PERFORMANCE ANALYSIS OF ENHANCED ADAPTIVE SCHEDULING SCHEME IN WIRELESS SENSOR NETWORKS

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Abstract: Wireless sensor network, has a great application potential. In this research, we consider the mobility of sink which can prolong the network lifetime of wireless sensor networks. Sink mobility, can be a random mobility and also be a controlled mobility. In this work, we consider the random mobility to improve the performance of the wireless sensor network. Schemes based on random mobility are effective and easy to implement. The drawbacks in controlled mobility systems such as Linear and circular mobility are discussed. In the proposed system, random mobility of sink is considered. Sink is designed to move towards the node which forward highest amount of packets. The location of that node is determined by the expectation maximization algorithm. The throughput, delivery ratio and the efficiency of network get improved by random mobility of sink.

Keywords: Delay-bounded Sink Mobility, Sink Scheduling Data Routing, Mobile sinks, Expectation Maximization.

1. INTRODUCTION

A wireless sensor network consists of number of sensors nodes, each of the node is capable of performing computational operations, storage and communication capability. The data collected by the node will be delivered to one or more sinks, generally via multi hop communication. The sensor nodes are operated with batteries. It is very difficult to replace the batteries of the sensor nodes. Sensor node energy is the most precious resource in a WSN Efficient utilization of energy to prolong the network lifetime of sensor node is very much needed.

WSN consists of sink as a data collection unit. Sensor nodes are present to sense and monitor the environment. Sensors have the ability to communicate with each other and also directly to the external base station (BS). The capacity limited power sources of small sensors constrain us from fully benefitting from WSNs. The traffic of the whole network will be converted to a specific set of sensor nodes by means of many-to-one traffic patterns. This will results in hotspot problem. Sink mobility is important to prolong the network lifetime in wireless sensor networks where the delay in information collection caused by moving the sink should be bounded. An efficient expectation-maximization (EM) algorithm is used to estimate the energy-based multisource localization in WSNs. The parameters such as decay factor, energy and location of sources can be obtained by EM technique. Sink mobility improve performance like energy consumption, network lifetime and end-to-end delay.

The EM algorithm is to decompose each sensor energy measurement, where the sensor energy is the superimposition of energy signals emitted from multiple sources. It decomposes the aggregated energy signal into individual components for different sources and then separately estimates the corresponding parameters. The EM algorithm is an efficient iterative procedure to estimate in the presence of missing or hidden data. An efficient sequential dominant-source (SDS) initialization scheme is used to provide better estimation accuracy. By analyzing the convergence rate of the EM algorithm the step size of the search scheme is obtained.

2. RELATED WORKS

Mobility management is one of the most important issues in wireless networks. There are number of sink mobility scheme are developed for sensor networks.

Zhong Zhi, Luo Da-Yong, Liu Shao-Qiang, Fan Xiao-Ping and Qu Zhi-Hua [2] proposed a scheme based on Gauss-Markov mobility model for adaptive localization. In order to improve the localization efficiency they use several strategy like perpendicular bisector, virtual repulsive and the velocity adjustment strategy. Yu Gu, Yusheng Ji, Jie Li and Baohua Zhao [1] described that network lifetime can be improved by mobile sink where the delay in collection of information should be bounded. Controlled mobility of sink in different trajectories is used to improve the efficiency.

YoungSang Yun and Ye Xia [3] describes that sink mobility can improve the lifetime of sensor networks A delay tolerance level is prescribed, that is there is no need to immediately send the data by nodes when it becomes available. The data is temporarily stored in the node and deliver to the sink whenever it is in the favorable location.

Wei Meng, Wendong Xiao and Lihua Xie [6] proposed an expectation-maximization algorithm to estimate the parameters such as location and energy of source, decay factor. In order to improve the estimation accuracy a scheme known as sequential dominant source is used. U. Nazir, M. A. Arshad, N. Shahid, S. H. Raza [5] describes different technique such as Distributed, Range and Beacon based localization technique to find the position of mobile nodes.

3. EXISTING METHOD

The existing system is designed for the controlled mobility of sink to improve the performance. It is shown that by properly setting the trajectory even limited mobility would significantly improve the network lifetime. The mobility of the sink is designed to move in controlled mobility. The issue in this design is the delay of the data delivery. Delay- bounded sink mobility (DeSM) problem is overcome by considering the induced sub problems and present efficient solutions for them.

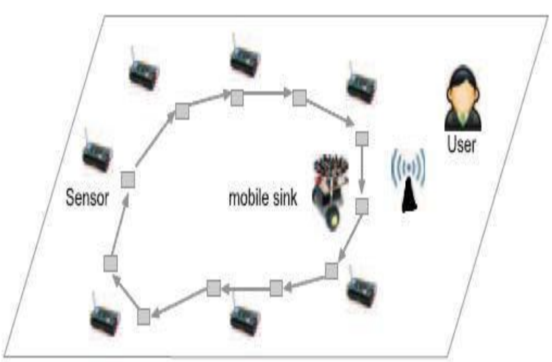

Figure 1: Architecture of WSN with a Mobile Sink

3.1 DeSM Problem

The reference architecture for a WSN shows that sensor nodes, which are stationary, keep monitoring the surrounding environment and generating data. A mobile sink is used to collect the sensed data by moving around the network. A unified framework is proposed in order to cover the main issues such as joint sink mobility, data routing and delay. Therefore, instead of tackling the problem directly, first discuss several induced sub problems. The sub problems are zero delay; infinite speed and Connected sink sites.

The sink has a maximum speed V max (in m/s). When the sink stays at one of sink sites, sensors start transmitting data to the sink through multi hop routing. This could cause a high delay in delivering of data packets.

For a node I, the data generation rate λi (in b/s) can be estimated accurately. The initial energy is denoted as Ei in Joule. The total energy consumption of node cannot exceed initial energy.

The energy for transmitting one bit data from nodes i to j is given as

$$eij\,(k)^{T} = \alpha + \beta\,(d i,j\,(k))^{\theta} \quad (3.1)$$

where α (in J/bit) and β (in J/bit) are constant coefficients, d(i,j(k)) is the distance between nodes I and j (in meter) and θ is the path loss index, it varies according to the environment condition. Total energy consumption at node i is given as

$$e^{i} = eij^{T}\,(\textstyle\sum lij \in L\ fij) + e^{R}\,(\textstyle\sum lji \in L fji) \quad (3.2)$$

where fij(k) is the amount of data from nodes i to j, L is the set of wireless links between sensors.

3.2 Extended SSDR Algorithm for DeSM

To solve the DeSM problem, the network graph should be divided into several connected sub graphs, each of which can be solved by Sink Scheduling Data Routing (SSDR) technique. The SSDR approach can be summarized as following three steps.

- Run the optimization to get the optimal solution.
- The depth-first search is used to find a path on the sink site graph that includes all the sink sites.
- After finding the path assign the visit time of every

point on the path and corresponding routes based on the data obtained in first step

E-SSDR is an optimal algorithm for the DeSM problem. The overall optimal solution is same as the sub graph with the longest network lifetime. If there is two sites from two different sub graphs, find a sink path including these two sites that meets the delay constraint. This is the contradiction. The steps involved in E-SSDR approach to solve the DeSM optimally are

- The graph is divided into connected sub graphs.
- Apply the SSDR approach to each sub graph and obtains the optimal sink path as well as corresponding routes.
- Choose the sub graph with the longest network lifetime as the output.

Three typical trajectories of the sink provide important insights for designing mobility schemes in real world mobile WSNs namely, Linear trajectory, and Circular trajectory.

4. PROPOSED METHOD

The sink is designed to move randomly within the network. In this architecture, mobile entities pick up data from sensors when in close range in sparse sensor networks. Sink is designed to move to the node according to the amount of packet forward from the node. The location of that node is determined by the Expectation Maximization technique.

4.1 Random Mobility

The increase in throughput and data fidelity can be achieved by random mobility of sink. The position is determined by selecting a uniform random distance which is the distance to travel along the newly defined direction. If the new position falls outside the network area, crops the position to fall on the boundary of the area. This is the simplest possible movement. This method is very robust; collecting data from the disconnected areas is difficult because faulty sensors or obstacles are presence.

4.2 EM Localization Technique

The expectation maximization algorithm enables parameter estimation in probabilistic models with incomplete data. The EM algorithm is used to find the maximum likelihood parameters of a statistical model in cases where the equations cannot be solved directly. In addition to unknown parameters and known data observations, the model involves the latent variables. There may be missing values among the data, or the model can be formulated simply by assuming the existence of additional unobserved data points. EM is an iterative optimization method to estimate some unknown parameters given from the given measurement data. In particular, there is a need to maximize the probability of the parameters from the data. EM algorithm can minimize the sum of squares of the distances between nodes and cluster centroids, the energy consumption is proportional to the sum of square of communication distance. Communication distance is the sum of distance between each hop from the communicating node to the cluster centroid. Therefore, there is a need to adapt the EM algorithm to minimize the sum of communication distance. The difference of communication distance and the direct distance between every node and centroids becomes shorter when node density increases.

The EM algorithm groups the nodes into a certain number of clusters to reduce energy consumption. The two dimensional EM algorithm is only based on an assumption that nodes are distributed according to a 2-dimentional Gaussian distribution. The expectation maximization algorithm accounts for the confidence of the model in each completion of the data. Expectation maximization has the advantage of being simple, robust for parameter estimation with incomplete data and easy to implement

4.3 Steps in EM Technique

The proposed EM technique provides alternates between the steps of probability distribution over completions of missing data, the current model known as the Expectation step (E- step) and then re-estimating the model parameters using these completions known as the maximization step (M- step).

4.4 E-Step

In the E-step, the missing data are estimated from the given observed data and the current estimate of the model parameters. By using the conditional expectation this can be achieved. Operate a Kalman filter or a minimum-variance smoother designed with current parameter estimates to obtain updated state estimates.

The signal energy received by the ith sensor from the kth source is given as by y_{ik} where i = 1,2,….,N, k = 1,2,….,K. The vector Y'_k represents the vector of signal energy received by N sensors from the kth source. In the algorithm, consider Y'_k , k=1,2…K as hidden variables.

In the Expectation-Step (E-Step) of the EM algorithm, it can obtain the expectation value of the hidden information Y'_k , k=1,2…K by

$$Y'_k(\theta_k) = S_k d_k + 1/K (Y\text{-}DS)^T \qquad (4.1)$$

where the second term is obtained by assuming that every element of $Y'_k(\theta_k)$ has an approximate noise variance σ^2/k. In the E-Step, it decomposes the received energy of sensors to get the hidden data Y'_k which represents the signal energy received by sensors from a source.

4.5 M-Step

In the M-step the model re-estimation of data as maximization of the expected log-likelihood of the within maximum-likelihood calculations to obtain updated parameter estimates. It eliminate the unknown parameter S_k by setting $S_k = Y'_k d'_k$, where d'_k is the pseudo inverse of the matrix.

$$d'_k = d^T_k (d_k \backslash d^T_k)^{-1} \qquad (4.2)$$

The modified negative log-likelihood function is given as

$$l(Y'_k / r_{sk}) = Y'_k (I - P_d)(I - P_d)^T Y'^T_k \qquad (4.3)$$

where P_d is a projection matrix is given as

$$P_d = d^T_k d_k / d^{2\,k} \qquad (4.4)$$

The unknown parameter S_k is given as

$$S_k = Y'_k d^T_k / d^2 \qquad (4.5)$$

The expectation maximization algorithm involves computing the probability distribution over start positions for each sequence in E-step and updating the frequencies based on the expected counts for each position in the M-step. For initialization EM proposes an SDS initialization scheme to get the initial location estimates for sources.

First it will sequentially select sensors that receive locally maximum received energy as the closest nodes to the sources and initiate the locations of the sources to their corresponding closest nodes. For parameter learning, the expectation maximization algorithm alternates between computing probabilities for assignments of each gene to each cluster (E-step) and updating the cluster means and covariance based on the set of genes predominantly belonging to that cluster (M-step). The expectation maximization algorithm involves computing the probability distribution over start positions for each sequence (E-step) and updating the frequencies based on the expected counts for each position (M-step) data is done. Filtered or smoothed state estimates

5. SIMULATION RESULTS

For simulation a group of 44 nodes have been considered in the NAM window. Nodes are schedule in random manner. Mobile Sink is used to collect the data. Throughputs, Packet Delivery ratio, End to End delay are obtained.

In the proposed random mobility EM technique is used to evaluate the parameters. The parameters are compared with the existing system. In the proposed system by using the EM technique the sink move towards the node which forward highest data packets so that the throughput, Delivery ratio are get increased than the existing system. End to End delay is decreased than the existing system.

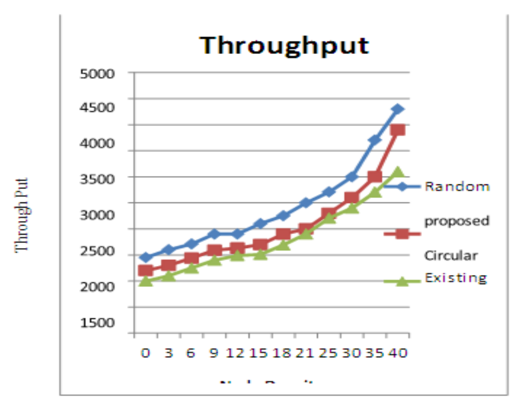

Figure 2: Node Density versus Throughput

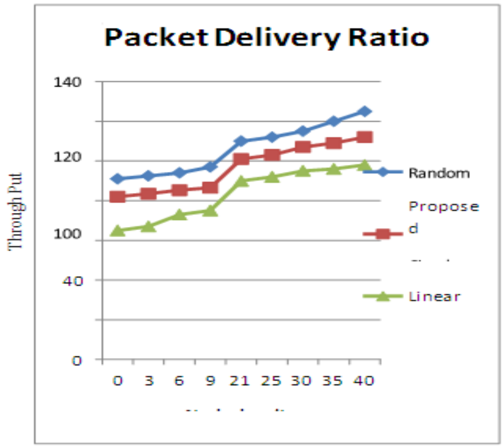

Figure 3: Node Density versus Throughput

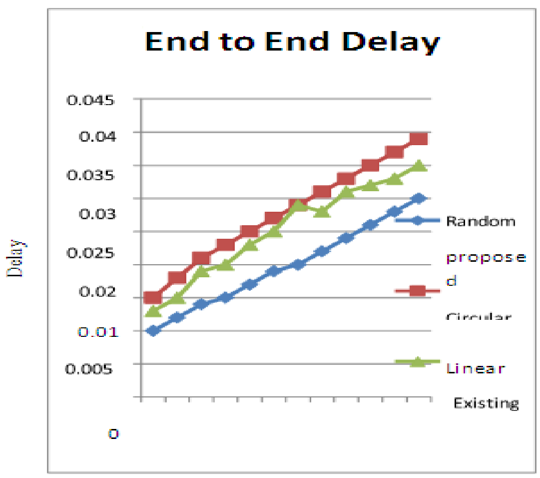

Figure 4: Time versus Delay

6. CONCLUSION

Wireless Sensor Network is a resource constrained network. It is necessary to guarantee the quality of data transmission and to increase the network lifetime. A unified framework is designed to analyze the sink mobility problem in WSNs with delay constraint in the existing method. The benefits of involving a mobile sink and the impact of network parameters such as the number of sensors, the delay bound on the network lifetime are studied. The proposed system is extended to reduce the delay in delivery of packets. In random mobility pattern, the mobile sink can move chaotically towards all directions at varying speeds. The network lifetime can be increased by random mobility of sink. The location of the node is determined by the expectation maximization algorithm. Sink move towards the node which deliver highest amount of packets, because of this throughput and packet delivery ratio are get increased.

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