A Simple Method for Positioning and Tracking in Wireless Sensor Networks

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Abstract—In this paper we develop a simple yet effective heuristic algorithm to estimate the location of a sensor node in wireless sensor networks. Our method utilizes a simple and inexpensive received signal strength (RSS) measurement at a node to maximize the maximum likelihood (ML) function in a localization problem. We show via numerical results that the location estimations obtained from the new method are more accurate compared to those of traditional techniques. The algorithm can also be easily used to track the movement of a node in wireless sensor networks.

Index Terms—Sensor networks, Positioning and movement tracking, Received signal strength (RSS).

I. INTRODUCTION

Wireless Sensor Networks are a series of autonomous nodes or hosts equipped with sensors that are spatially distributed and wirelessly connected together. There are many different applications for their use such as habitat monitoring, home networking, fleet tracking, as well as medical and military applications. For many applications using sensor networks, knowing the exact location where information was collected is critical. And constrained by cost and energy, accurate location estimation in sensor networks becomes a real challenge.

There has been much research into developing accurate methods to map out the network topology and locate mobile nodes within a sensor network. A general setting is to consider a sensor network consists of some nodes, called reference nodes, which obtain their coordinates via global positioning system (GPS) or from a network installer during deployment, and the rest of nodes must discover their own location. To this end, an unknown location sensor node can utilize a variety of distance and angle metrics to determine its coordinates such as received signal strength (RSS), time of arrival (ToA) or time difference of arrival (TDoA) parameter instead. In addition, angles between two incoming radio waves (AoA) can be measured using multiple ultrasound receivers or directional antennas to estimate the orientation of the sender and compliment the accuracy of other metric [4].

Due to the simplicity and inexpensive nature of the RSS parameter, in this paper we attempt to address the above limitation of the received signal strength based method, and to improve its accuracy by applying a heuristic search algorithm toward the true location coordinators. To this end, we formulate a localization problem as a maximum likelihood (ML) problem, and develop an iterative algorithm that maximizes the ML function of that problem. Our main contribution thus is the developing of a simple algorithm that make the RSS based method more suitable for accurate location estimation in wireless sensor networks. Another contribution of this paper is a novel tracking algorithm that tracks the movement of a node in wireless sensor networks by utilizing the above proposed method.

The rest of the paper is organized as follows. We investigate the weakness of the current existing RSS based techniques and develop a heuristic search algorithm for location estimation of a sensor node in Section II. We present our numerical results and compare with obtained coordinators using traditional methods in Section III. The applicability of our algorithm is demonstrated in Section IV. Finally, we conclude the paper in Section V.
II. PROPOSED LOCATION ALGORITHM

We develop in this section a heuristic algorithm to improve the accuracy of the location estimation obtained by methods utilizing the RSS measurements. Consider a wireless sensor network consisting of \( N \) references node. Our aim is to estimate the coordinates \((\hat{x}_i, \hat{y}_i)\) of a sensor node \( i \) that resides at an unknown location \((x_i, y_i)\) within the network. The following path loss model [6] is used to describe the received power (or received signal strength - RSS) at node \( i \) from reference node \( j \) (\( j \in N \))

\[ p_{ij} = p_0 - 10n \log_{10} \left( \frac{d_{ij}}{d_0} \right) + X_\sigma, \quad (1) \]

where \( p_0 \) is the received power in \( \text{dB} \) at a reference distance \( d_0 \), \( n \) is the path loss exponent, \( d_{ij} \) is an Euclidean distance between node \( i \) and node \( j \), and \( X_\sigma \) is a zero-mean Gaussian random variable in \( \text{dB} \) with \( \sigma > 0 \) standard deviation. The negative term in (1) is a path loss in \( \text{dB} \), and for indoor environments with \( d_0 = 1 \text{m} \), it can be expressed as follows [5]

\[ p_{L}(d_{ij}) = 20 \log_{10}(f) + 10n \log_{10}(d_{ij}) - 28 + X_\sigma, \quad (2) \]

where \( f \) is a transmitting frequency in MHz. Given the received power \( \hat{p}_{ij} \), from (1) and (2) the distance between node \( i \) and node \( j \) can be estimated as

\[ \hat{d}_{ij} = d_{ij} 10^{X_\sigma/10n}, \forall j \in N. \quad (3) \]

Having estimated the distances \( \hat{d}_{ij} \), there have been two common techniques proposed to find the coordinates of an unknown location sensor node, i.e. triangulation and trilateration methods [7]. In particular, triangulation is the process of finding coordinates and distance to a point using the law of sines given the measurements of angles and sides of the triangle formed by that point and two other known reference points. Trilateration, on the other hand, uses the known locations of two or more reference points, and the measured distance between the node and each reference point. At least three reference points are required to accurately and uniquely determine the relative location of a point using trilateration technique. An example of this would be the interception of three circles which results in only one intersecting point as illustrated in Fig. 1. If there are more than one intersecting points, the location is usually approximated as a center point of those points. Furthermore, the accuracy of the resulting location is reduced or no solution can be found when there are no intersections. This is mainly due to the fact that trilateration techniques are based entirely on the intersection between circles of radius that is calculated directly from the noise RSS measurements. For this reason trilateration technique is considered to be unreliable for location estimation.

It is, however, possible to estimate the unknown location using distances calculated from the noise RSS measurements without finding the resultant intersections. In particular, we can formulate an optimization problem to minimize the error of the estimated distance as follow

\[ \text{minimize}_{x_i, y_i} \sum_{j \neq i,j \in N} (\hat{d}_{ij} - d_{ij})^2, \quad (4) \]

where the Euclidean distance is given by

\[ d_{ij} = \sqrt{(\hat{x}_i - x_j)^2 + (\hat{y}_i - y_j)^2}. \]

It has been shown in [8] that the solution for the above optimization problem is the ML estimate that can be obtained by taking the minimum mean square error estimate (MMSE) of a system of equations. In practice, however, solving a set of equations using matrix solution for MMSE can be impractical especially when implementing in an energy constrained sensor network. For this reason, the authors in [1] proposed a two-stage heuristic algorithm to obtain the solution for (4) without solving the equations. In this heuristic method, the two stages were needed because the accuracy of the location estimation is sensitive to the error in \( \hat{d}_{ij} \).

In this paper we formulate a localization problem as a maximum likelihood problem with the following ML function

\[ \Lambda(p) = \prod_{j \neq i,j \in N} \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\hat{p}_{ij} - p_{ij}\right)^2/(2\sigma^2)}, \quad (5) \]

where \( p_{ij} \) is a received power at node \( i \) without the noise, and is given as

\[ p_{ij} = p_0 - 10n \log_{10} d_{ij}. \quad (6) \]

To maximize \( \Lambda(p) \), one can substitute (1) into (5) and then set the derivative of \( \Lambda(p) \) with respect to \( d_{ij} \) equal to zero as suggested in [2]. However, to avoid similar complexity problem in practical implementation as mentioned in the MMSE method, we rewrite (5) as

\[ \Lambda(p) = \frac{1}{(\sqrt{2\pi}\sigma)^N} e^{-\frac{1}{\sigma^2} \sum_{j \neq i,j \in N} (\hat{p}_{ij} - p_{ij})^2}. \quad (7) \]
It can be seen in (7) that the solution for the ML problem is the coordinates \((\hat{x}^M_L, \hat{y}^M_L)\) such that
\[
p^M_L = \arg \max_p \Lambda(p),
\]
which is equivalent to
\[
p^M_L = \arg \min_p \sum_{j \neq i, j \in N} (\hat{p}_{i,j} - p_{i,j})^2.
\]

Let \(\Delta = \sum_{j \neq i, j \in N} (\hat{p}_{i,j} - p_{i,j})^2\), the ML method that maximizes ML function in (5) now can be rewritten as to minimize \(\Delta\). The proposed heuristic algorithm (called minimum square error - MSE algorithm) is summarized as follows.

**Algorithm 1 Minimum Square Error (MSE) Algorithm**

**Require**: \(\varepsilon, \alpha, \kappa > 0\) and \(p_{i,j} \forall j \neq i, j \in N\)

1. \(\hat{x}_i(0) = x_0, \hat{y}_i(0) = y_0, k = 0, \Delta = 1 + \varepsilon \) // Initialization
2. Find \(\hat{x}_i^M_L, \hat{y}_i^M_L\) : minimize \(\Delta\)
3. while \(\Delta > \varepsilon\) do
4. \(\forall j \in N, \) Set \(p_{i,j}(k)\) based on (6)
5. Set \(\delta_{i,j}(k) = \hat{p}_{i,j}(k) - p_{i,j}\); \(\Delta = \sum_{j \neq i, j \in N} (\delta_{i,j}(k))^2\)
6. Find \(\max(\text{abs(}\delta_{i,j}(k))) \to h : \text{abs(}\delta_{i,h}(k)\)) = \max\)
7. if \(\delta_{i,h}(k) < 0\) then
8. Set \(\hat{x}_i(k), \hat{y}_i(k)\) closer to reference node \(h\) by \(\alpha\)
9. else
10. Set \(\hat{x}_i(k), \hat{y}_i(k)\) further from reference node \(h\) by \(\alpha\)
11. end if
12. break if \(k > \kappa\) and \(\Delta\) is unchanged
13. Set \(k = k + 1\)
14. end while

Note that the MSE algorithm is based on the received power values rather than the \(\delta_{i,j}\) estimated distances. It is simpler than the algorithm proposed in [1] because the accuracy of the location estimation is less sensitive to the error in the received RSS values than that to the error in the distances.

### III. RESULTS AND DISCUSSION

In this section we present various results for location estimation using the MSE algorithm and compare with values obtained from the traditional trilateration technique. The values of \(n\) and \(\sigma\) for various wireless indoor environments are given in Table I. For outdoor free space environment (2) is still applied but with \(n = 2\) and reduced effect of \(X_\sigma\). The parameters used in our numerical calculations are summarized at the bottom of Table I for indoor (LOS) and outdoor (free space) environments. We have also conducted some real measurements (shown in Fig. 2) using hardware from Jennic [10] to confirm the validity of those chosen parameters. Detail specifications of the transmitter-receiver module from Jennic can be found in [11].

Consider a random topology sensor network consisting of 8 reference sensor nodes. We assume that an unknown location node will be able to receive signal from at least three nodes \((N = 3)\) among 8 reference nodes. If the unknown location node receives signal from more than three reference nodes, it will only select the first three strongest signals as its references for estimating location. Figures 3 and 4 show the location estimations of a node with unknown location in a sensor network, using the traditional trilateration and the MSE methods, respectively. The intercepts between every pair of reference nodes in relation to the node with unknown location are also depicted in the figures.

Observe that the MSE method improves on the accuracy of the location estimation compared to that of the traditional trilateration method for both indoor and outdoor environment cases. Also note that the accuracy for the outdoor environment is higher compared to that of indoor because there is less variability in the received RSS values.

In Table II we compare the performance of the two algorithms (i.e. the current existing trilateration and the proposed MSE algorithm) in terms of the number of location estimations (in percentage) that fall within a given radius \(\varepsilon\) of the exact location. Here this percentage value represents our evaluation criteria to compare different algorithms. The results are collected over 1000 runs estimating the location of a node in a random 8-node topology wireless sensor network. We can see from the Table II that the proposed MSE algorithm outperforms the traditional trilateration technique. It is also interesting to see that there is no obvious improvement in the trilateration technique.
method when there is less variability in the received RSS values (outdoor case). In contrast, the accuracy of location estimation from the MSE method improves significantly in the outdoor environment.

In practice, however, only some nodes in a sensor network are reference nodes, and therefore the rest of nodes must discover its location through reference nodes or other nodes that have already estimated their position. Figure 5 shows the results using the MSE algorithm for such a scenario where there are only 3 reference nodes in an 8-node sensor network. Observe that the location estimation of some nodes becomes less accurate compared to that of results obtained from previous cases studied. It is because some nodes use an estimated location of another nodes to estimate its own coordinators and therefore magnify the error in the estimation process. Despite this error propagation, the MSE method still provides reasonably accurate results for a realistic scenario and always outperforms the traditional trilateration technique in all of the cases that we studied.

### Table II

<table>
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<tr>
<th>Percentage of Location Estimations That Fall Within ( \epsilon ) Radius of the Exact Position.</th>
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<tr>
<td>( \epsilon = 1 \text{m} )</td>
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<td>-----------------</td>
</tr>
<tr>
<td><strong>Method</strong></td>
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<tr>
<td>Trilateration</td>
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<td>MSE</td>
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FIG. 5. Incremental location estimation in wireless sensor networks.

### IV. Application for Sensor Node Tracking

We present in this section an application of the above proposed MSE method for movement tracking of a node or an object within a wireless sensor network. This scenario can be seen in many realistic applications such as monitoring animals, tracking the movement of targets or controlling an unmanned vehicle remotely. Let us consider a sensor network where every node has already established their location either via GPS (as a reference node) or using the incremental location estimation technique as shown in the previous section. The movement of a node can be tracked by repeatedly using the MSE algorithm over a predefined period of time. Alternatively, the node can broadcast a message to other nodes in a network requesting their position. Based on the received messages and RSS values, the node can then estimate its own location and track its movement. Figures 6, 7 show results obtained for indoor and outdoor environments, respectively.

### V. Conclusion

We have developed a heuristic algorithm (called MSE algorithm) for the maximum likelihood localization problem utilizing the received signal strength (RSS) values measured at an unknown location node in a wireless sensor network. Our results showed that the proposed MSE method outperformed the traditional trilateration technique and greatly improved on the accuracy of location estimation for various cases studied. We have also demonstrated the applicability and accuracy of the new method in both indoor (line of sight) and outdoor environments.
(free space) environments. Furthermore, due to its simplicity, the MSE algorithm can be easily implemented in an energy constrained wireless sensor network for location estimation purposes. Finally, we have shown that our simple method based on the RSS values can be used effectively to track the movement of a node in wireless sensor networks.

REFERENCES


