

# Improving Mobile Location Prediction Using the Grey Wolf Optimization Algorithm

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**Abstract**—The importance of locating a mobile phone has increased significantly during last decade for security and commercial reasons. Locating the mobile phone leads to locating people. This is done by using the most common propagation models in the mobile phone network design to calculate the distance between the mobile phone and the base station, in addition to using positioning algorithms to predict the location of the mobile station. In this work, three telecommunication towers that provide mobile phone service for Zain Iraq were selected, located within the Mahmudiya area in Baghdad as a case study, and a test drive was conducted to measure the signal strength received from these base stations at more than 10 points located within the coverage area of these base stations. The Okumura-HATA model, and the UMTS propagation model were used to calculate the distances. The Gray-Wolf algorithm was used to improve mobile phone position prediction.

**Keywords**—GWO, LBS, LOS, RSSI

## 1 Introduction

Wireless technologies have become available for public use due to the great development in radio technologies in addition to the change in the industry's tendency to build infrastructure for new networks. Nowadays it is a part of most people's daily life. People use cell phones on a daily basis and they constantly have them on hand. For this reason, the ability to indirectly track mobile phones has led to people being tracked. Information that some users have been somewhere at some time is not very useful in general, but may be very important and useful in specific contexts such as security and emergencies. Mobile operators are required to provide all information about their customers to law enforcement agencies if the agencies have court permission. Location Based Services (LBS) are very well established in emergency services because the callers are often too young or injured so they cannot report their precise position. The position of the caller should be available at the public safety answering point at the time the emergency call starts or very shortly after [1, 2]. Obstructions in the Line-Of-Sight (LOS) path between a mobile phone and a base station can cause localization errors. The Non-Line-Of-Sight (NLOS) error has long been seen as a major problem in local-

ization. As a result, it's critical to reduce or eliminate NLOS errors in location estimation. In practice, NLOS pathways change frequently due to environmental impacts. Moreover, the signals are reflected due to obstacles, and multiple scattered signal paths are formed, which is difficult to design precisely [3, 4]. Signal reflection properties vary as the frequency of the signal changes. Moreover, the reflection of the signal depends on many factors regarding the obstacle such as the obstacle material and shape. Therefore, the accurate modeling of NLOS errors cannot be achieved in practice [5, 6]. Algorithms, such as the hybrid algorithms, the Taylor series algorithm, and the grey wolf optimization algorithm, are used to predict the mobile location [7-12]. The purpose of this project is to estimate mobile location with the greatest precision possible with the use of grey wolf algorithm. The paper's structure is as follows: The methodology of mobile location estimation is given in Section 2. Methods of Received Signal Strength Indication (RSSI) are discussed in Section 3, while the Grey Wolf Optimization method is presented in Section 4 (GWOA). Part 5 is where the simulation results of the suggested methodologies are done, and the work's conclusions are shown in the last part.

## 2 Methodology estimation mobile location

To identify the mobile phone location, precise measurements of one BS are needed; if the measurements are error-free (this is ideal case). This project has developed the high accuracy of measuring receiver signal with error route. Three phases are included in the algorithm for estimating mobile location with path loss [13-17].

- a) **Dataset:** Measurements were taken by mobile service providers, and they depended on at least three different cell towers (BS) because of hearability.
- b) **Select a model for propagation.:** The propagation model aids in the calculation of path loss and distance between mobile and BS (for example, the UMTS model and the Hata model).
- c) **Estimating the Mobile Location:** The mobile location has been estimated using grey wolf optimization (GWO) algorithm, that help to select the highest accuracy measurements.

## 3 Received Signal Strength Indication (RSSI) measurement techniques

There are several localization techniques used for BS location estimation in wireless networks RSS is the most accuracy technology [18-23]. The project focus on one of the most popular range-based techniques that depends on RSSI, because the received signal asset is a function of distance. The RSSI technique implemented by the received signal strength measurements from three or more nearby known BS to find the mobile station location, as shown in Figure 1 [24]. The coverage area of each BS is denoted by a circles whose center is the BS location. The mobile position should lie at the area covered by the selected three BS. The distance between the unknown MS position and the three BSs has used to solve the following circles equations [25]:

$$\begin{aligned} (x - x_1)^2 + (y - y_1)^2 &= r_1^2 \\ (x - x_2)^2 + (y - y_2)^2 &= r_2^2 \\ (x - x_3)^2 + (y - y_3)^2 &= r_3^2 \end{aligned} \quad (1)$$

where  $(x, y)$  is the MS location coordinate, and  $(x_1, y_1)$ ,  $(x_2, y_2)$  and  $(x_3, y_3)$  are the coordinates of the midpoints of the circles that represent the coverage area of BS<sub>1</sub>, BS<sub>2</sub>, and BS<sub>3</sub> respectively. The  $r_1$ ,  $r_2$  and  $r_3$  are the distances between the three BSs and the MS. The crossing of the three circles will represent the unknown location of the MS as shown in Figure 1 [26].

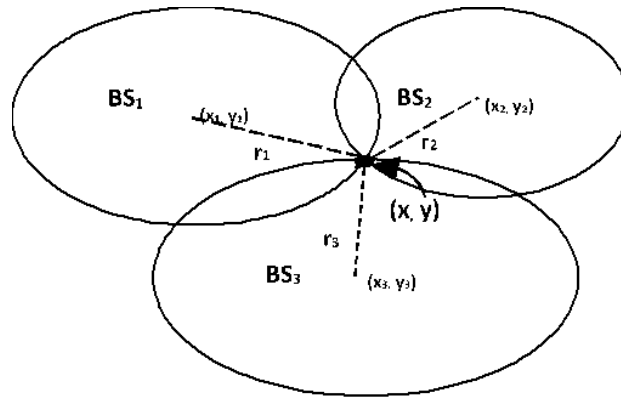


Fig. 1. Mobile location finding using three nearby base stations used RSSI technology

The RSSI localization technique is created by signal attenuation to calculate distance between the BS and the MS. The path loss is one of the major factors that affect the RSSI localization accuracy. In order to find the distance, the propagation path loss has selected as:

1. The UMTS model antenna height effect at path losses. The path loss at any distance (d) from the transmitting antenna  $P_L(d)$  is given by [27]:

$$P_{L_{UMTS}}(d) = 40[1 - 4 * 10^{-3}(\Delta h)] \log_{10}(d) - 18 \log_{10}(\Delta h) + 149.3 \quad (2)$$

Where,  $\Delta h$  is difference between BS and MS antenna heights. The distance be as a function of path loss implement and antenna height as:

$$d(P_L) = 10^{\left(\frac{P_{L_{UMTS}} - 149.3 + 18 \log_{10}(\Delta h)}{40(1 - 4 * 10^{-3} \Delta h)}\right)} \quad (3)$$

2. The HATA model frequency and tower height effect at path losses. The path loss at any distance (d) from the transmitting antenna is given by [28]:

$$P_{L_{HATA}}(d) = 158.3 - 13.82 \log(h_{BS}) + (44.9 - 6.55 \log(h_{BS})) \log(d) \quad (4)$$

Where,  $h_{BS}$  is BS antenna height. The distance be as a function of path loss implement and antenna height as:

$$d(P_{LHATA}) = 10^{\left(\frac{P_{LHATA}^{-158.3+13.82 \text{ Log}_{10}(h_{BS})}}{44.9-6.55 \text{ log}_{10}(h_{BS})}\right)} \quad (5)$$

#### 4 Grey Wolf optimization algorithm

The Grey Wolf algorithm is based on simple ideas and don't need gradient information to be used. In a lot of cases, it is used because it can avoid "local optima." This is why it's used in lots of different engineering fields. The GWO algorithm is one of the more fascinating ones since it uses group hunting. Grey wolf hunting is split into three groups, according to Muro et al. [29];

- a) track, pursue, and approach the prey.
- b) A hunter will chase the prey, circle around it, and surrounds it.
- c) attacking prey.

The four groups of grey wolves are named alpha, beta, delta, and omega, and are based on how they hunt. The group is led by the alpha wolf. They are in charge of establishing the regulations. This wolf has complete control over where he sleeps, hunts, and rests. These wolves are dominating because they order other wolves to obey them. Coming up with fresh ideas is assisted greatly by an alpha wolf. There are two types of wolves: beta wolves and alpha wolves. The alpha wolves are at the top. Beta wolves follow the alpha wolf's lead, listening, responding to what alpha says and helping them make decisions. If the alpha wolf dies, it also has certain rights to decide. Another type of animal is called "subordinate" or "delta." These are the next level of wolves, and they are also called "delta". These wolves belong to the groups of elders, sentinels, hunters, scouts, and caregivers. A group of wolves called "delta" follows the alphas and betas. They take care of wolves called "omega". Finally, Omega is the last group of wolves. They are the least powerful and are used as scapegoats when people don't like them. These wolves have to follow the rules of all the other dominant wolves, like the fox. There aren't a lot of Omegas, but in some cases, they can help other wolves deal with their own problems [30]. Grey wolves use two distinct strategies to hunt for prey: exploration and exploitation. Exploitation is the process of finding the optimal solution in a confined search area; encircling and assaulting for prey. In the exploration stage, grey wolves explore their prey in a wide search area, and this is called *searching prey*. Grey wolves know the location of prey and surround them while encircling them. The prey's position vector is specified in this phase, and additional search agents alter the prey's location depending on the best solution found. The following is the surrounding prey equation:

$$\begin{aligned} \bar{D} &= |\bar{C} \cdot \bar{X}_p(K) - \bar{X}(K)| \\ \bar{X}(K+1) &= \bar{X}_p(K) - \bar{A} \cdot \bar{D} \end{aligned} \quad (6)$$

There are two coefficient vectors,  $\bar{A}$  and  $\bar{C}$ . The position vector of the prey is shown as  $\bar{X}_p$ ,  $\bar{X}$  is the position vector. It's multiplication on an element-by-element basis.

The vectors  $\bar{A}$  and  $\bar{C}$  are computed as follows:

$$\bar{A} = 2\bar{a} \cdot \bar{r} - \bar{a} \tag{7}$$

$$\bar{C} = 2 \cdot \bar{r} \tag{8}$$

where

$\bar{a}$  is reduced linearly from two to zero in each iteration.

$\bar{r}$  is a random vector in the range [0, 1].

The search agent's location [X, Y] is modified in accordance with the position of the prey as determined so far [X\*, Y\*]. The coefficient vectors  $\bar{A}$  and  $\bar{C}$  are changed to get the optimal agent at various locations [31]. Grey wolves are led by alpha, with help from beta and delta. During the hunting phase, alpha is in charge. Because there is so much to look for, the best thing isn't always clear right away. Alpha is thought to be the best solution, Beta is thought to be the second best solution, and Delta is thought to be last. These three answers are kept and changed each time so that the lowest ranked solution, omega, moves up or down. The following equation governs hunting tactics:

$$\begin{aligned} \vec{D}_\alpha &= |\vec{C}_1 * \vec{X}_\alpha - \vec{X}| \\ \vec{D}_\beta &= |\vec{C}_2 * \vec{X}_\beta - \vec{X}| \\ \vec{D}_\delta &= |\vec{C}_3 * \vec{X}_\delta - \vec{X}| \end{aligned} \tag{9}$$

A modified distance vector is called  $\vec{D}_\alpha$ ,  $\vec{D}_\beta$ , and  $\vec{D}_\delta$ .  $\vec{C}_1$ ,  $\vec{C}_2$ , and  $\vec{C}_3$  are three coefficient vectors that help to adjust distance vector. At this time,  $\vec{X}$  is the position of the second grey wolf's vector (omega).

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 * \vec{D}_\alpha \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 * \vec{D}_\beta \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 * \vec{D}_\delta \end{aligned} \tag{10}$$

The alpha and distance vectors  $\vec{X}_\alpha$  and  $\vec{D}_\alpha$  represent the newly calculated position  $\vec{X}_1$  while the beta and distance vectors  $\vec{X}_\beta$  and  $\vec{D}_\beta$  represent the newly computed position  $\vec{X}_2$  while the three coefficient vectors  $\vec{A}_1$ ,  $\vec{A}_2$ , and  $\vec{A}_3$  are all calculated using (7).

$$\vec{X}(k + 1) = \frac{\sum_{i=1}^n \vec{X}_i}{n} \tag{11}$$

We now have  $\vec{X}(k + 1)$  representing our newly-determined finalized new position vector, which is derived from an average sum of all the locations gained via the use of the alpha, beta, and delta wolf ( $n = 3$ ).

The attacking prey phase helps candidate solutions identify the local solutions. In order to do a local search, the coefficient vector  $A$  changes its range between [-2a, 2a] and [2a, 0] over the course of generations.

A value of less than 1 means that search agents use these GWO operators to look for prey in the local area. They move their positions using the locations of alpha, beta, and delta, and then attack the prey in that direction. To solve this problem, a phase where the hunter looks for prey is added.

This phase helps them diverge from each other to find prey and converge to attack prey. If the value of the coefficient vector  $|A^r|$  is greater than one, the search agents depart from the prey and search for a new prey. Likewise, the parameter C vector is helpful in avoiding local optima, whereas the C vector value changes in a range of  $[0, 2]$ .

The GWO method is guided by the parameters  $A$  and  $C$  to find the best solutions in a global search area. The algorithmic flows of GWO are shown in Figure 2 [14].

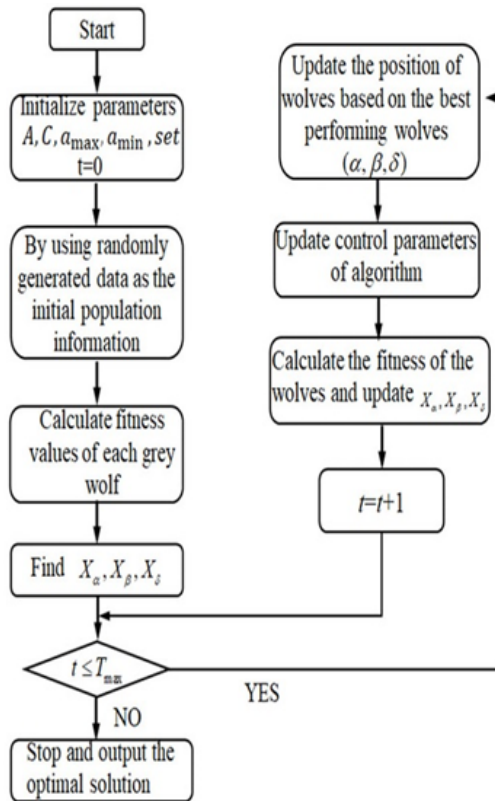


Fig. 2. Schematic diagram of the Grey Wolves Optimization (GWO) algorithms

## 5 Simulation results

The simulation begins by choosing the Mahmudiya area in Baghdad, which is an urban area provided with mobile phone service by Zain Iraq, where mobile phone towers cover most of this area. The locations of three towers were selected and ten points were selected for mobile phone within the coverage of these three towers as a case study. The locations of the base stations and all their information, including transmission frequencies are shown in Table 1.

**Table 1.** Base Stations Information

base station name	Cell ID	Antenna Height	Azimuth	RF plan Latitude	RF plan Longitude	TX power dBm	Frequency (base station to phone) MHz
base station 1	22085	24	0	33.068306	44.353611	42	2112.4
	22086	24	120	33.068306	44.353611	42	2112.4
	22088	24	0	33.068306	44.353611	42	2117.4
	22089	24	120	33.068306	44.353611	42	2117.4
Base station 2	22205	21	0	33.064167	44.347806	42	2112.4
	22206	21	120	33.064167	44.347806	42	2112.4
	22207	21	240	33.064167	44.347806	42	2112.4
	22208	21	0	33.064167	44.347806	42	2117.4
	22209	21	120	33.064167	44.347806	42	2117.4
	22200	21	240	33.064167	44.347806	42	2117.4
base station 3	24015	40	30	33.072711	44.340977	45	2112.4
	24016	40	110	33.072711	44.340977	45	2112.4
	24017	40	220	33.072711	44.340977	45	2112.4
	24018	40	30	33.072711	44.340977	45	2117.4
	24019	40	110	33.072711	44.340977	45	2117.4
	24010	40	220	33.072711	44.340977	45	2117.4
	43348	40	30	33.072711	44.340977	45	939
	43349	40	110	33.072711	44.340977	45	939
	43340	40	220	33.072711	44.340977	45	939

Table 2 shows the real locations of the ten points and the strength of the signal received from the three towers at each point.

**Table 2.** RSSI and locations for the ten points

Points	Latitude	Longitude	RSSI from Bs1	RSSI from Bs2	RSSI from Bs3
1	33.073621	44.342534	-86	-88	-50
2	33.073813	44.344936	-83	-87	-62
3	33.073521	44.34757	-83	-88	-66
4	33.072756	44.347574	-78	-85	-68
5	33.072059	44.346653	-78	-84	-67
6	33.068062	44.353722	-32	-80	-80
7	33.068145	44.353269	-38	-78	-80
8	33.068218	44.352761	-58	-76	-77
9	33.068318	44.35187	-54	-77	-77
10	33.068849	44.347467	-74	-74	-72

The GPS uses the geographical coordinate system, represented as longitude and latitude in degrees. They will need to be converted to the Cartesian coordinate system, represented as X and Y in meters, to be able to work with propagation models by Universal Transverse Mercator system (UTM). The location of the study area is in the UTM region 38 S. The BSs and the 10 locations GPS and UTM systems are shown in Table 3.

**Table 3.** The Cartesian coordinates of base stations and data set points

-	Latitude	Longitude	X	Y
BS1	33.068306	44.353611	439663.081725295	3659045.09468529
BS2	33.064167	44.347806	439118.356885490	3658589.57847897
BS3	33.072711	44.340977	438486.810374515	3659540.78299333
1	33.073621	44.342534	438632.775096279	3659640.75839279
2	33.073813	44.344936	438857.112199104	3659660.64287148
3	33.073521	44.347572	439102.956446940	3659626.73837601
4	33.072756	44.347574	439102.616090237	3659541.92600573
5	33.072059	44.346653	439016.167656478	3659465.18816862
6	33.068062	44.353722	439673.276659839	3659017.98004523
7	33.068145	44.353269	439631.047385331	3659027.44212766
8	33.068218	44.352761	439583.677308785	3659035.82739645
9	33.068318	44.351870	439500.574176809	3659047.42684147
10	33.068849	44.347467	439089.936587933	3659108.84130624

Calculating The geographical locations of these points are carried out by calculating the distance between each point and the three towers, which is done by calculating the bath loss using a specific propagation model. The HATA model and the UMTS model are used to calculate the distances. The UMTS propagation model applied Eq. 2 to calculate the path loss. It was calculated by compensating for the values of transmission frequency, sector height of the BS and the height of the MS, the distances between BSs with test drive location is as shown in Table 4.



**Table 4.** The distance between BSs with test drive location by UMTS Model

Locations	Distance to BS1	Distance to BS2	Distance to BS3
1	1211.98389697747	1174.86214584500	173.268751549786
2	1002.48819499313	1104.63885635854	392.039814717416
3	1002.48819499313	1174.86214584500	514.675487981598
4	730.662182592309	976.533452323594	589.705447699909
5	730.662182592309	918.164569167164	550.914638633207
6	39.8089173041653	717.553271296855	1334.27413994897
7	58.1856018602227	634.33835295869	1334.27413994897
8	206.189279184533	560.773868257464	1087.90904267956
9	160.094337205059	596.422972451485	1087.90904267956
10	567.317943520372	495.740701488213	774.173764159965

The path loss calculated by HATA model depends on transmitting frequency and the height of the BS, in addition to the height of the MS as salaried in Eq. 4. The distance between the MS and the BS has been calculated by the effect of the path losses in the HATA model as shown in the Table 5.

**Table 5.** The distance between BSs with test drive location by HATA Model

Locations	Distance to BS1	Distance to BS2	Distance to BS3
1	1237.53185264287	1272.50765799708	174.906022094533
2	1088.38698774546	1195.07752374670	417.484415963651
3	1088.38698774546	1272.50765799708	510.308823588822
4	789.497443834152	989.926841894347	623.772015133808
5	789.497443834152	989.926841894347	583.393541621975
6	41.1690354002141	770.097646284784	1302.36541034995
7	64.5321818939915	679.230444863765	1302.36541034995
8	204.990509529821	599.085063375480	1139.21137795027
9	169.072972187161	637.900316748443	1139.21137795027
10	572.688042799748	528.396387225530	762.462863424050

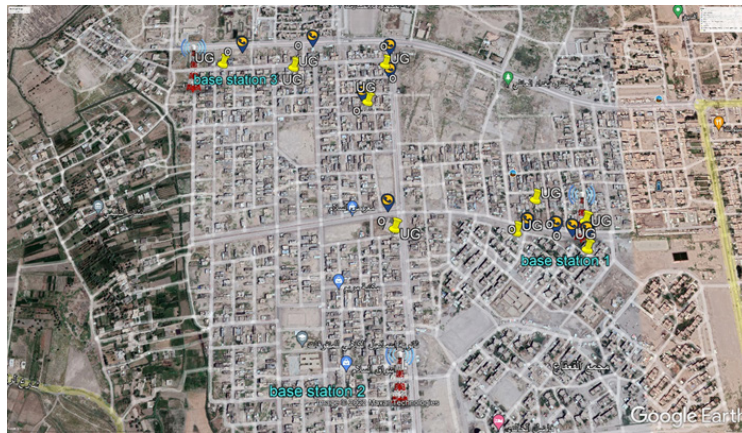
The propagation models show high difference in the distance because of the different scenarios to calculate the distance. However, the models are empirical models and depend on the region and the environment. For that the gray wolf optimization algorithm have been implemented in all result to have the estimated locations with high accuracy.

The GWO algorithm is used to estimate the location from the distance between the BSs and the MS that results in Table 6. The GWO is based on the service base station (BS1, BS2, or BS3) that has the strongest RSS. The GWO depends on the number of search agents and number of iterations. In the GWO program, the number of search agents is equal to 30 and 1000 iterations have been selected to give higher accuracy results.

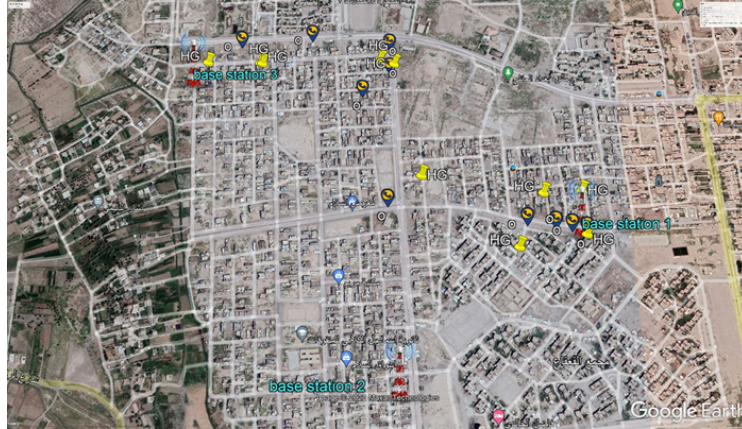
**Table 6.** The GWO algorithm estimation Locations

Loc.	UMTS model		HATA model	
	Latitude	Longitude	Latitude	Longitude
1	33.07271547	44.34182249	33.07271351	44.34145112
2	33.07272835	44.34426836	33.07272293	44.34323816
3	33.07272821	44.34424187	33.07272278	44.34320938
4	33.07274452	44.34735026	33.07274603	44.34763803
5	33.07162519	44.34674770	33.07274391	44.34723349
6	33.06811094	44.35361243	33.06886998	44.35360688
7	33.06735415	44.35361796	33.06767106	44.35361564
8	33.06789776	44.35144476	33.06733663	44.35153607
9	33.06872695	44.35210836	33.06883565	44.35239849
10	33.06800528	44.34766839	33.06920172	44.34856219

The GWO algorithm results on the geographical map of the study area. The Matlab program was linked with the Google Earth Pro program. The Figures 3 and 4 show the locations of the estimated points in different propagation models for test drive locations of the 10 locations.



**Fig. 3.** GWO with UMTS Model



**Fig. 4.** GWO with HATA Model

The root mean square error ( $rms_{error}$ ) for the GWO algorithm with three propagation models is shown in Table 7. The distance error is close to gathered for the three propagation models. The HATA model gives in all locations an error higher than the other two propagation models.

**Table 7.** The  $rms_{error}$  for the GWO with UMTS and HATA models

Loc.	UMTS Model	HATA Model
1	120	143
2	135	199
3	323	417
4	21	6
5	49	93
6	12	90
7	94	62
8	128	150
9	51	76
10	95	109

## 6 Conclusion

A driving test was conducted in Mahmudiya, an urban area equipped with a mobile phone service from Zain Iraq. The locations of three communication towers were selected in this area. The signal received from these towers was measured at 10 points. Calculating the distance between each point with the three towers was by calculating the path losses between the point and the tower using the HATA propagation model and the UMTS propagation model. Determining the location using the two diffusion models differs due to the different analysis of the received signal. We conclude from

this that the accuracy of the position analysis depends not only on the appropriate diffusion model, but also on the accuracy of the measurements of the received signal.

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