

Localization in Wireless Sensor Networks Using MDS with Inter-node Angle Estimation

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Abstract. Localization of Wireless Sensor Networks (WSN) is an important problem that has gained a lot of attention as can be seen in the survey papers [8, 9]. Among the many techniques that have been employed to obtain accurate localization under various underlying assumptions, Multi-Dimensional Scaling (MDS) provides a centralized solution given range measurements between nodes. However, dissimilarity matrix provided to MDS is incomplete due to missing range measurements between significant numbers of nodes. Researchers have used shortest distance computations on the basis of existing range measurements to provide an estimate of the actual range measurements. This leads to significant error in localization using MDS. In this work, we introduce an improved estimate of the shortest distances between nodes based on estimated angle between nodes. We do not assume AoA (Angle of Arrival) is available, however we estimate inter-node angle to help improve distance measures. Our results show significant improvement in the performance of MDS for localization of wireless sensor networks for both range-based and range-free noisy range network models. Our simulation verifies the result on both sparse and dense networks.

Keywords: Wireless sensor networks · Localization · MDS

1 Introduction

Most everyday electronic devices currently used are equipped with sensors. Due to availability of low cost sensors that can sense various aspects of the environment such as radiation, motion, pressure, temperature etc., numerous applications have been created that rely on processing the sensor data. However sensors have limited capability in computation, energy and storage. Once deployed, sensors transmit sensed data to a centralized server or nearest sink node. Often, sensors are deployed in environments that are subject to mobility such as automotive, underwater missions, vehicles involved in combat etc., and, therefore their locations change with time. Since equipping sensors with GPS consumes tremendous energy, the locations of sensors becomes unknown over time. Localization of Wireless Sensor Networks (WSN) is the problem of finding geolocation of sensor nodes under different models of sensor communication and sensor deployment. Anchor nodes are small subset of sensor nodes in a wireless sensor network that are aware of their locations due to being equipped with GPS or stay fixed throughout

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the mission. Various deployment environments have led to numerous techniques for localization.

Techniques for localization of wireless sensor networks can be categorized using various assumptions: whether sensor nodes remain stationary or mobile during execution of the localization algorithm; whether there are anchor nodes (*anchor based*) or no anchor nodes (*anchor free*); whether distance information between the nodes is available (*range-based*) or not (*range-free*).

The *range-based* approaches assume that sensors can find the distance to neighboring sensors within their sensing radius using RSSI signal strength, or time difference of arrival (TDoA) between radio signals or time of arrival of signal (ToA). In addition, angle of arrival (AOA) of a signal [11], has be used to assist in localization of the sensors. In range-free approach, nodes are aware of the presence of neighboring nodes, but do not have the range information to them.

The node based localization based algorithm called Sweeps was developed in [12] and is related to the iterative method called trilateration. A range based localization model that considers a Bayesian approach has been proposed in [13]. Wang et al. in [14] have proposed a range free localization algorithm as an improvement to regular DV-Hop algorithm.

Among the techniques used for localization MDS (Multi-Dimensional Scaling) is powerful and works in low time complexity. MDS can be centralized or distributed. Given hybrid distance and angle of arrival measurements, [1] provide the graphical properties that guarantee unique localizability in cooperative networks. Iterative multidimensional scaling (IT-MDS) and simulated annealing multidimensional scaling (SA-MDS), which are variations classical MDS was proposed in [2]. The authors demonstrate that these perform more reliably and accurately for distributed localization. The authors in [3] present a system of tracking mobile robots and mapping an unstructured environment, using up to 25 wireless sensor nodes in an indoor setting. In [4] that authors to propose a technique relevant to networks that may not be fully localizable. The authors design a framework for two dimensional network localization with an efficient component to correctly determine which nodes are 1ocaIizahle and which are not.

To obtain the distance matrix, the authors in [5] estimate the inter-tag distances using a triangular method. Then, classical MDS algorithms has been applied to determine the estimated locations of the tags. The authors in [6] propose an MDS based approach that can take advantage of additional information, such as estimated distances between neighbors or known positions for anchor nodes. The authors in [7] prove that for a network consisting of n sensors positioned randomly on a unit square and a given radio range $r = o(1)$, the resulting error is bounded, decreasing at a rate that is inversely proportional to r, when only connectivity information given. In [10], the authors address flip, rotation and translation ambiguities by exploiting the node velocities to correlate the relative maps at two consecutive instants. The authors introduce a new version of MDS, called enhanced Multidimensional Scaling (eMDS), which is able to handle these ambiguities.

In this paper we present a new way to estimate distances between those nodes for which direct range measurements are not available. We combine shortest path between nodes along with estimate of inter-node angle. Section 2 presents background of the MDS techniques, Sect. 3 describes the contribution of inter-angle estimation technique, Sect. 4 contains simulation results and Sect. 5 provides conclusion.

2 Background

We view the underlying graph of the network as a graph $G = (V, E)$, where V represent the set the nodes in the WSN, and the weight of an edge e in E between nodes u and v is the range measurement between nodes. In range-based deployment, each node is aware of the nodes within the radio range of the network. It is assumed that all nodes have the same radio range, called the radius of the network. In noise-free range measurement, each node knows the exact Euclidean distance between itself and its neighbors within the radius. In a noisy range measurement, we assume a Gaussian noise to the range measurement. In range-free deployment, each node is aware of the presence of nodes within the network radius, however, the range measurement is not known. In this case, we assume that range measurement between neighbors is the radius of the network.

The goal in all of the scenarios described above including range-based with noise-free range measurements, range-based with noisy range measurements and range-free deployments, is to find the location of the nodes each node v in V, with a mapping denoted by $m(v) = (x_v, y_v)$ such that Euclidean distance between $m(u)$ and $m(v)$ is equal to the range measurement between u and v for all nodes where range information is given.

Multidimensional Scaling (MDS) was originally created for visualizing dissimilarity of data. MDS takes as input a set of distance information between nodes assumed to be high dimensions and the distance is assumed to Euclidean distance in the dimension. In order to visualize the data, it is desirable that there be points created in lower dimensions such 2 or 3 dimensions, so that one can visualize the dissimilarity between data points. For 2 dimensional points, given $O(n^2)$ distances, i.e., distances between each pair of points is sufficient to solve n positions, however, the set of points would be subject to rotation, flip and translation and preserving the relative map. In application to localization however, we do not have all of the $O(n^2)$ distance measurements.

The dissimilarity matrix is referred to as proximity matrix P for our discussion. The goal to find the location vector, $L, = (li)$ where li represents the location of node i. Let p_{ij} represent the proximity between nodes i and j, and, Euclidean distance between location $l_i = (x_i, y_i)$ and $l_j = (x_j, y_j)$ as

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{1}$$

Class MDS solves for L such that $d_{ij} = f(p_{ij})$, where f is a linear transformation, given by $d_{ij} = a + b^* p_{ij}$.

A common approach to classical MDS is find D, the distance matrix between coordinates, as close to given proximity matrix P as possible, such that $I(P) = D + E$, where $I(P)$ is a linear transformation of P subject to minimizing the sum of squares of the error matrix E.

This is done by singular value decomposition (SVD) of the double centered matrix of square of P, which includes the following steps

a) Square the matrix P. Double center the squared matrix and call it the matrix K. Double centering a matrix is simply subtracting the row mean and column mean from each element of the matrix and adding the grand mean of the entire matrix to each element of the matrix and then multiplying the result by $-1/2$. That is

$$k_{ij} = -\frac{1}{2}\left(p_{ij}{}^2 - \frac{1}{n}\sum_{j=1}^{n} p_{ij}{}^2 - \frac{1}{n}\sum_{i=1}^{n} p_{ij}{}^2 + \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n} p_{ij}{}^2\right) \quad (2)$$

b) It is proved that an element in the double centered matrix is equal to

$$k_{ij} = x_i * x_j + y_i * y_j \quad (3)$$

c) Singular value decomposition is used on the double centered matrix K to obtain

$$K = UVU' \quad (4)$$

d) Now

$$L = UV^{\frac{1}{2}} \quad (5)$$

Applying classical MDS to localization involves providing the dissimilarity matrix which is equal to the distance information between nodes and using MDS to determine the location of sensor nodes. However, since range information between majority of nodes is not available, several "fillers" have been used to estimate distance between nodes that are not within the radio range, such as hop distance between nodes, or shortest distance between nodes. More accurate dissimilarity matrices, produce more accurate localization. In this paper, we present a new way to estimate distances between nodes when direct range measurements are not available. We combine shortest path between nodes along with estimate of angle as described in the next section.

3 Estimation of Euclidean Distances

While using classical MDS, given a dissimilarity matrix M of size $n \times n$ that contains the exact Euclidean distances between every pair of n nodes, MDS produces a set of n coordinate points in 2D as described in Sect. 2, where the distance between each pair of points is the corresponding weight in the dissimilarity matrix. Therefore, in order to use classical MDS for localization, one needs the distances between every pair of points that need to be localized. If ground truth is available, the result of MDS would be relative map that when rotated, reflected and translated using three anchors would result in the ground truth. In our application, in order to obtain the distance between nodes that are not

adjacent in the WSN, researchers have used shortest distance using Floyd's algorithm and Dijkstra's algorithm etc. While these provide shortest distances assuming that one travels along the edges of the graph, they do not translate well for determining Eucledean distances in network graphs. However, here explore how an intermediate node can help determine the direct Eucledean distance between nodes using the fact that the nodes are uniformly distributed in a given deployment area.

Given a network $G = (V, E)$ where each edge has a weight of network radius r (range-free case), or range measured between two nodes (range-based), we consider the number of nodes that possible neighbors of a node, i.e. the nodes that are within the network radius. Since each node knows the number of nodes within its radio range, even if it does not know the exact distance between itself and its neighbor(in range-free case), we estimate that the angle between two neighbors incident at a node v is $360/|N(v)|$ where $N(v)$ is the set of neighbors of the node v. This angle information is then used at each node to estimate the Euclidean distance two nodes. Given the angle $\angle ABC$, (see Fig. 1), the distance between A and C can be found using distance between A and B, B and C and the angle $\angle BAC$. The distance is then carried over to compute the length of the shortest path between two nodes.

The algorithm used for computing shortest distances is modified using

$$D(A, C) = D(A, B) + D(B, C) + D(A, B) * D(B, C) * cos(\angle ABC) \tag{6}$$

If nodes A and C have several nodes, then the min value of all of distances is used as an estimate of shortest between A and C.

We modify the shortest distance computation used in Floyd's algorithm using the distance computation above. It is important to note that distance between A and C is computed, it has impact on all shortest distances that use the edge (A,C) in the shortest path, thus propagating the enhance distance estimation throughout the network. See Fig. 1.

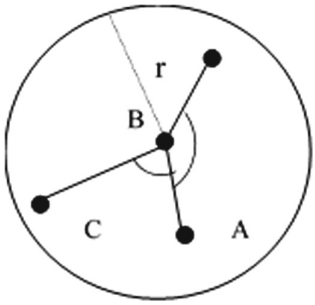

Fig. 1. Angle Estimation to computer the distance between A and C

4 Simulation Results

Simulation was performed on Matlab by creating a node layout of the Wireless Sensor Networks. The nodes were generated using a uniform distribution in a 100 by 100 unit square. For each simulation, the average of the performance of 50 networks are computed. The node density was varied between 200 and 400. The radii for sparse networks was between 10 and 14 and dense networks it was 15 to 20. Figure 2 shows sample network graphs of radius 12 (sparse) and radius 18 (dense).

Figure 3 shows that when the proposed technique of inter-angle estimation is used to compute shortest distances, the average error of the distance computed by MDS versus the ground truth is much smaller than using MDS with traditional shortest path computations. This is also true for all dense graphs with radii between 15 and 20 as shown in the same Fig. 3. It is also notable, as expected, as the network radius is higher the error is lower due to more distance being available due to larger number of node adjacencies.

Figures 4 demonstrates the results for connected networks for sparse and dense range-free graphs. In case of range free graphs, nodes can are aware of their neighbors but they are not aware of the exact distance between the node and its neighbors. We use radio range (radius) of the networks as the distance information to compute the dissimilarity matrix for MDS based localization. This leads to larger error by MDS in both traditional shortest distance computation and when inter-angle estimate is available. The error computed is error against the ground truth of the layout of the network where range measurements are available.

Figure 5 demonstrates the same performance on range based and range-free graphs with 400 nodes.

Next, we examine the effect of noise on the computation of angle estimation. The range measurements of perturbed with Gaussian noise with standard deviation of 0.1 to 0.7. Since we use 200 nodes and radius of 14, the noise in the range is from 0.7% to 5%. We compute the difference in the distance between localized nodes Figs. 5 and 6 are Note that the noise in the MDS data is much less when AoA estimation is used for computing shortest distances (Fig. 7).

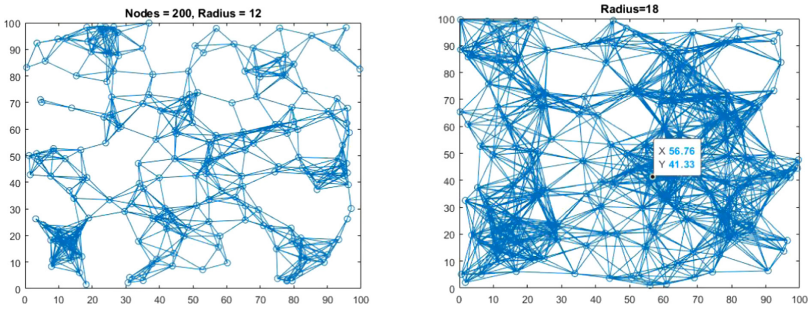

Fig. 2. Sample networks with 200 nodes and sensor radius of 12 and 18

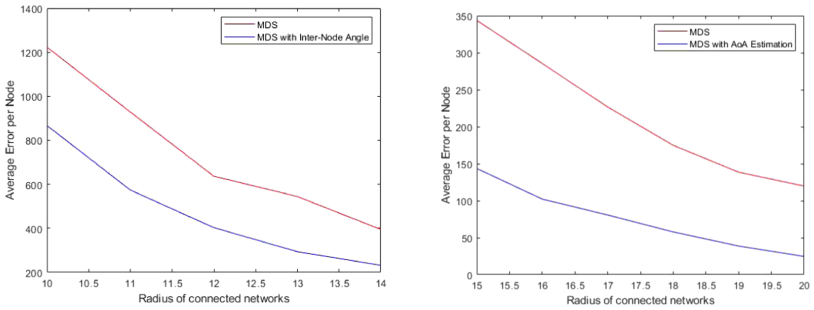

Fig. 3. Radius vs mean error in localization for range based networks

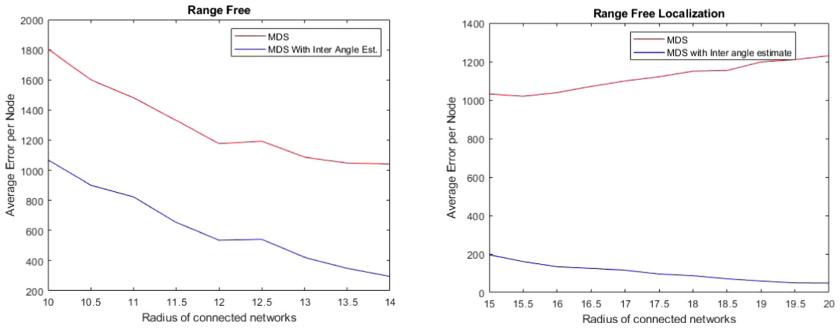

Fig. 4. Radius versus mean error in localization for range free network

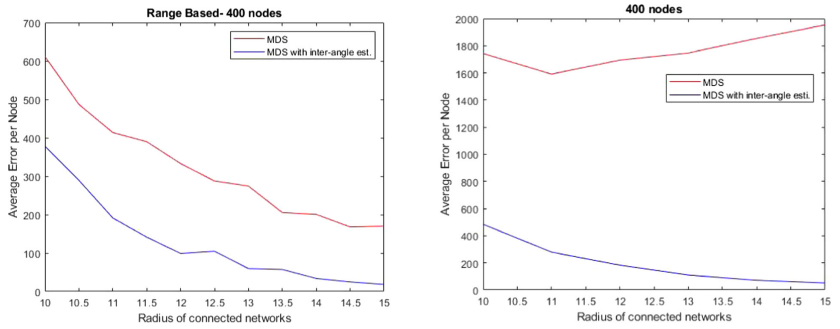

Fig. 5. Radius versus mean error in localization for 400 node networks

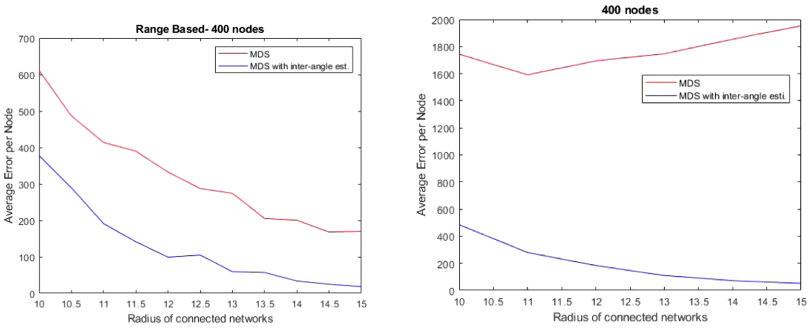

Fig. 6. Radius versus mean error in localization for 400 node networks

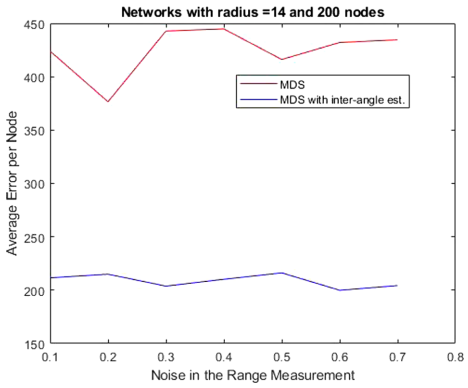

Fig. 7. Noise versus error in localization

5 Conclusion

In this paper, we present an effective technique to enhance the distance matrix provided to classical MDS localization. The enhancement is the technique in which shortest distances are computed between non-adjacent nodes. Using traditional techniques for finding shortest distances would use either Floyd's algorithm or Dijkstra's algorithm. The new technique use estimated angle between nodes assuming uniform distribution of nodes on the network. We have demonstrated that this significantly reduces localization error when using classical MDS for range free, range based computations even when there is noise in the range measurement.

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