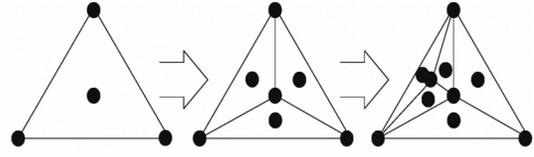


Figure 3. The correlation exploiting process.

$$\sigma_D [s_{XA}, s_{XB}, s_{XC}] = l_{4,4} \quad (13)$$

The $l_{4,4}$ is related to σ , θ_H , and the distances between any pairs among A, B, C , and D . The σ , θ_H are known parameters by the system. If we set the distance between A and D , $d_{A,D}$, to x , we have

$$d_{A,D} = d_{B,D} = d_{C,D} = x$$

$$d_{A,B} = d_{A,C} = d_{B,C} = 2x \cos \frac{\pi}{6}$$

Hence, by jointly considering the equations (8), (11), (13), $\sigma_D [s_{XA}, s_{XB}, s_{XC}]$ can be looked as a function of $x, f(x)$. To find the value of x that satisfied the system's requirements, the following function for x is solved.

$$\sigma_D [s_{XA}, s_{XB}, s_{XC}] = f(x) = \sigma_{TH} \quad (14)$$

It is important to note that, in reality, the locations of normal sensor nodes might not perfectly match the theoretical positions of a basic patch. However, as long as the density of the sensor nodes is high enough, there are always close enough sensors, which can be used to form basic patches.

B. Exploiting Complicate Correlation Models

As mentioned earlier, the strength of the correlation varies in different patches. If the correlation model is more complicated (smaller θ) compared with the basic correlation model, the mobile agent is required to spend more time in these patches for collecting the critical observations.

From Section IV.A, suppose a basic patch has been formed similar to Fig. 2, the shape of this patch is close to an equilateral triangle, where the mobile agent knows the locations of A, B, C , and D . It is easy to obtain the distances between any pair among A, B, C , and D . Currently, the unknown parameter is the correlation factor θ . The process of exploiting the correlation is described as follows:

Step 1: Using the Cholesky Decomposition, the $l_{4,4}$ in equation (13) is a function of $\theta, f(\theta)$. Solving equation

$$f(\theta) = \sigma_{TH} \quad (15)$$

the mobile agent can obtain an intuitive correlation factor, θ_I .

Step 2: The mobile agent visits A, B, C and D to collect the observation vector, $[s_{XA}, s_{XB}, s_{XC}, s_{XD}]$.

Step 3: Calculates the intuitive mean value of data from D , M_{DI} , using equation (12) and θ_I .

Step 4: Calculates the intuitive confidence interval of data from D , I_{DI} , $[M_{DI} - \sigma_{TH}, M_{DI} + \sigma_{TH}]$.

Step 5: Checks if s_{XD} is contained in the I_{DI} . If so, this patch passes the test, and the mobile agent moves into the next patch. If not, more complicated correlation is considered, and the

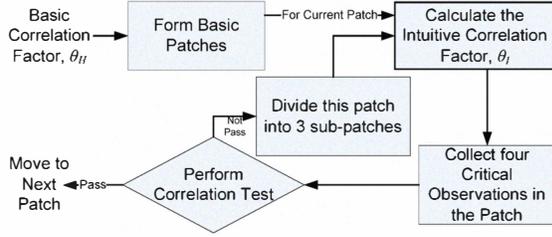


Figure 4. The flowchart of MVTS.

current investigated patch will be separated into three sub-patches. For each sub-patch, the entire exploiting process is repeated, until the patch eventually passes the test. The exploiting process is illustrated in Fig. 3. This exploiting process can let the mobile agent and the WSN system spend relatively less resources in relatively quiet areas, which are the patches with relatively stronger correlation. The flowchart of the entire MVTS process is demonstrated in Fig. 4.

V. PERFORMANCE EVALUATION

In this section, our proposed MVTS is evaluated using Matlab. The correlated background data are generated by equation (5). In order to show the applicability of MVTS, the ψ in (5) is produced different from Cholesky Decomposition. Because the covariance matrix, C_X , is a symmetric matrix, it always can find a specific ψ , where $\psi = \psi'$ and $\psi \psi' = C_X$.

$$\psi = \text{sqrtn}(C_X) \quad (16)$$

The $\text{sqrtn}(\bullet)$ is the matrix square root function in Matlab. The average distortion of the reconstructed data is defined as:

$$\frac{\sum_{i=1}^n |The\ Reconstructed\ Value_i - The\ Real\ Background\ Value_i|}{n} \quad (17)$$

where n is the number of sensor nodes. There are 51×51 sensor nodes uniformly distributed in a $500 \times 500 \text{m}^2$ sensor field, where two neighboring sensors in same row or column are departed by 10 meters. The predefined information threshold is set to 0.7258 (corresponding to $\sigma_{TH} = 0.5$). The basic correlation factor is set to 2000, and the speed of the mobile agent is 1 m/s.

A. Exploiting Basic Correlated Background Data

In this simulation, the background environmental data are generated from the basic correlation model, in which θ equals 2000, the basic patches are formed close to equilateral triangle with an approximate edge length of 60 meters. Fig. 5 contains the detailed performance of MVTS in the basic correlated environment. Fig. 5(1) displays the original background environmental data collected from all the sensor nodes in the sensor field, and Fig. 5(2) is the reconstructed filed data resulted from MVTS. As it can be seen, the similarity of these two sub-figures is very high. The trend of data distribution pattern is captured by the reconstructed data regardless of some negligible distortion. Fig. 5(3) demonstrates the visited sensor nodes' distribution in the sensor field in this scenario. In total, 151 sensor nodes are finally visited by the mobile agent, and another 2450 sensors stay dormant, which conserves the resources. The mobile agent leaves the majority of the patches

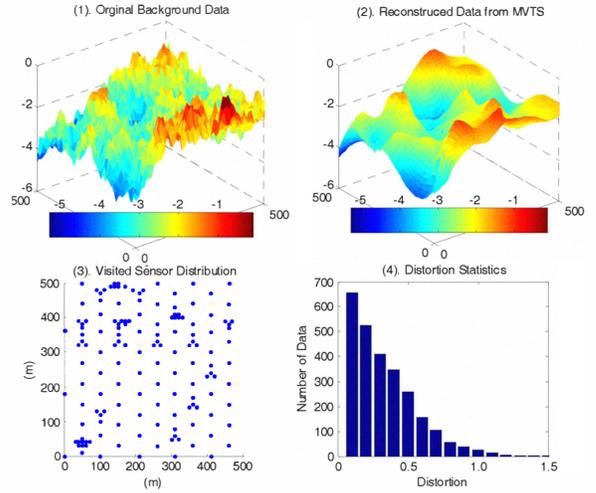


Figure 5. Details of MVTS in Basic Correlated Background Environmental Data Sensor Field.

just after visiting its 4 critical sensors. For the remaining patches, the mobile agent visits more sensors, due to the correlation factor estimation error. This error can not be avoided in the MVTS, however, the probability of this happening is quiet low, and it also helps the mobile agent to collect some extreme observations from the sensor field. Fig. 5(4) summarizes the distortion statistics of the reconstructed data and original data. The horizontal axis is the distortion level, and the vertical axis is the number of data falling into the corresponding distortion level. We can see that the majority of the reconstructed data have a very small distortion (< 0.5). As the distortion increases, the number of data decreases. The average distortion in this scenario is 0.28.

B. Exploiting Complicated Correlated Background Data

In this simulation, the complexity of the correlation model of the background environment is increased. The correlation factor applied in the top-left quarter of the sensor field is 1000, and the correlation factor applied in the bottom-right quarter of the sensor field is 500. In the remaining areas of the sensor field, the correlation factor is the basic value of 2000. Fig. 6 contains the detailed performance of MVTS in the complicated correlated environment. We can also see that the reconstructed data of the MVTS captures the trend of the original data. The data changes more dramatically in those relatively busy areas, which are at the top-left quarter and the bottom-right quarter of the sensor field. Firstly, by comparing Fig. 6(4) and Fig. 5(4), we can see that the distortion statistics for these two scenarios are similar, which means that the MVTS is able to hold the accuracy level of the application in the complicated environment. The average distortion in this scenario is 0.36. Fig. 6(3) demonstrates the visited sensor nodes' distribution in the complicated scenario. The visiting rates of mobile agent in these two relatively busy areas are obviously higher than those in quiet areas. Also, the visiting rate in the bottom-right area is even higher than that in the top-left area. This is caused by different correlation models used in these areas. These

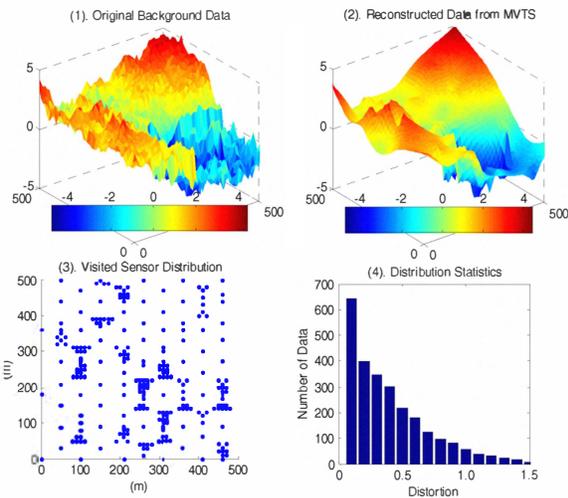


Figure 6. Details of MVTS in Complete Correlated Background Environmental Data Sensor Field

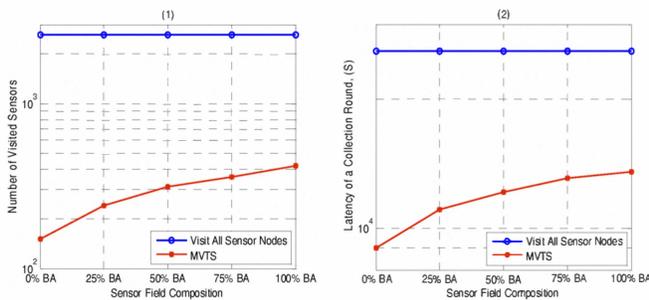


Figure 7. Advantages of MVTS.

differences in the visiting rates in the sensor field prove that the MVTS is able to collect and only collect critical observations from different correlated environments.

C. Advantages of the MVTS

In this simulation, we emphasize on the advantages that the proposed MVTS can bring to the WSN (in comparison to traditional methods, where all sensor nodes are accessed by the mobile agent). Two correlation models are considered in the sensor field. θ equals 2000 is referred to as quiet areas (QA) and the θ equals 500 is referred to as busy areas (BA).

Fig. 7(1) shows the comparison of the number of visited sensors in a collection round for the two methods. The horizontal axis is the percentage of busy areas covering the sensor field. In every scenario, the number of visited sensors obtained from the traditional method is 2601. Nevertheless, the number of visited sensors obtained from MVTS is kept increasing as the busy areas become larger and larger. However, in general, the MVTS visited a much less number of sensor nodes than the traditional method. The rationale for densely deployment of sensor nodes in the field is due to the fact that background environment is dynamically changing and it is impossible to be predicted. It almost always has some areas which become busy areas in the sensor field. Fig. 7(2)

shows the comparison of the time spent to finish one round of collection for the two methods. The trajectory of the traditional method is calculated from the Open Traveling Salesman Problem (OTSP). As expected, it consumes identical time to finish collection in all scenarios in the traditional method. On the other hand, the MVTS spends shorter time because the dormant sensor nodes are bypassed by the mobile agent.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, the spatial correlation of the field data in a uniformly deployed WSN is exploited by an intelligent mobile agent, where an optimization for accuracy and resource consumption is achieved. The novelty of our solution was based on the use of the previously unexplored MVTS, which drives the mobile agent to collect critical observations. The simulation results demonstrated the validity, in which the visiting rate in different areas is adaptively adjusted according to the spatial correlation, so that only the critical observations were collected and used for reconstructing the data representation of the sensor field. The future works include considering random deployments of sensor nodes and different node densities, which will increase the domain of applicability of this proposed scheme.

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