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Distributed Target Localization in Wireless Sensor Networks using Diffusion Adaptation

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Abstract

Localization is an important issue for wireless sensor networks. Target localization has attracted many researchers who work on location based services such as navigation, public transportation and so on. Localization algorithms may be performed in a centralized or distributed manner. In this paper we apply diffusion strategy to the Gauss Newton method and introduce a new distributed diffusion based target localization algorithm for wireless sensor networks. In our proposed method, each node knows its own location and estimates the location of target using received signal strength. Then, all nodes cooperate with their neighbors and share their measurements to improve the accuracy of their decisions. In our proposed diffusion based algorithm, each node can localize target individually using its own and neighbor's measurements, therefore, the power consumption decreases. Simulation results confirm that our proposed method improves the accuracy of target localization compared with alternative distributed consensus based target localization algorithms. Our proposed algorithm is also shown that is robust against network topology and is insensitive to uncertainty of sensor nodes' location.

Keywords: *distributed, cooperative, target localization, wireless sensor network, Gauss Newton*

1. Introduction

Wireless Sensor Networks (WSNs) are used in a wide range of applications from environment monitoring to complex navigation systems and may monitor environmental conditions and cooperate to share their information in the network [1]. WSNs are limited in computational resources and power consumption, therefore, many researchers are interested in designing algorithms and protocols considering such challenges [2-6]. Target localization as an important application of WSNs is used in navigation, public transportation and so on. A great variety of methods exist to estimate the location of target such as Time of Arrival (TOA), Time Difference of Arrival (TDOA), Angle of Arrival (AOA) and Received Signal Strength (RSS) measurements [7].

The problem of target localization can be solved by both centralized and distributed algorithms. In centralized methods, a fusion center is needed to acquire information from all sensor nodes, make the decision and share it with other sensors. In distributed algorithms, no central entity is needed; each sensor node makes the decision individually and may improve the accuracy of decision by cooperation with neighboring nodes [8]. Additionally, using centralized algorithms are expensive and sharing the information through the network introduces latency and increases power and network bandwidth consumption [9]. Distributed algorithms recently have been proposed for target localization [10-12]. Implementation of such algorithms lowers signaling overhead, makes them more adaptive to the network changes and more robust against the time-varying environment and node failures [8].

Authors in [5] study three types of range-free localization algorithms in the case of localization error and energy consumption of them and propose that positional accuracy is very important indicator for performance. Authors in [13] use bio-inspired algorithms to localize nodes using iterative methods and investigate localization problem in terms of computational time. In [14] a 3D localization algorithm is proposed for ship area networks. Authors in [14] assume that each node has variable communication range. The proposed algorithm in [15] considers a fully decentralized sensor network to estimate the target location using RSS, however, many

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practical limitations such as shadowing effect is not considered. In [16] authors introduce a consensus based decentralized Gauss Newton localization algorithm. In [16] all nodes cooperate and share their information to finally make decision on the location of target node.

Diffusion based strategy is recently proposed which is a fully distributed decision making process and outperforms the other distributed methods including the consensus [17]. In this paper, we apply the diffusion based strategy to the Gauss Newton method in order to localize the target in WSNs. In our proposed full decentralized diffusion based Gauss Newton target localization algorithm, each sensor node measures the RSS from target and shares it with its neighbors. Then, each sensor node localizes target in an autonomous manner and the decision of each node is different from other sensors' which depends on its own and its neighbor's measurement. One of the main advantages of our proposed algorithm is its performance in large networks. In large WSNs, our proposed diffusion based algorithm decreases the power consumption in target localization and hence improves the network lifetime.

The rest of this paper organized as follows: In section 2 we describe system model and problem formulation of consensus based Gauss Newton localization. The proposed distributed diffusion based Gauss Newton target localization method is introduced in section 3. Simulation results discussed in section 4 and finally conclusions are made in section 5.

2. System Model and Problem Formulation

Consider several nodes are randomly distributed in a WSN. The goal is to estimate the position of one target in the area which is covered by wireless sensors. We assume that each node measures the received power from target and communicates with other nodes. The received power at node *n* follows a lognormal distribution as introduced in (1).

$$P_{R_n}[\mathrm{dB}] = P_0 - 10 n_P \log\left(\frac{d_n}{d_0}\right) + \mathrm{X} \tag{1}$$

Where P_0 is the received power at reference distance d_0, n_p is the path-loss exponent, X is a zero mean Gaussian random variable with variance σ_{dB}^2 which models the shadowing effect and d_n is the distance between node *n* and target.

In order to find the position of target, first we need the estimated distance between target and all nodes. The maximum likelihood (ML) estimation of this distance is calculated by (2),

$$d_n = d_0 10^{\left(\frac{P_0 - P_{R_n}}{10 n_P}\right)} \tag{2}$$

Where P_{R_n} is the measured power at node *n*. Each node also estimates its distance to target using estimated position of target. To do this, first all nodes assume a position for target as an initial value, $[x_t, y_t]$, and update this value for a fixed number of iterations to reach the final value of their estimation toward the target. Therefore, the distance of the n^{th} node to the target is calculated using (3).

$$d_n^2 = (x_n - x_t)^2 + (y_n - y_t)^2 + (z_n - z_t)^2 \tag{3}$$

Nodes don't know the exact position of target, therefore, the estimated distance between nodes and target is noisy. Thus, a cost function is defined as (4) which is defined as the square difference of estimated and measured distance.

$$f(x) = \left(X^T X\right) 1_N - 2CX - b \tag{4}$$

Where $b_n = d_n^2 - (x_n^2 + y_n^2 + z_n^2)$, $b = [b_1, b_2, ..., b_N]^T$, $C = \begin{bmatrix} x_1 & y_1 & z_1 \\ \vdots & \vdots & \vdots \\ x_N & y_N & z_N \end{bmatrix}$, 1_N is a vector of all ones by the length of *N* and $X = [x_t, y_t, z_t]^T$ is the estimated location of target. It is obvious that the ideal cost function is zero when the exact position of target is reached. However, due to the noisy measurement and estimation errors, we need to minimize the cost function. The estimation of target position can be rewritten as an optimization problem (5) and centralized optimization methods such as [18] or distributed algorithms such as Gauss Newton [16] may be used to solve the problem (5).

$$x = \min_x \frac{1}{2} f(x)^T f(x) \tag{5}$$

Distributed Gauss-Newton localization is robust against shadowing effect, uncertainty in position of sensor nodes and network topology changes for target localization [16].

3. Diffusion Based Gauss Newton Localization

Here we want to localize the target with our proposed diffusion based algorithm. In this method each node shares its measurements with other nodes till they reach a consensus in an iterative manner. In our algorithm, each node localizes the target in an autonomous manner cooperating with neighbor nodes. The individual decision is not necessarily the same for all nodes and depends on the quality of measurements for node and its neighbors. Our proposed algorithm is described in Algorithm 1.

Algorithm 1 (proposed)
Diffusion based Gauss-Newton localization

1:	$x^{(0)}$: same initial value for all nodes
2:	for $k = 1:K$
3:	$\psi_{x,n}^{(k)} = \frac{1}{1+\lvert N_n \rvert} \sum_{j \in N_n} x_j^{(k)}, \psi_{y,n}^{(k)} = \frac{1}{1+\lvert N_n \rvert} \sum_{j \in N_n} y_j^{(k)}, \psi_{z,n}^{(k)} = \frac{1}{1+\lvert N_n \rvert} \sum_{j \in N_n} \hat{z}_j^{(k)}$
4:	$J_n^{(k)} = 2 \times [\psi_{x,n}^{(k)} - x_n, \psi_{y,n}^{(k)} - y_n, \psi_{z,n}^{(k)} - z_n]$
5:	$f_n(x^{(k)}) = (\psi_{x,n}^{(k)} - x_t)^2 + (\psi_{y,n}^{(k)} - y_t)^2 + (\psi_{y,n}^{(k)} - z_t)^2 - d_n^2$
6:	$\Delta_n^{(k)} = J_n^{(k)T} J_n^{(k)}$
7:	$\gamma_n^{(k)} = J_n^{(k)T} f_n(x^{(k)})$
8:	$\Delta_*^{(k)} = \frac{1}{1+\lvert N_n \rvert} \sum_{j \in N_n} \Delta_j^{(k)}$
9:	$\gamma_*^{(k)} = \frac{1}{1+\lvert N_n \rvert} \sum_{j \in N_n} \gamma_j^{(k)}$
10:	$h^{(k)} = \Delta_*^{(k)^{-1}} \gamma_*^{(k)}$
11:	$x^{(k+1)} = \begin{bmatrix} \psi_{x,n}^{(k)} \\ \psi_{y,n}^{(k)} \\ \psi_{z,n}^{(k)} \end{bmatrix} - h^{(k)}$
12:	end for

In Algorithm 1, *K* is the maximum number of iterations, *k* is the iteration index, *N* is the number of total nodes, *n* is the node index, N_n determines n^{th} node and its neighbors, *J* is the Jacobian matrix of defined cost function and parameter *h* is called the deviation value.

In the first step of the proposed diffusion based algorithm, the measurements of each node and its neighbors are combined and stored in an intermediate variable, ψ. Then in the next step, Jacobian and cost function are calculated using this intermediate variable. In the steps 8 and 9, Δ and γ are calculated using the shared information and finally the intermediate variable and deviation value, *h* are calculated to update the estimated position of target node. This procedure continues for a fixed number of iterations.

Due to this intermediate variable in the proposed diffusion based algorithm which is the average measurement of each node and its neighbors, the measurement information of nodes diffuses through the network and leads to a decrease in network power consumption. Another advantage of proposed algorithm appears in large networks. In proposed algorithm, each node decides on the location of target by local information with individual process and does not need to know the information of all nodes in the network, therefore in large networks, it performs better than previous methods like what is proposed in [16].

4. Simulation Results

Simulations are performed to evaluate the performance of our proposed algorithm. We compare our proposed algorithm with consensus based Gauss-Newton [16]. The simulation results are averaged for 100 realizations and in all simulations, the iteration number is set to 50. The network consists of 70 nodes scattered in a 100*100*30$[m^3]$ area. The considered environment shown in Figure 1. We assume that all nodes are able to communicate with their neighbors who are in its communication range. Parameters used for these simulations are summarized in Table 1.

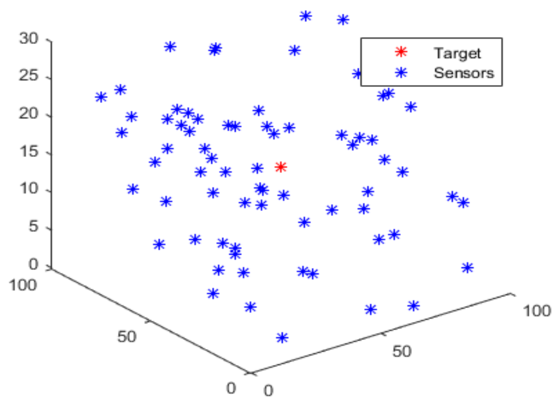


Figure 1. The Environment of Problem

Table 1. Simulation Parameters

parameter	value	parameter	value
P_0	0 [dBm]	n_P	2
d_0	1 [m]	σ_{dB}	2 [dBm]

Where P_0 is the received power at reference distance d_0, n_p is the path-loss exponent, *X* is a zero mean Gaussian random variable with variance σ_{dB}^2 which models the shadowing effect.

We consider four scenarios to evaluate the performance of proposed algorithm. In first scenario, we just apply the algorithms to localize the target with mentioned assumptions. In second one, we evaluate the effect of number of nodes participate in the algorithm. The third scenario considers uncertainty in the location of nodes and finally we move target in the environment to evaluate the effect of target placement on the performance of proposed algorithm. In the rest of this section, we investigate these simulations.

4.1. Convergence

In this simulation we assume that each node knows its location and they communicate to each other to localize a target. Target node is placed at the middle point of assumed environment. The result of target localization and its convergence is depicted in Figure 2 and Table 2.

Table 2. Simulation Results

Method	Initial value	Estimated location	RMSE [m]
Consensus [16]	[80,20,20]	[50.302 51.272 18.761]	3.982
Diffusion (proposed)	[80,20,20]	[49.675 49.921 16.426]	1.465

The results confirm that our proposed algorithm has an acceptable error the same as consensus [16] and the individual decision in our proposed algorithm decreases the localization error.

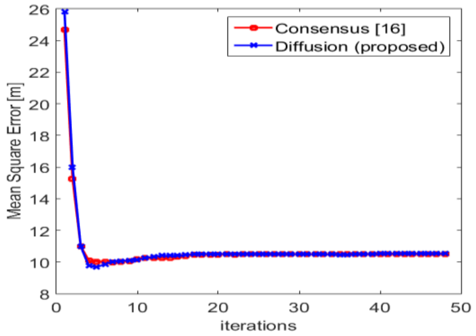


Figure 2. Convergence of Algorithms

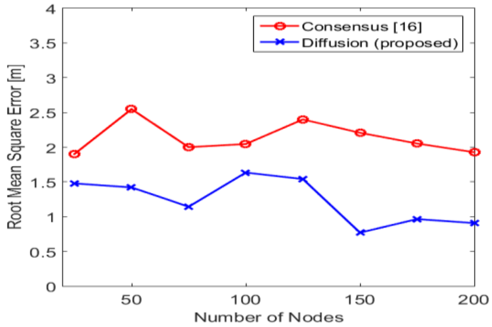


Figure 3. Effect of Network Topology Changes on Performance of Algorithms

Figure 2 shows the convergence procedure of localization for both algorithms; at first iterations, error is rather high, however, by more iterations (more cooperation between nodes), nodes can decide on the location of target and error decreases until the final value is reached.

4.2. Network Topology Changes

In the second scenario we investigate the effect of network topology changes (number of nodes in the network) on the performance of proposed algorithm. In this simulation, we change the number of nodes and place a target in the network. Results are depicted in Figure 3.

As depicted in Figure 3, the root mean square error of both of localization algorithms is in a limited range and increasing the number of nodes doesn’t affect the localization error considerably, although the proposed algorithm performs better. As mentioned before, one of the advantages of diffusion based algorithm appears in the large networks. When network size is large, network needs large amount of data communication to share measurements to all nodes of network. However in this situation, diffusion based algorithm does not need to share information to the whole network and each node shares information with its neighbors, therefore power consumption decreases, considerably.

4.3. Uncertainty in Location of Sensor Nodes

In the previous simulations, we assumed that each node of network knows its location, however in practical situations, nodes don't know their location exactly and they know it with some error. Therefore, in this simulation we assume each node knows its location approximately. Thus, we add a zero mean noise with different variances to the location of nodes and then try to localize the target (Figure 4).

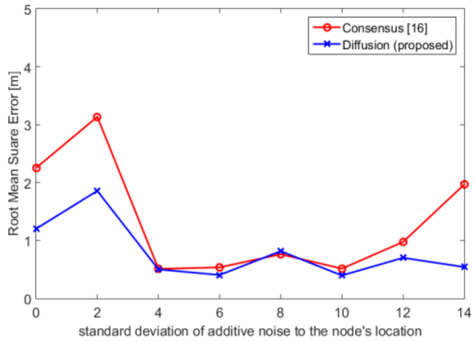


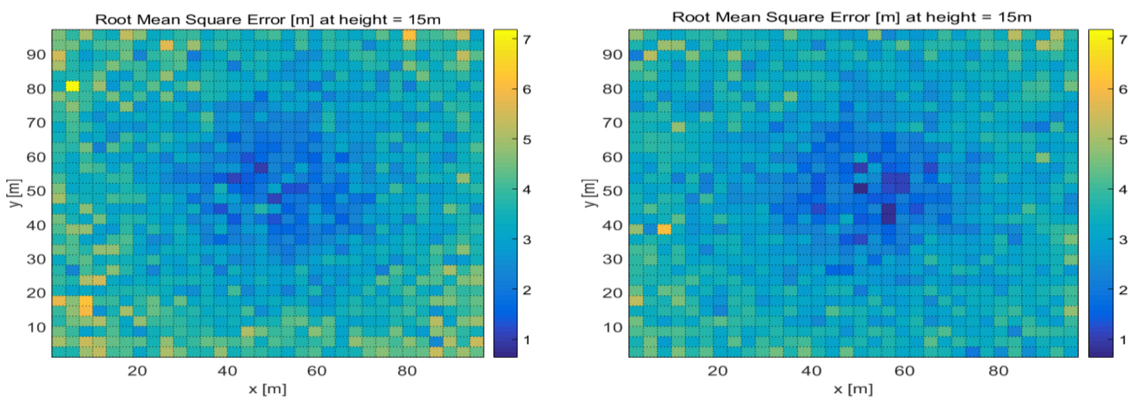
Figure 4. Effect of Uncertainty in the Location of Sensor Nodes

As depicted in Figure 4, the error is bounded and uncertainty in nodes' location does not affect the localization, considerably. Figure 4 also illustrates that nodes may localize the target even when they do not know their exact location.

4.4. Effect of target placement

In the previous simulations we assumed that target is located at the middle point of the assumed area. In this simulation we are going to evaluate the effect of target placement on the localization accuracy. Therefore, we place the target in all points of the area. Results are depicted in Figure 5.

Figures 5 shows that the localization error when the target is placed in the middle point of the area is less than the case when the target is in corner points. The reason is that in the middle part, several nodes surround the target while in the corner places, target is surrounded by less number of sensor nodes. These figures also illustrate that individual decision in diffusion based localization method don't affect localization error and both of algorithms perform almost the same, although the proposed diffusion based localization method performs better.



a) Consensus based [16] b) Diffusion based (proposed)

Figure 5. RMSE of Algorithms in the Environment

5. Conclusion

In this paper we proposed a new diffusion based Gauss Newton target localization for WSNs by applying diffusion strategy to Gauss Newton algorithm. In our proposed algorithm, nodes may localize the target individually, using their own and their neighbor measurements. Our proposed algorithm decreases the power consumption especially in large networks. Simulation results confirm that the proposed algorithm is robust against network topology and is insensitive to the uncertainty in nodes' locations. Our proposed algorithm also improves the accuracy of target localization in comparison with recent consensus based algorithms.

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