

# Localization in Wireless Sensor Networks using Bilateralation Enhanced by Negative Knowledge

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## ABSTRACT

Wireless sensor networks are widely used in data collection and processing due to versatility of its deployment and low cost for monitoring physical and environmental conditions such as pressure, temperature, etc. [1]. Typically, Wireless sensor networks (WSNs) contain thousands of nodes. Localization of WSN is the problem of determining the geo-locations of sensor nodes in the network under given constraints and information. Range-based localization algorithms [5] deal with finding the geo-locations given the distances between neighboring sensors that are within the radio range of the node. However, distance information is available only between two nodes within the radio range. In general, having distance information to localized nodes helps localize an unlocalized node. In this paper, a novel enhancement is proposed where a missing distance information between nodes is used to localize a node. It is demonstrated that using this negative knowledge leads to better performance in localizing both sparse and dense network graphs.

## General Terms

Wireless Sensor Networks

## Keywords

Wireless Sensor Networks, localization, range based, trilateration, bilateralation

## 1. INTRODUCTION

Wireless sensor networks have received considerable attention in the over last couple of decades [1, 6] especially due to proliferation of sensors in everyday devices includes smart homes, automotive systems, smart phones etc. Sensors have limited capability in computation, energy, storage and mobility. Wireless sensor networks are deployed in environmental monitoring, rescue missions, military surveillance etc. Once deployed, the sensors transmit sensed data to a centralized server or in many cases to the nearest sink node. Often, when deployed on a mobile unit such as automobiles, the sensors move over time. Since equipping sensors with GPS consumes tremendous energy resource, the locations of sensors becomes unknown over time. Localization is the problem if determining the geo-locations of sensors given different variety of information about the sensors. Due to the variety of applications that require the precise location of sensors, localization of nodes in WSN's has received considerable attention.

While localization problem is known to be computationally hard, there have been numerous approaches to localize as many nodes as possible in least amount of time. Localization of WSNs has been approached in number of ways as indicated in [1]. Broadly, localization techniques can be categorized

into range-based or range-free algorithms [8]. Range based algorithms assume that distance information between sensors is available as long the sensors are within the radio range of the sensors, and, sometimes noisy distances are considered. The distance information can be obtained using various measurement techniques for ranging such as RSSI (Received Signal Strength Indicator), TOA (Time of Arrival), TDOA (Time Difference of Arrival) to name a few. Localization algorithms can also categorized into anchor based or anchor free algorithms. In anchor based algorithms, several nodes known as *anchors* know their geo location either due to presence of GPS, or due be manual fixed placement ahead of time. In anchor free algorithms, on the other hand, relative locations are computed within the network map. A third way to categorize localization algorithm is whether the algorithm is distributed or centralized. In distributed algorithms messages are passed between neighboring sensors and local maps are stitched into a global map. In addition to the basic techniques mentioned here, there have been literature related in indoor, outdoor and underwater localization. In addition, if the nodes are mobile during the algorithm, mobile WSN algorithms are considered [4].

For range based localization techniques, the determination of geo-locations given a set of known locations or angles can be based on trilateration, triangulation, robust quadrilaterals, or based on connectivity information given by rigid subgraphs. Classical Multidimensional Scaling (MDS) can be used in addition to Iterative MDS to minimize errors of localization [9].

Trilateration is a well-known geometric technique for determining the location of a node given the distance to three other nodes whose locations are already known. The process of trilateration begins by identifying an unlocalized node in the network and localizing it if it has distance to three neighbors that are localized. Initially, nodes that are adjacent to three anchors are localized. The localized now act as anchors to localize other unlocalized nodes. The process of trilateration stops when there are no unlocalized with three neighbors that are localized. The success of trilateration is therefore sensitive to the location of the anchors within the network and order of localization of the unlocalized nodes. Trilateration stops progressing, even if there are several nodes with known locations in the network. In [7], an anchor free localization is proposed on the basis of trilateration. In [3], an anchor based distributed algorithm for localization using trilateration extension is proposed.

Bilateralation refers to a node having distance information to two neighbors. This provides two possible positions for the unlocalized node. Clearly, additional information is needed in order use bilateralation for determining the location of the unlocalized node. Bilateralation techniques[2,3] have been used

with and without range measurements. In this paper, the idea of enhanced bilateration is introduced in which the lack of third distance information is, in fact, used to localize an unlocalized node. Given two possible positions of a node, lack of distance information to a localized node is used to determine which of the two positions of the unlocalized node is indeed the correct location. This idea is iteratively applied by examining any node that is localized that does not have an edge to the second possible position, confirming the position of the unlocalized node. The process of trilateration technique is continued after the application of bilateration with negative knowledge until no further bilaterations or trilaterations are possible.

## 2. NEGATIVE KNOWLEDGE WITH BILATERATION

In this section, the novel idea of negative knowledge enhancement for bilateration is described. Represent the WSN as a network graph  $G = (V, E)$  with vertices representing sensor nodes. Some of the vertices are marked as *anchors* and the locations of anchors is known a-priori and does not change throughout the localization algorithm. It is assumed all nodes in the network have the same sensor radius and whenever two nodes are within distance of sensor radius  $s$ , there is an edge between them in the network graph. The vertices that are not anchors are initially set to *unlocalized* and all anchors are set to *localized*. The goal of the localization algorithm is to find unlocalized nodes and determine their location, if possible. Once location is determined, the unlocalized node becomes *localized*. The performance of the algorithm is measured by how many nodes become localized.

Thus, given a network graph  $G = (V, E)$  with vertices  $V$  and edges  $E$  whose edge weights represent distance between the nodes, the problem of localization is to find the geo-locations  $(x_i, y_i)$  of each node  $v_i$  in  $V$  such that distance between the nodes  $v_i$  and  $v_j$  of  $V$  is same as the edge weight  $e_{ij}$  in  $E$ .

Here, the process of finding node's unique location by trilateration is described. That is, given the distance from the node  $P$  to three nodes  $P_1, P_2, P_3$  as  $d_1, d_2$  and  $d_3$  respectively, and, if  $P_1, P_2$  and  $P_3$  are localized, the location of the node  $P$  can be found using geometric properties on 2D plane. See Figure 1.

Given,  $P_1 = (x_1, y_1)$ ,  $P_2 = (x_2, y_2)$ , and  $P_3 = (x_3, y_3)$ , the coordinates the  $P = (x, y)$  can be found by solving the following three equations:

$$(x - x_1)^2 + (y - y_1)^2 = d_1^2$$

$$(x - x_2)^2 + (y - y_2)^2 = d_2^2$$

$$(x - x_3)^2 + (y - y_3)^2 = d_3^2$$

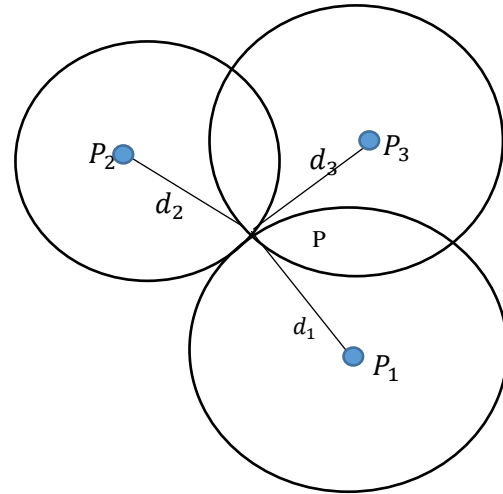


Figure 1: Trilateration

which essentially is a solution to the equation

$$2MX = b \quad \text{----- Eq. (1)}$$

where

$$M = \begin{bmatrix} 2(x_3 - x_1) & 2(y_3 - y_1) \\ 2(x_3 - x_2) & 2(y_3 - y_2) \end{bmatrix}$$

and

$$b = \begin{bmatrix} d_1^2 - d_3^2 - x_1^2 - y_1^2 + x_3^2 + y_3^2 \\ d_1^2 - d_2^2 - x_1^2 - y_1^2 + x_2^2 + y_2^2 \end{bmatrix}$$

and

$$X = \begin{bmatrix} x \\ y \end{bmatrix}$$

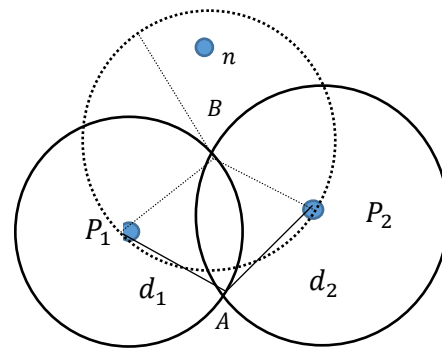


Figure 2: Negative Knowledge Localization

However, in the case where  $P$  is adjacent to only two other localized nodes in the graph, say  $P_1$  and  $P_2$ , with distances  $d_1$  and  $d_2$ , then clearly,  $P$  must be at the intersection of two circles with centers  $P_1$  and  $P_2$  and radii  $d_1$  and  $d_2$ , respectively. Let us name the two possible locations  $A$  and  $B$  for node  $P$ . See Figure 2. A novel approach is proposed where missing distance information from a localized node is used to determine the location of  $P$  as either  $A$  or  $B$ . This is done by looking at two possible locations of the point  $P$ ,  $A$  and  $B$ , which is at the intersection of two circles centered at  $P_1$  and  $P_2$  and radii of  $d_1$  and  $d_2$ . Let us assume that there is a localized node  $n$  within the sensor radius  $s$  of the possible location  $B$  of node  $P$ , and since there is no edge between  $n$  and  $P$  then the

location of  $P$  would be at  $A$ . Similarly, if there is a node  $n$ , within the sensor radius  $s$  of the possible location  $A$  of node  $P$ , and since there is no edge between  $n$  and  $P$  then the location of  $P$  would be at  $B$ . This is proved in *Theorem 1* below:

*Theorem 1:*

Assume that the possibility of trilateration has been tested for the unlocalized node  $P$  in a network graph. Given distances to two localized nodes  $P_1$  and  $P_2$  from  $P$ , and a localized node  $n$  within sensor radius of one of the two possible locations, then the node  $P$  is localizable.

*Proof:*

Let  $A$  and  $B$  be the two intersecting points of the circles around  $P_1$  and  $P_2$  with radii  $d_1$  and  $d_2$  respectively. The possibility of the node  $P$  being at location  $A$  or  $B$  is now examined. Assume that there a sensor node  $n$  that located within the circle of radius equal to the sensor radius of the network with center at  $B$ . Clearly there is no edge between the point  $P$  and the node  $n$ . Otherwise, trilateration would have been possible for the point  $P$  and this contradicts the assumption of the theorem. Clearly, node  $P$  cannot be at location  $B$ . It must be located at location  $A$ . Thus the absence of edge between a localized node  $n$  and the node  $P$  tells us the location of node  $P$  as being at location  $A$ .

Thus, the algorithm uses bilateration enhanced by negative knowledge, an unlocalized node  $P$  is identified with two edges to localized nodes  $P_1$  and  $P_2$  and finds the two intersection points of the circles formed by centers  $P_1$  and  $P_2$  and radii  $d_1$  and  $d_2$  as shown in Figure 2. The location of  $A$  and  $B$  is computed using the intersecting points of the equations below.

$$(x - x_1)^2 + (y - y_1)^2 = d_1^2$$

$$(x - x_2)^2 + (y - y_2)^2 = d_2^2$$

Then when a node  $n$  is identified as described in Theorem. Using the location of node  $n$ , the position of node  $P$  is determined. However, it is possible that there is no localized node exists within the sensor radius of  $B$  in which case, an attempt is made to find a localized node around  $A$  and similar procedure is repeated. If neither circles  $A$  and  $B$ , both do not have a localized node within sensor radius, then the algorithm moves on to localize other nodes in the network and return to localizing  $P$  in the next iteration.

### 3. LOCALIZATION ALGORITHM USING BILATERATION WITH NEGATIVE KNOWLEDGE

**BEGIN:** Mark all of the *anchor* nodes as localized nodes.

**LOOP :** Repeat the following trilateration step and negative knowledge bilateration step until no additional nodes can be localized or all nodes are localized:

**Trilateration Step:** If there is an unlocalized node that is adjacent to three localized nodes, i.e localize the node using the equation (1) and add it to the list of localized nodes.

**Bilateration Step:** If there is an unlocalized node that is adjacent to two localized nodes, then find the two possible positions using bilateration. If a localized node  $n$  is found in the sensor radius of two possible positions, then localize the node using the

**Theorem 1.** Add this node to the list of localized nodes.

**UNTIL** there is no change in the list of localized nodes.

## 4. SIMULATION RESULTS

The simulation was performed on Matlab with randomly generated network graphs with position of the nodes uniformly distributed on a 100 by 100 unit square. Anchors were randomly chosen among the sensors. For sparse graphs, the sensor radius was varied between 10 to 16. Figure 3 shows the number of localized nodes for a sparse networks with radii between 10 to 16. The red curve indicates localized nodes when enhanced bilateration is used and blue curve indicates the number of localized nodes when just trilateration is used. The results show that for all of these cases the negative knowledge enhanced trilateration performs far superior to just trilateration.

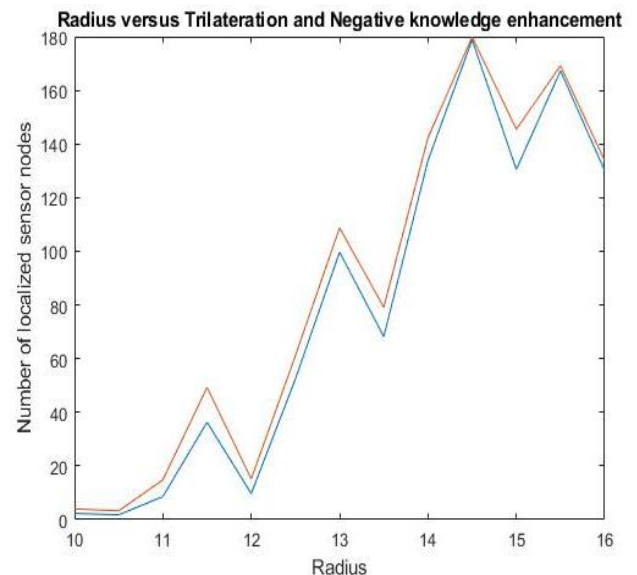
The number of anchors in this experiment was is very small which is about 6%. Note that anchor placement was random.

For highly sparse graphs, as shown in Figure 5 and Figure 6 as expected, the negative knowledge localization performs better than that of just a single trilateration. Note that as number of anchors are increased, the performance difference still remains. The data was averaged over 50 graphs in each radius generated at random.

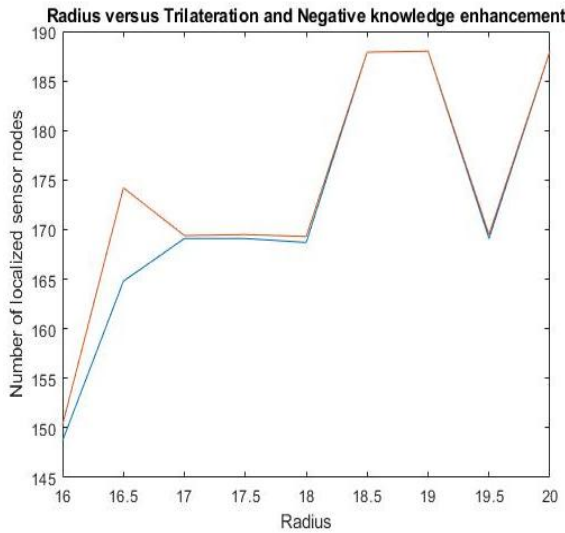
The results show as the number of anchors is varied from 10% to 30% randomly distribute that the negative knowledge performs better than trilateration especially in sparse graphs.

Figures 4 and 7 show the results of highly dense graphs where the Negative Knowledge enhance bilateration performs equally well or better than trilateration. .

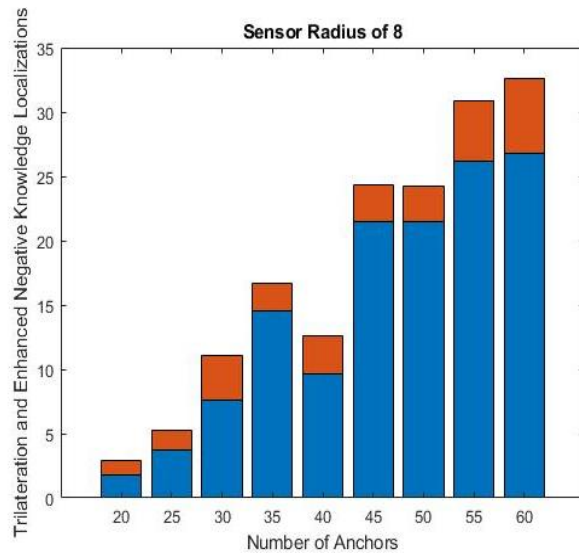
In conclusion, it is shown that the negative knowledge enhanced bilateration performs better than trilateration in all cases.



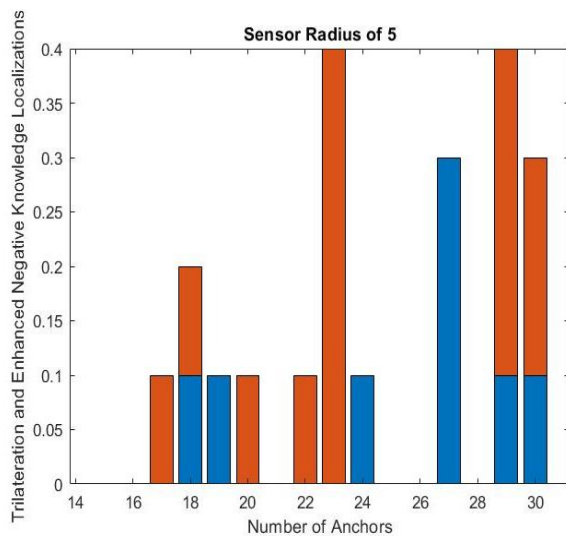
**Figure 3: Number of Localized Nodes versus Radius for Sparse Graphs**



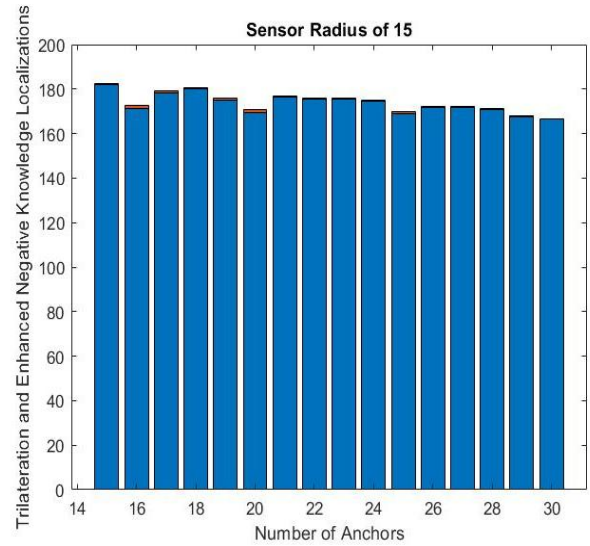
**Figure 4: Number of Localized Nodes versus Radius for Sparse Graphs**



**Figure 5: Number of Anchors versus Localization on Sparse Graph**



**Figure 6: Number of Nodes Localized versus Number of Anchors on Graphs of Radius 5**



**Figure 7: Number of Nodes Localized versus Number of Anchors on Graphs of Radius 15**

## 5. CONCLUSIONS AND FUTURE WORK

In this paper, an enhancement to bilateration was introduced so that missing distance between a localized node and unlocalized node can be used as a tool for localizing unlocalized node. It was verified using simulation that this negative knowledge enhancement localizes more nodes in both sparse graphs and dense graphs than traditional trilateration.

Future research exploration would involve iteration of this technique and using underlying graph properties for additional ways to enhance bilateration.

## 6. REFERENCES

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