Sensor Selection Heuristic in Sensor Networks

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ABSTRACT

We consider the problem of sensor selection so as to minimise error in estimated location of target. An algorithm based on selecting a sensor in a direction in which the error is minimized has been proposed. The ideal direction is obtained by minimising one of the measures obtained from the intersecting region of the error annuli. The algorithm has a linear computational complexity and is better suited in comparison with the information theoretic approaches. We have addressed the problem of finding out an average number of sensors after which there is no improvement in the accuracy of estimated location.

***Index Terms*— Target localization, Sensor selection, Trilateration**

I. INTRODUCTION

We consider the problem of estimating the location of a moving target 'T' in a 2 dimensional plane. A collection of sensors are spread across the plane. The locations of the sensors are known to a central server. The sensors can communicate with the central server on multi hop paths established and maintained by routing protocols [1], [2].

The target tracking network operates in two states: the surveillance state during the absence of any target and the tracking state which is in response to a moving target. Thus, the power saving operations, which is of critical importance for extending network lifetime, should be operative in two different modes as well. In this paper, we study the power saving operations in both states of network operations. During surveillance state, only that number of nodes are awake which ensure that the target is detected as soon as it enters the region. In tracking state, the sensors in the neighbourhood of target wake up and start tracking the target. The clocks on all the sensors are time synchronised [3], [4], [5]. When the target comes in the range of sensors, the sensors estimate the distance at which the target is located at an instant of time. The sensors then send the measurements to the central server and the central server estimates the location of the target.

The position of the target can be determined when distance measurements from a set of minimum three sensors are available. The error in the location estimate can be reduced by using measurements from an increasing number of sensors. However, using a large number of sensors involves taking large number of measurements and communicating all measurements to the central server. This consumes battery power and thereby reduces the life of the sensor network.

Firstly, though using increasing number of measurements improve the accuracy of location estimate, there is a marginal improvement in accuracy after a while. We address the problem of finding out an average number of sensors after which there is no significant improvement in the accuracy of estimated location. In this paper, we show that while 3 is the minimum number of measurements to determine the location of the target, 4 measurements give good results.

Secondly, it is necessary to point out which 3 or 4 sensors should be chosen for location estimation. Improvement in accuracy due to measurement from one set of sensors may be very different from improvement in accuracy due to measurement of another set of sensors. This depends upon the position of the sensor and the measurement error. Use of selected sensors help in obtaining a better quality localization information of the target. In this paper, we address the problem of ”given 2 sensors, select 3^{rd} or 4^{th} sensor to improve the given estimate of target location”.

We use least square estimation to estimate the location with n distance measurements. Our results are applicable to maximum likelihood estimation as well.

Location determination is a fundamental problem in wireless mobile network applications. It arises in robotics, navigation and surveillance. In [6] on tracking networks, location of the object is approximated as the location of sensor when the object comes in the range of that sensor. The location resolution is the sensing range of a sensor. The resolution improves when measurement from multiple sensors are considered. Distance can be estimated using signal strength as in [7], [8]. Distance estimation with TDOA techniques gives better accuracy as used in [9], [10]. [11] presents acoustic target tracking in which there are cluster heads which know positions of its slave sensors. Data gathered from slave sensors is processed by the cluster head to generate localization results. [12] describes dynamic convoy tree based collaborative method of tracking objects. Nodes within range of the object form a convoy tree and collaborate to locate the object.

The localization problem has been solved using Bayesian filtering techniques where the state of the target is represented by a probabilistic distribution. This approach is used effectively in robotics [13], [14], [15] and sensor networks [16], [17], [18], [19], [20].

Information theoretic approach is used in [16], [17] to address sensor selection and data aggregation problem. Entropy based approach was proposed in [19]. We present a method to select sensors on the basis of ideal direction in which the sensor should be selected. This does not require high computations power. We have considered more conservative error model as opposed to Gaussian error in information theoretic probability distribution based techniques.

II. Error Models

Uniform distribution model leads to the most conservative estimate of uncertainty giving the largest standard deviation. We have used multiplicative and additive uniform distribution error models to make simulations robust.

Let d_i^A and d_i^M be the actual and measured distance between target and the i^{th} sensor. Let ε_{meas} be the fractional error in measurement.

A. Uniform random additive error

Let e_i^a be the error in the distance measurement of i^{th} sensor.

$$
\begin{aligned}
e_i^a &= d_i^A - d_i^M \\
d_i^M &= d_i^A + \gamma \frac{\varepsilon_{meas}}{2}
\end{aligned}
$$

with $-1 \geq \gamma \leq 1$.

The error is uniformly distributed with endpoints as $-\frac{\varepsilon_{meas}}{2}$ and $+\frac{\varepsilon_{meas}}{2}$ with a standard deviation σ^a and mean zero.

$$
\begin{aligned}
e_i^a &= [-\frac{\varepsilon_{meas}}{2}, \frac{\varepsilon_{meas}}{2}] \\
\sigma^a &= \frac{1}{\sqrt{3}} (\frac{\varepsilon_{meas}}{2})
\end{aligned}
$$

Measurement error for chosen n sensors is $Emeas_n^a$ with a mean $Emeas_{mean}^a$.

$$
\begin{aligned}
Emeas_n^a &= \sqrt{\sum_{i=1}^{i=n} (e_i^a)^2} \\
Emeas_{mean}^a &= \frac{\varepsilon_{meas}}{4}
\end{aligned}
$$

The mean $Emeas_{mean}^a$ is independent of of distance from target.

B. Uniform random multiplicative error

Let e_i^m be the error in the distance measurement of i^{th} sensor.

$$
\begin{aligned}
e_i^m &= d_i^A - d_i^M \\
d_i^M &= (1 + \gamma \frac{\varepsilon_{meas}}{2}) d_i^A
\end{aligned}
$$

with $-1 \geq \gamma \leq 1$.

The error is uniformly distributed with endpoints as $(1 - \frac{\varepsilon_{meas}}{2}) d_i^A$ and $(1 + \frac{\varepsilon_{meas}}{2}) d_i^A$ with a standard deviation as σ^m and mean as zero.

$$
\begin{aligned}
e_i^m &= [-\frac{\varepsilon_{meas}}{2} d_i^A, +\frac{\varepsilon_{meas}}{2} d_i^A] \\
\sigma^m &= \frac{1}{\sqrt{3}} (\frac{\varepsilon_{meas}}{2}) d_i^A
\end{aligned}
$$

Measurement error for chosen n sensors is $Emeas_n^m$ with mean $Emeas_{mean}^m$.

$$
\begin{aligned}
Emeas_n^m &= \sqrt{\sum_{i=1}^{i=n} (e_i^m)^2} \\
Emeas_{mean}^m &= \frac{\varepsilon_{meas}}{4} \sqrt{\sum_{i=1}^{i=n} {d_i^A}^2}
\end{aligned}
$$

$Emeas_{mean}^m$ is dependent on the distance from the target.

Multiplicative error in distance measurement is more interesting in comparison with additive error in measurement since in real life, the error is dependent on the distance from which measurement has been done. The distance estimates in wireless radio networks is obtained with Radio Signal Strength (RSSI) measurement or TDOA. In both cases, the error in measurement is dependent on the distance from the node. Thus the multiplicative error model is more relevant. We have considered the multiplicative error model as the basis of all our discussions. Corresponding discussion and results for additive error model have been described in the Appendix.

III. Least Square Estimate

n distance measurements d_i, $i = 1 \ldots n$ from n sensor locations (x_i, y_i) to unknown location (x, y) result into a non linear system of n equations. Refer equation 1.

$$(x - x_i)^2 + (y - y_i)^2 = d_i^{M^2} \qquad (1)$$

with $i = 1, \ldots, n$.

While estimating location, a least square estimate to n non linear equations is to be found out. Following optimisation problem needs to be solved.

$$minimise \quad \sum_{i=1}^{i=n} e_i^{m2} \qquad (2)$$

The problem of local minima and large number of computations in optimization techniques can be circumvented by choosing an appropriate initial guess. The initial guess is obtained by solving a linear system of equations resulting out of subtraction of non linear equations in 1. This results into an overdetermined system of linear equations that can be represented as matrix equation $Ar = C$. r is chosen such that average error in all the equation in the linear system is minimized. This is achieved by using *pseudo-inverse* of matrix A. Using solution of the linear system as an initial guess, any suitable optimization technique can be used to find solution to optimization problem in equation 2. Results with Steepest Descent and Levenberg Marquardt have been presented.

No. of iterations	**Acc. 0.01%**	**Acc. 0.1%**	**Acc. 1%**	**Acc. 10%**
Steepest Descent	2	3	4	8
Levenberg Marquardt	6	6	6	6

TABLE I

Convergence in optimization techniques

It is observed from both fig. 1, 2 and table I that the initial guess is good since the optimization

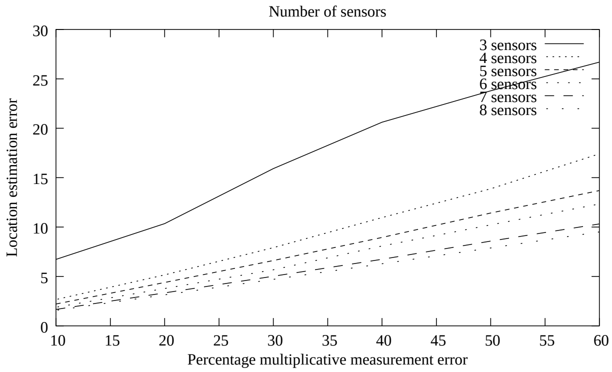

Fig. 1. Measurement error vs. Location estimation error

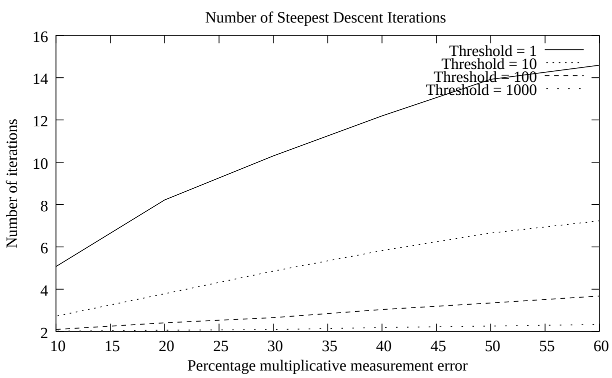

Fig. 2. Convergence: Number of iterations

techniques have a fast convergence. As seen in fig. 2 Steepest Descent converges in less than 20 iterations and in 6 iterations in case of Levenberg Marquardt. There is significant improvement in the location estimation error with optimization over the initial guess as seen in table II. Location estimation error with the optimized techniques is 7% as against the initial guess with error of 18% with three sensors. With four sensors the intila guess has an error of 5% and the error with optimized technique is just 2.6%.

IV. Optimum number of sensors

Multiple measurements improve the accuracy of location estimate and reaches a saturation point after some number of measurements. As can be seen from figure 3, 4 sensors are enough to gain a good accuracy after which the improvement in accuracy is not significant. See Table II, the error reduces by 62.8% when the number of sensors increase from three to four and less than 3.85% when number of sensors increase from four to five.

Error in Estimates	**3 Sensors**	**4 Sensors**	**5 Sensors**
Initial estimate	18%	5%	4.1%
Optimised estimate	7%	2.6%	2.5%

TABLE II

Location estimation accuracy and number of sensors

V. Sensor Selection

The relative positions of sensors with respect to each other and with respect to the target position play an important role in location estimation accuracy [21]. Choosing suitable sensors would avoid communication overheads and still satisfy the loca-

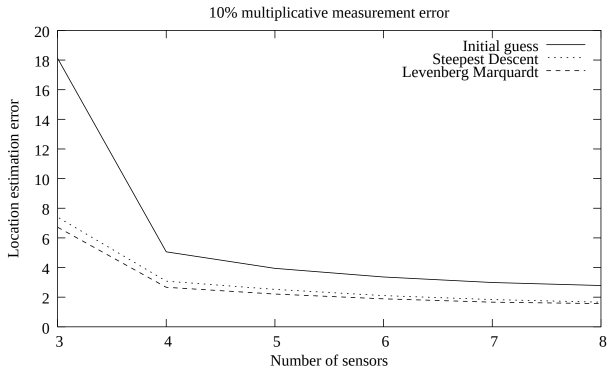

Fig. 3. Location estimation error in initial guess and in optimised result

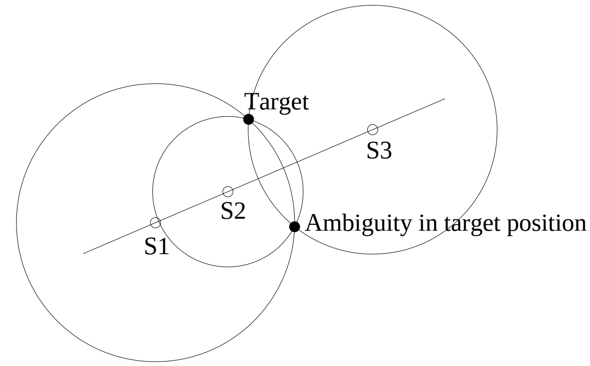

Fig. 4. Ambiguity in target location in case of collinear sensors

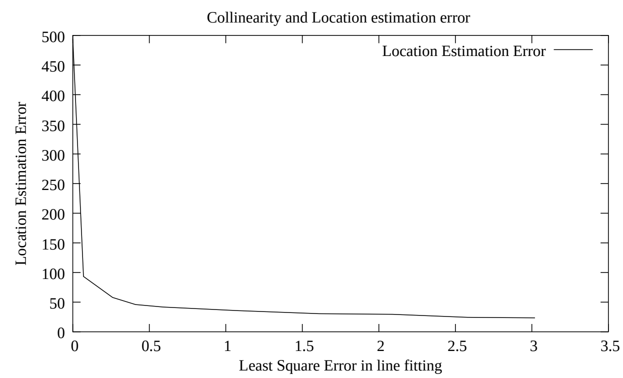

Fig. 5. Effect of collinearity on location estimation error

tion estimation accuracy constraints. Now we would like to mathematically establish the factors which affect location estimation accuracy. Based on these factors sensor selection policies can be made.

A. Collinearity

When the sensors are collinear, no more information is added as compared when information is available from only two sensors as seen in figure 4. The ambiguity in the sensor position is not resolved. The ambiguity gets resolved only when a non collinear sensor is chosen.

Simulations with a definition of measure of collinearity have been done. The measure of collinearity is defined as the residual error while trying to fit a line passing through the given n sensors. Fig. 5 shows a plot of location estimation error with respect to the residual error in least square error line fitting. When the residual error is low, the sensors are almost collinear and the location estimation error in such cases is very high.

As seen in fig. 6, the direction of collinearity is dependent upon the perpendicular distance *xcoord* of the target from the line passing through the two sensors and the distance d from the target.

$$\theta = \pi - cos^{-1}(\frac{x}{d}) \tag{3}$$

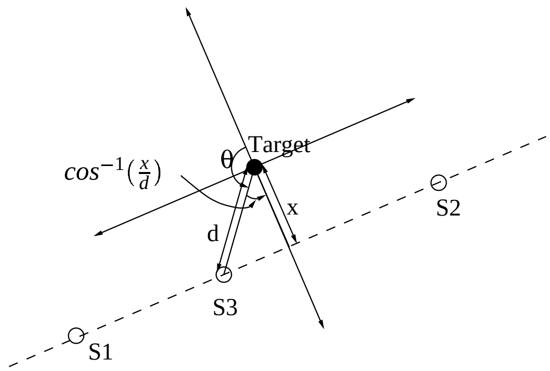

Fig. 6. Direction of collinearity

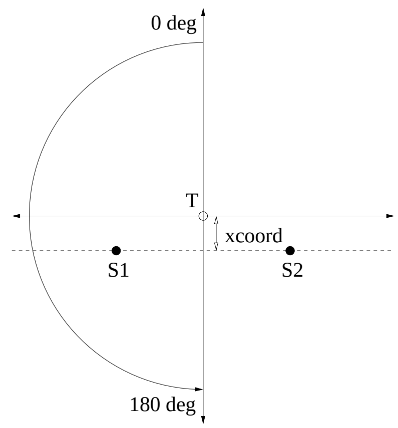

Fig. 7. Experimental Setup

where θ is the direction in which the sensor becomes collinear with the rest of the two sensors (refer fig 6), x = $xcoord$ = perpendicular distance to the line passing through the $n-1$ sensors, d is the distance of the sensor from the target and $x < d$. Refer fig. 7, 6. In the simulation setup, two sensors were placed at an equal distance from the target with $x = 50$. The third sensor at a distance d was placed at different angles from 0 to π. Refer fig. 7. The average location estimation error at angles from was plotted. refer fig. 8 where $x = 50$. As can be seen the collinear direction is at 120^o when $d = 91$ and is 161^o when $d = 51$. In another case (refer fig. 9) with $x = 100$, the collinear direction is 180^o.

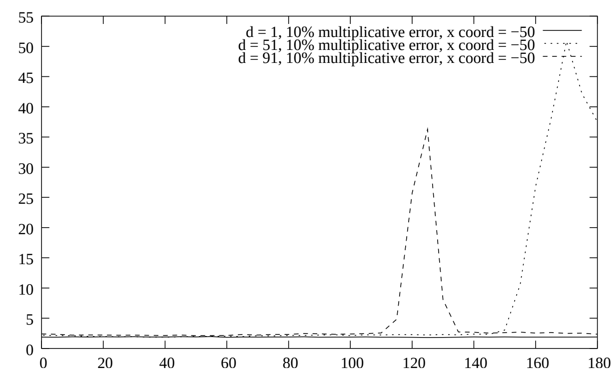

Fig. 8. 10% multiplicative error, x = 50

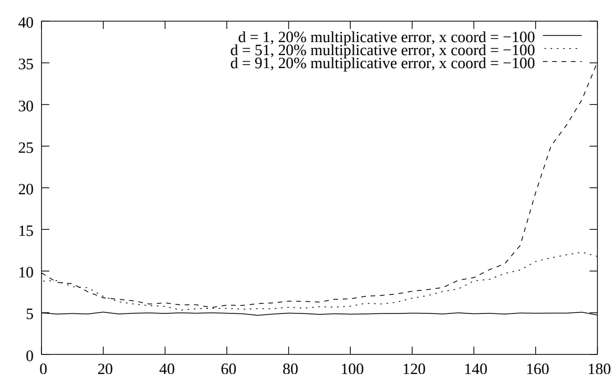

Fig. 9. 20% multiplicative error, x = 100

B. Distance from the target

In case of multiplicative error in measurement, error is proportional to the distance to be measured.

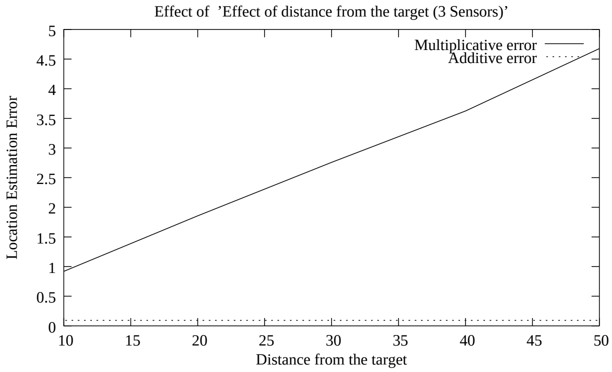

Fig. 10. Effect of distance on location estimation error

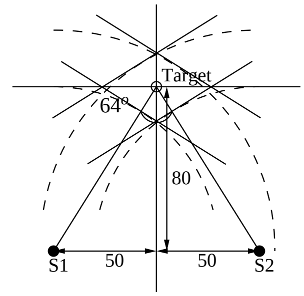

Fig. 11. Linear approximation

Lower the distance from the target, lower is the error in measurement of distance and thus lower the resultant error in localization. Sensors were placed at a constant distance from the target. Location estimation error was observed at different distance from target. As seen in fig. 10, the error is linearly increasing with the distance from the target. We assume that all the nodes are not so much near that target that they interfere with each others measurement. Distance is immaterial in case of additive error model since the error is not dependent on the distance as seen in section on Error Models.

C. Ideal Direction

Given position of one sensor, obtaining the ideal direction in which to choose the next sensor is trivial. It is obvious that the ideal direction is perpendicular to the line passing through the target and the first sensor. However, measurements from two sensors still leave ambiguity in sensor location as in the case of collinear sensors. Thus, measurement from more than two sensors is necessary. In case of given $n-1$ sensors, there is an ideal direction in which the n^{th} sensor should be chosen, where $n \geq 3$. The technique of finding ideal direction in case of choosing the third sensor has been detailed in the next section. Given the sensor position of two sensors, there is an ideal direction in which if we choose the third sensor, the error is low compared to other directions. Thus a sensor should be chosen such that it is in the ideal direction and nearest to the target as well.

The argument in the paper has been based on the intersection polygon of error annuli. The probability that sensor is located in this region is maximum in the intersection region since the likelihood function

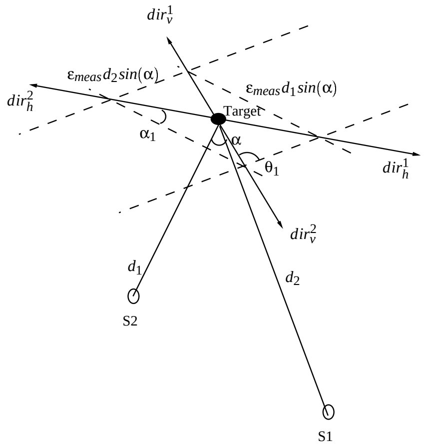

Fig. 12. Ideal direction in case of multiplicative error

$p(z_i \mid x)$ 4 is maximum in the intersection region.

$$p(z \mid x) = c1 \prod_{i=1}^{i=n} p(z_i \mid x) \tag{4}$$

where z_i, $i = 1 \ldots n$ are the measurements from n sensors, x is the target state, $p(z \mid x)$ is the likelihood function which is proportional to the product of $p(z_i \mid x), i = 1 \ldots n$ when x is uniformly distributed and z_i are conditionally independent w.r.t x, $p(z_i \mid x)$ is the probability of measurement z_i when the target state is x. This is dependent upon the error model of the measurement.

If distance measurements have a fractional error of ε_{meas}, the maximum probability region of the estimated position is the overlapping area of intersecting annulus of width ε_{meas} in case of additive error and $\varepsilon_{meas} d_i^A$ in case of multiplicative error [21]. If the area is large then the error will be large as well. For the purpose of computational simplicity for the low capability sensors we consider a linear approximation of area of intersection of annuli as a parallelogram as shown in fig. 11.

Refer fig. 12 for multiplicative error model Fig. 25 in appendix is for additive error model. The paper discusses choosing third sensor given two sensors. The same technique is applied for choosing n^{th} sensor, given $n-1$ sensors.

Refer fig. 12, α is the visual angle made by two sensors with the target. The direction of longest axis is dependent on θ_1 when $\alpha > \frac{\pi}{2}$. In this case the ideal direction is dir_v^1, dir_v^2.

$$\begin{aligned}
\theta_1 &= tan^{-1} \frac{d_2 sin(\alpha)}{d_1 + d_2 cos(\alpha)} \\
dir_v^1 &= AoA_2 + \frac{\pi}{2} + \theta_1 \\
dir_v^2 &= dir_v^1 - \pi = AoA_2 - \frac{\pi}{2} + \theta_1
\end{aligned}$$

When $\alpha < \frac{\pi}{2}$ the direction of longest axis is dependent upon α_1. The ideal direction in this case is dir_h^1, dir_h^2.

$$
\begin{aligned}
\alpha_1 &= tan^{-1}\frac{d_1 sin(\alpha)}{d_2 + d_1 cos(\alpha)} \\
dir_h^1 &= AoA_1 + \frac{\pi}{2} + \alpha_1 \\
dir_h^2 &= dir_v^1 - \pi = AoA_1 - \frac{\pi}{2} + \alpha_1
\end{aligned}
$$

The ideal direction is chosen as the direction of the longest axis of the intersection polygon. This will ensure that the next intersection polygon will have a smaller longest axis. A comparison has been made between the reduction in the length of longest axis, reduction area , reduction in circumference of the intersection polygon versus the location estimation error.

D. *Time Complexity*

The time complexity of finding intersection of two polygons is $O(a+b)$ [22] where a and b are number of vertices of the two polygons. Intersection of two parallelograms (four vertices each) is required for selection of the r^{rd} sensor. To select 4^{th} sensor, intersection of two polygons, one parallelogram with 4 vertices and the other with worst case 6 vertices is required. Thus the time complexity is of $O(n)$ where n is number of vertices of polygon which does not exceed 6 for choice of up to 4^{th} sensor.

VI. Direction based Algorithm

$ChosenSet_1$ = ϕ;

$ChosenSet_2$ = ϕ;

$ChosenSensor$ = $NULL$;

- Compute ideal direction = $IdealDir$
- Compute collinearity direction = $CollDir$
- for (sensor s_i, i = 1 to n)
  - Compute angle of arrival of s_i = $AoAS_i$
  - $DiffIdeal$ = $IdealDir$ - $AoAS_i$
    * if ($DiffIdeal \leq \delta_1$)
    * $ChosenSet_1$ = $ChosenSet_1 \cup s_i$
    * endif
- endfor
- for (sensor $s_i \in ChosenSet_1$, i = 1 to cardinality of $ChosenSet_1$)
  - $DiffColl$ = $CollDir$ - $AoAS_i$
    * if ($DiffColl \leq \delta_2$)
    * $ChosenSet_2$ = $ChosenSet_2 \cup s_i$
    * endif
- endfor

- for (sensor $s_i \in ChosenSet_2$, i = 1 to cardinality of $ChosenSet_2$)
  - $ChosenSensor = s_i$ which has minimum distance from the target (applicable to only multiplicative error model)
- endfor

The complexity of the above algorithm is $O(n)$ where n is the number of sensors assuming that all the n sensors do not get chosen in collinear set or ideal direction set.

VII. Simulation and Results

The target was assumed to be at the origin of the coordinate system. The setup is shown in fig. 7. Measurements from two sensors were available. Results have been plotted for different positions of two sensors in fig. 13, 14, 15, 16. In setup (refer fig 13), two sensors are placed at same distance from the target at the origin. The visual angle α made by the two sensors is obtuse. Error in location estimation was computed for every possible position for the third sensor such that the target is within the range of the sensor. The total range of the location estimation error for different positions was computed and was divided into four ranges. A different symbol was printed for different range of location estimation error.

- X (cross) : error $\geq$ 1.5 (average error)
- * (star) : (average error) $\leq$ error $<$ 1.5 (average error)
- + (plus) : 0.5 (average error) $\leq$ error $<$ (average error)
- . (dot) : 0.5 (average error) $\leq$ error

As can be seen in fig. 13 the region of lowest estimation error (dot) is in direction of the bisector of the visual angle which is same as the direction perpendicular to the line passing through the two sensors. It can be observed that the error is maximum for the positions which are collinear to the two sensors. In fig. 14, the two sensors are at equal distance and the visual angle is acute. It can be noted that the region of lowest estimation error is the bisector of the external angle of the visual angle in the triangle formed by the two sensors and the target. This direction is parallel to the line passing through the two sensors. There is no significant error in these cases. In fig. 15, the visual angle is obtuse and the distances of two sensor are unequal. In such a case, the ideal direction is in the direction of the longest axis of the intersection polygon. In this case the direction computed is 30.208^o. In fig. 16, the visual angle is acute, ideal direction is in the direction of the longest axis of the intersection polygon. In this case the direction computed is -84.873^o. There is an error of around 5^o in both the cases. This error is due to the linearization approximation of intersection area as a parallelogram.

In addition to the longest axis of the intersection polygon, the area of the intersection polygon and circumference of the intersection polygon can be measures of expected location estimation error. These three measures have been compared. See figure 17 for location estimation error vs length of longest axis, fig. 18 for location estimation error vs area, fig. 19 for location estimation error vs circumference. It can be observed that the measure of length of the longest axis represents error in estimation of location. Location estimation error is high when the length of the longest axis is high and low when the length of longest axis is low.

The results where next sensor has been selected on the basis of direction of longest axis are presented in fig. 20. It can be observed how the location

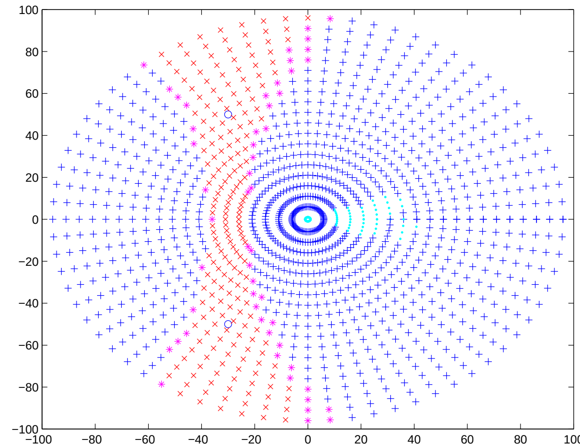

Fig. 13. Symmetrical placement of sensors, visual angle $\alpha > \frac{\pi}{2}$

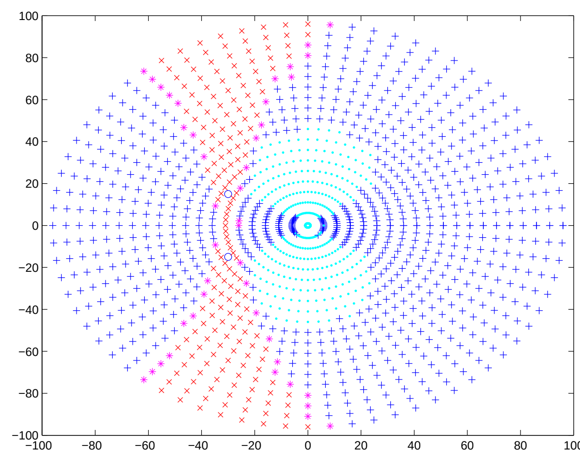

Fig. 14. Symmetrical placement of sensors, visual angle $\alpha < \frac{\pi}{2}$

estimation error reduces with length of the longest axis as next sensor (third and fourth) is picked up in the direction of longest axis.

Refer fig. 21, 22 for one of the sensor selection scenario. The 2 sensors which are already selected are shown with circles. The next two selected sensors are shown dark. The error with selected 4 sensors is the minimum, that is 5.0712 as compared

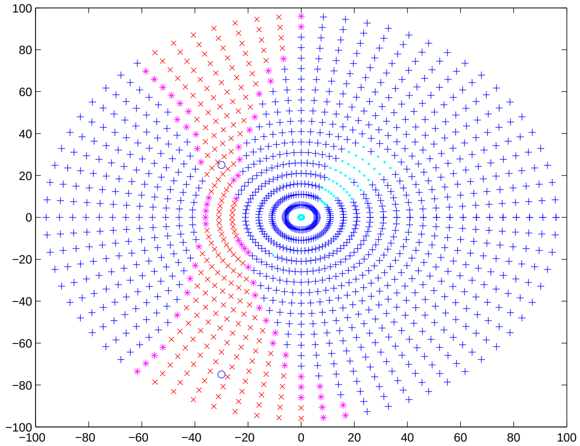

Fig. 15. Unsymmetrical placement of sensors, visual angle $\alpha > \frac{\pi}{2}$

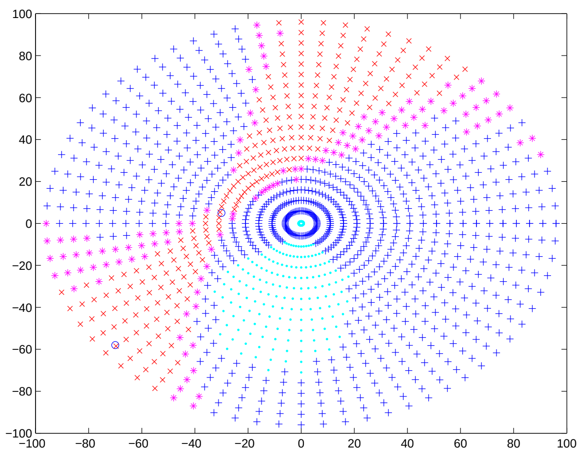

Fig. 16. Unsymmetrical placement of sensors, visual angle $\alpha < \frac{\pi}{2}$

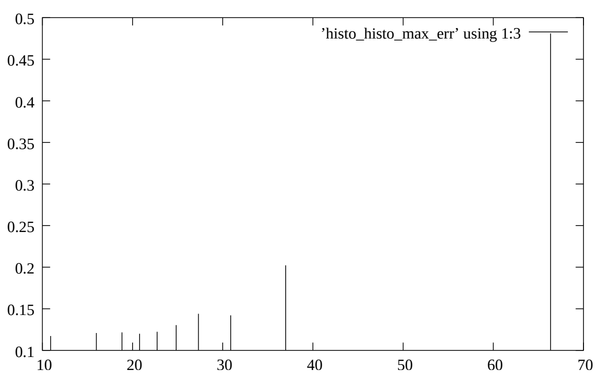

Fig. 17. Length of longest axis vs. error

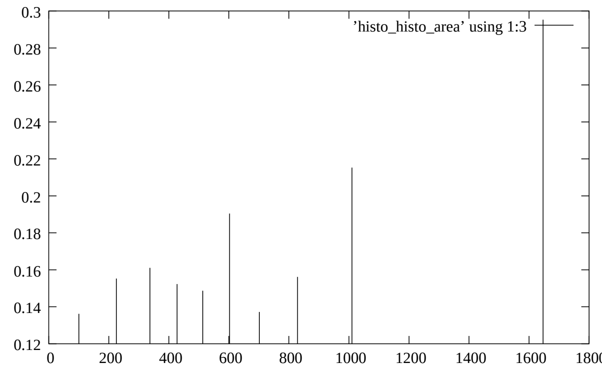

Fig. 18. Area vs. error

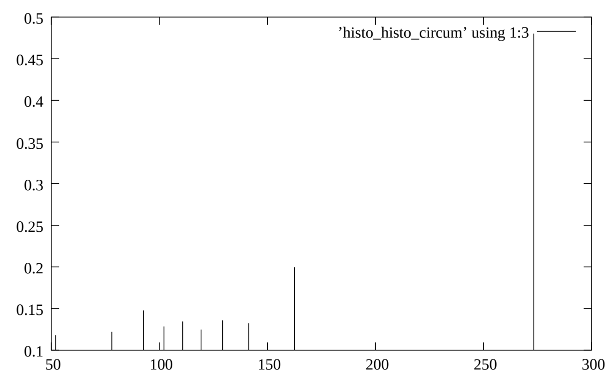

Fig. 19. Circumference vs. error

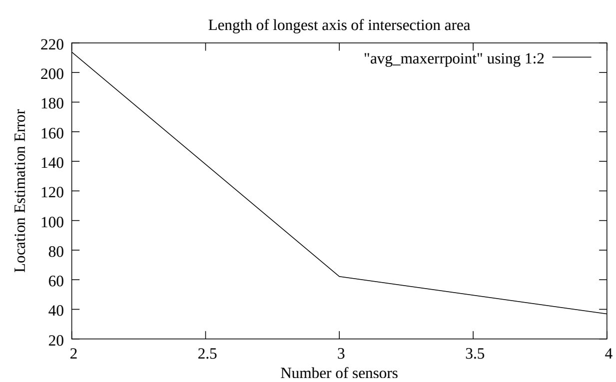

Fig. 20. Reduction in length of longest axis

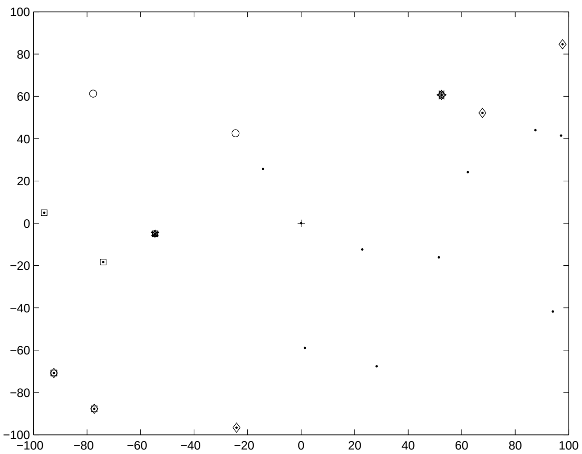

Fig. 21. Sensor Selection Scenario 1

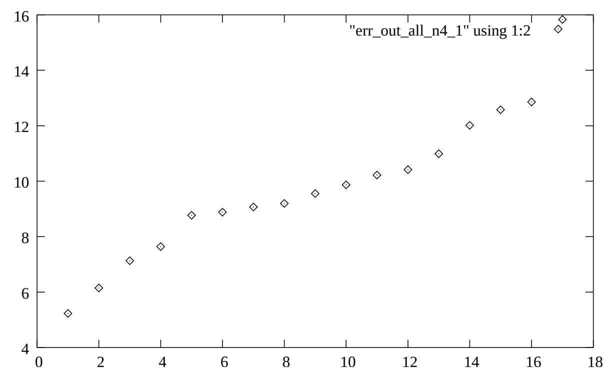

Fig. 22. Error with all combinations of 4 sensors: Scenario 1

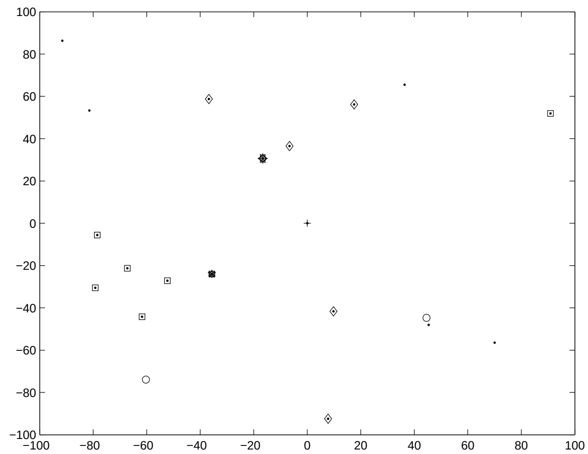

Fig. 23. Sensor Selection Scenario 2

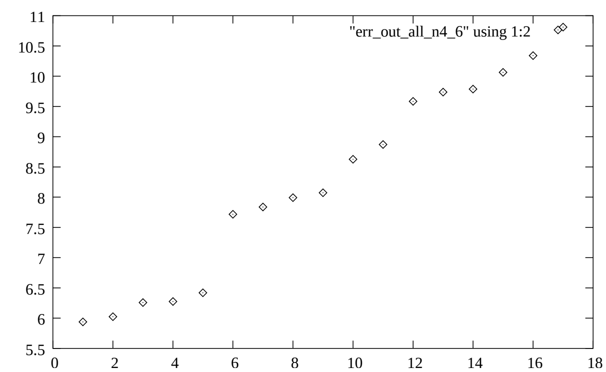

Fig. 24. Error with all combinations of 4 sensors: Scenario 2

with any other combinations of 4 sensors. Refer fig. 23, 24 for another sensor selection scenario. The error with selected 4 sensors is 6.0665 which is not the minimum, but is within best 5 combinations of 4 sensors.

Table III shows the comparison of location estimation error with randomly selected 3 and 4 sensors vs. sensors selected with our algorithm. As it can be seen, there is an improvement of 60.4% in case of 3 sensors and 30.213% improvement in case of 4 sensors. With 4 sensors selected with our algorithm, there is an improvement of 80.165% when only three sensors are selected randomly. See table IV.

VIII. Conclusion

In this paper, we show that while 3 is the minimum number of measurements to determine the location of the target, 4 measurements give good results. We address the problem of ”given 2

Location Error	3 Sensors	4 Sensors
Random Sensors	22.941	9.9914
Selected Sensors	9.0812	6.9727
Improvement	60.416%	30.213%

TABLE III

IMPROVEMENT WITH SENSOR SELECTION

Location Error	3 Random Sens.	4 Selec. Sens.	Improvement over 3 random Sens.
	22.941	6.9727	80.165%

TABLE IV

IMPROVEMENT WITH 4 SELECTED SENSOR OVER WORST CASE SCENARIO OF 3 RANDOM SENSORS

sensors, select 3^{rd} or 4^{th} sensor to improve the given estimate of target location". An algorithm based on selecting a sensor in a direction in which the error is minimized has been proposed. The ideal direction is obtained by minimising one of the measures obtained from the intersecting region of the error annuli. The algorithm has a linear computational complexity and is better suited in comparison with the information theoretic approaches. There is small error of 5^o in the mathematically computed ideal direction and the experimental results which is due to linear approximation of intersection area as a polygon. We show that the ideal direction can be chosen in the direction of longest axis of the intersection area. This measure gives better results than the measure of area and circumference of the intersection area. There is an improvement of 80.165% with 4 sensors selected with the proposed algorithm over worst case location estimation error with 3 randomly selected sensors.

IX. APPENDIX

Refer figure 25 and 26 for uniform additive error model.

The ideal direction in case of two sensors at equal distance from the target behaves in the same manner as of the additive error. Refer fig. 25 in appendix. In this case the ideal directions are the bisectors of the visual angle or the bisectors of the exterior angle of triangle formed by the two sensors and the target.

Thus, we can conclude that if the distance of two sensors are equal/comparable

- If the visual angle $\angle\alpha$ is $> \frac{\pi}{2}$
  - the ideal direction is at bisector of the $\angle\alpha$ (interior angle bisector).
- If the visual angle $\angle\alpha$ is $< \frac{\pi}{2}$

– the ideal direction is perpendicular to the bisector of the $\angle\alpha$ (exterior angle bisector).

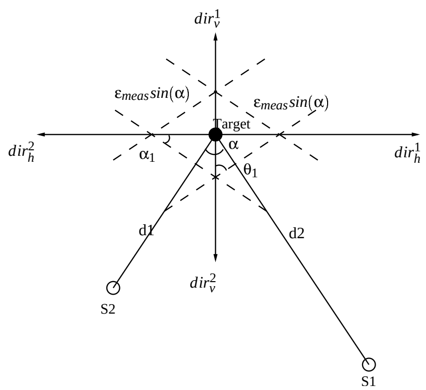

Fig. 25. Ideal direction in case of additive error

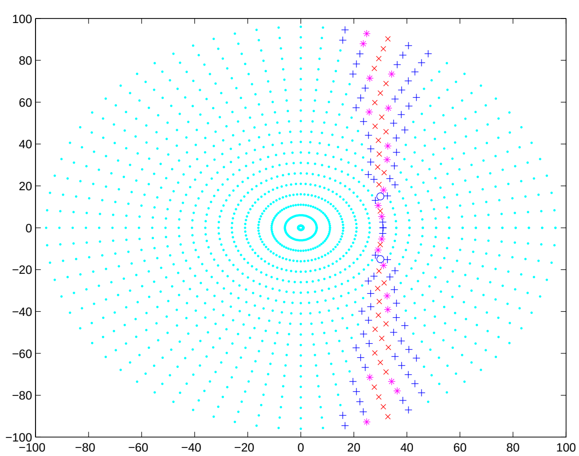

Fig. 26. Additive measurement error

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