

NLOS Error Mitigation in Cellular Positioning using PSO Optimization Algorithm

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Abstract—Non-Line-Of-Sight conditions pose a major challenge to cellular radio positioning. Such conditions, when the direct Line-Of-Sight path is blocked, result in additional propagation delay for the signal, additional attenuation, and an angular bias. Therefore, many researchers have proposed various algorithms to mitigate the measured error caused by this phenomenon. This paper presents the procedure for improving accuracy of determining the mobile station location in cellular radio networks in Non-Line-of-Sight propagation environment, based on the Time Of Arrival oriented estimator using the Particle Swarm Optimization algorithm. In computer science, Particle Swarm Optimization is an evolutionary computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. The proposed algorithm uses the repeating Time-Of-Arrival test measurements using the four base stations and for simulation selects the measurement combination that give the smallest region enclosed by the overlap of four circles. In this way, the smallest intersect area of the four Time-Of-Arrival circles is obtained, and therefore the smallest positioning error. After that, we consider the complete problem as a combinatorial optimization problem with the corresponding object function that represents the nonlinear relationship between the intersection of the four circles and the mobile station location. The Particle Swarm Optimization finds the optimal solution of the object function and efficiently determines the mobile station location. The simulation results show that the proposed method outperforms conventional algorithms such as the Weighted Least Squares and the Levenberg-Marquardt method.

Keywords-TOA methods; NLOS propagation; metaheuristic optimization; PSO optimization algorithm;

I. INTRODUCTION

In Time-Of-Arrival (TOA) based cellular radio positioning, one of the dominant factors that affect the positioning accuracy is the Non-Line-Of-Sight (NLOS) signal propagation that happens when the direct, straight radio path between the mobile station (MS) and the base station (BS) is blocked. To have good MS location estimation performance, location algorithms require the presence of a direct or Line-Of-Sight (LOS) path between the MS and the BS. In most practical situation, the signal propagation from the MS to the BS and vice versa is obstructed. NLOS propagation exists in a variety of scenarios, such as in dense urban environments, inside buildings and in forests. Compared with the LOS conditions, the signal arriving at the MS from the BS takes a path that is longer and arrives from a different direction than direct path. For the TOA location systems, the extra propagation distance of the NLOS path directly corresponds to a positive added NLOS error to the true range between the MS and the BS. A typical NLOS ranging error introduced by NLOS propagation in the wireless cellular networks on average is several hundred meters [1].

To protect location estimates from NLOS error corruption, several approaches for identification and mitigation NLOS error have been addressed in literature [2–25].

For instance, reference [2] observes that NLOS TOA range measurements have greater variance than the variance of LOS TOA range measurements and develops a time-history based hypothesis test to identify NLOS TOA range measurements. This method attempts to reconstruct LOS TOA measurements from a time history of LOS and NLOS TOA measurements and assumes knowledge of the NLOS standard deviation for identifying NLOS BSs. Decision theoretic framework for NLOS identification is formulated in [3], where the NLOS error is modeled as a non-zero mean Gaussian random variable.

For an unknown NLOS error distribution, residual weighting algorithms are proposed in [4–6]. The residual based approach basically relies on a large number of measurements which are grouped into subsets. Location estimates from each subset of measurements are evaluated by its residual. The final location estimate is obtained either by weighting the different results or by only using some selected measurements. This weight-based approach performs relatively well when there are sufficient LOS measurements.

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In [7], an error statistics based method is proposed, which assumes the NLOS bias has certain distribution such that statistical parameter estimation can be applied. The accuracy of this method largely depends on the accuracy of the NLOS bias distribution model. If the model does not well represent the feature of the NLOS bias, the location estimation accuracy will degrade significantly.

The paper [8] proposes a Taylor-Series Least Squares estimator (TSLs) that can reduce the NLOS effect to a certain extent. However, LOS measurements are needed. When there is no LOS measurements available, the estimation refinement phase fails.

The constrained optimization method described in [9–13] exploits optimization techniques and geometrical constraints. This method is particularly suitable when the majority of the measurements are NLOS corrupted, and there is no *a priori* statistics information. In [9], a constrained optimization based location algorithm is proposed to jointly estimation the unknown location and bias by using the Sequential Quadratic Programming (SQP) algorithm. Constrained nonlinear least squares TOA algorithms was presented in [10–12] and they exploit the fact that the NLOS corrupted TOA measurements are larger than the true LOS ranges. In the Range Scaling Algorithm (RSA) in [13], which operates with only three BSs, the NLOS error is mitigated using TOA adjustment by scaling the NLOS corrupted TOA measurements using factors that are estimated from a constrained nonlinear optimization process.

The propagation model based method [14–16] either directly employs existing propagation models or empirically develops a model based on experimental results. Then, statistical estimation and detection theory is applied. With the assumptions that the total number of the measurements is greater than the minimum required and the NLOS measurements are identifiable, paper [17] proposes an enhanced TOA-based localization algorithm. It contains two parts: a combination stage and a Maximum Likelihood (ML) estimator. The proposed algorithm has an advantage that it does not require the information of the distribution of the NLOS bias. The ML estimator is also proposed in [18].

On the other hand, the database-based method [19–20] makes use of signature database that is established *a priori* through an extensive survey. When the mobile terminal is to be located, some measurements are performed, and the results are forwarded to the location server in which the unknown location is estimated by comparing the measured data with the recorded fingerprints.

A new localization scheme based on the metaheuristic concept of optimization uses the Hybrid Taguchi-Genetic Algorithm (HTGA) [21] and the Particle Swarm Optimization (PSO) algorithm presented in [22–25]. In this paper we propose an efficient method to reduce the NLOS effect where the TOA measurement error is assumed to be uniformly distributed. Proposed algorithm utilizes the intersection of three and four TOA circles based on the PSO optimization technique to estimate the MS location in NLOS environments.

The rest of the paper is organized as follows. Proposed measurement model is given in Section II. Section III briefly describes the PSO algorithm. The simulation results are presented in Section IV, and the concluding remarks are provided in Section V.

II. MEASUREMENT MODEL

The system model under consideration is a Wideband Code Division Multiple Access (WCDMA) cellular system. We focus on the case of microcells and two dimensional (2-D) mobile location. The network considered consists of four BSs, whose 2-D location is known as (x_i, y_i) , $i=1..4$, and the MS whose location is to be determined. The unknown coordinates of the MS are denoted by (x, y) . Only four BSs are available to positioning, because signal measurements are limited by *hearability*. *Hearability* is defined as the ability to simultaneously receive signals with sufficient power from neighboring BSs [26]. *Hearability* occurs on a downlink when the MS is close to the serving BS, so its signals block signals from the distant BSs. The true Euclidean distance between the i th BS and the MS is given by

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2}, \quad i=1..4. \quad (1)$$

The TOA range estimation is a widely used method that calculates the distance between the MS and the BS by measuring the propagation time of signals and multiplying it by the velocity of light. In the presence of measurement noise and possible NLOS error, the measured distance between the MS and i th BS can be modeled as follows:

$$r_i = c t_i = d_i + b_i + n_i, \quad i=1..4. \quad (2)$$

where c is the speed of light, t_i is the measured propagation time (TOA) of the signal from the MS to the i th BS or vice versa, n_i represents the measurement noise which is modeled as a Gaussian random variable with zero mean and variance σ_i^2 ($n_i \sim \text{Norm}(0, \sigma_i^2)$), and b_i is the extra distance (positive NLOS bias) in addition to the LOS distance, which is due to the blockage of the LOS path. In the presence of an LOS path between the MS and the i th BS, $b_i = 0$.

In practice, the NLOS distance error b_i is often modeled as a random variable that is uniformly distributed in the interval $[b_{i\min}, b_{i\max}]$, (we denote it as $b_i \sim U(b_{i\min}, b_{i\max})$), with the following probability density function [13,22]:

$$p_{\text{NLOS}}(b_i) = \begin{cases} \frac{1}{b_{i\max} - b_{i\min}}, & b_i \in [b_{i\min}, b_{i\max}] \\ 0, & \text{otherwise} \end{cases}. \quad (3)$$

In two dimensions, the TOA range measurement from each BS specifies the radius of a circle that has the BS located at the center and the MS on the circumference, under error-free conditions. The four circles intersect at a point if there is no measured error or NLOS bias, and the point is the MS position. Because of the positive NLOS bias over the true distance, four TOA circles overlap one another and form different intersection regions on the plane that may be convex or non-convex. According to the geometrical interpretation depicted in Fig. 1, the MS location should be inside the region (VV₁W₁W) enclosed by the overlap of four circles. Then, the MS location estimation problem can be formulated as a nonlinear combinatorial optimization problem with both nonlinear and linear constraints. In [27], the object function to be minimized is taken to be the sum of the square of the distance from the MS location to the points of intersection of the range circles closest to it (i.e., points V, V₁, W₁ and W in Fig. 1).

The coordinates of V, V_1, W_1 and W are (V_x, V_y) , (V_{1x}, V_{1y}) , (W_{1x}, W_{1y}) and (W_x, W_y) , respectively.

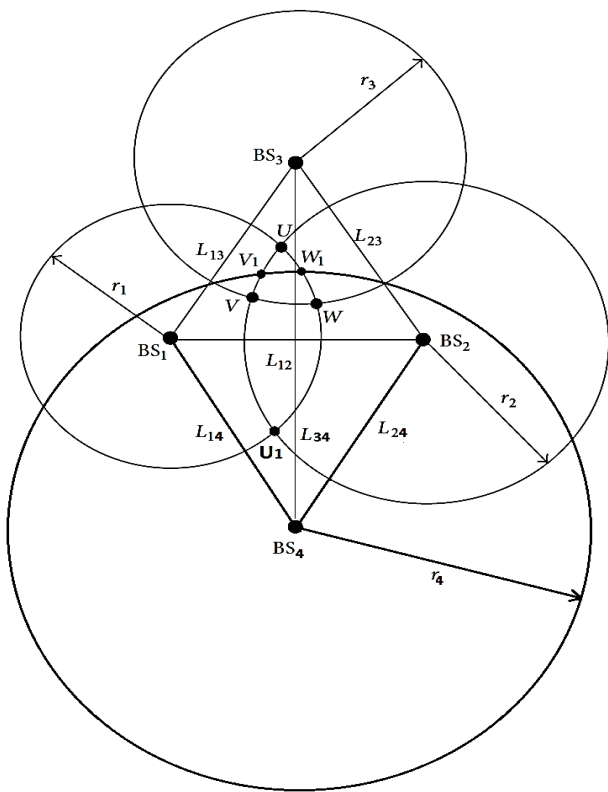


Figure 1. Geometric layout of the four TOA circles

The objective function to be minimized for the nonlinear optimization problem is, therefore:

$$\begin{aligned}
 F(x, y) = & (x - V_x)^2 + (y - V_y)^2 + (x - V_{1x})^2 + \\
 & (y - V_{1y})^2 + (x - W_x)^2 + (y - W_y)^2 + \\
 & (y - W_{1x})^2 + (y - W_{1y})^2. \quad (4)
 \end{aligned}$$

In nature, the above cost function is the well-known Nonlinear Least Squares problem (NLS).

The possible MS location has to satisfy the following constraints simultaneously:

$$(x - x_i)^2 + (y - y_i)^2 \leq r_i^2, \quad i=1, \dots, 4. \quad (5)$$

Obviously, the ranges of coordinates of the MS are the minimum and maximum among the four intersection points V, V_1, W_1 and W :

$$x_{\min} = \min\{V_x, V_{1x}, W_{1x}, W_x\}. \quad (6)$$

$$x_{\max} = \max\{V_x, V_{1x}, W_{1x}, W_x\}. \quad (7)$$

$$y_{\min} = \min\{V_y, V_{1y}, W_{1y}, W_y\}. \quad (8)$$

$$y_{\max} = \max\{V_y, V_{1y}, W_{1y}, W_y\}. \quad (9)$$

III. PARTICLE SWARM OPTIMIZATION

To improve accuracy in a wireless location system, various methods to obtain the MS location have been proposed in the literature. Generally, it is very difficult to find the optimal solution of the NLS optimization problem (4), and one of the most known algorithms that tries to achieve this is the gradient-based Levenberg-Marquardt (LM) method. To solve (4), many studies have proposed near-optimal searching methods based on swarm intelligence, such as the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO) algorithm [22]. Due to its good properties, in this paper we suggest the PSO algorithm to minimize the given object function and estimate the MS location. In this case, the objective function is called the fitness function. PSO is a population-based optimization technique which belongs to category of the Evolutionary Computation (EC) for solving global optimization problems. PSO has been proposed by Eberhard and Kennedy in 1995, subsequently developed in thousands of scientific papers, and applied to many diverse problems, for instance neural networks training, data mining, signal processing and optimal design of experiments. PSO is a swarm intelligence metaheuristic inspired by the group of animals, for example bird and fish flocks. PSO is similar to a GA in that the system is initialized with a population of random solutions. It is unlike a GA, however, in that each potential solution is also assigned a randomized velocity, and the potential solutions is called particles, are then flown through the problem search space looking for the optimal position to land. A particle, during the generations, adjusts its position according to its own experience as well as the experience of neighboring particles. PSO system combines local search method (through self experience) with global search methods (through neighboring experience), attempting to balance exploration and exploitation.

Each particle keeps track of its coordinates in the problem search space which are associated with the best solution (fitness) it has achieved so far. This local fitness value is called p_{best} . Another best value that is tracked by the global search is the overall best value obtained so far by any particle in the population. This global fitness value is called g_{best} . The original process for implementing the standard version of PSO is as follows [28]. The PSO algorithm begins by creating the initial particles with random positions and velocities on n dimensions in the problem space. It evaluates the objective fitness function at each particle location, and updates the best (lowest) local and global fitness value and the best locations for both of them. After that, an algorithm changes the velocity and position of the particle according to equations (10) and (11) respectively:

$$\begin{aligned}
 \mathbf{v}_i(t+1) = & \mathbf{v}_i(t) + c_1 \varphi_1 [\mathbf{p}_i(t) - \mathbf{x}_i(t)] + \\
 & c_2 \varphi_2 [\mathbf{g}(t) - \mathbf{x}_i(t)]. \quad (10)
 \end{aligned}$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1). \quad (11)$$

where $\mathbf{v}_i = [v_{i1} \ v_{i2} \ \dots \ v_{in}]$ is called the velocity for particle i , which represents the distance to be travelled by this particle from its current position, $\mathbf{x}_i = [x_{i1} \ x_{i2} \ \dots \ x_{in}]$ represent the position of particle i , $\mathbf{p}_i = [p_{i1} \ p_{i2} \ \dots \ p_{in}]$ represents the best previous position of particle i (i.e., local-best position or its

experience), $\mathbf{g} = [g_1 \ g_2 \ \dots \ g_n]$ represents the best position among all particles in the population (i.e., global-best position or neighboring experience), φ_1 and φ_2 are two independently uniformly distributed random variable in the range $[0, 1]$, c_1 and c_2 are positive numbers parameters is called acceleration coefficients that guide each particle toward the individual best and the swarm best positions, respectively.

The first part of (10) represents the previous velocity of the particle, which serve as a memory of the previous flight direction. This memory term can be visualized as a momentum, which prevents the particle from drastically changing its direction and biases it towards the current position. The second part is called the cognition part and it indicates the personal experience of the particle. The effect of this term is that particles are drawn back to their own best positions. The third part represents the cooperation among particles and is therefore named as the social component. The effect of this term is that each particle is also drawn towards the best position found by its neighbor [29].

Particle's velocity on each dimension is clamped to a maximum velocity \mathbf{v}_{imax} . If the velocity on that dimension to exceed \mathbf{v}_{imax} , then the velocity on that dimension is limited to \mathbf{v}_{imax} . The value of \mathbf{v}_{imax} is specified by the user, according to the characteristics of the problem. Therefore, a maximum velocity is an important parameter. It determines the resolution with which regions between the present position and the target (best so far) position are searched. If it is too high, particles might fly past good solutions. If it is too small, on the other hand, particles could become trapped in local optima, unable to move far enough to reach a better position in the problem space. This parameter is thus the only parameter which is routinely adjusted, and we often set it at about 10-20% of the dynamic range of the variable on each dimension.

The acceleration constants c_1 and c_2 in (10) represent the weighting of the stochastic acceleration terms that pull each particle toward p_{best} and g_{best} positions. These two parameters are among the most important parameters of the algorithm in that they control the balance between exploration and exploitation tendencies. A relatively high value of c_1 will encourage the particles to move toward their local best experiences, while higher values of c_2 will result in faster convergence to the global best position [28]. Both acceleration constants are commonly set to 2 for almost all applications. The population size is selected based on specific problem. Population sizes of 20-50 particles are most common.

The concept of an inertia weight is introduced in order to maintenance balance between exploration and exploitation. The velocity update equation is identical to (10) with the addition of the inertia weight ω as a multiplying factor of \mathbf{v}_i . The use of the inertia weight improved performance in a number of applications. Many different research works have focused on inertia weight parameter, and different strategies have been proposed ever since. As originally developed in [30], ω often is decreased linearly from ω_{max} to ω_{min} during a run as follows:

$$\omega(t) = \begin{cases} \frac{t}{T}(\omega_{min} - \omega_{max}) + \omega_{max}, & t < T \\ \omega_{min}, & t > T \end{cases} \quad (12)$$

In (12), ω_{max} is initial value of the inertia weight commonly set to 0.9, ω_{min} is final value of the inertia weight commonly set

to 0.4, t is the current iteration and T is the maximum number of the allowed iterations. Iterations proceed until the algorithm reaches a stopping criterion. The algorithm is terminated after a given maximum number of iterations, or after reaching a sufficiently good solution. The stopping criterion often used in practice is stagnation: if the best global fitness value does not improve for a given number of PSO iterations, the algorithm stops. Finally, the best global position is taken to be approximation of the optimum solution.

The PSO algorithm only requires a fitness function to measure the quality of a solution, which reduces the computational complexity. The fitness function can be non-differentiable (only values of the fitness function are used). The method can be applied to optimization problems of large dimensions, often producing quality solutions more rapidly than alternative methods. PSO is less sensitive to a good initial solution and the constraints of the objective function. PSO can escape the local minima problem. PSO is easily incorporated with other optimization tools. One of the reasons that PSO is attractive is that there are very few parameters to adjust. Because of these advantages, the PSO algorithm has been used for approaches that can be used across a wide range of applications, as well as for specific applications focused on specific requirements.

IV. SIMULATION RESULTS

The performance of the location calculation algorithm was examined with the cell layout as shown in Fig. 2. Simulations were performed for cellular environment with the four WCDMA BSs and with cells of radii 1 km, assuming that BS₁ is the serving BS. Without loss of generality, the coordinates of the available BSs were set to BS₁ (0, 0), BS₂ (1732 m, 0), BS₃ (866 m, 1500 m) and BS₄ (866 m, -1500 m). The MS location chosen randomly according to a uniform distribution within the area covered by the polygon formed by the points BS₁, A, B and C. In this area, *hearibility* problem described in Section II is expressed. Regarding the NLOS effects in the simulations, the NLOS range error was modeled as a uniformly distributed random variable which gives equal probability of taking low or high NLOS values. The NLOS propagation model is called the uniformly distributed noise model (3), where the TOA measurement error is assumed to be uniformly distributed over $[b_{imin}, b_{imax}]$, for $i=1..4$.

When the range of the MS from a serving BS is small, there is a possibility that the NLOS range error for the other BSs is large enough that the range circle for the serving BS lies fully within the range circles for the other BSs. Then, the proposed algorithm will not be applicable. However, it was found during simulations that this scenario occurs less than 2% of the time. To ensure that this does not occur, we add the condition that if $r_i > L_{1i} + r_1$ (where L_{1i} is distance between the serving BS₁ and i th BS for $i=2,3,4$), then readjust the measured TOAs according to $r_i = L_{1i} + r_1$. This guarantees at least one intersection point for the two range circles so that the algorithm can be applied [27].

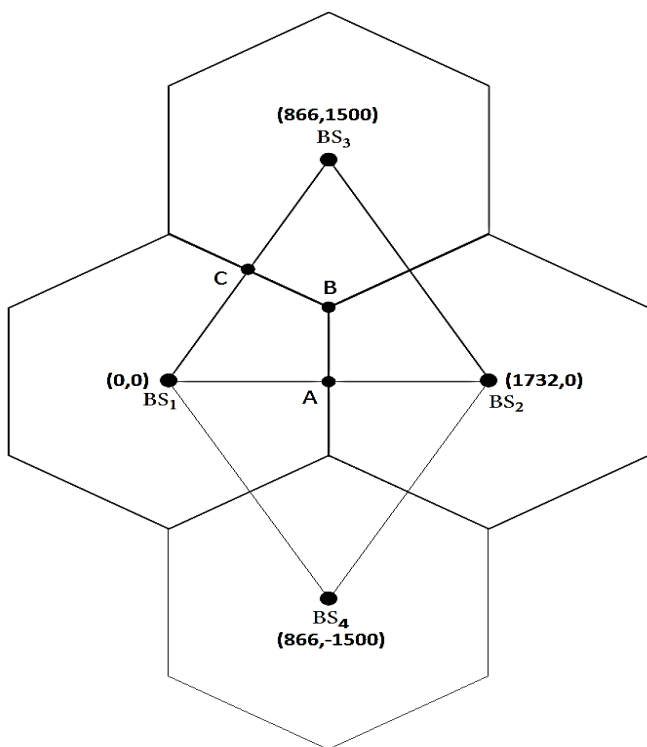


Figure 2. Cellular system with the four WCDMA BSs

For this experiment, we analyzed the four ranges of the NLOS error (3) and set the upper and lower bounds as follows: $b_{i\max}[m] \in \{200,300,400,500\}$ and $b_{i\min}[m] = 0$, for $i=1..4$. The impact of the measurement error is neglected.

According to cell geometry shown in Fig. 2, one thousand independent trials are performed for each simulation range of the NLOS error in the region of interest. For each trial at the MS location that is estimated, a several test measurements are performed and thus obtained a several measurement combinations using the four BSs. This is done to increase the probability of sampling a low NLOS error. Then, the reference measurement combination is selected that give the smallest region enclosed by the overlap of four circles, which is calculated between all measurement combinations. In this way, the smallest intersect area of the four TOA circles is obtained, and consequently the smallest positioning error. Generally, increase the number of test measurements can significantly improve the location accuracy. However, the processing time of the positioning algorithm also increases, so that the number of test measurements needs to be adjusted to this fact.

The initial PSO population are randomly distributed within the area limited by (6)–(9). The procedure uses the penalty functions that penalize infeasible solutions by increasing their fitness values in proportion to their degrees of constraint violation. The population size is set to 40 particles. Other PSO parameters are set as follows: $c_1 = c_2 = 2$, $\omega_{\max} = 0.9$ and $\omega_{\min} = 0.4$. The maximum number of PSO iterations is set to 500. The algorithm stops if one of two conditions is satisfied: the best global fitness value has not improved significantly for two adjacent iterations (the absolute change is not greater than 10^{-4}), or after reaching a maximum of 500 iterations. Finally, the coordinate of the final iteration is the MS location estimation.

To verify the performance of the proposed PSO algorithm, we compared it to the classical positioning methods such as the Weighted Least Squares (WLS) and the gradient-based Levenberg-Marquardt (LM) method. As is known, the TOA measurements are converted into a set of circular equations, from which the MS location can be determined with the knowledge of the BS geometry. The basic idea of the WLS algorithm is to reorganize the nonlinear equations obtained from the TOA measurements into linear equations. These linear equations are then solved in an optimum manner by selecting the appropriate weighting matrix [31]. The results provided by the WLS are often used as the initial location estimates for more advanced estimation algorithms, such as the iterative algorithms. The iterative optimization is another iterative approach for position estimation. Typically, the iterative optimization-based algorithms can achieve better location accuracy than noniterative algorithms (such as the WLS), especially when there are relatively large NLOS errors in TOA measurements. The iterative LM algorithm is used to solve NLS problem (4). The LM algorithm interpolates between the Gauss-Newton algorithm (GN) and the method of gradient-descent. The LM algorithm is more robust than the GN algorithm, which means that in many cases it finds a solution even if it starts very far of the final minimum [32].

In particular, the simulation was performed for cellular configuration with three BSs (BS₁, BS₂ and BS₃) and better results were obtained than those mentioned in a similar study [22]. The location accuracy is measured in terms of Root Mean Square Error (RMSE) between the actual MS location and the estimated MS location.

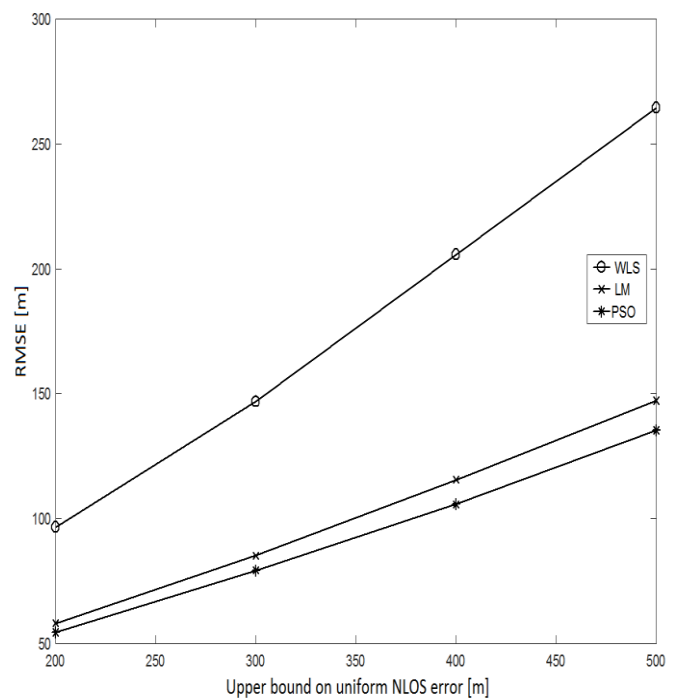


Figure 3. RMSE versus the upper bound of NLOS errors, case with 3 BSs

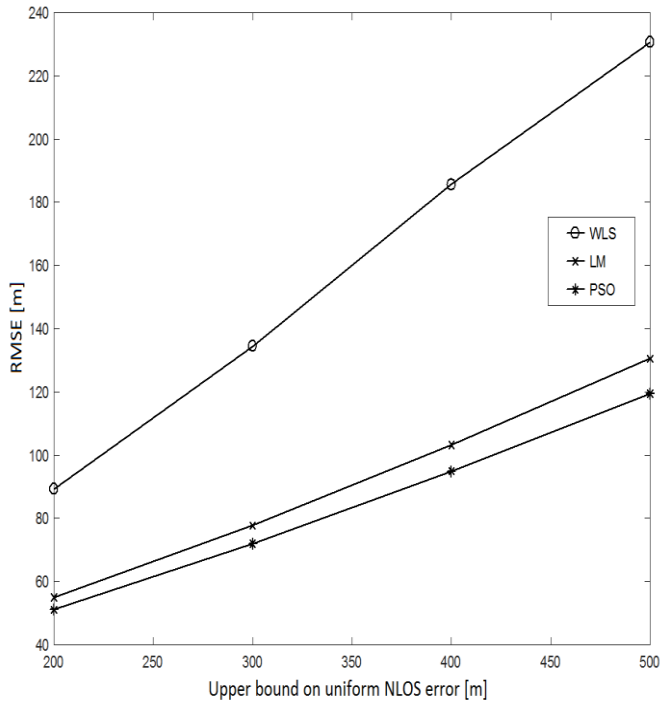


Figure 4. RMSE versus the upper bound of NLOS errors, case with 4 BSs

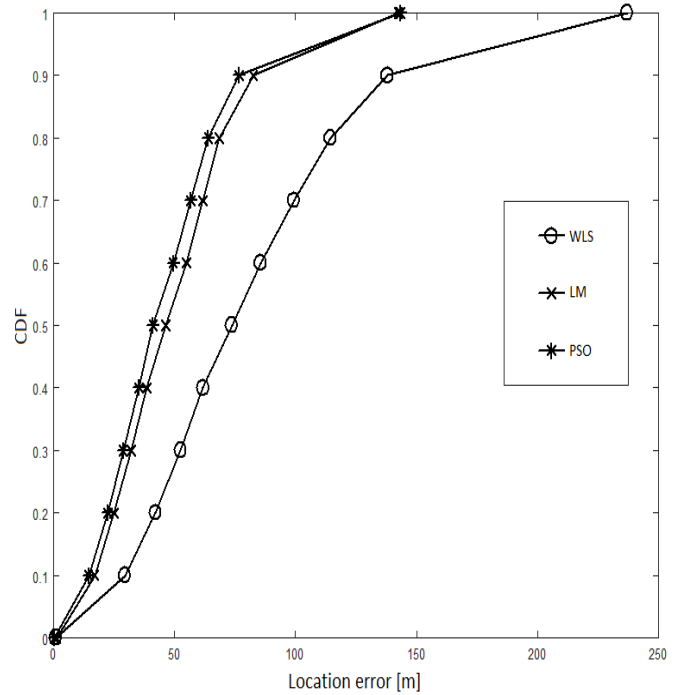


Figure 6. CDF of the location error for $b_{imax}=200$ m, case with 4 BSs

The effects of various methods with the different upper bounds of NLOS error on the average location error (RMSE) for the cellular system with three and four BSs respectively are shown in Figs. 3 and 4. In both cases, for each from one thousand trials, ten test measurements were performed [25].

The location accuracy using the proposed PSO algorithm is also shown by the cumulative distribution function (CDF) curves of location errors [25]. The CDFs curves of location errors for different algorithms with the upper bound of NLOS error set to 200 m for the cellular configuration with three and four BSs respectively are shown in Figs. 5 and 6.

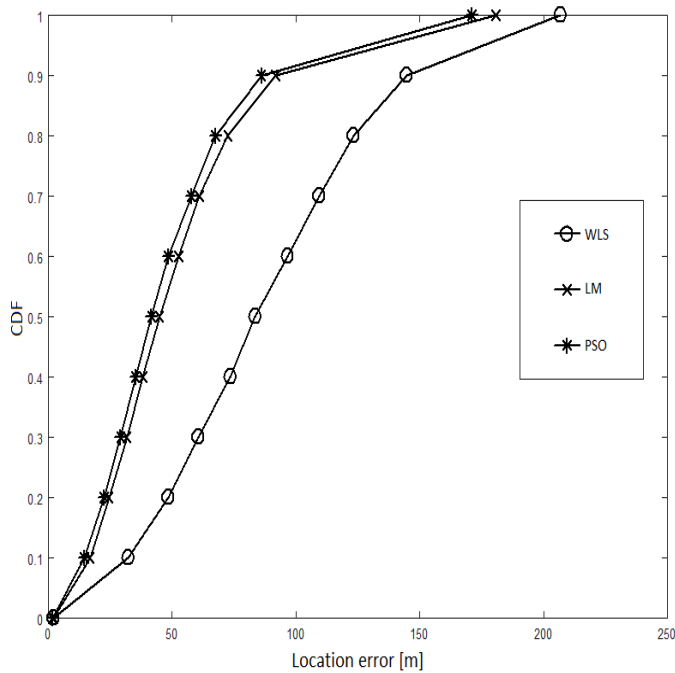


Figure 5. CDF of the location error for $b_{max}=200$ m, case with 3 BSs

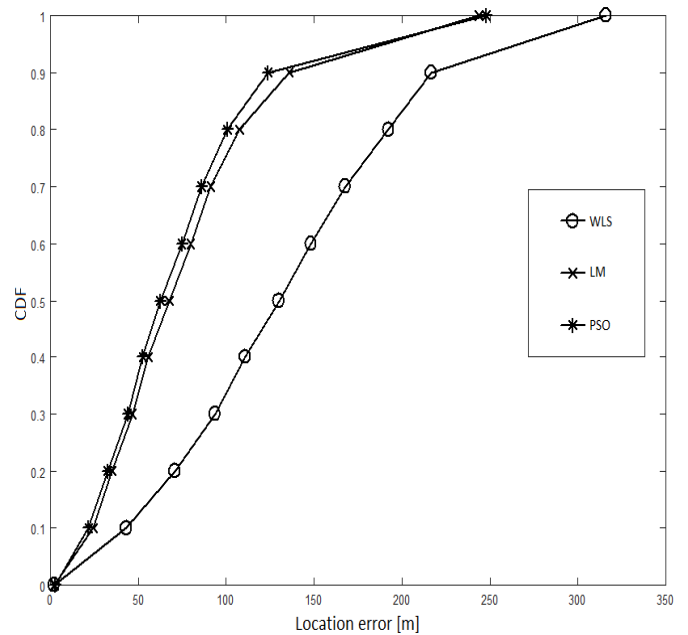


Figure 7. CDF of the location error for $b_{max}=300$ m, case with 3 BSs

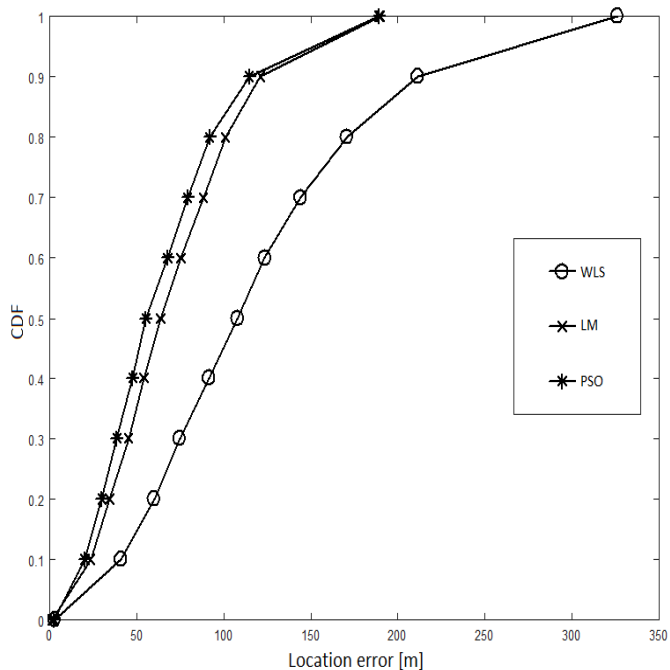


Figure 8. CDF of the location error for $b_{\max}=300$ m, case with 4 BSs

Also, in Fig. 7 and Fig. 8 are shown the CDFs curves of location errors for different algorithms with the upper bound of NLOS error set to 300 m for the cellular configuration with three and four BSs respectively.

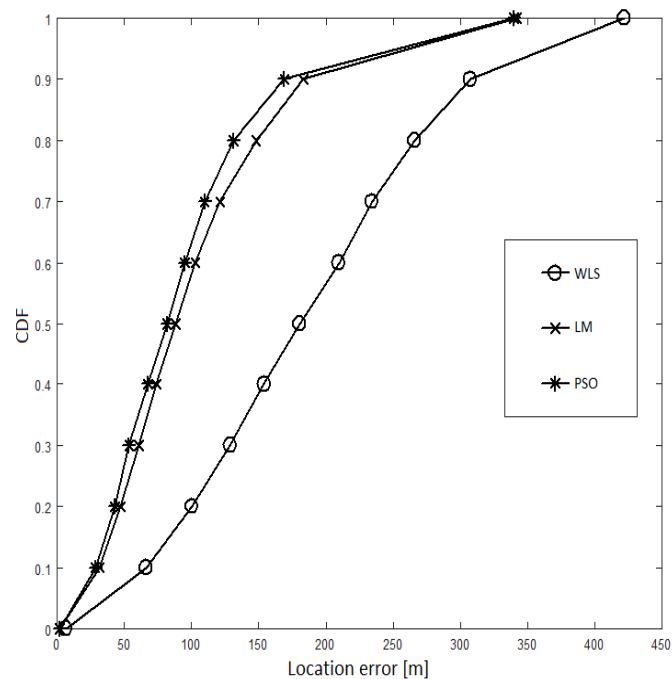


Figure 9. CDF of the location error for $b_{\max}=400$ m, case with 3 BSs

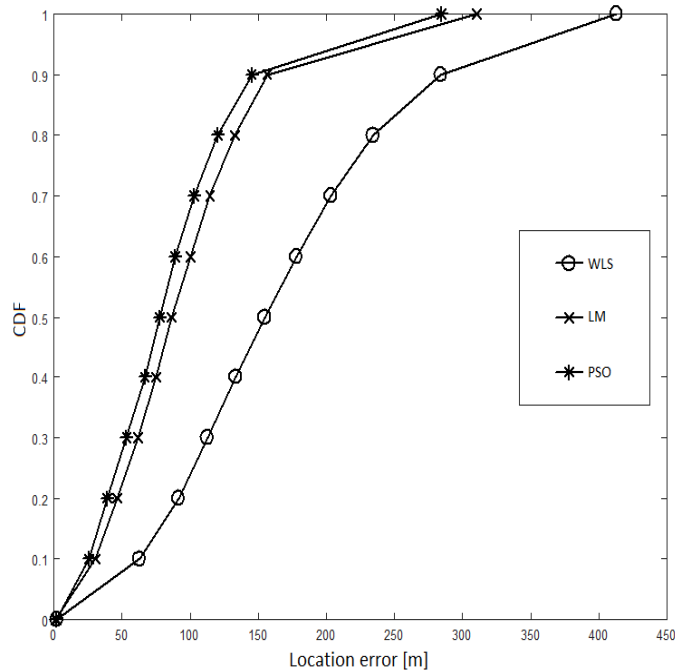


Figure 10. CDF of the location error for $b_{\max}=400$ m, case with 4 BSs

Further, in Fig. 9 and Fig. 10 are shown the same curves of location errors for the given algorithms with the upper bound of NLOS error set to 400 m for the cellular system with three and four BSs respectively.

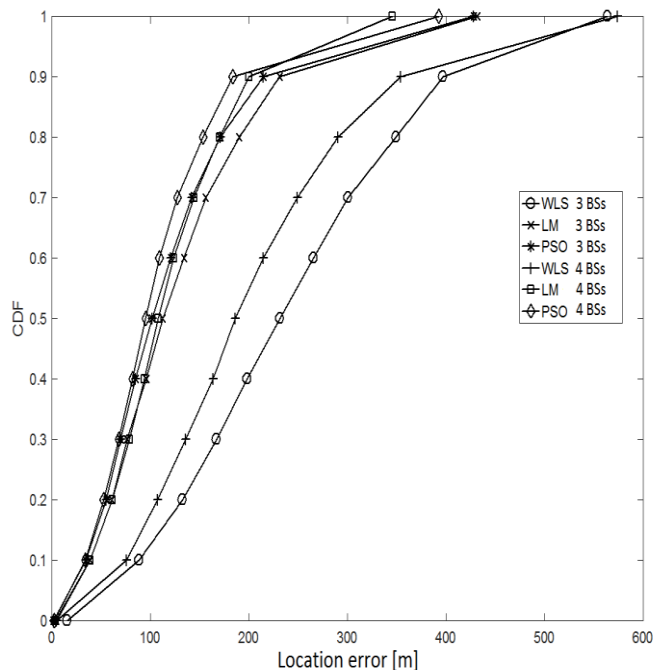


Figure 11. CDF of the location error for $b_{\max}=500$ m, both cases

Finally, in a slightly different way than illustrations from the previous figures, in Fig. 11 are shown the CDFs curves of location errors for the WLS, LM and PSO algorithms with the

upper bound of NLOS error set to 500 m for both cellular configurations. As expected, with increase the number of available BSs, the positioning error is to a certain extent reduced. Compared with the existing methods (the WLS and the LM), the accuracy of the MS location indeed improved with the proposed PSO algorithm in all situations [25].

V. CONCLUSION

The NLOS propagation is one of the main problems that affects the positioning performance. In this paper, we investigated a method for mitigating the NLOS errors that corrupts the TOA range measurements in the cellular radio environment. A new metaheuristic algorithm based on PSO is addressed to increase the location accuracy. The simulation results show that the proposed PSO algorithm provide improvement over traditional location algorithm for the various microcellular configuration. Taking into account the above facts as well as the possibility of improving the basic PSO algorithm by hybridization with other optimization methods [23–24], this algorithm can be a variant of a potential solution for the TOA-based cellular positioning systems in NLOS environments.

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