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Accurate and energy efficient cluster based partial multihop localization scheme for WSN based on antithetic markov process

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Abstract: Localization schemes for sensor network systems should work with inexpensive off-the-shelf hardware, scale to large networks, and also achieve good accuracy in the presence of irregularities and obstacles in the deployment area. Clustering is a standard approach for achieving efficient and accurate performance in wireless sensor networks. Traditionally, clustering algorithms aim at generating a number of disjoint clusters that satisfy some advanced criteria. MCL is a version of Markov localization, a family of probabilistic approaches that have recently been applied with great practical success. In this paper, we formulate a novel cluster based partial multihop localization scheme for WSN based on antithetic markov process which variance reduction method for increasing the accuracy of Markov chain Monte Carlo algorithm for computing the dominant Eigen pair of a matrix computation. We also propose a randomized multi-hop localization scheme, based on an accurate analysis of hop progress in a WSN with randomly deployed sensors and arbitrary node density. By deriving the expected hop progress from a network model for WSNs in terms of network parameters, the distance between any pair of sensors can be accurately computed with the help of antithetic markov process. The proposed localization algorithms all can be implemented partially asynchronously in networks. Finally, extensive simulations are conducted to demonstrate the efficiency and accuracy of the proposed multihop localization algorithms.
Keywords: antithetic, energy, localization, Markov process, partial multihop, wireless sensor.

I. Introduction and related work

Many wireless sensor network applications require information about the geographic location of each sensor node. Besides the typical application of correlating sensor readings with physical locations, approximate geographical localization is also needed for many sensor network applications[1],[2]. A fundamental problem in designing sensor network is localization – determining the location of sensors. Location information is used to detect and record events, or to route packets using geometric-aware routing, *e.g.*, [3]. Manually recording and entering the positions of each sensor node is impractical for very large sensor networks. To address the problem of assigning an approximate geographic coordinate to each sensor node, many automated localization algorithms have been developed.

To obtain the information required for node locations, researchers proposed many approaches that make different assumptions: (1) quantitative ranging/directionality measurements [4–8]; (2) long range beacons [9,10]; A more reasonable solution to the localization problem is to allow some nodes (called *seeds*) to have their location information at all times, and allow other nodes to infer their locations by exchanging information with seeds.

Localization algorithms can be divided into two categories: *range-based* and *range-free*. In range-based algorithms, nodes estimate their distance to seeds using some specialized hardware.
These measurements are used in methods like triangulation or trilateration [11], which are based on the idea that a node location is uniquely specified when at least the coordinates of three reference points are available for a node. Although the use of range measurements results in a fine grained localization scheme, range-based algorithms require the sensors contain hardware to make range measurements. Range-free algorithms do not use radio signal strengths, angle of arrival of signals or distance measurements and do not need any special hardware. Range-free algorithms require that each node knows

(a) which nodes are within radio range
(b) their location estimates.
(c) the (ideal) radio range of sensors.

No other information is used for localization. Thus, range free techniques are more cost-effective because they do not require sensors to be equipped with any special hardware, but use less information than range-based algorithms. Some energy efficient algorithm called WMCL which can achieve both high sampling efficiency and high localization accuracy in various scenarics [12] in supervisor localization the central problem investigated is how to synthesize local controllers for individual agents such that the resultant controlled behavior is identical with that achieved by global supervision[13]. Performing clustering on a sensor network deployment prior to localization has two advantages. First, it creates a regular pattern from which location information can be extracted. Second, it helps reduce the amount of communication overhead since only the cluster-heads need to be involved in the initial phase of the localization. In cluster-based MDS scheme for range-free localization, CMDS for short, which addresses the shortcomings of MDS-MAP and yields higher accuracy in all environments [16] also some cluster based localization using received signal strength indicator (RSSI) were proposed in past decade [17]

The MCL[18] based algorithm has two steps. In the *prediction step*, the sensor node uses a motion model to predict its possible location within a two dimensional Cartesian space based on previous samples and its movement. In the *filtering step*, the node uses a filtering mechanism to eliminate those predicted locations which are inconsistent with the current sensor information. Simulation results show that the MCL algorithm gives lower estimation error than both Centroid [14] and the Amorphous [15] localization algorithms but author don't consider other high level parameter of wireless sensor network like TOA and RSSI.

A number of clustering protocols have been proposed for wireless sensor networks. Most of these protocols aim at formation of stable clusters in wireless sensor networks; where node location is mostly fixed. Clustering protocols for wireless sensor network can be categorized as non-location based and location based routing protocols. This type of algorithm becomes very inefficient in case of large area sensor networks due to single-hop communication of cluster heads to the sink.

In this paper we propose a new scheme for WSN based on antithetic markov process which variance reduction method for increasing the accuracy of Markov chain Monte Carlo algorithm for computing the dominant eigen pair of a matrix computation by using our method we increase the energy and accuracy of localization which analyze the highlevel parameter of WSN. The clustering process in the proposed method is a decentralized process, which is carried out by sensor nodes autonomously, without any radio communication to the sink thus saving the node energy. The cluster head rotation depends on the residual energy of a cluster head and rotation frequency/timing is based on energy consumption of sensor nodes for various tasks performed by them during the lifetime of sensor network. This ensures balanced energy consumption of all sensor nodes present in a cluster, resulting in prolonged network lifetime. In best of our knowledge it is the first time we propose the cluster based partial multihop Localization algorithm for WSN with antithetic markov process.

II. Proposed localization algorithm

In Proposed Localization method we employ the antithetic variance reduction method for increasing the accuracy of Markov chain Monte Carlo algorithm for computing the dominant Eigen pair of a matrix. Some numerical example shows that the proposed method is efficient.

A. *Antithetic variates*

The method of antithetic variates attempts to reduce variance by introducing negative dependence between pairs of replication node. In this technique, we generate two identically distribution samples, X_1 and X_2 and then let the unbiased estimator for θˆas

$$\hat{\theta} = \frac{X_1 + X_2}{2} \qquad (1)$$

Obviously, we see

$$\mathrm{Var}\,(\hat{\theta}) = \frac{\mathrm{Var}(X_1) + \mathrm{Var}(X_2) + 2\,\mathrm{cov}(X_1, X_2)}{4} \qquad (2)$$

Therefore, we have

$$\mathrm{Var}\,(\hat{\theta}) = \mathrm{var}(X) / 2 + \mathrm{Cov}(X_1, X2) / 2 < \mathrm{var}(X) \qquad (3)$$

If and only if $\mathrm{Cov}(X_1,X_2) < 0$

Let us Consider $X_i = h\,(U_i)$,$X_i\hat{} = h(1- U_i)$ (4)

Where $U_i = U_1^{(i)} \ldots\ldots\ldots U_m^{(i)})$ and

$1\text{-}U_i = (1\text{-}U_1^{(i)}, \ldots\ldots, 1\text{-}U_m^{(i)})$

For i=1,2,……n. (ie) $E(X_i)=E(\ \ _i)=\theta$

Also, for monotone function *h*, it can easily be shows that the covariance of X_i , X_{i-1} is negative.

So the estimator $Zi= X_i + \ \ _I / 2$ is better than the usual estimator.

B. *matrix computations for locating the sensor in geographical area*

Suppose a matrix $A = \{a_{ij}\}^{n}_{I,j=1}$ ie known sensor will assign in the particular area.Now consider the following markov chain T_i with length i

$$T_i : k_0 \to k_1 \to \ldots\ldots\ldots \to k_i \quad (5)$$

where for J = 1,2,…….i , k_j€ {1,2,…..n) are natural random numbers. The statistical natures of constructing the chain followed by

$$p(k_0=\alpha)=P_\alpha \text{ , } P(k_j = \beta \mid k_{j-1}=\alpha)=P_{\alpha\beta} \quad (6)$$

where P_α and $P_{\alpha\beta}$ show the probability of starting chain from the node and transition probability .

Now define the random variable for unknown node deployment, Let W_j using the following recursion for

$$W_0=h_{k0} / p_{k0} \text{ , } W_j=W_{j-1} (a_{k(j-1)k(j)}) / (p_{k(j-1)k(j)}) \quad (7)$$

Where, j = 1,….i

From all possible permissible densities we choose the following

$$P=\{P_\alpha\}^n_{\alpha=1} \text{ , } P_\alpha=|h\alpha| / \quad (8)$$

$$P=\{P_{\alpha,\beta}\}^n_{\alpha,\beta=1} \text{ , } P_{\alpha,\beta}=|a_{\alpha,\beta}| / \quad (9)$$

where α=1,…..

The choice of the initial density vector and the transition density matrix leads to an Almost Optimal Monte Carlo (MAO) algorithm.

III. PRELIMINARIES

A. *Assumptions*

We make the following assumptions in this paper,

- All sensor nodes are able to communicate with the cluster head after initial deployment. The cluster head also knows the location of the sensors through an initial setup process.
- The cluster head has more computation power than the sensor nodes. The cluster-based approach in this work assumes that the cluster head is responsible for computation,and the sensor nodes are functioning mainly as data collection devices.
- To simplify the energy analysis, the time for sending a certain amount of data is assumed different nodes to the cluster head is ignored in the discussion on energy consumption.

Also, all sensor nodes are assumed to be homogeneous, therefore the energy consumption for sensing is the same to each sensor node.

B. *Sensor Detection Model*

The sensor detection model converts the physical sensing signals to probability-based values in evaluating the confidence level about the data collected by the sensor. Consider an *n* by *m* sensor field grid and assume that there are *k* sensors deployed in the initial sensor deployment stage. Each sensor has a detection range *r*. Assume that sensor $S_i, 1\leq i\leq k$ is deployed at point (x_i,y_i). For any point *P* with coordinates (*x; y*) on the sensor field grid, we denote the Euclidean distance between s_i and *P* as $d(s_i; P)$, i.e.$d(s_i; P) = \sqrt{(x_i - x)^2 + (y_i - y)^2}$ it shows the probability-based sensor detection model that expresses the coverage $C_{xy}(S_i)$ of the grid point *P* at (*x; y*) by Sensor S_i

$$C_{xy}(S_i) = \begin{cases} o, r + r_e \leq d(s_i, P) \\ e^{-\lambda a^\beta}, r_e > r - d(s_i, P) \\ 1, r - r_e > d(s_i, P) \end{cases}$$

where R_e ($R_e < r$) is a measure of the uncertainty in sensor detection, $a = d(S_i; P) - (r - r_e)$, and λ and β are parameters that measure detection probability when a target is at distance greater than *re* but within a distance from the sensor. The distances are measured in units of grid points. Different values of the parameters α and β yield different translations reflected by different detection probabilities, which can be viewed as the characteristics of various types of physical sensors.

IV. PROBLEM FORMULATION

A. *Problem statement*

The positional error tolerance D from an application is located on object O. The maximum amount of energy saving by calculating the minimizing the probability of exceeding the positional error bound D to indulge the energy saving methods.

The approach we used for reducing the energy consumption that is energy saving methods can be done dynamically adapting the sampling rate of location information which was based on the positional error model. In order to achieve a good performance we calculate the accurate predict mobility level which is located using the sensors that are attached on the mobile targets. We will sure that the prediction is 100% correct according to it we will calculate the probability of occasionally specified positional error bound. The goal of our energy-saving methods is minimizing the nonconformance rate.

B. *Performance metrics*

- Energy consumption: it measures the amount of power consumption on a tracked mobile target under an energy-saving method; and
- Non-conformance rate: it is computed as the probability of occurrences when the positional error exceeds the application's error tolerance requirement.

C. *Positional Error Model*

We process the positional error from the two error sources in a localization system. The first one is estimation error and the second one is freshness problem. The estimation error is calculated by the positioning engine in which the position of a tracked object is taken. The measurement problems calculate the object is at P_{e1} instead of $P_{t1.}$ In the second source freshness problem is processed by the concept of location sample within a sampling interval. The Two consecutive position samples p_{e1} and p_{e2} are calculated for a moving target at times t_1 and $t_{2.}$ The application requests the position of this moving target at time t_a and $t_1 < t_a < t_2$, the position provided to the application is p_{e1}, which is no longer the most up-to-date position of this mobile target. The position information is expected by positioning engine that must be perfect at the sampling time. The application might still understanding positional error that is proportional to the length of the sampling interval, also called the delay access error.

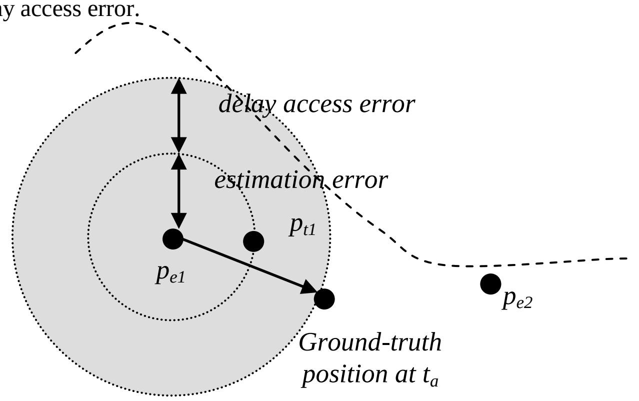


Figure 1.Sampling error sources

The model is derived for positional error; we present a brief description for our localization system works and explain any associated parameters that impact its positional accuracy.

This localization system is collected of infrastructure and mobile components. Our infrastructure component consists of beacon nodes installed on the ceiling of a deployed environment. Since beacon nodes are hardwired to the building's power source, energy saving for the infrastructure component is *not* our target.

Every button can take out a record of the receiving power of beacon packets, and a sensor network infrastructure relays this record, pairs of beacon-id and signal-strength back to our positioning engine which is running on a remote server. This positioning engine is already developed in our lab. It runs a hybrid algorithm combining signal strength (SS) fingerprint and SS propagation model. The positioning engine collects enough SS information from a mobile badge and then it guesses the badge's current position. The current position is forwarded to a location middleware, which then reports the current position to the application. At the same time, our energy-saving methods calculate a sleep time for a mobile badge, during which the radio interface on the mobile badge can be turned off to conserve power.

D. *Energy-Efficient Design*

The Communication is the main energy consumer in wireless systems; so the energy-efficient issue has received much awareness. This reduces the sources of power consumption within mobile terminals by the lead in low-power design within the physical layer. The energy efficient protocols such as adaptive error and power control are applied for MAC layer of wireless networks and power conserving protocols within the LLC layer. The network layer develops the Power-aware protocols by the trade-off between frequent topology updates (resulting in improved routing) and precious bandwidth consumed by increased update messages. The saving battery power within the transport layer lies in sensitivity to wireless environment. The handle losses analyze by the Selective acknowledgements and explicit loss notification. In the application layer, techniques are developed specifically for different applications. This sampling mechanism is mainly focused on improving energy efficiency to support location-aware applications.

E. *Range Estimation Techniques*

There are various methods for developing the range estimations. Generally these mechanisms are requiring signal transmissions between the observer and the target observed. The common differences are properties of calibration methods and the usage of signal sources. The adaptive sampling mechanism is independent and complementary for the range belief methods. So the frequency of range estimations can be optimized for energy-efficiency. The most common methods use sonic, ultrasonic, and RF as signal sources. The statement is that signal propagates with

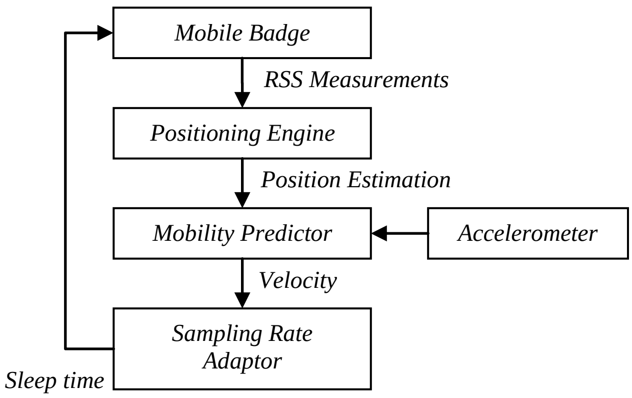
constant velocity, TOA (time of arrival), by measuring the signal propagation time, is the most common method for estimating the distance. AOA (angle of arrival) is a network-based technique exploiting the geometric property of the arriving signal. By calculating the angle of the signal's arrival at more than one receiver, AOA is able to give a more precise location. TDOA (time difference of arrival) is also network-based. It trial the time difference instead of the angle to infer distance. We also some hybrid approaches such as TOA, AOA, and TDOA and this are still an active research topic in the field of localization.
The other technique measures the received signal strength indication (RSSI). These practices develop the decaying model of electronic-magnetic field to translate RSSI at the corresponding distance. The frequency bands used for transmission vary.

F. *Energy-Saving Solutions*

The error tolerance (*D*) from an application equal to the overall error, we obtain the *longest* possible *sleep_time* for a mobile badge while meeting the specified positional error tolerance. The reason for choosing the longest sleep time is to maximize the amount of power saving since the radio on the mobile badge is turned off. Therefore, this longest *sleep_time* is calculated using the following equation:

Sleep_time = (Error_tolerance – Estimation_error / target_velocity) (10)

There is one *unknown variable* in Equation (10): *target_velocity*. Since this unknown variable is dynamic over time, our energy-saving methods need to continuously *predict* target_velocity's current value before using this equation. In addition, our energy-saving methods also need to change *sleep_time* based on current predicted values of *target_velocity*. We provide a summary of all parameters in the positional error model. These parameters are categorized into a control parameter, known system parameters, an unknown variable requiring prediction, and application specified input.



This method is based on a *constant velocity* model to predict the current velocity of a mobile badge. The current velocity is calculated as the immediate velocity from the most recent two location samples according to the following equation:

$$target\_velocity = \frac{position(t_i) - position(t_{i-1})}{t_i - t_{i-1}} . \qquad (11)$$

A potential problem with this prediction heuristic is that a small amount of estimation error from the positioning engine significantly impacts the prediction accuracy, causing either under-estimation or over-estimation of velocity.

V. MULTI-HOP PARTIAL CLUSTERING METHOD

In order to design good algorithm for WSN, multi-hop Partial clustering algorithm assume the following techniques to achieve the design goals stated: 1) each node can use power control to set the transmit power and evaluate the distance by the transmit ; 2) each node is equipped with directional antennas, which can evaluate orientation information from the receiving signal; 3) each node can perform data aggregation and compression to fuse the receiving data packets and its own data packet into a constant data packet . Furthermore, each node owns a different ID. The operation of multi-hop clustering algorithm is also divided into rounds. Each round includes two phases: cluster head selection phase, cluster formulation phase.

A. *Cluster head selection*

In the cluster head selection phase, two bound variables: node's residual energy and distance among cluster heads, are introduced, so that nodes who hold a large residual energy will have a better chance to become cluster heads. The specific process of the cluster head election is as follows. Each node transmits its residual energy message to cluster head in its last transmission slot per round. When the cluster head receives all messages during the last frame, it chooses three nodes with the largest residual energy as preliminary cluster heads (CHpre) and broadcasts the message to its non-cluster head nodes. Each CHpre sets a timer, and time of each timer is inversely to the residual energy. When time of one timer is first over, the CHprep broadcasts a message to let all the nodes in the network know, and the rest two CHpreps become non-cluster head nodes after receiving the message. Once the first cluster head is elected, the rest CHs are elected among the CHpreps of other clusters with a bound variable—average radius of cluster *R.* That is CHpreps , which distances between each other are most closest to *R* , will become cluster heads.

$$R=\sqrt{\frac{s}{\pi.n.p}} \quad \text{.....(12)}$$

B. Cluster formation Units

Once nodes have elected themselves to be cluster heads, the cluster heads broadcast the resultant message using a non-persistent carrier-sensor multiple access (CSMA) MAC protocol. This message is a small message containing the node's ID. Each non-cluster head node determines its cluster for this round by choosing the cluster head that requires the minimum communication energy, based on the received signal strength of the advertisement from each cluster head. According to the direction of join-request message and the transmit power from each node, the cluster head estimates the orientation and distance information of each node. Once the cluster head has received all join-request messages, based on the whole cluster structure and distance information, the cluster head calculates a optimal multi-hop data transmission path for each node.

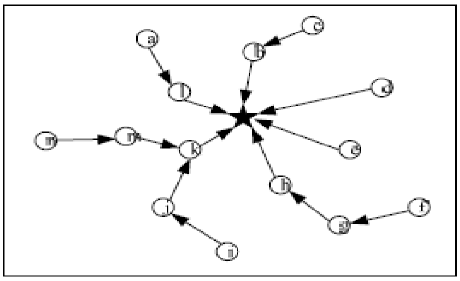


Figure:2 Each node chooses its optimal multi-hop data transmission path to reduce energy dissipation

The optimal multi-hop data transmission path for each node is shown in Fig. 2. When a node chooses an another node as its next-hop node, the chosen node must satisfy two demands. Firstly, the chosen node must have a closer distance to the cluster head. Secondly, the angle composing by the original node, the original node's next-hop node, and the original node's secondary-hop node or cluster head must be an obtuse angle. If the next-hop node does not satisfy the secondary demand, the original node will choose the secondary-hop node as its next-hop node and calculate whether or not satisfy the demands. Therefore, the reason node *i* choosing node *j* as its next-hop node in Fig. 2 is

$$d^2_{i-j} + d^2_{j-k} < d^2_{i-k} \qquad (13)$$

where d^2_{i-j}, d^2_{j-k}, d^2_{i-k} are the distance between node *i* and node *j* , node *j* and node *k* , node *i* and node *k* respectively. Once the cluster head has calculated the optimal multi-hop paths, it broadcasts the resultant message and TDMA code to the cluster. All the non-cluster nodes look for their optimal transmission paths from the advisement message. To reduce conflict rate of data transmission, in the paper, we assume node which has the more hops will occupy the more front of the transmission slot per frame.

VI. PARTIAL CLUSTERING METHODS

In partial clustering, the field is first partitioned into cells and then a sub-area is selected within each cell. In order to maintain connectivity, the partition and the sub-area selection need to satisfy the following two conditions.

Condition 1: Any sensor in a sub-area is connected directly to all sensors in the sub-areas within neighboring cells.
Condition 2: Within a cell, sensors outside the sub-area can communicate directly with any sensor in the sub-area.
Comparing partial clustering with clustering, denoting by Dp and Dc the respective average duty cycle, we have the Following

$$D_p = n_p /N \quad \text{And} \quad D_c = n_c /N \qquad (14)$$

where n_p and n_c are the number of cells in a partial clustering and standard clustering methods, respectively. Thus so long as np < nc, partial clustering achieves lower average duty cycle.

The sub-areas are chosen as the shaded co-centered squares, as illustrated in Figures 3(a) and (b). For any square cell, the 4 square cells adjacent to its sides are considered its neighboring clusters. From Figure 3(b), we can see that the largest distance from any sensor in a cell to a node in the sub-area of the cell is less than R. Furthermore, the largest distance between two nodes in neighboring sub-areas equals R.

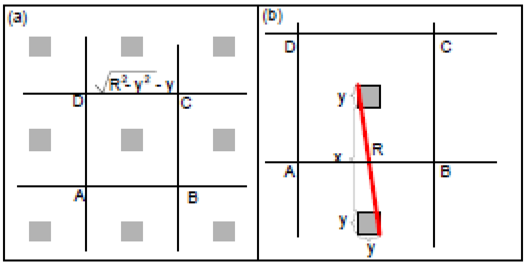


Figure:3 (a) **P-S(y)**: One sensor needs to be chosen in each shaded sub-area. (b) Details of **P-S(y)**: Square ABCD is a cell.

The side length y is also easily obtainable from Figure 3(b). We can see that the largest distance from any sensor in a cell to a node in the sub-area of the cell is less than R. Furthermore, the largest distance between two nodes in neighboring sub-areas equals R.

The key to the distributed partial clustering algorithm is illustrated in Figure 4. In a the hexagon based partial clustering essentially attempts to form a .ring. of active nodes (12 of them to be precise) around an area in which all nodes can go to sleep. If a node can Find such a ring of nodes (subsequently called *supports*) to be active, then the node can safely switch off (such a node is subsequently called a *head*). Once this ring of supports are identified, all other nodes surrounded by this ring can also become heads and switch off. The head node will be off for a pre-specified period of time and wake up; the ring of supports will be relieved of their role, and the process will repeat. A node that is neither a head nor a support will be called a *regular* node.

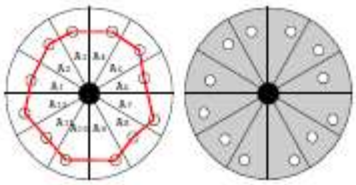


Fig. 4. Partition of the communication area of the head node (in dark) and the connected ring of supports (in white). All non-support sensors inside the big circle are potential heads

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VII. RADIO MODEL DESIGN

This section introduces a radio model, which dynamically determines which power level setting should be used to transmit between two nodes. Using the power level setting, the cost of transmissions are calculated based off the chip specifications to ensure an accurate estimation. Estimating RSSI Received Signal Strength Indication (RSSI) is used to determine which power level setting is needed to transmit directly between two nodes. To estimate the RSSI we can use one of the existing radio models, which can be isotropic or anisotropic. Since the main goal of this work is to increase realism of our model, an anisotropic model is used to estimate the RSSI. The model chosen for our implementation is the Radio Irregularity Model (RIM) because of its ability to simulate differences in sending power amongst different pieces of hardware and anisotropic path loss. The RIM model builds upon the simple isotropic models that by adjusting the Sending
Power and Path Loss variables. For Path Loss they introduce a degree of irregularity (DOI) parameter to assign unique path loss in each direction. RIM also adjusted the sending power variable for each node to account for differences in hardware. Using this model we input the sending power level in decibels and the distance between the two nodes to estimate the RSSI when sending between them. The Path Loss calculation performed in RIM can be based on several existing isotropic models such as the Free Space Propagation model, Two-Ray Model or the Hata model [19].

RSSI = Sending power - pathloss + fading

In most work, authors assume that the power level can be adjusted to the exact needs and calculate the energy cost using these exact values. In reality this is not the case as the radio can only be adjusted to one of the associated power levels and not set to the exact transmission power needed. Using the assumption that there is an infinite amount of transmission levels, previous work makes the assumption that the longer links will cost more to transmit a packet. In many situations two links of different lengths will need to transmit at the same power level setting in order for the packet to be received and therefore the cost to transmit over different distances can be equivalent.

Procedure to control the Transmission power (T, R) based on Makov process

Step: 1 Node Connected <- True (or) False
Step: 2 for each i € P do
Step: 3 Sensor Power level < - i
Step: 4 if (Estimate RSSI (T, R) ≥ RSSI $_{min}$) then
Step: 5 connected <- True
Step: 6 break
Step: 7 end if
Step: 8 end for
Step: 9 return transmission cost (T.Power level)

From the power control method we first initializing connected to false or true on line 1, which means that these two motes cannot communicate. Then find the ideal power level that T will use to transmit the packet to R. The for loop beginning on line 2 starts with the lowest available power level and continues up to the greatest. On line 3, the transmission power level for the transmitter mote is adjusted before estimating the RSSI with the set power level on line 4. If the estimated RSSI is greater than the predefined minimum RSSI, the nodes are able to communicate at this power level. The loop then terminates and the transmission cost at that power level is calculated.

A relay is included in the set *RE* if the source-relay channel is sufficiently reliable and the relay has sufficient battery energy remaining to achieve the target SNR. The best relay node is selected from subset *RE* using the following three selection strategies.

Minimal transmit power (MTP)*:* Choose the node with the minimal transmit power,

$$K^{*}_{MTP} = \arg \quad P_{k,d} \qquad (15)$$

Maximal energy-efficiency index (MEI): Define the energy efficiency index of the *k*-th relay as the ratio of *ek* to *Pk,d* and select the relay with the maximal index, *i.e.*,

$$K^{*}_{MEI} = \arg \quad e_k/P_{k,d} \qquad (16)$$

That is, the node whose transmit power occupies the least portion of its current residual energy is chosen.

Minimal outage probability (MOP): In this scheme, we select the node with the smallest outage Probability after it is chosen to transmit. We apply the strategy to the case with the discrete power level by choosing

$$K^{*}_{MOP} = \arg \quad P_{out,c}(e - P_{k,d}1_k)$$

$$= \arg \quad P_{out,c}(e - P_{k,d}) / P_{out,c}(e_k) \qquad (17)$$

VIII. Simulation Model

Our multipath routing protocol is implemented in the ns-2 network simulator. In all our simulations, we consider a square sensor field of size L. Inside the field, M static sensor nodes are deployed randomly. The value of M is varied from 50 to 250. Each node has a fixed radio range of 40 meters. The node density is maintained at a constant level of $50/160^2$ nodes/m^2.

The positions of the source and sink nodes are shown in Figure 5.Figure 5 also shows the multiple paths determined by the multipath routing protocol with 250 nodes for each topology setting. In these configurations, the sinks and sources are located far from each other. The minimum distance between any pair of sink and source is larger than L/2. Such settings facilitate our evaluation of the protocol where the routing path has to traverse a large area in the sensor field. We also assume that the source nodes detect different stimulus. Thus, their event data cannot be aggregated. We adopt the ns-2 radio energy model and assign each node with the same initial energy level of 10 J at the beginning of each simulation in order to keep the simulation

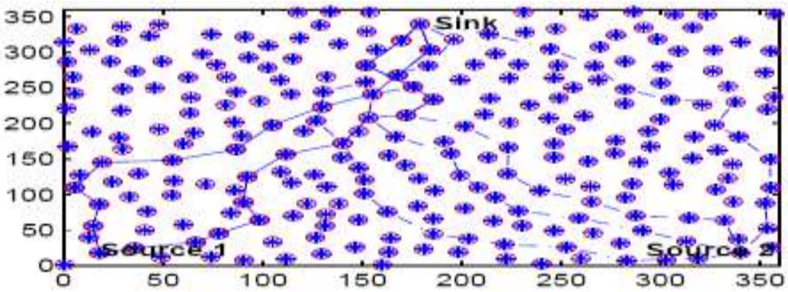

Figure 5: Configurations of sink and source nodes

Item	Value
Node density	$50/160^2$
Number of nodes	50, 100, 150, 200, 250
Data packet size	64 bytes
Control packet size	32 bytes
Idle power	35 mW
Receive power	395 mW
Transmit power	660 mW
Node initial energy	10 J
Node radio range	40 m
Bandwidth (802.11)	1.6 Mbps

Table :1 Simulation parameter

We further assume that each sensor node carries an omni antenna and the energy consumptions for idle time, transmission and reception are 35 mW, 660 mW, and 395 mW respectively. The energy dissipation for data processing in the node is neglected in our simulations. In Table 1, we summarize the simulation parameters.

In a first set of experiments, the computational time of the proposed algorithm with discrete power control was compared against the computational time of MCL and AMCL.Typically, as the number of nodes increase in a WSN, the computational time needed to localize the nodes also increases. In the case for proposed algorithm, the increase is much smaller than that of MCL and AMCL, as demonstrated in Figure 6 and Figure 7.

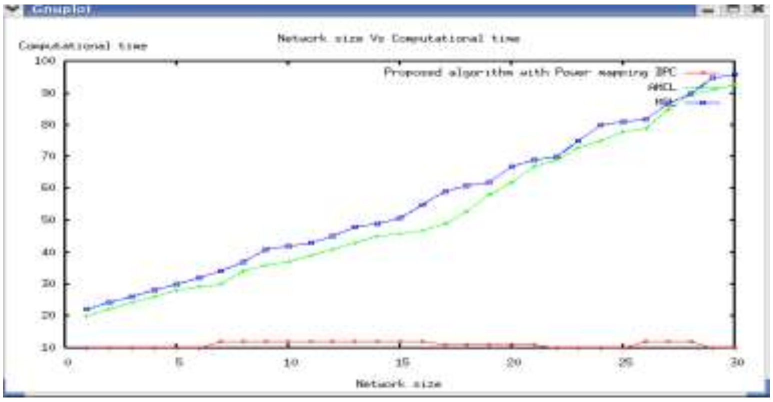

Figure: 6 Computational Time of Proposed method versus AMCL and MCL for Networks of Size10, 20, 30 Nodes.

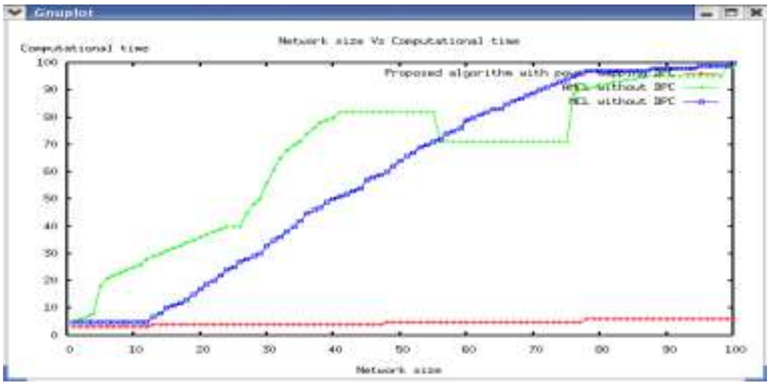

Figure: 7 Computational Time of Proposed method versus AMCL and MCL for Networks of Size50, 70, 100 Nodes.

As shown in Figure 6 and Figure 7, the computational time of MCL and AMCL increases linearly with respect to the network size. As the number of nodes increases, it becomes apparent that the original AMCL algorithm will not be able to provide sufficiently accurate results, as it takes significantly more time to localize the mobile node, thus providing out-dated location estimates. On the other hand, our proposed demonstrates a very small increase in execution time with an increase of the network size, thus providing up-to-date and (at least potentially) accurate results by using discrete power control method. This allows our method to be applied at shorter time intervals.

In order to demonstrate the effectiveness of low computational time and the importance of obtaining results as close to real-time as possible, the mean localization errors of our proposed method compared with MCL and AMCL.

IX. CONCLUSION

In this paper, we formulate a novel cluster based partial multihop localization scheme for WSN based on antithetic markov process which variance reduction method for increasing the accuracy of Markov chain Monte Carlo algorithm for computing the dominant eigen pair of a matrix computation. We also propose a randomized multi-hop localization scheme, based on an accurate analysis of hop progress in a WSN with randomly deployed sensors and arbitrary node density. By deriving the expected hop progress from a network model for WSNs in terms of network parameters, the distance between any pair of sensors can be accurately computed with the help of antithetic markov process. The proposed localization algorithms all can be implemented partially asynchronously in networks. Finally, extensive simulations are conducted to demonstrate the efficiency and accuracy of the proposed multihop localization algorithms.

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