A NOVEL SELF LOCALIZATION APPROACH FOR SENSORS

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Abstract

This paper presents a modification of 3N Time of Arrival (TOA) and a reliable Time Difference of Arrival (TDOA) based localization algorithms. TDOA is formulated using the parametric equations of the hyperbolas whose intersections are candidate locations for the nodes to be localized. TDOA algorithm is guaranteed to find all possible relevant solutions, even when implemented on a computational node with limited capability. Monte-Carlo simulations were used to assess the performance for both algorithms.

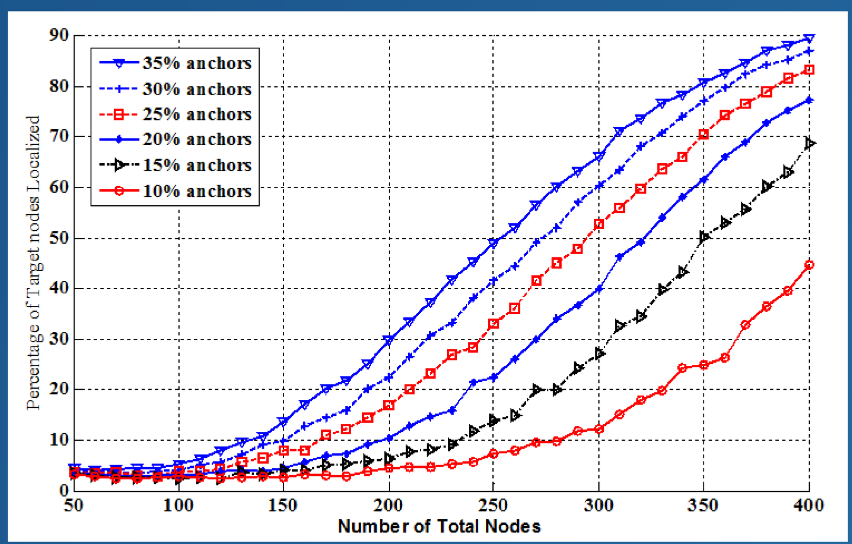
Time of Arrival Based Localization

We propose the following modification for 3N Time of Arrival (TOA) based localization algorithm. While the algorithm is being run, the target nodes that are localized are now position-aware and possess the capability to share their positions. This newly found position-aware node is introduced into the pseudo anchor list and the neighboring network is intimated of this change and gradual increase of the position-aware nodes in the network enable an enhanced localization performance

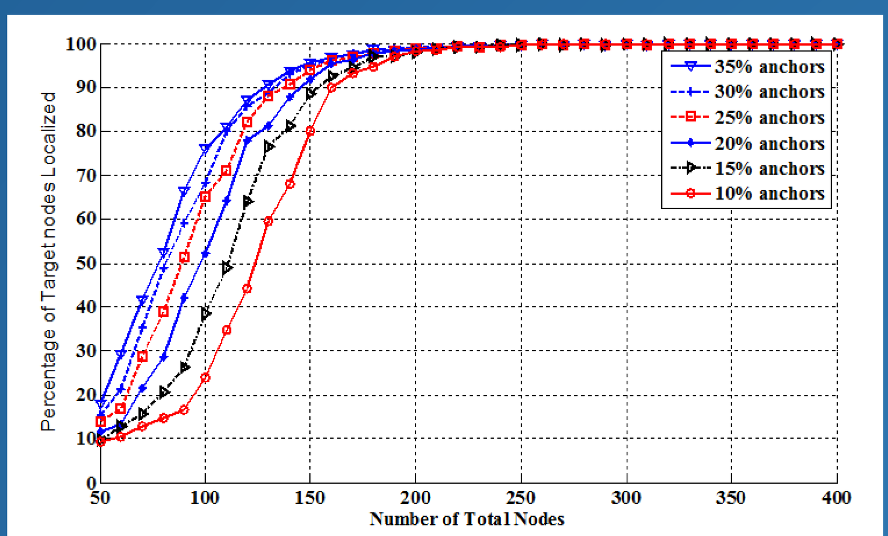
Modified 3N Algorithm

1. While there are target nodes
   a) if maximum number of iterations is exceeded, stop (some targets are not located)
   b) if less than three anchor nodes are in range, skip this node and goto step 1 to consider another target node
   c) if there are three or more anchor nodes in range, find the closest three anchor nodes and use them to locate the target node
   d) Add the localized target node into the pseudo-anchor list and remove it from target list
2. goto step 1, consider the next in target list.

Figure 1a is produced by varying the percentage of anchor nodes for a constant communication range of 8% of the field dimension, the point where the localization performance of the algorithm shows a substantial gain moves toward the lower density of nodes. Figure 1b shows the effect of input parameters on the localization performance due to the increase of communication range, the performance dramatically increases even with much lower node densities.



(a)



(b)

Figure 1. (a) 8% range of the field dimension

(b) 15% range of the field dimension

Hyperbolic Position Location Algorithm

The simulation results of the performance of the proposed hyperbolic location estimator are presented. The performance of the algorithm due to varied parameters is studied. The test scenario is Ad-Hoc and experiment work flow is designed selecting only the most widely accepted assumptions such as all nodes are homogeneous, i.e all the nodes have similar capabilities and node placement is completely random in the environment. Ideal environment was assumed where no channel is noise free and all the input metrics are error free. The simulation includes a square field area of 100x100 units. Here, three anchors or pseudo-anchors are needed to completely locate a target node, including the resolution of ambiguity as shown in Figure 2 In essence D2-D1, D3-D1 are used to find 1, 2 or 3 candidates, then the measurement D3-D2 is used to resolve the ambiguity.

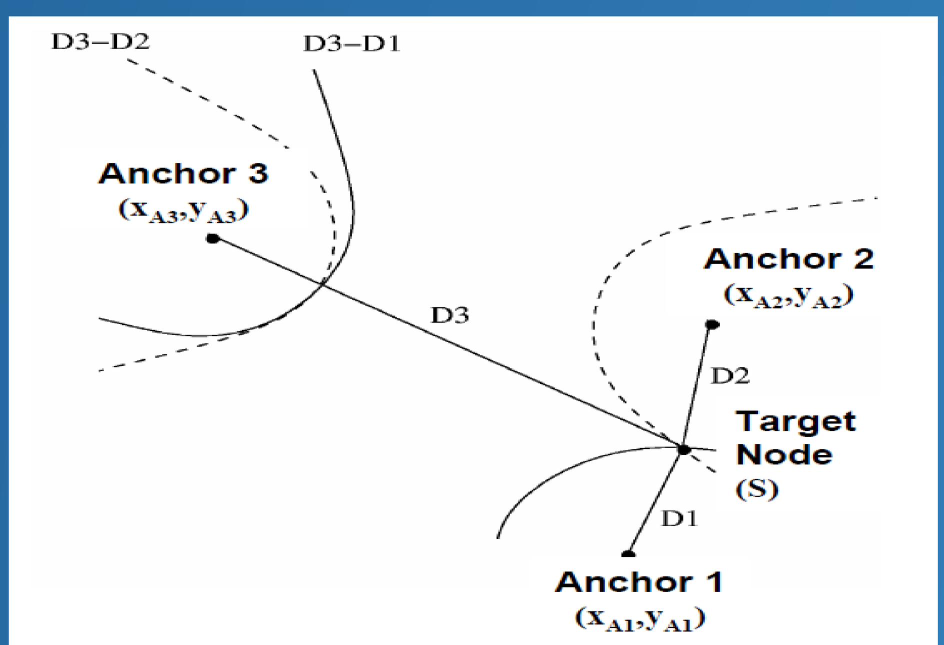


Figure 2. Hyperbolic lines of position

Parametric Method for Hyperbaraolic Location

A mathematical model is developed for the hyperbolic position estimator that is based on parametric equations. The equations of the rotated first hyperbola and second hyperbola are

$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} \cos\theta_1 & -\sin\theta_1 \\ \sin\theta_1 & \cos\theta_1 \end{bmatrix} \begin{bmatrix} a_1 \sec t_1 \\ b_1 \tan t_1 \end{bmatrix} + \begin{bmatrix} h_1 \\ k_1 \end{bmatrix} \quad (1) \qquad \begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} \cos\theta_2 & -\sin\theta_2 \\ \sin\theta_2 & \cos\theta_2 \end{bmatrix} \begin{bmatrix} a_2 \sec t_2 \\ b_2 \tan t_2 \end{bmatrix} + \begin{bmatrix} h_2 \\ k_2 \end{bmatrix} \quad (2)$$

Equating $x_1(t_1) = x_2(t_2)$ and multipliying $\cos\theta_1$ and $y_1(t_1) = y_2(t_2)$ and multipliying $\sin\theta_1$ then adding two equations leads to

$$-a_1 \sec t_1 = e_1 + e_2 \sec t_2 + e_3 \tan t_2 \quad (3)$$

Equating $x_1(t_1) = x_2(t_2)$ and multipliying $\sin\theta_1$ and $y_1(t_1) = y_2(t_2)$ and multipliying $-\cos\theta_1$ then adding two equations leads to

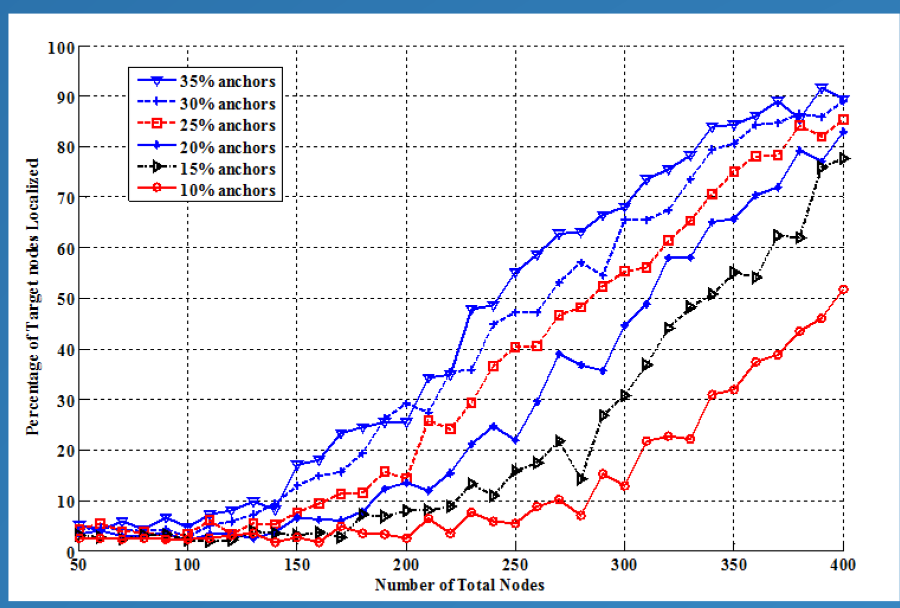
$$b_1 \tan t_1 = f_1 + f_2 \sec t_2 + f_3 \tan t_2 \quad (4)$$

To eliminate ambiguities due to multivaluedness, one can use equation

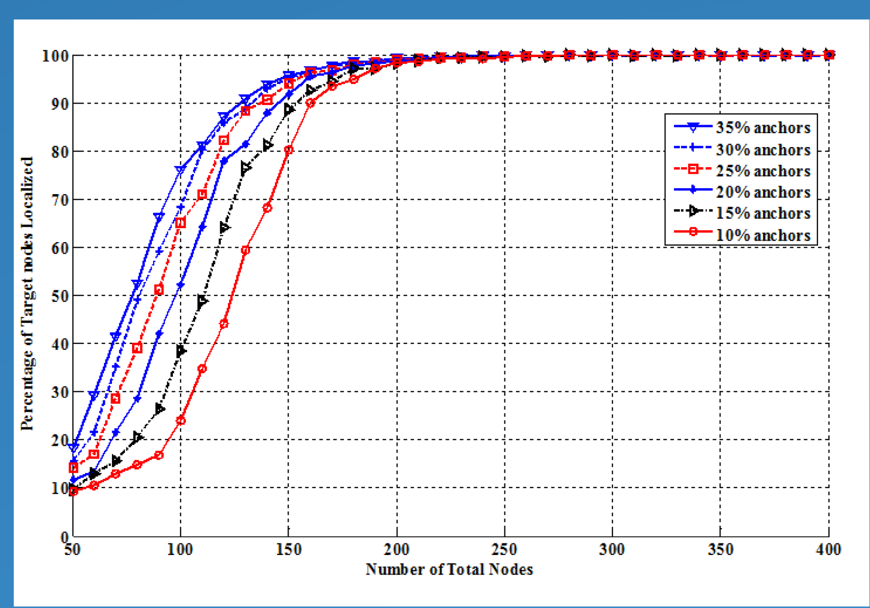
$$\begin{aligned} t_1 &= \tan^{-1}\left(\frac{f_1 + f_2 \sec t_2 + f_3 \tan t_2}{b_1}\right), \\ F &= \sec(t_1) - \left(\frac{e_1 + e_2 \sec t_2 + e_3 \tan t_2}{-a_1}\right), \\ t_{\text{int}} &= t_1(\,find\,(diff\,(sign(F)))) \qquad t_1 \in (-\pi/2, \pi/2) \end{aligned} \quad (5)$$

$$\begin{aligned} f_1 &= (h_1 - h_2)\sin\theta_1 + (k_1 - k_2)\cos\theta_1, \\ f_2 &= -a_2(\sin\theta_1\cos\theta_2 - \cos\theta_1\sin\theta_2), \\ f_3 &= b_2(\sin\theta_1\sin\theta_2 + \cos\theta_1\cos\theta_2). \end{aligned} \quad (6) \qquad \begin{aligned} e_1 &= (h_1 - h_2)\cos\theta_1 + (k_1 - k_2)\sin\theta_1, \\ e_2 &= -a_2(\cos\theta_1\cos\theta_2 + \sin\theta_1\sin\theta_2), \\ e_3 &= b_2(\cos\theta_1\sin\theta_2 - \sin\theta_1\cos\theta_2). \end{aligned} \quad (7)$$

In Figure 3a the anchor percentage is varied from 10% of the total nodes to 35%. The communications range is kept constant at 8% of the field dimension. At this set of parameters, the density of nodes increased from 50 nodes to 400 nodes and the localization performance shows that even with 35% anchor nodes present and the density at 400 nodes, the localized nodes reach around 88% nodes localized. With low anchor nodes percentage (10%) and a density of 400 nodes present in the field, the localization reaches only 50% of nodes localized. In Figure 3b, the communications range is kept constant at 15% of the field dimension. The localization performance of the algorithm with the parameters at 10% nodes reaches the almost 100% nodes localized at the density of around 200 nodes. At anchor percentage of 35%, the performance reaches almost 90% nodes localized at around 125 nodes.



(a)



(b)

Figure 3. (a) 8% range of the field dimension

(b) 15% range of the field dimension

Conclusions

A modified 3N localization algorithm was developed and tested. It immediately uses the knowledge of newly localized nodes for the enhanced performance of the localization of other target nodes. The simulations conducted have shown that the introduction of the knowledge of newly localized nodes into the network enhances its localization capability, but that if the nodes cannot be located by the 3N algorithm because of the limitations on range and sparsity of the anchors, then those nodes will not be localized by the modified algorithm either. We showed through extensive Monte-Carlo simulation, that the communication range is a crucial context parameter that is found to be tightly coupled with the localization performance.

A parametric-equation based TDOA localization algorithm is developed and studied. This algorithm is guaranteed to find all the candidate locations even when the hyperbolas are degenerate. Monte-Carlo simulations of the proposed algorithm showed that the intersections are guaranteed to be found when they exist, and that the TDOA effectiveness in localizing nodes in a network is similar to that of TOA. Since TDOA is less demanding of the hardware, requiring less synchronization for instance, one can argue that TDOA is the best alternative especially that the algorithm here is not significantly more expensive computationally.