# QUALITY IMPROVEMENT OF TRACKING AND POSITIONING OF MOBILE SYSTEMS

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**Abstract-** In this initial research phase a novel model for mobile node localization and tracking has been developed for Wireless Interfaced Networks for Next Generation communication. The precise location tracking or the localization of a mobile user can play a vital role in Line of Sight (LS) as well as Non-Line of Sight (NLOS) communication paradigm which is of course a key component of future oriented interfaced communication networks (Wireless Sensor networks and Wireless Mobile Communication systems). To ensure optimal performance in terms of higher data communication rate, minimal data drop, higher throughout and energy etc, the optimization in node localization plays a vital role. There are a number of factors that might cause degradation of signals and communication linkage in the wireless mobile communication. In this initial research phase, i have emphasized over localization or mobile node tracking in sensor based Wireless Mobile network, also called Wireless Interface network

**Keywords-** Non-Line of Sight, Wireless Sensor Network, RSSI, Mobile Node, Betien.

## I. INTRODUCTION

Wireless Interface Network has great potential to be employed in next generation communication system for broadband utilities, Indoor communication systems, industrial applications etc. In major NLOS based communication scenarios, due to varied signal degradation factors the radio signals gets varied resulting into the inevitable requirements of optimal Received Signal Strength Indicator (RSSI) calibration. Taking into consideration of the recent researches for wireless mobile communication system node localization and tracking, especially in case of NLOS communication paradigms, the RSSI factor has been considered primarily. To strengthen the performance and effectiveness, the Gray Prediction approaches, Dynamic triangular (DTN) location approach etc have been advocated a lot. Thus, considering these all motivations in this research phase, i have employed a grey prediction algorithm for RSSI estimation in NLOS wireless environment. Here, for specific case of Interfaced wireless communication with mobile users in NLOS environment, i have employed the Dynamic Triangulation approach that gives precise results.

Here, it must be noted, that in this research phase, i emphasize in putting the foundation of localization and mobile node tracking. As per research proposal, i supposed to enhance the overall localization and tracking system using varied optimization and localization approaches. These all research modelling and development would be disused in ascending research phase.

Theoretically, in general, the mobile node localization or tracking is accomplished be estimating distance parameters existing with wireless radio link or network betien one node to another or betien one mobile node to the other base station. In case of Interface communication, the mobile users are mobile while one terminal remains static as base station in LOS or NLOS communication environment. In proposed research work, i have modeled our system to function with LOS as ill as NLOS scenarios. More precisely to evaluate the robust performance, i using NLOS environment to estimate performance.

## II. IMPLEMENTATION OF VARIOUS LOCALIZATION SCHEMES.

There are a number of approaches for node localization and as per research proposal and uniqueness of the proposed research initiatives, here in this research a number of paradigms have been explored at first so as to ensure an optimal solution for location estimation in mobile wireless communication scenario. In major applications, and especially in case of wireless mobile communication with interface network, the localization of source terminal becomes inevitable so as to accomplish QoS communication and efficient data transmission. In this presented research work a number of localization schemes have been considered for performing localization in varied circumstances and respective efficiency has been evaluated. Ultimately a novel RSSI based weight predicted localization paradigm for mobile node localization has been developed for next generation interfaced wireless network. In this research work, we have developed the two – dimensional (2-D) node localization scheme. Taking into consideration of non-linear behaviors in the network conditions, here non-linear as well as linear schemes have been developed. Initially the non-linear approaches have been employed such as maximum likelihood ad non-linear least square approach for localization which was further enhanced with linearization and respective algorithms were evaluated for performance.

In the initial phase of research work, here conventional Maximum likelihood scheme and non-linear least square algorithm have been applied to perform localization. Later considering the possible enhancements and optimistic goal to schemes were explored for localization. To make conventional Linear Least Square scheme more effective the generalization was done using weight factor incorporation, where weight linear least square outperformed convectional linear least square approach. In this work, to examine the effectiveness of the proposed systems, Cramer Rao Lower Bound was also calculated and the respective performances of all localization paradigms were evaluated. Here the cramer rao bound was calculated for the variance for all the unbiased localization paradigms and respective performance evaluation was done. In this research work received signal strength indicator approach and time of arrival paradigm have been employed for localization of nodes. In the initial phase time of arrival has been considered for exploring the best approach for localization, where in the second step RSSI potential has been employed for mobile node localization and positioning.

The novelty of this research work exist in the fact that there are multiple transceivers in this research work which certain circular equations are formed resulting into more precise and accurate localization. This is because of the fact that the doing so would facilitate the conversion of noisy time of arrival into certain circular equations which could be employed for localization. Majority of existing systems have employed the two time or arrival circles for localization which given two possible position of node that can't be stated as a novel scheme. The set of circular equations retrieved in the proposed system can be employed for processing with optimization schemes.

A brief of the developed research model can be understood by observing the following expressions and discussions. Consider = [, ]$T$represents certain location of a node and similarly $l$ = [$l$ , $l$ ]$T$represents the available information or the coordinate of certain nth sensor or node n, = 1,2,3…,$N$, where$N \geq 3$. Here in this implemented research model minimal 3 nodes have been taken into consideration. Thus, the respective distance between certain passive source or nth sensor transceiver or receiver is given by, which can be estimated by following expression.

$$d_n = \|x - x_n\|_2 = \sqrt{(x - x_n)^2 + (y - y_n)^2}, n = 1,2,2 \ldots, N.$$

Without taking into consideration of any generalized losses, in this research model it has been assumed that the source node transmits signal at t=0 and the signal is received at nth receiver at time$t$. Thus the inter-relationship between distance and time can be retrieved simply by

$$t_n = \frac{d_n}{c}, n = 1,2, \ldots, N.$$

But in practice it has been realized that time of arrival based approaches might be effected by measurement errors. Resulting into the need of range measurement which was done by multiplying $t_n$by$c$ and it has been denoted as$r_{loc,n}$ .

$$r_{loc,n} = d_n + E_{R\_loc,n} = \sqrt{(x - x_l)^2 + (y - y_l)^2} + E_{R\_loc,n}$$

Where$E_{R_loc,n}$ represents measurement error possible in range measurement $r_{loc,n}$.

Further it can be expressed as

$$r_{loc} = f_{loc}(x) + E_{R\_loc}$$

Where,

$$r_{loc} = \begin{bmatrix} r_{loc,1} & r_{loc,2} & \cdots & r_{loc,L} \\ E_{R\_loc,1} & E_{R\_loc,2} & \cdots & E_{R\_loc,L} \end{bmatrix}^T$$

And

$$f_{loc}(x) = d = \begin{bmatrix} (x - x_1)^2 + (y - y_1)^2 \\ (x - x_2)^2 + (y - y_2)^2 \\ \vdots \\ (x - x_N)^2 + (y - y_N)^2 \end{bmatrix}$$

Here, $f_{loc}(x)$depicts a known function that has been parameterized by $x$ which represents a noise free vector. In fact in this research work, the node localization issue is based on time of arrival based estimation of x with provided range measurement$\{r_{loc}\}$. To estimate system performance with Craner Rao lower bound it has been taken into consideration that $\{r_{loc}\}$ are existing with zero-mean uncorrelated Gaussian processes with available variances of $\{\sigma_{loc,n}{}^2\}$.

For each stated range measurement the respective probability density function (PDF) has been obtained and is given by a variable $P(r_{loc,n})$ has the has the form of

e in correspond of a weighted form of non-linear least square which is in fact maximum likelihood.

To facilitate the maximization, we have taken into consideration of a logarithmic version, given by

$$ln(P(r_{loc})) = ln\left(\frac{1}{(2\pi)^{N/2}|C_{TOA}|^{1/2}}\right) - \frac{1}{2}(r_{loc} - d)^T C_{loc}{}^{-1}(r_{loc} - d)$$

In the expressed equations, the first term can be observed as the independent function of the location parameter, and therefore optimizing the above equation could result into the equivalence of the results of the optimization of the second term and in such a way the maximum likelihood could be obtained as

$$\hat{x} = arg \min_{\tilde{x}}(\mathrm{r_{loc}} - \mathrm{f_{loc}}(\tilde{x}))C_{loc}{}^{-1}(\mathrm{r_{loc}} - \mathrm{f_{loc}}(\tilde{x}))$$

In other words it can be stated as

$$\hat{x} = arg \min_{\tilde{x}} C_{ML}(\tilde{x})$$

i)Linear Schemes for Localization

In this research work, the fundamental concept of utilizing linear localization schemes was to transform the nonlinear expressions of time of arrival localization scheme into equivalent linear equations having zero-mean disturbances with errors in range measurement as negligible. Now, after transformation the optimization cost function becomes a unimodel that can assure to get global optimized solution for precise localization. Thus, in this research phase, three approaches called, linear least square, enhanced weighted linear least square and subspace estimator have been employed for localization. Here the novelty is implementation is the consideration of weighted linear least square which is the enhanced weighted form of linear least square scheme of localization. Here it has been found the weighted linear least square can achieve better precise and accurate localization if the mean and variance of the linear equations are computed with weight factor. The last scheme employed in this research phase was subspace estimator that relates the location vector x with the squared pair wise distances existing between the source node and the receiver in wireless network and here the localization has been accomplished using eigenvalue decomposition scheme.

ii)Implementation of Linear Least Square for Localization:

The linear least square approach converts the cost function optimization equations into linear form of x and then using conventional least square the localization is accomplished.

Conversion of time of arrival range measurements into equivalent linear models of$x$,

$$r^2_{loc,n} = (x - x_n)^2 + (y - y_n)^2 + E^2_{loc,n} + 2E_{loc,n}\sqrt{(x - x_n)^2 + (y - y_n)^2},\ n = 1, 2 \dots N$$

$$m_{loc,n} = E^2_{loc,n} + 2E_{loc,n}\sqrt{(x - x_n)^2 + (y - y_n)^2}$$

$$r^2_{loc,n} = (x - x_n)^2 + (y - y_n)^2 + m_{loc,n}$$

iii)Implementation of Nonlinear Approaches for Localization

In non-linear approach of localization it has been tried to achieve the location of source node using conventional non-linear least square algorithm and maximum likelihood approach of localization estimation. Here it has not been assured to accomplished global convergence because of its multimodal cost optimization function. Furthermore, here it was explored with Non-Linear least Square because of its efficiency with unknown or unavailable noise information. To explore further enhancement the weighted version Non-linear least square algorithm which is nothing else but the Maximum likelihood was developed and employed by using noise variance. The developed system exhibited more optimal results to achieve CRLB.

iv)Implementation of Maximum Likelihood based Localization

Consider a scenario with known error distribution; the maximum likelihood scheme optimizes the probability density function of the localization. In case of zero-mean Gaussian distribution, it can be stated that the optimization or maximization would be in correspond of a weighted form of non-linear least square which is in fact maximum likelihood. To facilitate the maximization, we have taken into consideration of a logarithmic version, given by

$$ln\big(P(r_{loc})\big) = ln\left(\frac{1}{(2\pi)^{N/2}|C_{TOA}|^{1/2}}\right) - \frac{1}{2}(r_{loc} - d)^T {C_{loc}}^{-1}(r_{loc} - d)$$

In the expressed equations, the first term can be observed as the independent function of the location parameter, and therefore optimizing the above equation could result into the equivalence of the results of the optimization of the second term and in such a way the maximum likelihood could be obtained.

## III. IMPLEMENTATION OF CRAMER RAO BOUND

In this research work, the prime objective of employing Cramer Rao Lower Bound is to generate the corresponding Fisher information matrix where the diagonal elements of the Fisher information matrix inverse are supposed to be the minimal achievable variance values. The generic process for estimating Cramer Rao lower bound can be stated in the following three steps:

1. Estimate the second order derivatives of the logarithm of the probability distribution function estimation with respect to$x$ that is$\partial^2 ln\frac{p(r)}{\partial x \partial x^T}$.
2. Consider the expected value of $\partial^2 ln\frac{p(r)}{\partial x \partial x^T}$ to form Fisher Information matrix$I(x) = E\left\{\partial^2 ln\frac{p(r)}{\partial x \partial x^T}\right\}$.
3. Now obtain the Cramer Rao lower bound for available $x$ and $y$ by $[I^{-1}(x)]_{1,1}$and $[I^{-1}(x)]_{2,2}$ respectively.

In case of implemented Zero-mean Gaussian distribution $I(x)$is estimated by

$$I(x) = \left[\frac{\partial f(x)}{\partial x}\right]^T C^{-1}\left[\frac{\partial f(x)}{\partial x}\right]$$

Where C represents the covariance matrix.

In this research work, Cramer Rao lower bound has been estimated by above expression and its component $\left[\frac{\partial f(x)}{\partial x}\right]$ is estimated by

$$\left[\frac{\partial f(x)}{\partial x}\right] = \begin{bmatrix} \frac{x - x_1}{\sqrt{(x - x_1)^2 + (y - y_1)^2}} & \frac{y - y_1}{\sqrt{(x - x_1)^2 + (y - y_1)^2}} \\ \frac{x - x_2}{\sqrt{(x - x_2)^2 + (y - y_2)^2}} & \frac{y - y_2}{\sqrt{(x - x_1)^2 + (y - y_1)^2}} \\ \vdots & \vdots \\ \frac{x - N}{\sqrt{(x - x_1)^2 + (y - y_N)^2}} & \frac{y - y_N}{\sqrt{(x - x_1)^2 + (y - y_N)^2}} \end{bmatrix}$$

Further simplifying it

$$= \begin{bmatrix} \frac{x - x_1}{d_1} & \frac{y - y_1}{d_1} \\ \frac{x - x_2}{d_2} & \frac{y - y_2}{d_2} \\ \vdots & \vdots \\ \frac{x - x_N}{d_N} & \frac{y - y_N}{d_N} \end{bmatrix}$$

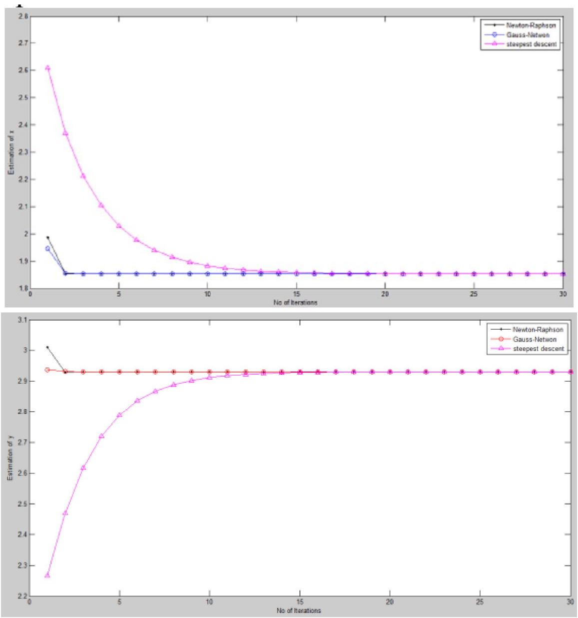
The ultimate CRLB can be obtained by $[I^{-1}(x)]_{1,1} + [I^{-1}(x)]_{2,2}$.

## IV. RESULT

In this research phase the entire models developed and accomplished analysis was carried out in 6 steps. These phases of implementation and evaluation are as follows:

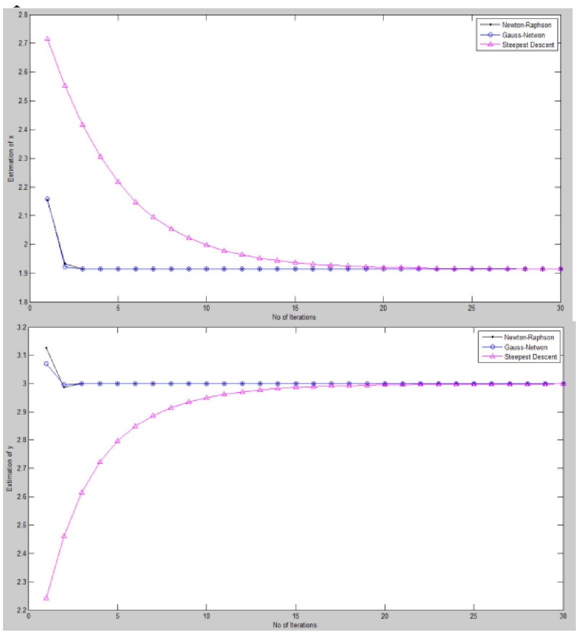
Phase-1

Fig 1- Performance Analysis for Newton-Ramphson, Gauss-Netwon and Steepest Descent local search optimization based node Localization



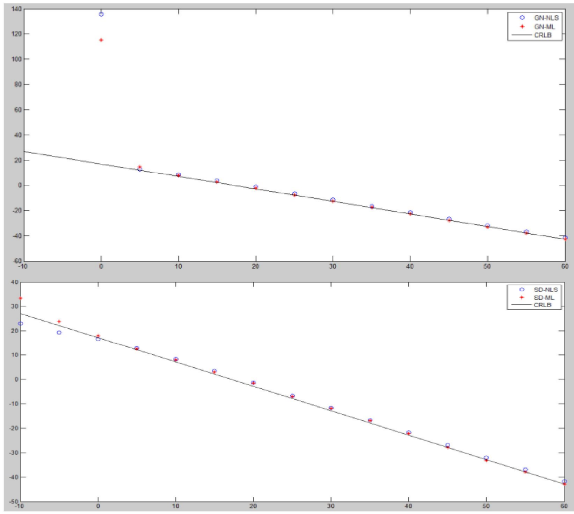
Phase-2

Fig 2- Performance Analysis for Newton-Ramphson, Gauss-Netwon and Steepest Descent local search optimization based node Localization.



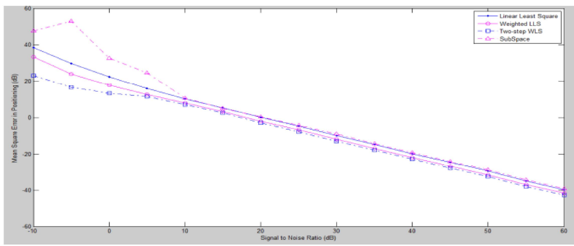
Phase-3

Fig 3-.Non-Linear Least Square, Maximum Likelihood, Gauss Newton-Non-Linear Space, Steepest Descent Non-linear least square scheme, Steepest Descent –Maximum Likelihood based Localization.



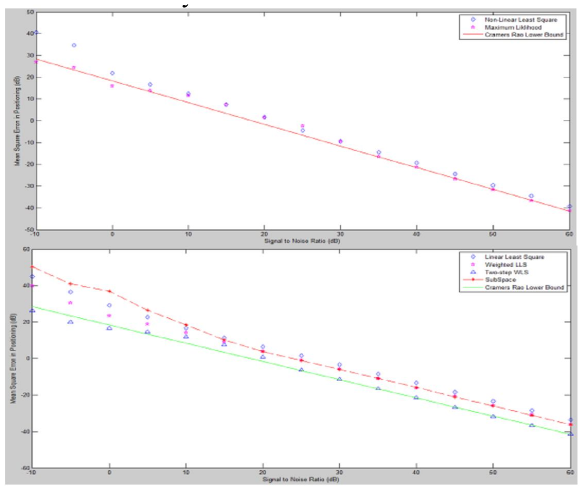
Phase-4

Fig 4-Performance Analysis with LLS, Non-Linear L, Weighted LLS, Two-step WLS, ML, SubSpace and Cramer Rao Lower Bound Analysis



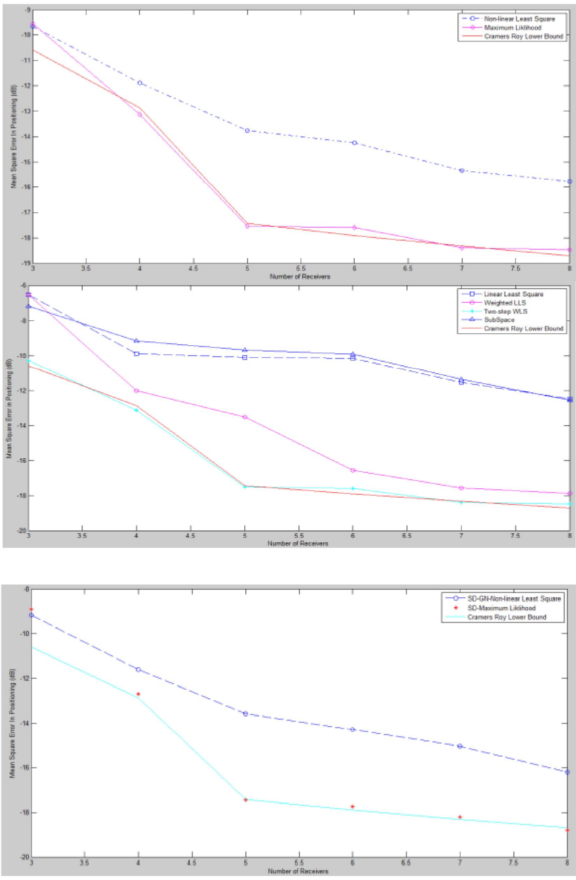
Phase-5

Fig 5-Localization Performance Analysis with Linear Least Square, Weighted Linear Least Square, Two-step Weighted Least Square, Subspace estimation based localization analysis.



Phase-6

Fig 6 -Maximum Likelihood, Gauss Newton and Steepest Descent based local search optimization based Maximum Likelihood, Subspace Estimation, Linear Least Square, Non-linear Least Square, Gauss Newton and Steepest Descent based Non-linear least square based localization, enhanced weighted Linear Least Square and Two-step weighted Linear Least Square based localization schemes and its performance analysis with Cramer Rao Lower Bound.



## CONCLUSION

In this research work, we have found that the mean square error for localization in maximum likelihood estimator scheme has exhibited better performance and can be considered as the optimal solution to achieve cramer rao lower bound in minimal iterations with higher signal to noise ratio outcomes. In this research model in the last phase, the implementation of two-step weighted linear least square scheme has accomplished better response at higher signal to noise ratio. And other paradigms of localization have exhibited sub-optimal accuracy in localization. Here it has also been observed that the two optimal localization schemes maximum likelihood and two step weighted linear least square has exhibited less mean square error in localization which was found to be less than Cramer Rao bound with $SNR \le 0dB$ and it is because their evaluation becomes biased for higher disturbances and noise situations.

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