MIMO POSITIONING FOR IMT-ADVANCED SYSTEMS BASED ON GEOMETRY APPROACH IN NLOS ENVIRONMENTS

A. Awang Md Isa, G. Markarian

School of Computing and Communications,
Lancaster University, United Kingdom

Email: {a.awangmdisa, g.markarian}@lancaster.ac.uk

Abstract

In wireless communications, one of the main problems that deteriorate the accuracy of location and positioning (L&P) estimation is non line of sight (NLOS) propagation. With the advances of multiple input multiple output (MIMO) technology as one of the features of International Mobile Telecommunications-Advanced (IMT-Advanced) systems, it has become feasible to adopt the technology into the mobile location scenario. By exploiting the multipath characteristics of the MIMO system, it is possible to estimate the position of mobile stations (MS) by considering the capability of MIMO to mitigate the effects of non line of sight (NLOS) conditions. In this paper we developed geometric approach by utilizing the advantages of MIMO system and employ the time of arrival (TOA) as range measurements for improving location estimation in various NLOS environments. The performance of the proposed method has been evaluated through computer simulation. The results of our simulation demonstrate the advantages of the proposed algorithm in comparison with the conventional LLS algorithm meeting the Federal Communications Commission (FCC) requirements.

Keywords: *Location and Positioning (L&P), multiple input multiple output (MIMO), time of arrival (TOA), non-line of sight (NLOS)*

I. INTRODUCTION

In recent years, location detection and positioning in wireless technology have attracted huge interest of researchers and contribute a major benefit to both the society and the industry. By knowing a user's position, various applications such as tracking, location sensitive billing, public safety and enhanced emergency services, intelligent transportation systems (ITS), and etc [1] can be made possible. Due to high demand on unlimited services and applications, wireless broadband communications are becoming more popular since the users are provided with "anywhere and at any time" kind of service. With the emergence of International Mobile Telecommunications-Advanced (IMT-Advanced), the technology is able to fulfill the most important features of the next generation wireless systems. Indeed, IMT-Advanced have some unique features that can be employed for enhancing the positioning accuracy [2, 3] especially MIMO which can be applied for improving mobile location estimation accuracy.

Fundamentally, the MS position can be determined using various parameters such as signal strength (SS), angle of arrival (AOA), time of arrival (TOA), time difference of arrival (TDOA), hybrid methods, and etc [1, 4, 5]. The accuracy of mobile location schemes depends on the propagation conditions of wireless channels. If the line of sight (LOS) propagation exists between the MS and the all base stations (BSs), high location estimation accuracy can be achieved. Practically, however, due to multipath and NLOS problems of the wireless environments, precise estimation of these parameters at multiple BSs imposes greater challenges, which result in poor accuracy in the estimation of MS location, no matter which method is employed.

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Therefore, positioning with an NLOS can causes considerable degradation of mobile location accuracy.

This problem was addressed in many location algorithms that concentrate on identifying and mitigating the NLOS errors. The algorithm proposed in [6] uses signal measurements at a set of participating BSs and weighting techniques to mitigate NLOS effects. But if the propagations at all BSs are NLOS, this algorithm cannot improve the location accuracy. A new linear lines of position method (LLOP) presented in [7] has made the estimation of the unknown MS location easier than traditional geometrical approach of calculating the intersection of the circular lines of position (CLOP) [8]. LLOP algorithm can mitigate the NLOS error as well as the measurement noise. However, all the papers described above only consider the SISO antenna mode configuration. On the other hand, only a single of TOA measurement is considered between the BS and MS. With the advances in radio miniaturization and integration of MIMO technology; recently it has become feasible to adopt the technology into the mobile location scenario [9]. By exploiting the multipath characteristics of the MIMO system, it is possible to determine the position of MS by considering the capability of MIMO to mitigate the NLOS conditions.

Basically, there are two approaches that can be used in computing the estimation of a location, namely statistical and geometrical approach. In this paper, we adopt the second approach by using parameter measurements of TOA for MIMO system by adopting the technique proposed in [7]. This method is based on the inherent geometrical relationship between the BS locations and the TOA measurements. The traditional geometric approach in determining the position of an MS by solving the intersection of the CLOP. When NLOS errors are introduced into the TOA measurements, the CLOP will not intersect at a point. This has lead to more statistically justifiable methods such as linear least squares (LLS) [8, 10]. When approaching location estimation through the geometric point of view, solving this set of equations is inconvenient task which can be made simpler through a different interpretation of the location geometry. Therefore, instead of using CLOP for TOA-based location, a new geometry approach based on the LLOP method can be introduced along with the MIMO system in which it is capable to reduce the NLOS errors, namely multiple linear line of position (MLOP).

The remainder of this paper is organized as follows. In Section II, we briefly explained literature review including modeling the NLOS error, linear least square estimation and linear lines of position algorithm. In Section III, we present the system models used to perform the simulation results. The new geometrical algorithm based on MLOP for MIMO system at three BSs has been proposed in Section IV. Section V discusses the performance of the proposed algorithm evaluated via computer simulations. Finally, our concluding remarks are given in section VI.

II. LITERATURE REVIEW

A. Modeling the NLOS Error

Basically, the time of arrival (TOA) data fusion methods is based on combining of the TOA of the MS signal when arriving at three BSs. Therefore, the TOA measurement can be used to calculate the range between BS and MS. Since the wireless signals travel at the constant speed of light, so that the distance of between BS and MS is directly proportional to the TOA measurement which is based on LOS measurement with the absence of any source of errors, and given as

$$r_i = \Delta_{TOA} \times c \tag{1}$$

where r_i is a distance between the BS and MS, $\Delta_{TOA}= t_i= t_o$ where t_i represents the TOA associated to the BS_i, to represents the reference time of transmission of the BS signals.

However, the TOA measurement is corrupted by the noise and possible NLOS effects. Therefore, the range measurement between BS and MS for MIMO configurations, $\delta_i(t_i)$ can be modeled as

$$\delta_i(t_i) = r_i(t_i) + n_i(t_i) + NLOS_i(t_i) \qquad (2)$$

where $r_i(t_i)$ is the true distance between BS_i and MS, $n_i(t_i)$ represents the Gaussian measurement noise and $NLOS_i(t_i)$ denotes the NLOS error range at time sample t_i. $_i = 1,2,..., M$, where M is number of available BS.

We can express the estimated range measurements corresponding to coordinates of BS and MS as following:

$$\delta_{i,n} = \sqrt{(x_i - x_e)^2 + (y_i - y_e)^2} \qquad (3)$$

where (x_i,y_i) and (x_e,y_e) are the coordinates of ith BS and the estimated MS's position, respectively. The true distance, $r_i(t_i)$ between the MS and the ith BS can be represented as

$$r_i = \sqrt{(x_i - x_u)^2 + (y_i - y_u)^2} \qquad (4)$$

where (x_u,y_u) indicates the true position of MS.

Generally, $NLOS_i(t_i)$ can assumed different values depending on the relative positions of the MS, BSs and scatterers or obstacles along the transmission path. In addition, because the NLOS error is positive, the measured range is greater than true range and it is assumed that the measurement noise is a zero mean Gaussian random distribution with relatively small standard deviation and is negligible as compared to NLOS error.

The statistics of the random variable, $NLOS_i(t_i)$, therefore, can be expected to depend on parameters such as the environment and network topology. The fact that the NLOS error is location-dependent makes it extremely difficult to justify the use of any particular probability distribution function. Based on the measurements provided in [11], a clipped Gaussian distribution was used in the simulation work in [12] to model NLOS range errors to evaluate the performance of conventional location algorithms in NLOS. However the mean and variance for $NLOS_i(t_i)$ observed in [11] reflect the conditions in that particular measurement environment only. In the absence of real world results, it becomes necessary to assume simplified models for the purpose of simulations. For purpose of illustration, only macrocellular models with uniform scatterer distributions are considered such as uniform distribution model, ring of scatterer (ROS), circular disk of scatterer model (CDSM) and reverse circular disk scatterer model (RCDSM) [13, 14]. The models are illustrated in Fig. 1.

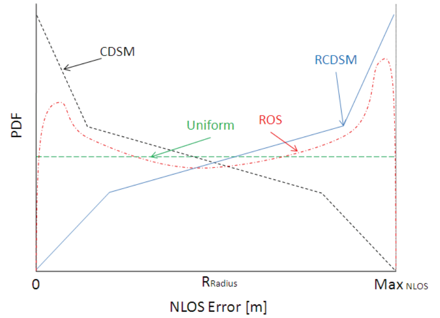


Fig. 1 Probability of Density Function (PDF) for the NLOS Error Models

The CDSM model is a higher likelihood for LOS conditions or range close to zero than higher NLOS error values. In the other words, the CDSM model is used for situations that both LOS and NLOS exist, but the LOS is more considerable than NLOS. In contrast, for opposite situations, we consider the RCDSM distribution that emphasize on NLOS compared to LOS. Next the third model of NLOS error namely ROS model consists of high probability of large NLOS error and of near-zero NLOS error. Finally, the fourth model of NLOS error was modeled as uniformly distribution random variable which gives equal probability of taking low and high NLOS values.

B. Linear Least Squares Estimation

Linear least squares (LLS) [7, 15] approach is a suboptimal positioning technique which provides a solution with low computational complexity. Therefore, it can be employed for applications that require fast and low complexity implementation with reasonable positioning accuracy. In addition, for applications that require precise location estimation, LLS can be used to obtain initial position estimate for initializing high-accuracy positioning algorithms, such as non linear least squares (NLLS) [15] and linearization based on Taylor series [8]. A good initialization can significantly decrease the computational complexity and the final location error of a high accuracy technique. Therefore, performance analysis of the LLS is important from multiple perspectives. In this paper, LLS is utilized for performance comparison with the developed algorithm.

The LLS approach begins with the set of equations (4) where each distance measurement is assumed to define a circle of uncertain region. Based on trilateration method with distance measurements of at least three available BS, the intersection at one point can be obtained by using LLS approach. These equations can be simplified by solving intersections off circles and presenting in the matrix form as following [15] and explained in Fig. 2.

$$\mathbf{A}\boldsymbol{x} = \mathbf{b} \tag{5}$$

where

$$\mathbf{A} = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \\ \vdots & \vdots \\ x_n - x_1 & y_n - y_1 \end{bmatrix}, \ \boldsymbol{x} = \begin{bmatrix} x - x_1 \\ y - y_1 \end{bmatrix}, \ \mathbf{b} = \begin{bmatrix} b_{21} \\ b_{31} \\ \vdots \\ b_{n1} \end{bmatrix} \tag{6}$$

with

$$b_{ij} = 0.5\left[r_j^2 - r_i^2 + d_{ij}^2 \right] \tag{7}$$

and

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{8}$$

where i=1,2,…,n and n denotes the number of available BSs. d_{ij} represents the distance between BS_i and BS_j and is the serving BS.

From (5), the LLS solution can be obtained as [15, 16]

$$\hat{\boldsymbol{x}} = \left(\mathbf{A}^T\mathbf{A}\right)^{-1}\mathbf{A}^T\mathbf{b} + \mathbf{X} \tag{9}$$

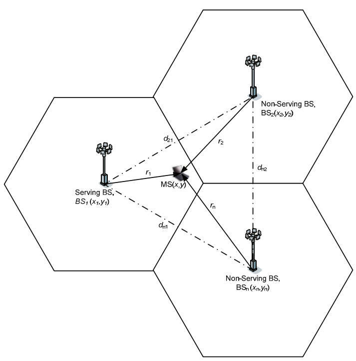


Fig. 2 LLS Geometry Calculation Using TOA

where $\hat{\boldsymbol{x}}$ is the 2-D desired vector of MS coordinates and position of serving BS, denoted by X= $[x_i, y_i]^T$.

C. Linear Lines of Position Algorithm

It has been mentioned in Section I, there are two approaches that can be used for obtaining the location of a MS given measurements of SS, AOAs, TOAs or

TDOAs. The straightforward approach is to use a geometric interpretation of the measurements and compute the intersections of the lines. A LLOP method is presented [7] which makes it easier estimating the unknown MS location than the other approaches calculating the intersection of the CLOP. In the LLOP method straight lines of position, rather than CLOP is used to estimate the location of MS as shown in Fig. 3 where the dotted straight lines are linear lines of position and the three circles are circular lines of position. However, the paper only considers SISO antenna mode configuration where only one TOA measurement is taken into consideration from each BS, whereas we focus on MIMO antenna mode configurations where more TOA signals can be employed to estimate the location of MS as shown in Fig. 6. We consider the numbers of circles developed for each BS is proportional with the multiplication of number of transmitter antenna, N_t and number of receiver antenna, N_r. Fig. 6 illustrates an example of geometry of TOA based location for MIMO 2x1 when three BSs are involved and it can be extended for others MIMO antenna configurations. In the Section IV, geometric solutions for the location problem are developed for MIMO2x1 antenna mode configuration. To simplify the mathematics, only location in two dimensions is considered and we assume that all available BSs have the same antenna mode configurations.

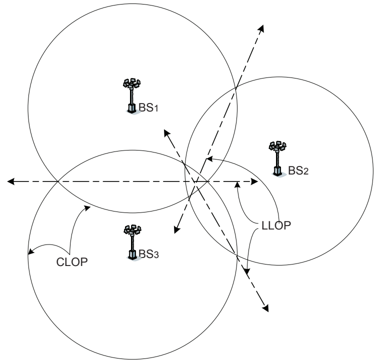


Fig. 3 The geometry of location showing circular and linear lines of position for SISO antenna mode configurations

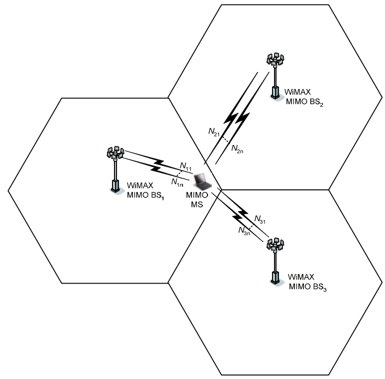


Fig. 4 The Architecture of MIMO WiMAX System

III. IMT-ADVANCED SYSTEM MODEL

The IMT-Advanced model used is according to the IEEE802.16e standard, which is based on cellular system [17]. In this scenario, the model consists of minimum three synchronized WiMAX BS and a MS with capability of MIMO antenna mode as depicted in Fig. 4.

We consider the MIMO antenna is diversity antenna, so that only TOA measurements are taken into account. In the WiMAX downlink, there is a preamble which consist of a known OFDM(A) symbol that can be used to attain initial synchronization between the BSs and the MS [17]. Therefore, under the assumption that transmitter and receiver are perfectly synchronized, the MS is able to identify the TOA signals from each MIMO antenna based on detection of downlink preamble signals that are transmitted by each WiMAX MIMO BS as shown in Fig. 5 which was obtained as a result of IMT-Advanced simulation.

Furthermore, in MIMO-OFDM(A), the received signal at each antenna is a superposition of the signals transmitted from the N_t transmit antennas. Thus, the preambles for each transmit antenna need to be transmitted without interfering with each other. It is assumed that noise processes at different receiver MIMO antennae are independent and that there is sufficient separation between all antenna pairs so that different channel coefficients can be observed at different antennas.

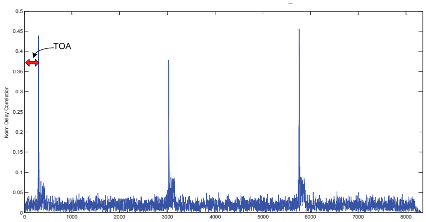


Fig. 5 TOA Detection Using Preamble Delay Correlation Conjugate Symmetry Search (SNR 10 dB)

In addition of preamble signal used in determination of TOA, the location of WiMAX BSs must be known a *priori*. In [17], WiMAX BSs broadcast periodically their location-based services (LBS) information to MSs via the LBS_ADV message. The LBS_ADV message shall include the BS's coordinate. In addition it is assumed that, at any time the MS can receive forward-link pilot (preamble) signals from particular MIMO antennae of its home BS and at least two neighboring BS. Upon receiving the location service request, the MS position can be calculated by using the proposed algorithm as explained in Section IV.

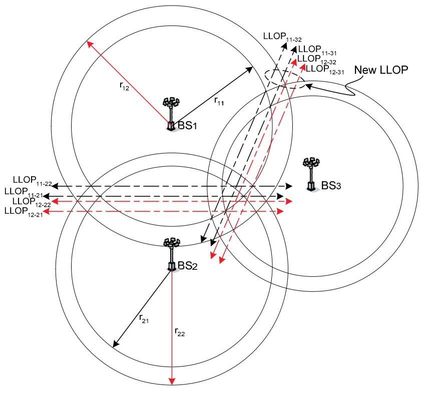
IV. PROPOSED GEOMETRICAL APPROACH OF NEW MULTIPLE LINES OF POSITION (MLOP) FOR MIMO SYSTEM

Let us assume that the measurement noise is a zero mean AWGN, which is negligible in comparison with NLOS noise. Furthermore, we assume that the NLOS error distribution is positive. In this case the measured range will be greater than true range. Recall that in conventional trilateration method, using at least three BSs to resolve ambiguities, the MS position for MIMO antenna mode configurations is given by the intersection of circles as illustrated in Fig. 6 (with the dotted straight lines were ignored).

The approach presented here for calculating the intersection of the multiple circles is shown in Fig 6, where the dotted lined straight lines represent the LLOP and the circles are CLOP. Fig. 7 on the other hand shows the enlarged view of multiple LLOP that provide the possible few estimations of MS location from the intersection of the straight lines. According to Fig. 6, each pair of circles can intersect with at most two points which can be used to define a straight line. For instance, in the case of MIMO 2x1 there are four straight lines have been projected. The intersection of these lines provides the possible estimation of the MS location. Therefore, the lines define new lines of position namely multiple linear lines of position (MLOP). In order to determine the equations for the new MLOPs, we begin with the original CLOP equations as given in (4) for $i = j, 2, \ldots, N$, where N is the number of BS. Consider BSj as the serving cell and $j = 1$. The new line which passes through the intersection of the two circular of LOPs for those two BSs can be found by squaring and differentiating the ranges in (4). More specifically, firstly, we calculate the range of each TOA signal from the serving cell, BS_1.

$$r_{j,n} = \sqrt{\left(x_j - x_e\right)^2 + \left(y_j - y_e\right)^2} \qquad (10)$$

for $j = 1$ and $n = 1,2,,\ldots N_t \times N_r$ where N_t is number of antenna at transmitter and N_r is number of antenna at receiver. (x_j, y_j) and (x_e, y_e) denote the coordinates of serving BS and estimated MS's position, respectively. Please note that the antenna spacing is negligible.



Next by squaring and differentiating between BSs and serving BS, BS_1, the new line i.e straight line method can be found. For BS_1 and BS_2, we found that for every *n*;

$$r_{1,n}{}^2 - r_{2,n}{}^2 - \|BS_1\|^2 + \|BS_2\|^2 = -2(x_e(x_1 - x_2) + y_e(y_1 - y_2)) \tag{11}$$

A similar MLOP can be generated for BS_1 and BS_3 for every *n*;

$$r_{1,n}{}^2 - r_{3,n}{}^2 - \|BS_1\|^2 + \|BS_3\|^2 = -2(x_e(x_1 - x_3) + y_e(y_1 - y_3)) \tag{12}$$

If there are more than three BSs involved, MLOP can be determined as same procedure as the above equation where for BS_1 and BS_i for every *n*;

$$r_{1,n}{}^2 - r_{i,n}{}^2 - \|BS_1\|^2 + \|BS_i\|^2 = -2(x_e(x_1 - x_i) + y_e(y_1 - y_i)) \tag{13}$$

Therefore, generally the above equations can be extended to *i* BS;

$$r_{j,n}{}^2 - r_{i,n}{}^2 - \|BS_j\|^2 + \|BS_i\|^2 = -2(x_e(x_j - x_i) + y_e(y_j - y_i)) \tag{14}$$

where;

$$\|BS_j\|^2 = x_j{}^2 + y_j{}^2; \quad j = 1$$

$$\|BS_i\|^2 = x_i{}^2 + y_i{}^2; \quad i = 2, \ldots, N \text{ and } i \neq j$$

We could then find the position of MS by solving the new MLOP for each TOA signal among all BSs with BS_1 as serving cell (reference BS). From (11), it can be simplified to

$$y_e = \frac{A_1 - x_e(x_1 - x_2)}{(y_1 - y_2)} \tag{15}$$

where

$$A_1 = \frac{1}{2}\left[r_{2,n}{}^2 - r_{1,n}{}^2 + \|BS_1\|^2 - \|BS_2\|^2\right]$$

The same procedure is then applied to the equation (5) gives

$$y_e = \frac{B_1 - x_e(x_1 - x_3)}{(y_1 - y_3)} \tag{16}$$

where

$$B_1 = \frac{1}{2}\left[r_{3,n}{}^2 - r_{1,n}{}^2 + \|BS_1\|^2 - \|BS_3\|^2\right]$$

By substituting (15) into (16); and solving for x-coordinate of x_e , we get

$$x_e = \frac{B_1(y_1 - y_2) - A_1(y_1 - y_3)}{(x_1 - x_3)(y_1 - y_2) - (x_1 - x_2)(y_1 - y_3)} \tag{17}$$

This can be generalised for any BS i in finding x-coordinate of x_e results

$$x_e = \frac{B_i(y_1 - y_i) - A_i(y_1 - y_{(i+1)})}{C_i} \tag{18}$$

Following the same procedure for any BS i in finding y coordinate of y_e is

$$y_e = \frac{A_i(x_1 - x_{(i+1)}) - B_i(x_1 - x_i)}{C_i} \tag{19}$$

where

$$A_i = \frac{1}{2}\left[r_{i,n}{}^2 - r_{1,n}{}^2 + \|BS_1\|^2 - \|BS_i\|^2 \right]$$

$$B_i = \frac{1}{2}\left[r_{(i+1),n}{}^2 - r_{1,n}{}^2 + \|BS_1\|^2 - \|BS_{(i+1)}\|^2 \right]$$

$$C_i = \left(x_1 - x_{(i+1)}\right)\left(y_1 - y_i\right) - \left(x_1 - x_i\right)\left(y_1 - y_{(i+1)}\right)$$

for $i = 1, 2, \ldots N-1$

Thus, given the positions of the BSs and the range measurements, $r_i = ct_i$ an estimate of the MS's location can be obtained using (18) and (19). Also, note that this method can be used when there are measurement errors and the circles do not all intersect at a single point. In the case of MIMO, we consider all measured TOA signals in determining the position of the BSs.

It can be observed that the number of possible location estimations using this technique (MLOP) is greatly increased as compare to the CLOP (such as LLS algorithm) meaning that the developed MLOP algorithms may yield various intersection points instead of a single common point. Fig. 8 shows the location estimation distribution using LLS algorithm and MLOP algorithm for antenna mode of MIMO4x2 with 1000 number of samples. As can be seen in Fig. 8(a) estimate positions of MS are randomly distributed where possible numbers of MS positions are same with number of samples i.e 1000 locations. On the other hand, according to Fig. 8 (b), a hexagon shape is formed from the total number of possible of MS positions as in (20) i.e in this case there are 4096K possible locations in 1000 samples. It can be expected that the increasing numbers of possibilities of MS location produce the better optimal location estimation by averaging all the intersection points. It is however, increasing number of intersection points resulting in high processing time and finally can reduce the location estimation accuracy, especially in the case on moving MS. Therefore, determination of optimal intersection points which will produce the same results in term of location accuracy with lower processing time must be investigated.

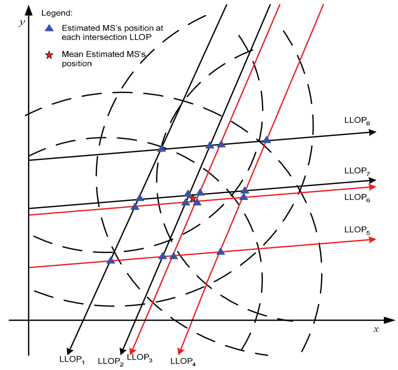
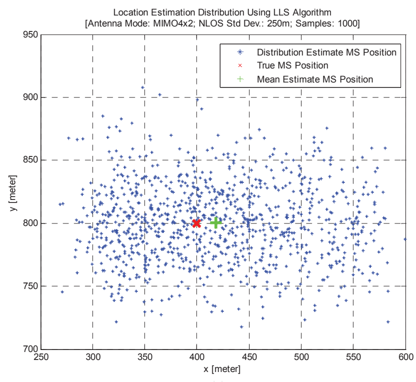
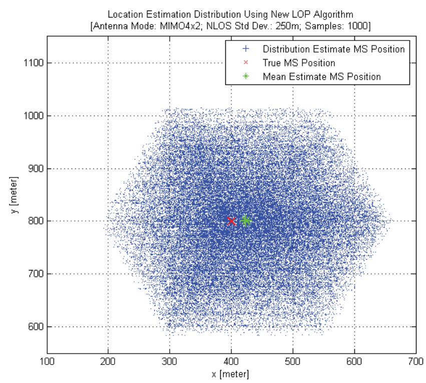


Fig. 7 Multiple LLOPs for MIMO 2x1 Antenna System



(a)



(b)

Fig. 8 Location Estimation Distributions Using (a) LLS Algorithm (b) New MLOP Algorithm

A. Determination of Feasible Intersection Points in MLOP

The selection of optimal intersection points in MLOP algorithm is based on analysis performed on Table I. In this analysis, we consider the number of available BS, N is 3 with the several of antenna mode configurations. Note that we assume no LOS and single scattering for all TOA paths. In other words, because the NLOS error is positive, the measured range is greater than true range and it is assumed that the measurement noise is a zero mean Gaussian random distribution with relatively small standard deviation and is negligible as compared to NLOS error. The NLOS noise is simulated to be uniform distribution over the interval [0m, 250m]. It can be observed that from Table I, the RMSE mean and standard deviation location errors for various MIMO antenna mode configurations are nearly same for both AS and OS points. For example MIMO 2x1 antenna with selection AS points is 16 and OS points is 4 produce RMSE location errors of 90.54m and 90.78m, respectively. The similar trend also can be observed for the other MIMO antenna mode configurations. We found that with selection of OS points, it can reduce the number of points about square of multiplication of number of transmitter antenna, Nt and number of receiver antenna, Nr. Therefore, the number of feasible intersections for possible location estimation of MS can be determined as following

$$\varphi_{est} = \left(N_t \times N_r\right)^2 \times \left(N - 2\right) \tag{20}$$

The most common method of estimating the MS position is by averaging all the feasible intersection points in (20) and given as following

$$\boldsymbol{x}_{avg} = \left(\frac{1}{\varphi_{est}} \sum_{i=1}^{\varphi_{est}} x_{e_i}, \frac{1}{\varphi_{est}} \sum_{i=1}^{\varphi_{est}} y_{e_i} \right) \tag{21}$$

where $\boldsymbol{x}_{avg} = \left(x_{avg}, y_{avg}\right)$ represents the location of estimated MS.

However, not all the feasible intersections provide information of the same value for location estimation. There exist various methods proposed in [18] which can be employed for achieving high accuracy of MS position with less effort. In this paper we propose the Distance-Weighted method which promises additional improvements in system accuracy.

B. Distance-Weighted Technique

The distance-weighted technique can be dynamically adjusted with reference to the distance square between the estimated MS location and the average MS location. The detailed steps are as follows:

Step 1: Find all the feasible intersections of the MLOP.

Table I: Analysis Of Location Error at Various Points Of Intersections With Different Antenna Mode Configurations

Antenna Mode Configurations	Selection of Intersection Points		Equations	RMSE [meter]	
				Mean	Std Dev
MIMO2x1	AS	16	$(N_t \times N_r)^4 \times$	90.54	45.12
	OS	4	$(N_t \times N_r)^2 \times$	90.78	45.69
MIMO2x2	AS	256	$(N_t \times N_r)^4 \times$	62.87	31.04
	OS	16	$(N_t \times N_r)^2 \times$	63.58	32.15
MIMO4x2	AS	4096	$(N_t \times N_r)^4 \times$	44.78	23.31
	OS	64	$(N_t \times N_r)^2 \times$	43.92	23.65
MIMO4x4	AS	65536	$(N_t \times N_r)^4 \times$	31.74	17.38
	OS	256	$(N_t \times N_r)^2 \times$	32.34	17.83

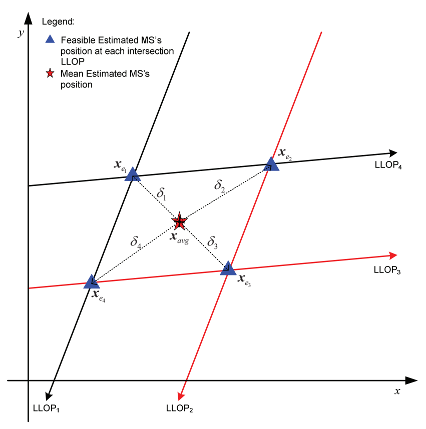


Fig. 9 Distance Weighted Method for MIMO2x1 Antenna System

Step 2: The MS location is estimated by averaging these remaining feasible intersections given in (21).

Step 3: Referring to Fig. 9, we calculate the distance, between each remaining feasible intersection $\boldsymbol{x}_{e_i} = (x_{e_i}, y_{e_i})$ and the average location given in (21)

$$\delta_i = \left\| \boldsymbol{x}_{avg} - \boldsymbol{x}_{e_i} \right\|; \quad 1 \le i \le \varphi_{est} \qquad (22)$$

where $\|.\|$ denotes the norm operation over a vector with $\|.\| = \sqrt{(.)^T(.)}$.

Step 4: Set the weight for the ith remaining feasible intersection to $\frac{1}{\delta_i^2}$.

Finally, the estimated MS position, $\hat{\boldsymbol{x}}_{avg}$ can be calculated as

$$\hat{\boldsymbol{x}}_{avg} = \left(\frac{\sum_{i=1}^{\varphi_{est}} x_{e_i} \times \frac{1}{(\delta_i^2)}}{\sum_{i=1}^{\varphi_{est}} \frac{1}{(\delta_i^2)}}, \frac{\sum_{i=1}^{\varphi_{est}} y_{e_i} \times \frac{1}{(\delta_i^2)}}{\sum_{i=1}^{\varphi_{est}} \frac{1}{(\delta_i^2)}} \right)$$

V. SIMULATION AND DISCUSSION

The performance of the proposed algorithm is investigated via computer simulation where a comparison is made between SISO and various MIMO antenna mode configurations and the algorithm is also compared to LLS algorithm. In this work, the location estimation accuracy is checked for the situations of 3 BSs and simulations are performed under the assumption of macrocell cellular environments. The geometric coordinates of BSs are $BS1(x_1 = 500,\ y_1 = 3750)$ $BS2(x_2 = 2250,\ y_2 = 4500)$ $BS3(x_3 = 2250,\ y_3 = 3000)$, and the geometric coordinate of true MS is $MS(x_u = 1500,\ y_u = 3750)$. All units are expressed in meter. The simulated parameters have been selected similar to that IEEE802.16e downlink system and the dispersive delay properties of the channel introduce range errors up to 600m [19]. The simulated location error has the total number of 1000 different data sets and the estimation MS position is obtained by averaging over all the 1000 estimates. It is however, the feasible estimates MS position for each independent data sets is acquired using the method proposed in Section IV-B. The TOA measurements are created by calculating the true distance from a MS position to the known BS with MIMO capability and were each corrupted by NLOS errors.

A. Effects of the NLOS Distribution

In order to analyses the effect of the NLOS errors on the performance of location estimation, four models of NLOS models were generated according to different probability density functions such as CDSM model, RCDSM model, ROS model and uniform distribution as illustrated in Fig. 1. The NLOS range errors are modeled as positive random variables having support over [0, 600m], generated according to various NLOS models explained in Section II-A.

Fig. 10 show the performance of the MLOP algorithm for MIMO 2x2 and MIMO 4x4 on CDSM, RCDSM, ROS and uniform models. It can be seen that from Fig. 10(a) and Fig. 10(b) for the CDSM that has weakest NLOS features, the accuracy of location estimation is greater than other situations, but ROS perform slighty poor while RCDSM and uniform models have only minor degradation. It is shown that CDSM has satisfy the FCC requirement of 67% (below 100m) and 95% (below 300m) of the time for both antenna mode configurations while the other NLOS models do not satisfy for the 67% of location error for the case of MIMO2x2 antenna mode configuration.

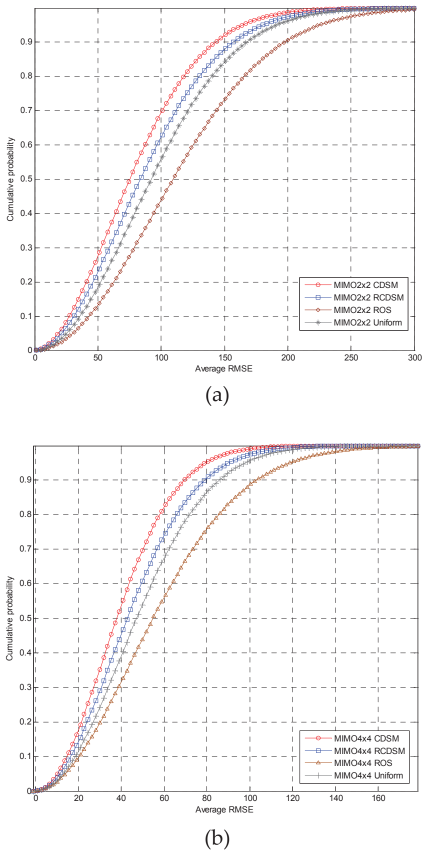


Fig. 10 The CDF of location error of the MLOP algorithm for (a) MIMO 2x2 (b) MIMO 4x4 on CDSM, RCDSM, ROS and Uniform NLOS Models

Meanwhile, Fig. 11 shows the cumulative distribution functions of the average RMSE location error of the algorithms for various antenna mode configurations when the range errors are generated using the CDSM model. It can be seen that under the case of MIMO antenna mode configurations, the MLOP algorithm perform very well than the LLS algorithm for the error model considered. Meanwhile, under the case of SISO antenna mode configuration, we can see that the performance both MLOP and LLS algorithms are nearly identical.

B. Effect of the Number of NLOS BSs

Simulations were performed to study how the average location error is affected by the number of BSs that do not have an LOS path to MS when MLOP algorithm are employed for various antenna mode configurations. Except for the case when all BSs are NLOS, the serving BS was assumed to be LOS with the MS. However, the algorithms do not have prior knowlegde of the LOS and NLOS status of the BSs. This performance also was compared with LLS algorithm as shown in the Fig. 12. As can be observed, the average location error increase with the number of NLOS BSs for SISO antenna, but the average location error for MIMO antennas only rises up with one NLOS BS and then it dramatically decreases when two and more NLOS BSs are involved. In other words, we can say that the MIMO antenna configurations are capable to mitigate the effect of NLOS errors. It can also be seen that MLOP algorithm performed better than LLS algorithm in spite of the number of NLOS BSs.

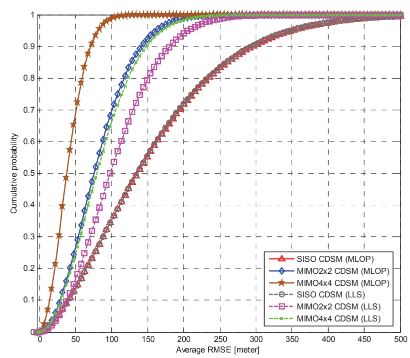


Fig. 11 The CDF of the Location Error of the MLOP and LLS algorithms for Different Antenna Mode Configurations on the CDSM Model

C. Effect of Magnitude of NLOS on Location Accuracy

The radius of scatterers, R_d determines the maximum magnitude of NLOS error with CDSM, namely $2R_d$. For uniformly distributed noise, the NLOS error can be any value in the range $(0,U_N)$ where U_N is the upper bound. Finally, simulations were performed to examine how the MLOP algorithm compares against the LLS algorithm for various antenna mode configurations when R_d and U_N are varied.

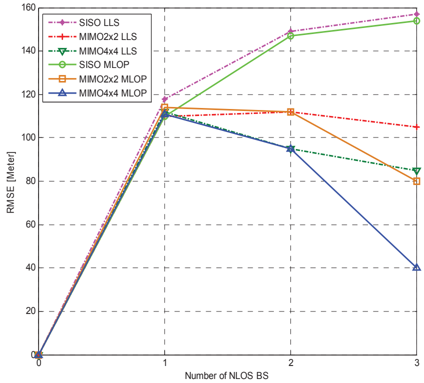


Fig. 12 Average RMSE For Different Antenna Configurations Versus the Number of NLOS BSs

Fig. 13 shows the average RMSE location error versus the radius of scatterer of CDSM, R_d. Generally, it is can be expected that the perfomance of any location algorithm deteriotes when the amount of noise, in this case NLOS error, in range measurement increases. It can be observed from Fig. 13 that the sensitivity of the MLOP algorithm to increase in maximum NLOS magnitude is less than the LLS algorithm for MIMO2x2 and MIMO 4x4 systems, however different in the case of SISO where the CDFs for LLS and MLOP algorithms perform nearly identical with increase of R_d.

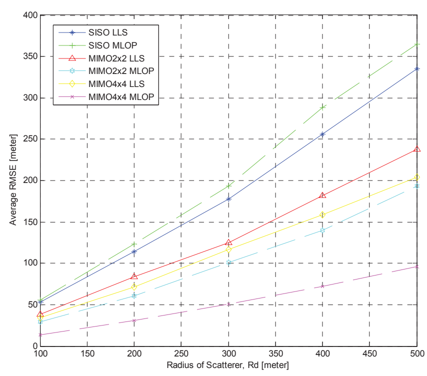


Fig. 13 Average RMSE Location Erros versus the Disc Radius of CDSM, R_d

On the other hand, Fig. 14 shows the average RMSE location erros versus the upper bound on uniform NLOS error, U_N. It can be observed that the performance of MIMO antenna mode configurations using the MLOP algorithm are much better than the MIMO antenna mode configurations using the LLS algorithm whereas performance for SISO antenna mode configurations is nearly similar for both algorithms. It has been shown that the MLOP algorithms can further improve the accuracy of location estimation with MIMO antenna mode configurations.

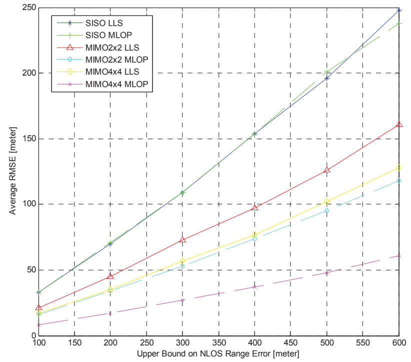


Fig. 14 Average RMSE Location Erros versus the Upper Bound on Uniform NLOS Error

VI. CONCLUSION

In this paper we presented a geometrical approach using MLOP technique for MIMO antenna mode configuration in IMT-Advanced networks for location estimation with range measurements from only three BSs in the NLOS environments and their performances have been compared with SISO antenna. The technique utilizes relationships drawn from the geometry of the BSs and ranges linear LOP, and it does not require discrimination between LOS and NLOS range measurements. The geometrical solution found the intersection of the MLOPs and used the distance-weighted of those intersections to find better location estimation. Simulation results showed the location estimation accuracy of MLOP was much better when compared to that of the LLS for MIMO antenna mode configurations. It was observed that the average location error for MIMO antennas decrease when two and more NLOS BSs were involved. Simulations also showed that the upper bound of the uniform error distribution have an influence on the location estimation accuracy The location error of MLOP for various MIMO antenna mode configurations is less than 0.1km for 67% of the time, and less than 0.17km for 95% of the time. The results of the simulation compliance to the location accuracy demand of E-911 requirements [20]. Hence it is proven that enabling the MIMO antenna mode configurations in IMT-Advanced positioning systems using MLOP algorithm can further improve their location accuracy even in the severe NLOS conditions.

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