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Data Aggregation for Spatially Correlated data using Polynomial Regression in 3D Wireless Sensor Network

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Abstract: Sensor nodes observing events, occurring in close proximity, gather data that are highly co-related. This work uses a polynomial regression technique to exploit the spatial correlation of the data in a three dimensional sensor network. The sensing nodes, sense the physical attribute and report their position coordinates (x, y, z) and the sensed value to the nearest tree node. Another set of nodes, categorized as the tree nodes, are responsible for generating a polynomial function of the received data and transmit the coefficients of regression to the parent tree node. The approach proceeds from the bottom to the top. The query from the sink, receives a polynomial function which is generated by the root node of the tree in each cluster to compute the attribute value at any location within the boundary. The proposed approach aims to save a lot of energy in the sensor network. Simulations, performed for different tree heights, indicate that a tree with a depth of four gives the best results.

Keywords: Data aggregation, Energy efficiency, Spatial correlation.

I. INTRODUCTION

Sensor nodes, in a wireless sensor network, are deployed to capture physical or environmental attribute. The wireless communication and some level of intelligence for signal processing and networking of the data, enables the sensor nodes to process the captured data and deliver it to the sink node in a multi hop fashion. The root node, also known as the sink, acts as an accumulator of all the data being sensed by the nodes. Sensor networks have different real life applications such as, habitat monitoring, military applications etc.

Large scale wireless sensor networks suffer from energy problems. Hence energy saving techniques are employed. The operation of wireless sensor networks depends on the data which is sensed and transmitted to the root node. The collection of sensor nodes monitors events and transmit their data. Dense deployments of sensor nodes allow some kind of correlation between the data being sensed by them. The two kinds of correlation that can exist in any given sensor network are:

Spatial Correlation: Densely deployed sensor nodes produce data that are spatially correlated. The distance between the nodes determines the degree of correlation.

Temporal Correlation: Periodic observations from nodes generate data that shows temporal correlation. It has been observed that many physical phenomena show temporal correlation between each consecutive observation of a sensor node. The degree of correlation depends upon the temporal variation characteristics of the phenomenon.

In this paper, we have proposed a scheme that uses a polynomial regression technique to exploit the spatial correlation of the data in a three dimensional sensor network. The sensing nodes, sense the physical attribute and report their position coordinates (x, y, z) and the sensed value to the nearest tree node. Another set of nodes, categorized as the tree nodes, are responsible for generating a polynomial function of the received data and transmit the coefficients of regression to the parent tree node. The approach proceeds from the bottom to the top. The query from the sink, receives a polynomial function which is generated by the root node of the tree in each cluster to compute the attribute value at any location within the boundary.

The rest of the paper is organized under the following headings: section II describes the related work in the field of data aggregation in WSNs. The section III presents the proposed approach. The simulation results are presented in section IV. The section VI concludes the proposed approach.

II. LITERATURE REVIEW

Data aggregation can be done via data aggregation tree (flat networks) or by a clustering strategy if the network is hierarchical. Considering the two types of networks, flat networks have equal nodes and connections are set up between nodes that are within each other’s radio range, although constrained by connectivity conditions and available resources. A hierarchical network unlike the flat network has all nodes typically function both as switches/routers. One node in each cluster is selected as the cluster head (CH) [14]. In a hierarchical network, the number of tiers can vary according to the number of sensor nodes. The cluster head is responsible for routing the traffic, which essentially flows through the cluster head in every cluster. On the other hand, the gateway nodes are responsible for maintaining connectivity among neighbouring cluster heads. The hierarchical network architecture is energy efficient for collecting and aggregating data from the entire WSN or all nodes within a larger target region, using knowledge of their relative locations, but the flat network architecture is often considered for transferring the sensor data between source-destination pairs separated by a large number of hops.

Data correlation is an extensive field of research and a huge amount of literature exists to study data correlation in WSN [16]. The authors in [3, 4, and 5] explore the theoretical aspects of the correlation. The aim of the study of these works is to find the optimum rate to compress redundant information in the sensor observations. A recent work in [6], studies the relation between spatiotemporal bandwidth, distortion, and power in large scale WSNs.

Recent years have witnessed extensive research on in-network aggregation for WSNs [5]. Enachescu et al. in [8] propose a very simple opportunistic aggregation scheme with near optimum performance under widely varying scales of correlation. The scheme, proposed as Opportunistic Aggregation scheme, that sends the data from a sensor to the central agent over a shortest path. The authors formalize a notion of correlation that can vary according to a parameter k. The expected collision time of "nearby" walks on the grid to the optimum cost of scale-free aggregation is then related. A randomized algorithm is used for routing information on a grid of sensors that satisfies the appropriate collision time condition. The proposed approach thus proves that the proposed scheme is a constant factor approximation (in expectation) to the optimum aggregation tree simultaneously for all correlation parameters k. In-line data aggregation is essential for WSNs where the energy resources are limited. Intanagonwiwat et al. have proposed an aggregation scheme in [8]. The authors propose an approach based on adjusting the aggregation points which results in increased path sharing and reduced overall consumption of energy. First a greedy incremental tree is created which is responsible for the establishment of a shortest path to the first source to the sink and hence the name, greedy. The other sources are incrementally connected at the closest point on the existing tree. The results show that greedy aggregation can achieve up to 45% energy savings over opportunistic aggregation in high-density networks without adversely impacting latency or robustness.

Zhong et al. have presented an ultra-low power MAC scheme. When not in use, the radio devices can be turned off to save energy. The advantage of this approach is its ability to take advantage of the redundant data built in the network. The lost data can be efficiently recovered at the destination on the basis of the data from the lost data’s neighborhood. The high spatial correlation between the data in close proximity allows the recovery from the vast data available.

A Tree based polynomial regression algorithm, (TREG) is proposed by Banerjee et al. in [7]. The method proposed in [7] is based on the degree of correlation between the sensor data. The authors propose to use a multiple attribute-based binary tree [11, 15], which with the help of a polynomial regression function, generates aggregated data at the root node. The proposed approach is limited to 2D space in which the nodes sensing the data, run a regression function to find a polynomial in the space coordinates (x, y). The coefficients of the function are forwarded by each node and hence the raw data need not be sent. At every level, a regression polynomial is found increasing the efficiency of the approximation function. The transmission of coefficients, instead of the raw data, allows a constant data packet size for all the nodes, thereby saving a lot of energy.

In this paper, a novel data aggregation algorithm has been proposed to exploit the spatial correlation of the data in a three dimensional sensor network by using polynomial regression technique. The proposed algorithm is analyzed on the basis of simulation results which prove the proposed algorithm to be better and efficient than the existing approaches for data aggregation in a 3D space.

III.PROPOSED APPROACH

The proposed scheme uses a polynomial function based regression technique for the purpose of effective and energy efficient data aggregation in WSN. The technique is effective for three dimensional space, and hence a wide area of application.

In the present work, the sensing field is divided into a number of clusters. Each cluster constructs a tree, through which the data is propagated to the root node. The simulation results for randomly deployed sensor nodes are presented with different node densities. The results showing the comparison of using a single binary tree instead of several small binary trees in the cluster are also presented.

A. Assumptions

We make the following assumptions in our work

1. The sensor nodes are stationary.
2. Each node knows its location coordinates (x, y, z) in the three dimensional space.
3. For all the simulations, we have assumed a binary tree.
4. We assume a collision free MAC protocol.
5. Energy consumed for computation is negligible as compared to energy consumed for data transmission and data reception [8, 9, 10].

B. Description of the scheme

Our scheme is based on the fact that there is a correlation between attribute values and the location. Multiple sensors, in close proximity, can detect the same event and give almost similar readings. The basic objective here, being the aggregation of the sensed data in such a way so as to reduce the data redundancy.

i) Clustering

The clustering includes cluster head selection and cluster formation process.

In the **cluster head selection** process each sensor node chooses a random number between 0 and 1 separately [9]. A node becomes the cluster head, if this number is lower than the calculated threshold for the node.

In the **cluster formation** process each cluster head broadcasts a join message within the sensing field [12, 13]. On reception of the “join” message each non cluster head sensor node, decides to join the cluster head, if it receives the join message more than once then the sensor node joins the nearest cluster head. After a constant time interval cluster head receives join request messages from all the non-cluster head sensor nodes which intend to join it. After cluster formation each cluster head work as the root node and create a tree in cluster. Cluster head randomly choose the sensor nodes for tree formation.

ii) Tree formation algorithm

A tree is formed within the cluster through which the sensed data is propagated to the root node. The steps of the tree formation algorithm can be summarized as:

1. Select the cluster head node as the root of the binary tree. Using the value of tree height (h), the number of nodes in the tree is computed.
2. $Number\ of\ Tree\ Nodes = Nt = 2(h+1)- 1$
3. The number of tree nodes to be selected = $(Nt - 1)$.
4. Randomly select $(Nt - 1)$ sensor nodes.
5. The distance for the randomly-selected node is then computed (from the root node).
6. Two nodes with minimum distance from the root node (closest to the root node) will become its children.
7. For all the remaining nodes compute their distance from both the newly assigned child nodes.
8. Two nodes closest to the first node will become its children.
9. Similarly, two nodes closest to the second node, will become its children.
10. The process terminates when the tree formation is complete.

The tree formation takes place from top to bottom. It starts with the root node that we initialize first. The number of tree nodes is randomly selected. But, how and at what level of the binary tree a node will join the tree is determined by finding the distance between the nodes. Initially the root has two child positions available. Out of the selected nodes, two nearest to the root will become its children. Then from the remaining nodes, the two nearest to each child will become that child's children. The algorithm thus progresses from top to bottom till the tree formation is complete. After completion the tree formation we have three type of nodes in the network viz. the root node, the tree nodes and the sensing nodes.The sensing nodes are responsible for capturing the attribute value and report it to the nearest tree node. Each data packet, sent to the tree node, consists of:

- Sensed value of the parameter
- Its coordinates in space (x, y, z)

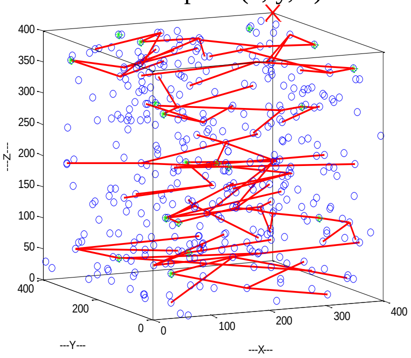


Fig. 1. Tree formation in cluster (Height 2)

Many nodes send their data to the tree node. The tree node, on receiving the data from multiple sensing nodes, runs the polynomial regression function to get the coefficients of regression. The polynomial function in our approach is given by:

$$t = F(x, y, z) \qquad (1)$$

$$F(x,y,z) = b_0 + b_1 z + b_2 y + b_3 yz + b_4 x + b_5 xz + b_6 xy + b_7 xyz \qquad (2)$$

Each tree node, then computes the range of coordinates (using the values of the coordinates sent from different sensing nodes). The computed range is given by $(x_{min}, x_{max}, y_{min}, y_{max}, z_{min}, z_{max})$. Thus the minimum and maximum value of x, y and z components of the coordinates is calculated. The eight coefficients of regression, are then sent to the parent node, as well as the range of coordinates for which the coefficients have been computed. The parent tree node on receiving the coefficients from its children has the following three sets of data:

1. Coefficients of regression + Range of Coordinates sent from first child
2. Coefficients of regression + Range of Coordinates sent from second child
3. Sensed data + Coordinates sent from nearby sensing nodes.

The parent tree node uses the data set 1 to randomly generate points (x, y, z) such that each generated point lies within the range of coordinates received in data set 1. It then uses the coefficients of regression received in data set 1 to compute the attribute values at the randomly generated points. So ultimately it gets the data (x, y, z, t) where "t" is the attribute value at point (x, y, z) in space. It does a similar computation for the second set of data. The third set of data that it received from the sensing nodes, is already in the form (x, y, z, t). Now the parent node uses the combined data set for polynomial regression. It computes the coefficients of regression for the same polynomial function and the combined set of data using equation 2.

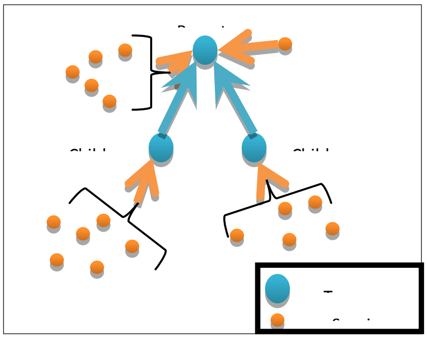
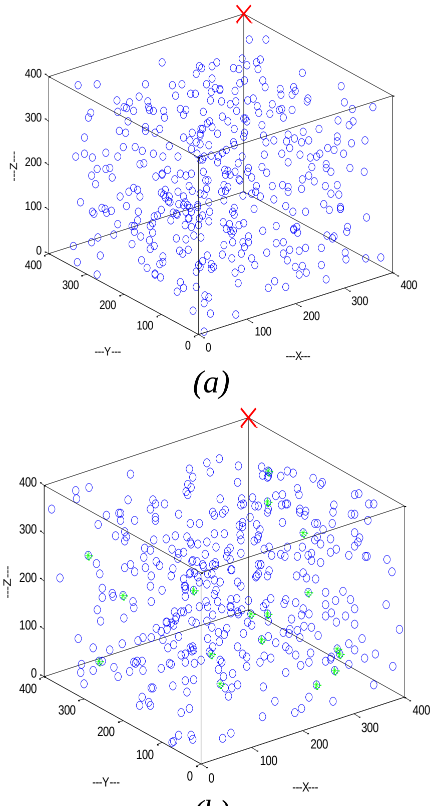


Fig. 2. Data transmission between nodes

It also computes the overall range of coordinates from the three sets of data. It then sends the coefficients of regression and the range of coordinates to its parent tree node. This process starts at the leaf nodes and stops at the root. At the end of the process the root has the polynomial function that represents the attribute value as a function of coordinates in space. Instead of querying the network for attribute value at any point (x, y, z), the root node can now use this polynomial function to compute the attribute value for any node in the network using its (x, y, z) value.

IV. SIMULATION RESULTS

The simulation results for randomly deployed sensor nodes in a regular grid pattern in a $400\,m \times 400\,m \times 400\,m$ volume of space. The figure 3 (a) shows a sensor field in which the sensors have been deployed randomly and the figure 3 (b) represents the cluster head selected in sensing field. The cluster head act as the root node for every tree formed within the cluster.



(a)

(b)

Fig. 3. (a) Randomly Deployed Sensor nodes. (b) Cluster head as root node in cluster

A randomly generated temperature value which is spatially correlated in a region is used for the purpose of simulations.

The following parameters were assumed as:

TABLE I
SIMULATION PARAMETERS

Parameter	Value
The energy consumed to receive 1 bit	10 pJ
Initial energy of each sensor node	1 mJ
The energy consumed to transmit 1 bit	10 pJ

Simulations are performed for different tree heights, from 2 to 5 in a varying network density (i.e. number of nodes in the network). The results are evaluated under the following metrics:

1. The accuracy of the approximation of the sensed parameter over the entire region in percentage error
2. Percentage of Compression achieved
3. Energy Consumed in the tree nodes.

A. Percentage error

We computed the percentage error as follows

$$Error = \frac{|T_{actual} - T_{computed}|}{T_{actual}} \times 100 \quad (3)$$

Where T_{actual} is the actual temperature value at a point and $T_{computed}$ is the computed temperature with proposed scheme.

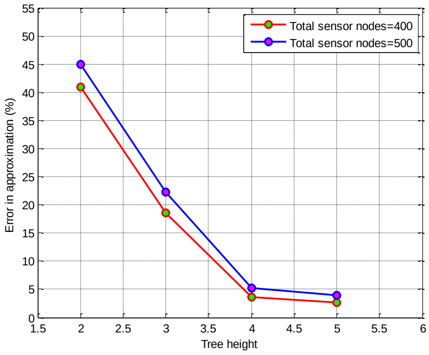


Fig. 4. Percentage Error vs. Tree Height

In Figure 4, shows a decrease in the percentage error as the height of the tree increases. As the tree height increases, a larger area can be covered leading to a better sensed parameter over the region. The maximum error is obtained with the tree with depth 2. A tree with a height of 4, covers the entire network and is able to approximate the network more efficiently. Although there is not much significant improvement in accuracy as the tree height increases from 4 to 5.

B. Data compression

Data packets of the same size, is transmitted by each node to their parent node. This transmission is independent of the number of sensing nodes reporting their data to the tree node. The regression prohibits every tree node to transmit all the data that it received from sensing nodes. Percentage compression is computed and is given by:

$$Compression = \frac{|B_{inp\ ut} - B_{output}|}{B_{input}} \times 100 \quad (4)$$

Where, B_{output} and B_{input} are the bits transmitted and bits received by the tree nodes respectively. It is observed that compression increases with an increase in the number of nodes in the network increase.

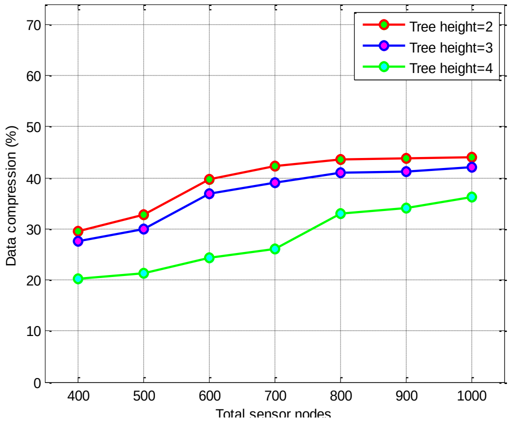


Fig. 5. Percentage Compression vs. Number of Nodes

The figure 5 shows the data compression is not proportional to the tree height. With increasing the tree height, the data compression percentages decrease because of a large number of tree nodes are associate in the tree.

C. Energy consumed in tree nodes

Calculation of energy consumed in tree nodes is based on the assumption that all the tree nodes have already received the data from the sensing nodes. The graph indicates that the energy consumed in the tree is not dependent on the number of nodes in the network. This is expected as number of transmissions in the tree remains the same for a given tree height as shown in figure 6.

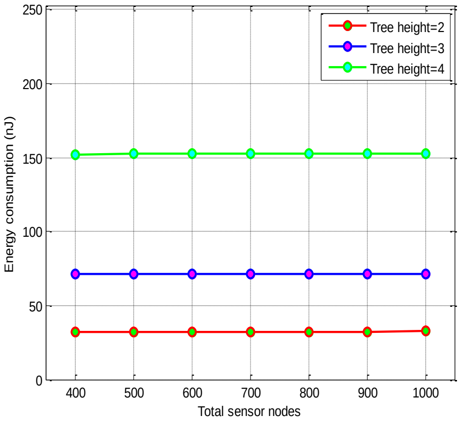


Fig. 6. Energy Consumed in Tree Nodes

D. Comparison with two-dimensional polynomial regression scheme

The Figure 7, compares, a two dimensional TREG scheme [7] with the proposed scheme. Results prove that it is more in percentage error as the two dimensional TREG scheme considers only the two dimensions in the sensing space.

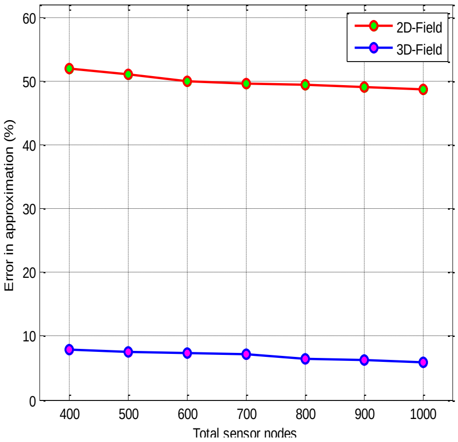


Fig. 7. Two Dimensional Approximation versus three Dimensional

V. Performance Analysis

A. Advantages

The scheme has following advantages:

1. For a polynomial with eight coefficients, the polynomial regression function requires eight unique and independent sets of data. If the size of the data set increases, unlike the previous approaches, the proposed approach partitions the data and generates a set of coefficients, which are individually sent. Even if the size of the data set decreases, the proposed approach can efficiently generate the coefficients.
2. Reduced number of transmissions and therefore reduced energy consumption.
3. The coefficients of regression and minimum and maximum coordinates are only sent to the parent node. Reduced data size saves energy.
4. The regression scheme when employed on the data, it reduces the data redundancy.

B. Limitations

The limitations of the proposed approach are:

1. Results are presented for the specific temperature model. A different set may produce different results
2. A different set might require different function to efficiently approximate the pattern.

VI. Conclusions and Future Work

The Proposed scheme exploits the spatial correlation of attributes in a three dimensional sensor network. The heart of the proposed scheme is an attribute-based tree in the clustered network and polynomial regression at every tree node when a dimension of the data is less. The root node computes the value of physical attribute at any point in the sensor network by inputting the coefficients of that point in a polynomial function. The simulation result shows that the proposed technique performs better than the previous technique.

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