Information Driven Approach for Sensor Positioning in Wireless Sensor Networks

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Abstract: Wireless Sensor Networks (WSNs) are amongst the most important of the new emerging technologies and have shown an explosive growth in recent years for monitoring physical phenomena. Large scale WSNs face various challenges such as lack of coverage, large deployment areas and need of efficient sensor positioning. This paper introduces an approach for sensor management by using Kriging interpolation. The proposed technique affords monitoring of phenomena of interest in a distributed manner. A very good accuracy is achieved by using the available data coming from different sensor nodes. This is illustrated over an example for temperature monitoring.

Keywords: Wireless Sensor Network, Kriging, Sensor Positioning, Experimental Variogram

1 Introduction

WSN's are very promising for monitoring extraordinary diverse environments. A WSN consists of wireless nodes that are able to sense some physical information, process and transfer it to each other by establishing wireless ad-hoc networks. A WSN consists of tiny sensor nodes each capable of sensing some phenomenon, process data and communicate with its neighbours [C93]. These tiny sensor nodes are deployed in the target field in large numbers and they collaborate to form ad hoc networks. A node in a sensor network is generally performing two tasks simultaneously, sensing and communicating.
One of the primary issues for WSN deployment is the life of the network. Since these networks are normally battery powered, large scale, dispersed over a large geographic area and often are out of reach in hazardous environments, maintenance (such as battery replacement) is not feasible. Sensor management is an important problem that needs efficient solutions both is static and dynamic, known and unknown environment.
In this paper we propose an approach for sensor management based onthe Kriging interpolation technique. Many interpolation models exist that can be varying in complexity and accuracy.However, we are using the Kriging technique for interpolation in those areas where the sensors are unable to sense the physical phenomena. The remaining part of this paper is organized in the following way. Section 2 presents related works and an overview of Kriging interpolating techniques. Section 3 formulates the problem of interest and Section 4 describes the proposed information driven approach for information management. Finally, section 5 presents the main results, followed by the appropriate conclusions in Section 6.

2 Related Work

In the past few years energy efficiency in WSNs has received significant attention. Research work on the configuration of a network topology, with good (or required) connectivity, by using minimal power consumption (such as minimizing the maximum power of nodes or minimizing the total power consumption of all nodes), has been done [WBW01, RR02, SRS99].One of the methods to reduce power consumption and to solve the coverage problem is the use of interpolation techniques. In this work we apply the Kriging interpolation.

Kriging is a statistical tool developed by Matheron (1963) and named in honour of D.G. Krige. Originally Kriging was developed for mining and geology. Kriging has been used for other spatial estimation applications, such as analyzing and modelling air quality data [SF79]. Kriging is a way to interpolate spatial data as an automatic contouring program world. In a more precise manner, Kriging can be defined as an optimal linear unbiased estimator of a spatial variable at a particular site or geographic area. Kriging assigns low weights to distant samples and high weights to nearest samples, but also takes into account the relative position of the samples to each other and the site or area being estimated. Matechik and Stytz [MS94], used Kriging to interpolate 3-D magnetic resonance imaging (MRI) data. They observed that Kriging is a preferable interpolation method, because it provides the user with an estimate of the introduced interpolation error.

2.1 Kriging Interpolation Techniques

Often, it is not feasible to deploy a dense WSN in such a high density in order to be able to observe desired phenomena at every point in the sensing field. Factors that influence this feasibility are deployment cost, the physical size of the device and the life of the sensor node. Therefore, to overcome these problems a mechanism needs to be introduced in order to interpolate values at intermediate points

between sensor nodes. In this work we propose a spatial correlation in WSN data to interpolate temperature at locations that are not covered by the sensor network. Simple approximation methods are available as well, e.g. computation of an average could be applied as spatial interpolation. However, such methods are often the quite inaccurate. Kriging methods are a family of techniques to interpolate a random field at unobserved locations by using values of nearby locations, minimizing the estimation variance from a predefined covariance model.

There are different types of Kriging techniques for interpolation e.g. simple Kriging, ordinary Kriging and universal Kriging. In our research work ordinary Kriging is used. In ordinary Kriging, a spatial phenomenon Z is assumed to be represented by its realizations $Z(x_1)$, $Z(x_2)$. . . $Z(x_n)$ at locations x_1, x_2. . . x_n. Then the Kriging interpolator of Z at a point x_0 is given by [AKJ05]:

$$Z\hat{}(x_0) = \sum_{i=1}^{n} \left(\lambda_i \, Z(xi) \right),$$

where λ_i are the weights fulfilling the unbiasedness condition, i.e., $\sum_{i=1}^{n}(\lambda i) = 1$ and the expected error is $E\,[Z\hat{}\,(x_0) - Z(x_0)] = 0$ [SRS99]. The Kriging technique provides an optimal estimate in the sense that it minimizes the estimation variance and is unbiased [AKJ05]. It can be shown that the optimal weights λ_i for the Kriging interpolator can be computed from the following system of linear equations [CA98]

$$\Lambda = \mathrm{A}^{-1}\,\mathrm{B},$$

$$\begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_n \end{pmatrix} = \begin{pmatrix} \gamma(x_1,x1) \ldots\ldots\ldots \gamma(x_1,x_n) \\ \vdots \\ \gamma(x_n,x_1) \ldots\ldots\ldots \gamma(x_n,x_n) \end{pmatrix}^{-1} \begin{pmatrix} \gamma(x_1,x^*) \\ \vdots \\ \gamma(x_n,x^*) \end{pmatrix},$$

where Λ is a vector comprising the weights, A is the spatial correlation matrix of sample locations x_1, x_2, . . ., x_n and b is a vector whose elements represent the spatial correlation between x_0 and each x_i { x_1, x_2, . . . , x_n }. All correlations are based on an appropriate variogram model defined for the spatial phenomenon under observation [CA98].

3 Problem Formulation

In this study, for a given number of moving sensors, we propose a method to find the optimal positioning of sensor nodes in order to extract maximum information about the environment. Different strategies are used to guide the sensors displacements toward the optimal placement in the sense of estimating the desired physical phenomena. At each time step, the current available measurements along with the previous time measurements are used to predict the phenomena in the entire region of interest. This prediction is performed using a Kriging technique until a condition of convergence is reached.

4 Sensor Management Based on Information Criteria

One popular application of WSN is to monitor a given physical phenomena in an area of interest generally called a sensor field. After having established the network, each node is capable to monitor a region depending of its sensing range. The sensing and communication range of a sensor node depends on its corresponding power and nature. Ideally, the sensor networks are supposed to be able to monitor the entire sensing field by combining all the pieces of information coming from its sensor nodes. However, for large regions, this total coverage demands a large number of sensor and therefore a costly and energy demanding system. To overcome this problem, a limited and reasonable number of moving sensors is a natural solution. The area of interest is a square (N x N) meters and the physical phenomena to be monitored is the temperature. In the current study, the temperature is supposed to be static in relation to the time evolution for simplicity.

To simulate the spatial distribution of the temperature, 'n' number of heating sources are placed in the sensor field (see figure 1). Each heat source $(\mathrm{H_i})_{i=1\ldots n}$ is assumed to create a Gaussian distributed temperature centered on its position A_i, with a mean T_i and standard deviation σ_i. Following this Gaussian distribution chosen for the heat sources, the temperature at any point M= (x, y) if we assume the presence of only one heat source is given by

$$T_{A_i} = T_i * \left(\frac{1}{\sqrt{2\pi\sigma_i^2}} exp^{-\left(\frac{|A_i - \mathrm{M}|^2}{2\sigma_i^2}\right)}\right),$$

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Then, the temperature T at any point M with n numbers of heat sources is given by $T = \sum_{i=1}^{n} T_{A_i}$. Furthermore, m moving sensor nodes are initially randomly deployed in the sensor field. It is assumed that each sensor takes uniformly several measurements inside a hexagon with the half diagonal taken to be the sensing range $'r_i'$. The hexagonal shape is chosen since it allows covering entirely the squared region of interest (see figure 1). As prior information, the squared region can be subdivided into a finite number of hexagons. The hexagon centers define possible positions of the deployed sensors. In addition, in one step, the sensor movements are constrained to the six neighbored hexagons around the current position. As stated previously, inside each hexagon, each sensor is assumed to uniformly take several measurements.

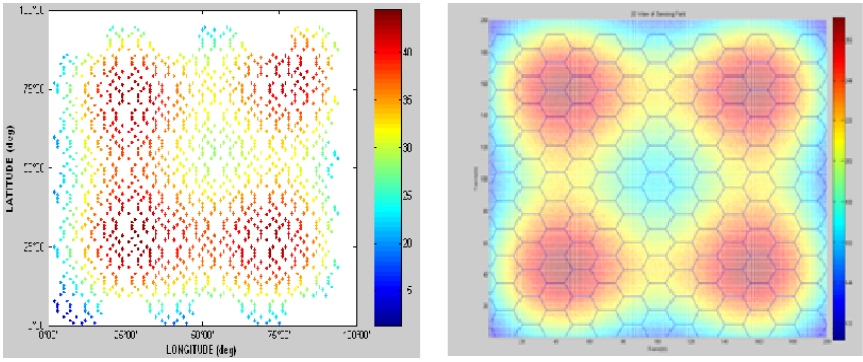

Figure 1: 2D view of the spatial distribution of the temperature

4.1 An Algorithm for a Collaboration to Perform an Optimal Sensor Management

We have randomly installed m number of sensors in the area of interest and each sensor is supposed to measure the temperature of the environment in its sensing range and calculates the average at the centre of hexagon to reduce the transmission across the network. Sensors are deployed randomly in the field of interest and each sensor takes uniformly distributed measurements from the experimental field in its sensing range. After taking a measurement, it is processed it and each sensor broadcasts its current information to all other nodes. All nodes are accepting and saving the measurements in their memory table for Kriging interpolation in uncovered region. After this step each node contains the same information in its memory table. In the first iteration each sensor has m measurements from m sensing nodes to perform the Kriging interpolation. On the kth iteration each sensor memory table contains $k * m$ measurement used to perform Kriging. Therefore, during the time evolution, each sensor posses more and more information about its environment that is used for enhancing both the global estimation and the sensor placement in the experimental field. There are different strategies to relocate the sensor node in the environment by using different information criteria. The algorithm is given below:

Procedure *MiniMax based Algorithm* (Grid, $\{s_1, s_2, \cdots, s_m\}$), where m is the number of sensors
1-Deploy heat source ($\{h_1, h_2, \cdots, h_n\}$)
2- Deploy nodes randomly ($\{s_1, s_2, \cdots, s_m\}$)
3- Set *loops* = 0; Set *MaxLoops* =MAX LOOPS;
4- Take measurement for all ($\{s_1, s_2, \cdots, s_m\}$)
5- Calculate Averg_Temp. for all ($\{s_1, s_2, \cdots, s_m\}$)
6- Broadcast to all ($\{s_1, s_2, \cdots, s_m\}$)
7- Accept & integrate for all ($\{s_1, s_2, \cdots, s_m\}$)
8- Perform kriging for ($\{s_1, s_2, \cdots, s_m\}$) to enhance vision
9- Calculate Measure of Performance
10- Select P% MiniMax from predicted temperature
11- Choose target closest to each sensor and eliminate from target array
12- Check d > TH (threshold)
13 Relocate one step closer to the selected target; end; stop

There are different strategies to relocate the sensor nodes in the experimental field environment.

4.1.1 MiniMax Temperature Based Strategy for Sensor Relocation

By using the information contained in the memory table of sensing node, each sensor performs Kriging in the non-visited area to the predict temperature. The predicted temperature values are ordered in a decreasing order from (Maximum to Minimum).After performing Kriging interpolation P% of Maxima &P% of Minima is chosen from the predicted values of non-visited area. The selected values are used for sensor relocation in the environment to gather the information about the field of interest. Each sensor

selects its next location target from that selected predicted values. The sensor which is closer to the Maximum value in the list moves one step closer to its target. The selected target is eliminated from the target vector and all the entries also removed from target array which is within defined threshold distance before the next sensor selects its target for relocation. When the entire sensors select their target, then at new position measurements are taken again and integrated with the existing information in the memory. The Mean Square Error and energy of the visited region are calculated to measure the performance of the system. The whole the process is repeated until the entire area is visited.

4.1.2 Maximum Absolute Error Based Strategy for Sensor Relocation

Each node performs the interpolation in unknown regions and calculates the absolute error at common location of the predicted temperature between two consecutive iterations. P% of maximum error is selected from the absolute error table for sensor relocation. Each sensor selects its target from selected target list. Each sensor measure the distance from its current location to the Maximum value in the target list. The sensor which has the least distance, that sensor moves one step closer to that selected target. Other entries which are within the defined threshold distance of the selected target are also removed to get new target list to prevent duplication. Then next sensor selects its target from the target list and removes the entries which are within the threshold distance of its selected target. After this process of target selection each sensor moves one step closer to its selected target, each sensor measures the temperature again and the whole previous process is repeated until the defined conditions are met.

4.1.3 Manual Relocation of Sensors

In this scheme sensors are relocated in the environment manually. The search process starts from top left corner of the field and the sensor moves one step to the next hexagon towards right. At the end of the row the sensor moves to the next row and this process continues until whole field is searched. At each iteration the performance metric is calculated to check the performance of the network.

4.1.4 MiniMax Error Based Strategy for Sensor Relocation

After Kriging in the non-visited area, then the absolute error is calculated at common locations in the experimental field between two consecutive iterations. The P% of Maxima & P% Minima is chosen from the absolute error table for sensor relocation. This selected P% values are used for sensor positioning in the environment to gather the more information about the field of interest. Each sensor selects its target from the target array, which is closer to its current position and that sensor moves one step closer to its selected target. The selected target is eliminated from the target vector and all the entries also removed from target array which is within the threshold distance before the next sensor selects its target for movement and checks the distance between selected targets. If the distance it is less than TH (threshold), the sensor selects its new target from the remaining list and this process will continue until last sensor selects its target.

4.1.5 MiniMax Temperature Based Strategy for Sensor Relocation by using Sensor Group

This strategy is the same as the strategy described above in the section 4.1.1. Then P% of Maxima& P% Minima is chosen from the predicted values of non-visited area. These selected values are used for sensor positioning in the environment to gather the information about the field of interest. Sensors divided into two groups are called Maxima and Minima group. Each sensor measures the distance from its current position to the target position which is selected from the predicted data. The sensor which is closer to the top value either from Maxima or Minima list, that sensor moves one step closer to that location. The other values in the target array which are within the defined threshold distance of the selected target are removed from the corresponding list before other sensor selects its target. The corresponding group flag is added one to its previous value and if the defined number of sensor in the group is already reached the required number, then corresponding target group is dropped from target selection for other sensors. This process will continue until last sensor select its target.

4.1.6 MiniMax Error Based Strategy for Sensor Relocation by using Sensor Group

In this strategy after interpolation absolute error is calculated between two consecutive iterations. Next P% is selected from the maximum and minimum error for sensor relocation to a new position. This is almost the same strategy as described in section 4.1.4. In this strategy sensors are divided into two groups, called Maxima and Minima group respectively. Each sensor measures the distance from its current position to all the target positions, the sensor which is closer to the top value either from Maxima or Minima target list, that sensor moves one step closer to that position. The other entries which are within defined threshold distance of the selected target are removed from the corresponding list before the other sensor selects its target. The corresponding group flag is added one to its previous value and if the defined number of sensor in the group is already reached the required number, then corresponding group is dropped from target selection for all other sensors. This process will continue until last sensor selects its target.

$$\mathrm{AAE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{T}_{i-1}^{p} - \mathrm{T}_{i}^{p}),\ \mathrm{AAE}^{i} = \frac{1}{n}\sum_{j=1}^{nk}|(\mathrm{T}_{j-1}^{p} - \mathrm{T}_{j}^{p})| \quad ,\ k = (j-1)\times 4$$

where T_{i}^{p} is the current iteration prediction, T_{i-1}^{p} Previous iteration prediction

5. Metric of Performance

5.1.1 Mean Square Error as Measure of Performance

The mean square error (MSE)

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{T}_{i}^{t} - \mathrm{T}_{i}^{p})^{2}$$

is used to characterize the accuracy of the Kriging process. Here T_{i}^{p} is the predicted temperature at the ith iteration, T_{i}^{t} is the ground truth (true temperature), *N* is the number of predicted values per iteration (i.e., *n* varies from iteration to iteration, decreasing by 4)In the following figure the average error is plotted and it is the average error between measured and interpolated data and it is showing that it is decreasing while the number of iteration is increasing (number of measurements).The graph is showing a comparison between different search techniques. The blue line is manual search and the all the other line are crossponds to intelligent search technique. The intelligent search techniques have faster convergence as compared with the manual search.

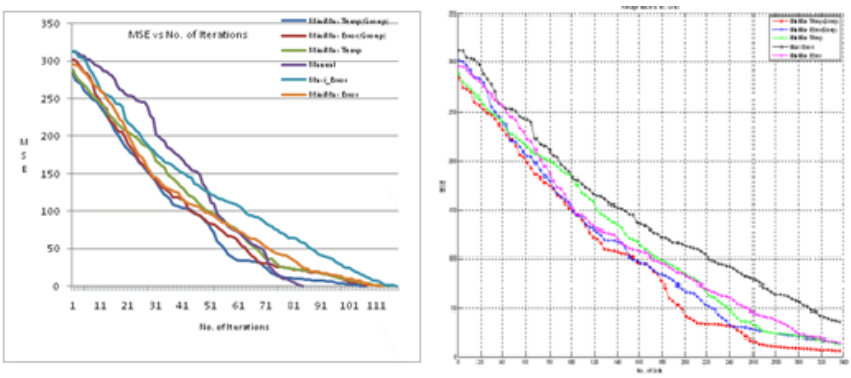

Figure 2: Average mean square error

The intelligence search technique is giving better convergence results as compared with the manual search and it is almost zero at the end. Therefore, intelligence search technique is better than the manual search process.

5.1.2 Energy as Measure of Performance

As a measure of performance of the proposed algorithm, we consider the total energy of the current iteration, divided by the total energy of the environment.

$$\mathrm{E}_{\mathrm{M_P}} = \frac{\sum_{j=1}^{k}(\mathrm{T_j}^{m})^{2}}{\sum_{i=1}^{f}(\mathrm{T_f}^{t})^{2}}$$

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In each iteration measure of performance is calculated and it is increasing as the number of iterations is increasing. By increasing the iteration the information about the environment is increasing and it is showing how quickly the sensing node reaches out the higher temperature.
where E_{M_P} is the energy measure of performance, calculated at each sensor node, k is the number of measurements, increased by 4 in each iteration, f is the total number of points, T_j^m : is the measured temperature in each iteration, T_f^t : is the total temperature of the environment. In the following graph the energy as measure of performance is plotted to compare the performance of three different strategies.

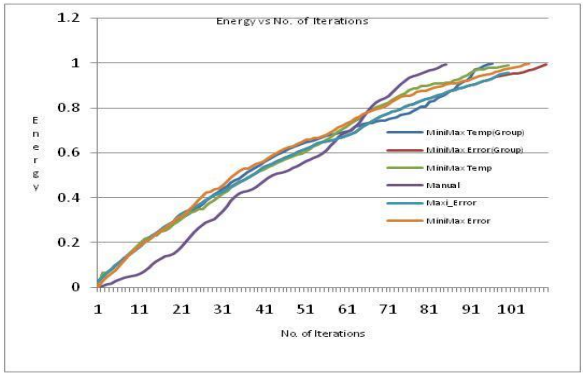

Figure 3: Energy as measure performance by different strategies

The error based sensor relocation is performed very well and reaching high energy zones more quickly as compared to other schemes. Therefore, one can conclude that the error based sensor relocation is performing well and the best scheme to relocate sensors in an experimental.

6. Conclusions

This paper is focused on a sensor positioning problem in a static environment. The challenge is to perform the interpolation with high accuracy and minimum communication costs. To overcome this problem a two step technique is developed. First, the spatial correlation in WSNs is modeled by using the processed data and after that interpolates data in the areas with lack of coverage. Our distributed interpolation technique is highly scalable as compared with the centralized interpolation technique for node positioning. A technique for sensor positioning is proposed based on Kriging interpolation. Their performance is compared with a technique which positions the sensors manually in the monitored environment with respect to accuracy, energy and computational complexity. Accurate results are reported.

The future work will be concerned different techniques, that use error based maps for sensor positioning in dynamic environments, for optimal movement and achieving a maximum global view of the sensing field.

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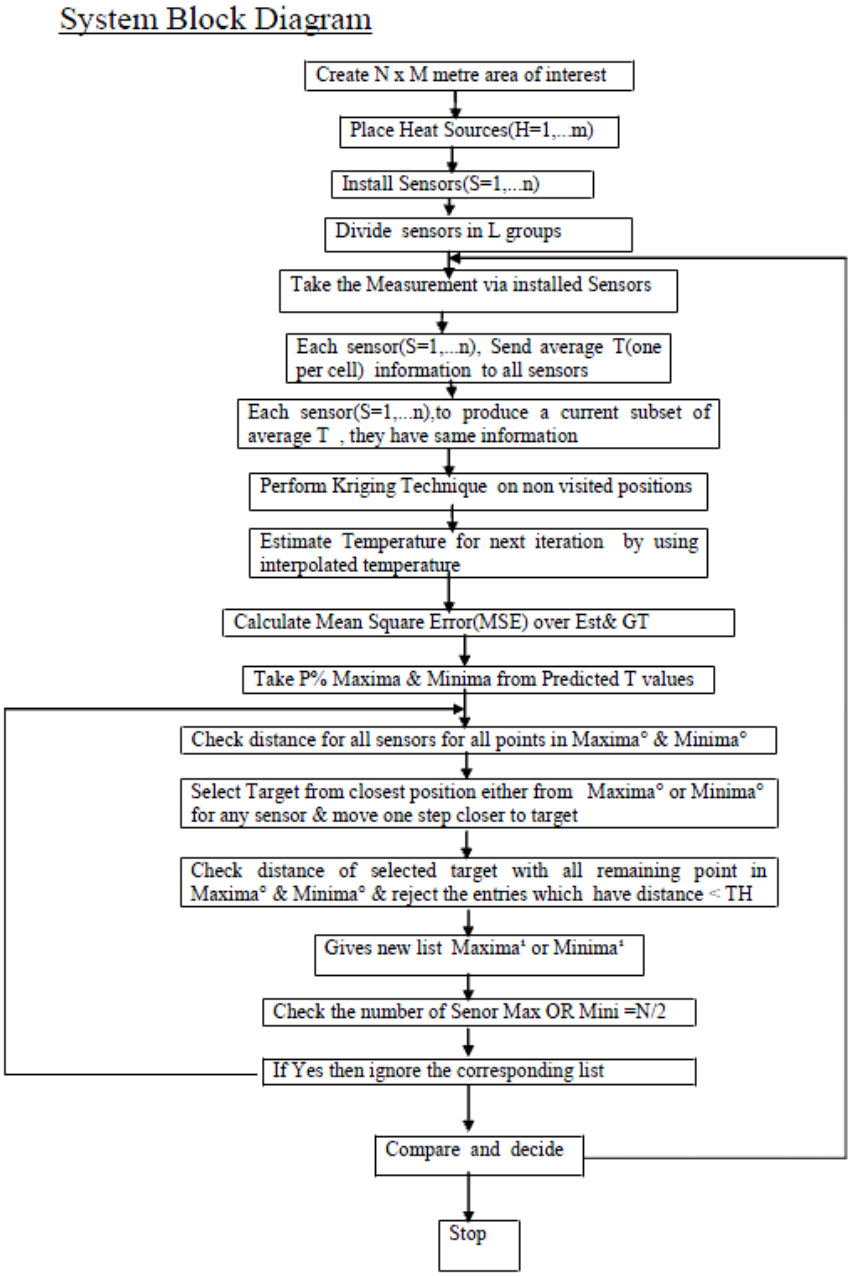

Figure 1: System block diagram

4 Sensor Management Based on Information Criteria

One popular application of WSN is to monitor a given physical phenomena in an area of interest generally called a sensor field. After having established the network, each node is capable to monitor a region depending of its sensing range. The sensing and communication range of a sensor node depends on its corresponding power and nature. Ideally, the sensor networks are supposed to be able to monitor the entire sensing field by combining all the pieces of information coming from its sensor nodes. However, for large regions, this total coverage demands a large number of sensor and therefore a costly and energy demanding system. To overcome this problem, a limited and reasonable number of moving sensors is a natural solution. The area of interest is a square (N x N) meters and the physical phenomena to be monitored is the temperature. In the current study, the temperature is supposed to be static in relation to the time evolution for simplicity.

To simulate the spatial distribution of the temperature, 'n' number of heating sources are placed in the sensor field (see figure 1). Each heat source $(H_i)_{i=1...n}$ is assumed to create a Gaussian distributed temperature centered on its position A_i, with a mean T_i and standard deviation σ_i. Following this Gaussian distribution chosen for the heat sources, the temperature at any point M= (x, y) if we assume the presence of only one heat source is given by

$$T_{A_i} = T_i * \left(\frac{1}{\sqrt{2\pi\sigma_i^2}} exp^{-\left(\frac{|A_i - M|^2}{2\sigma_i^2}\right)}\right),$$

Then, the temperature T at any point M with n numbers of heat sources is given by $T = \sum_{i=1}^{n} T_{A_i}$. Furthermore, m moving sensor nodes are initially randomly deployed in the sensor field. It is assumed that each sensor takes uniformly several measurements inside a hexagon with the half diagonal taken to be the sensing range $'r_i'$. The hexagonal shape is chosen since it allows covering entirely the squared region of interest (see figure 1). As prior information, the squared region can be subdivided into a finite number of hexagons. The hexagon centers define possible positions of the deployed sensors. In addition, in one step, the sensor movements are constrained to the six neighbored hexagons around the current position. As stated previously, inside each hexagon, each sensor is assumed to uniformly take several measurements.

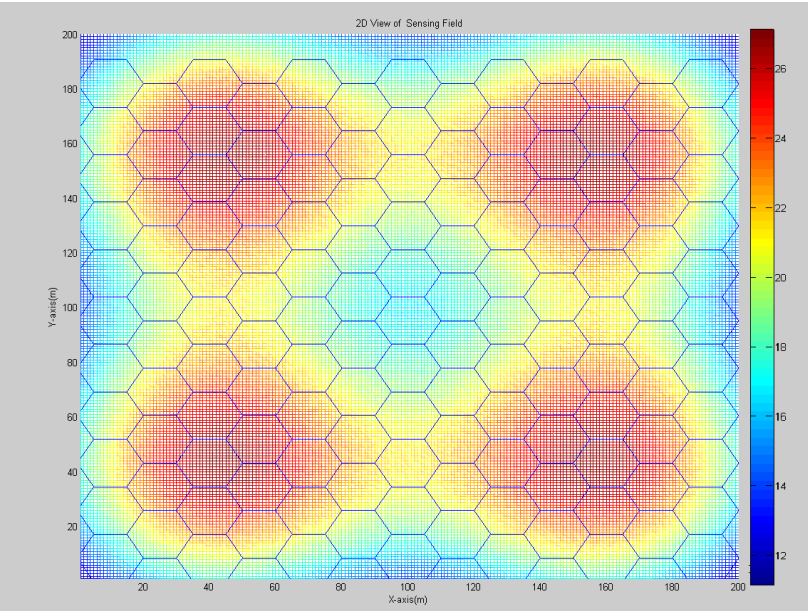

Figure 2: 2D view of the spatial distribution of the temperature

4.1 An Algorithm for a Collaboration to Perform an Optimal Sensor Management

We have randomly installed m number of sensors in the area of interest and each sensor is supposed to measure the temperature of the environment in its sensing range and calculates the average at the centre of hexagon to reduce the transmission across the network. Sensors are deployed randomly in the field of interest and each sensor takes uniformly distributed measurements from the experimental field in its sensing range. After taking a measurement, it is processed it and each sensor broadcasts its current information to all other nodes. All nodes are accepting and saving the measurements in their memory table for Kriging interpolation in uncovered region. After this step each node contains the same information in its memory table. In the first iteration each sensor has m measurements from m sensing nodes to perform the Kriging interpolation. On the kth iteration each sensor memory table contains $k * m$ measurement used to perform Kriging. Therefore, during the time evolution, each sensor posses more and more information about its environment that is used for enhancing both the global estimation and the sensor placement in the experimental field. There are different strategies to relocate the sensor node in the environment by using different information criteria.

4.1.1 MiniMax Temperature Based Strategy for Sensor Relocation

By using the information contained in the memory table of sensing node, each sensor performs Kriging in the non-visited area to the predict temperature. The predicted temperature values are ordered in a decreasing order from (Maximum to Minimum).
The algorithm is given below:

Procedure *MiniMax based Algorithm* (Grid, $\{s_1, s_2, \cdots, s_m\}$)

1-Deploy heat source ($\{h_1, h_2, \cdots, h_n\}$)
2-Deploy nodes randomly ($\{s_1, s_2, \cdots, s_m\}$)
3-Set *loops* = 0;
4-Set *MaxLoops* =MAX LOOPS;
5-Take measurement for all ($\{s_1, s_2, \cdots, s_m\}$)
6-Calculate Averg_Temp. for all ($\{s_1, s_2, \cdots, s_m\}$)
7-Broadcast to all ($\{s_1, s_2, \cdots, s_m\}$)
8-Accept & integrate for all ($\{s_1, s_2, \cdots, s_m\}$)
9-Perform kriging for ($\{s_1, s_2, \cdots, s_m\}$) to enhance vision
10- Select P% MiniMax from predicted temperature
11- Choose target closest to each sensor and eliminate from target array
12- Check d > TH (threshold)
13 -Relocate one step closer to selected target
14- End
15-Stop

After performing Kriging interpolation P% of Maxima &P% Minima is chosen from the predicted values of non-visited area. The selected values are used for sensor relocation in the environment to gather the information about the field of interest. Each sensor selects its next location target from that selected P% predicted values. The sensor which is shortest distance to the Maximum or Minima value in the list moves one step closer to that target. The selected target is eliminated from the target vector and all the entries also removed from target array which is within defined threshold distance before the next sensor selects its target for relocation. When the entire sensors select their target, then at new position measurements are taken again and integrated with the existing information in the memory. The Mean Square Error and energy of the visited region are calculated to measure the performance of the system. The whole the process is repeated until the entire area is visited.

4.1.2 Maximum Absolute Error Based Strategy for Sensor Relocation

Each node performs the interpolation in unknown regions and calculates the absolute error at common location of the predicted temperature between two consecutive iterations. P% of maximum error is selected from the absolute error table for sensor relocation. Each sensor selects its target from selected target list. Each sensor measure the distance from its current location to the Maximum value in the target list. The sensor which has the least distance, that sensor moves one step closer to that selected target. Other entries which are within the defined threshold distance of the selected target are also removed to get new target list to prevent duplication. Then next sensor selects its target from the target list and removes the entries which are within the threshold distance of its selected target. After this process of target selection each sensor moves one step closer to its selected target, each sensor measures the temperature again and the whole previous process is repeated until the defined conditions are met.

The algorithm is given below:

Procedure *Error based Algorithm* (Grid, $\{s_1, s_1, \cdots, s_m\}$)
1- Set *loops* = 0;
2- For *si* _ $\{s_1, s_1, \cdots, s_m\}$
3- Measure Temperatures

$$T = \sum_{i=1}^{n} T_{A_i}$$

4- For s_i _ $\{s_1, s_1, \cdots, s_m\}$ *broadcast current T(x,y)*
5- End,end
6- For s_i _ $\{s_1, s_1, \cdots, s_m\}$
7- Perform Kriging si _ $\{s_1, s_1, \cdots, s_m\}$

$$\hat{Z}(x_0) = \sum_{i=1}^{n} \left(\lambda i \; Z\,(xi)\right)$$

8- Find mean square error

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(T_i^t - T_i^p)^2$$

9- For all nodes s_i _ $\{s_1, s_1, \cdots, s_m\}$ Calculate AAE

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$$AAE = \frac{1}{n}\sum_{i=1}^{n}(T_{i-1}^{p} - T_{i}^{p})$$

10- For all nodes s_i _ $\{s_1, s_1, \cdots, s_m\}$ Locate Max_Error
11- Calculate PER_MEASURE

$$E\_M\_P = \frac{\sum_{j=1}^{k}(T_j^{m})^2}{\sum_{i=1}^{f}(T_f^{t})^2}$$

12- MOVE_ONE_STEP closer to Target
13- End
14- End

Symbol	Explanation
s_i	Sensing node
AAE	Absolute Average Error
Ti	True Temperature at any Point
Pi	Predicted Value at any point
$\hat{Z}(x_0)$	Kriging Prediction
λ	Weight used by Kriging
m	Number of sensing nodes
E_ M_P	Energy as measure of performance
T_j^m	Temperature Measured values in each iterations
T_f^t	Is the ground truth

4.1.3 Manual Relocation of Sensors

In this scheme sensors are relocated in the environment manually. The search process starts from top left corner of the field and the sensor moves one step to the next hexagon towards right. At the end of the row the sensor moves to the next row and this process continues until whole field is searched. At each iteration the performance metric is calculated to check the performance of the network.

4.1.4 MiniMax Error Based Strategy for Sensor Relocation

After Kriging in the non-visited area, then the absolute error is calculated at common locations in the experimental field between two consecutive iterations. The P% of Maxima & P% Minima is chosen from the absolute error table for sensor relocation. These selected values are used for sensor positioning in the environment to gather the more information about the field of interest. Each sensor selects its target from the target array, and that sensor moves one step closer to its selected target. The selected target is eliminated from the target vector and all the entries also removed from target array which is within the threshold distance before the next sensor selects its target for movement and checks the distance between selected targets. If the distance it is less than TH (threshold), the sensor selects its new target from the remaining list and this process will continue until last sensor selects its target.

4.1.5 MiniMax Temperature Based Strategy for Sensor Relocation by using Sensor Group

This strategy is the same as the strategy described above in the section 4.1.1. Then P% of Maxima& P% Minima is chosen from the predicted values of non-visited area. These selected values are used for sensor positioning in the environment to gather the information about the field of interest. Sensors divided into two groups are called Maxima and Minima group. Each sensor measures the distance from its current position to the target position which is selected from the predicted data. The sensor which is closer to the top value either from Maxima or Minima list, that sensor moves one step closer to that location. The other values in the target array which are within the defined threshold distance of the selected target are removed from the corresponding list before other sensor selects its target. The corresponding group flag is added one to its previous value and if the defined number of sensor in the group is already reached the required number, then corresponding target group is dropped from target selection for other sensors. This process will continue until last sensor select its target.

4.1.6 MiniMax Error Based Strategy for Sensor Relocation by using Sensor Group

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In this strategy after interpolation absolute error is calculated between two consecutive iterations. Next P% is selected from the maximum and P% from minimum error for sensor relocation to a new position. This is almost the same strategy as described in section 4.1.4. In this strategy sensors are divided into two groups, called Maxima and Minima group respectively. Each sensor measures the distance from its current position to all the target positions, the sensor which is closer to the top value either from Maxima or Minima target list, that sensor moves one step closer to that position. The other value which is within defined threshold distance of the selected target is removed from the corresponding list before the other sensor selects its target. The corresponding group flag is added one to its previous value and if the defined number of sensor in the group is already reached the required number, then corresponding group is dropped from target selection for all other sensors. This process will continue until last sensor selects its target.

$$\mathrm{AAE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{T}_{i-1}^{p} - \mathrm{T}_{i}^{p}),\ \mathrm{AAE}^{i} = \frac{1}{n}\sum_{j=1}^{nk}|(\mathrm{T}_{j-1}^{p} - \mathrm{T}_{j}^{p})| \quad ,\ k = (j-1)\times 4$$

where T_{i}^{p} is the current iteration prediction, T_{i-1}^{p} Previous iteration prediction

5. Metric of Performance:

5.1.1 Mean Square Error as Measure of Performance:

The mean square error (MSE)

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{T}_{i}^{t} - \mathrm{T}_{i}^{p})^{2}$$

is used to characterize the accuracy of the Kriging process. Here T_{i}^{p} is the predicted temperature at the ith iteration, T_{i}^{t} is the ground truth (true temperature), *N* is the number of predicted values per iteration (i.e., *n* varies from iteration to iteration, decreasing by 4)In the following figure the average error is plotted and it is the average error between measured and interpolated data and it is showing that it is decreasing while the number of iteration is increasing (number of measurements).The graph is showing a comparison between different search techniques. The blue line is manual search and the all the other lines are corresponds to intelligent search technique. The intelligent search techniques have faster convergence as compared with the manual search.

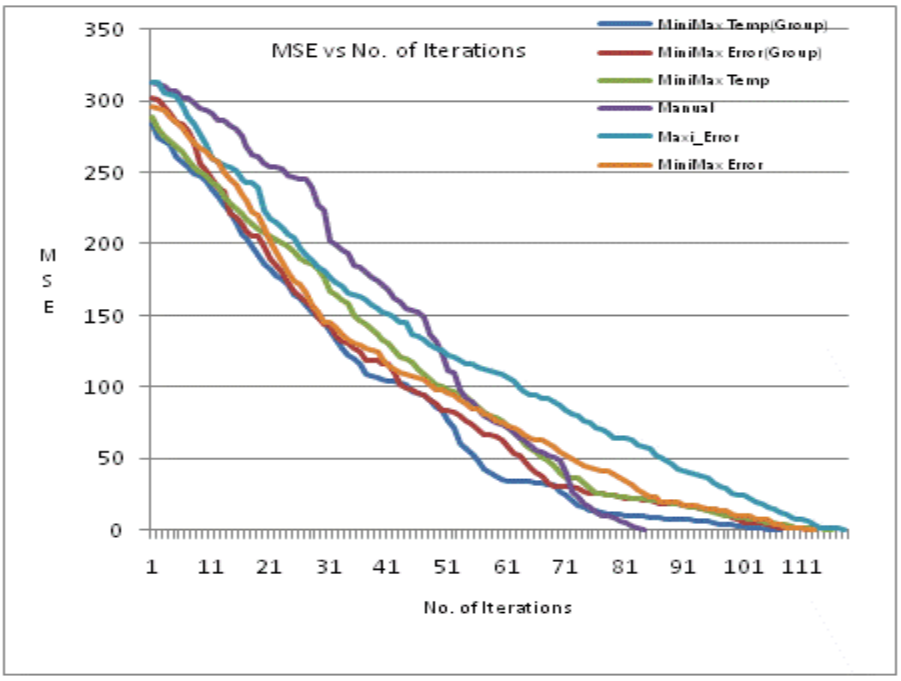

Figure 3: Average mean square error by different strategies per iteration

In the following graph the MSE is plotted against the number of measured cell.

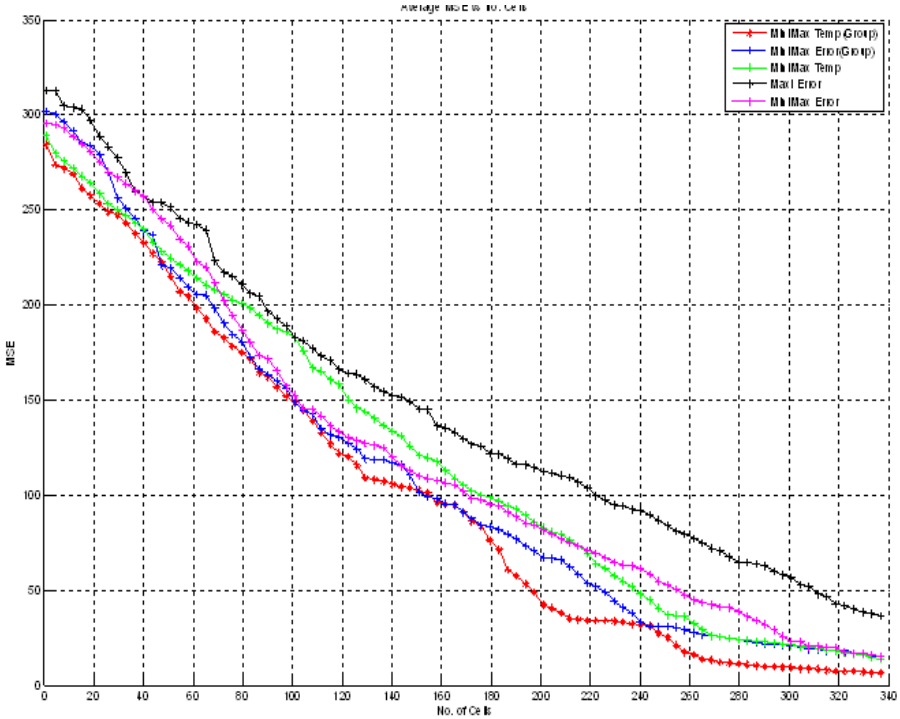

Figure 4: Average mean square error by different strategies (No. Cells)

The intelligence search technique is giving better convergence results as compared with the manual search and it is almost zero at the end. Therefore, intelligence search technique is better than the manual search process.

5.1.2 Energy as Measure of Performance

As a measure of performance of the proposed algorithm, we consider the total energy of the current iteration, divided by the total energy of the environment.

$$E_{M_P} = \frac{\sum_{j=1}^{k} (T_j^{\,m})^2}{\sum_{i=1}^{f} (T_f^{\,t})^2}$$

In each iteration measure of performance is calculated and it is increasing as the number of iterations is increasing. By increasing the iteration the information about the environment is increasing and it is showing how quickly the sensing node reaches out the higher temperature.

where E_{M_P} is the energy measure of performance, calculated at each sensor node, k is the number of measurements, increased by 4 in each iteration, f is the total number of points, $T_j^{\,m}$: is the measured temperature in each iteration, $T_f^{\,t}$: is the total temperature of the environment. In the following graph the energy as measure of performance is plotted to compare the performance of three different strategies.

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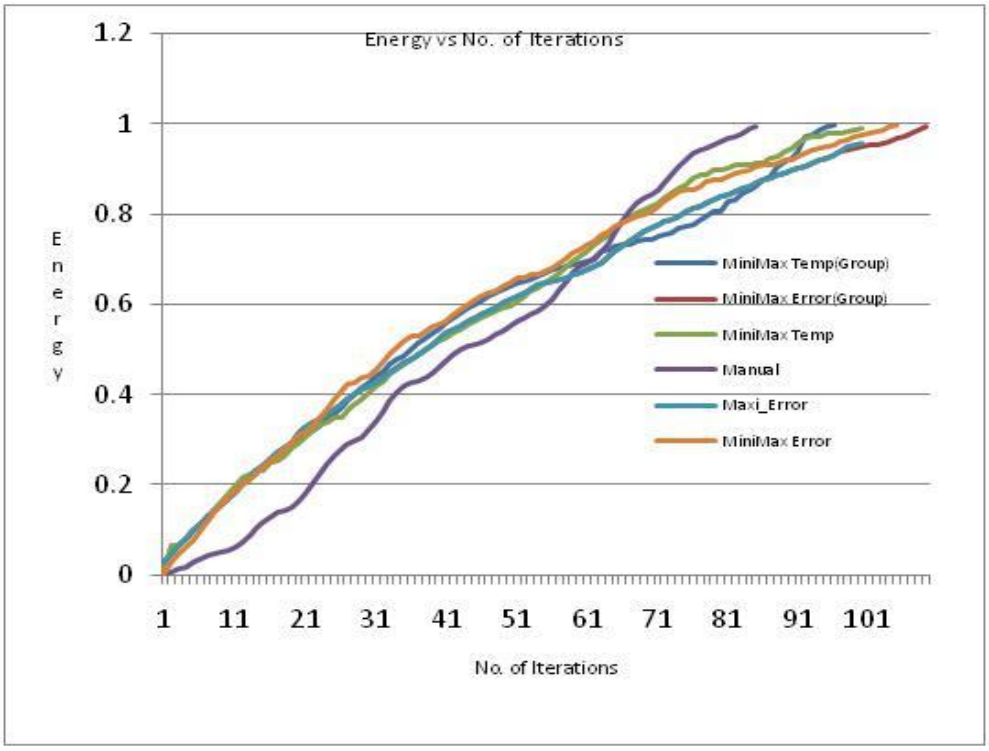

Figure 5: Energy as measure performance by different strategies

The error based sensor relocation is performed very well and reaching high energy zones more quickly as compared to other schemes. Therefore, one can conclude that the error based sensor relocation is performing well and the best scheme to relocate sensors in an experimental.

6. Conclusions

This paper is focused on a sensor positioning problem in a static environment. The challenge is to perform the interpolation with high accuracy and minimum communication costs. To overcome this problem a two step technique is developed. First, the spatial correlation in WSNs is modeled by using the processed data and after that interpolates data in the areas with lack of coverage. Our distributed interpolation technique is highly scalable as compared with the centralized interpolation technique for node positioning. A technique for sensor positioning is proposed based on Kriging interpolation. Their performance is compared with a technique which positions the sensors manually in the monitored environment with respect to accuracy, energy and computational complexity. Accurate results are reported.

The future work will be focused on techniques, that use error based maps for sensor positioning in dynamic environments, for optimal movement and achieving a maximum global view of the sensing field.

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