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Position Estimation in WiMAX Networks using Received Signal Strength

By

Tamer Yehya* Yahya Mohasseb** Ashraf Mahran*

Abstract:

During the last decade, the need for highly precise positioning services, for both military and civilian applications, has grown significantly. Unfortunately, in some environments such as dense urban or indoor areas, the Global Navigation Satellite System (GNSS) suffers from poor precision and lack of satellite visibility. Therefore, another positioning system is required to replace or augment GNSS in those environments. The use of Signals of OPportunity (SoOP) is one example of these complementary systems. Previous work explored different positioning techniques using SoOP from a wide variety of sources including; cellular phone signals, analog and digital TV, as well as audio signals. This paper focuses on the use of WiMAX signals, which is rapidly finding its way in the military environment, as a SoOP for position estimation. The positioning technique in this work is based on the Received Signal Strength (RSS) technique. Moreover, Kalman filter will be used to improve the position estimation results of that system.

Keywords:
Localization, SoOP, Non-GNSS, WiMAX, Received Signal Strength

1. Introduction:

Global Navigation Satellite Systems (GNSS) are designed to provide highly accurate positioning information. However, they require satellite

* Avionics Department, MTC, a.mahran@ieee.org
** Communication Department, MTC, mohasseb.1@gmail.com

visibility and adequate received signal levels. For seamless positioning, other systems were proposed to replace or augment GNSS in such environments [1]. Navigation using Signals of Opportunity (SoOP) is one of the alternative non-GNSS systems. These signals can be any radio frequency signals designed mainly for communication rather than navigation. Consequently, they are optimized for provision of adequate coverage and can be of relatively high power and able to penetrate buildings. Moreover, the key advantage of SoOP is that they do not require additional infrastructure. However, since SoOP are not immediately adequate for navigation as communication signals they are not always time synchronized, suffer from significant multipath effects and, in the absence of line-of-sight (LOS), signal timing estimation can be quite challenging [2]. Other challenges may arise from the need to make all transmitter locations known, and the lack of worldwide coverage as in GNSS.

In particular, the idea of using WiMAX signals, which is relevant to the work presented in this paper, is similar to the use of GSM signals that relies on the wireless network itself by using the available information like the cell ID. However this method has a limited accuracy [3]. On the other hand, using other network information like the received signal strength (RSS), time of arrival (TOA), or time difference of arrival (TDOA) gives better accuracy but requires additional measurements. Some of these measurements are not easily obtained, like TOA, which needs synchronization, and some are easy to obtain, like RSS measurements.

Despite its limited accuracy, the RSS- based localization method has been used in many positioning systems since it presents a cheap and convenient method. The basic idea in RSS-based localization is to compare all measured RSS values to a model of RSS for each position and then determine the position that gives the best match. The two most common models are; the general exponential path loss model, and a dedicated Power Map (PM) constructed offline for the region of interest [3]. The first alternative is the most common strategy and is the simplest to deploy. The most famous exponential path loss model is known as the Okumura–Hata (OH) model [4] which assumes that, in a log power scale, the RSS value linearly decreases with the distance to the antenna. This is quite a crude approximation, where the noise level is high and further depends on multipath and non-line-of-sight (NLOS) conditions.

Several researches have been carried out to improve the accuracy of RSS-based positioning techniques. In [5], the authors used the model in [6] to track a target using different path loss exponents for the each link between the terminal and the base stations (BSs). This resulted in better localization accuracy than the conventional localization methods that use the same path loss exponent for all the links. Furthermore, the authors of [7] proposed the use of an RSS statistical lognormal model and a sequential Monte Carlo localization technique to get better localization accuracy. The lognormal model was also used in [8] to estimate the mobile location, and the authors succeeded in mitigating the influence of the propagation environment by using the differences in signal attenuations. In [9] position estimation was conducted in the city of Brussels using WiMAX signals, and their results show that 67% of the positioning error are less than 220m, they generate a path-loss model for the area under study, and enhanced the results by using the power maps.

In this work, we use RSS observations for estimating the positions in WiMAX networks, depending on the method described in [9]. The position is calculated via the triangulation algorithm. As the exponential path loss model suffers from scattering, reflection and obstruction [9], we will use the Kalman filter (KF) for estimating the actual position in order to improve accuracy.

In the following section, we briefly introduce the WiMAX signals and the method to obtain the received signal strength from it. Section III illustrates the path-loss model and the position estimation technique. Section IV describes the Kalman filter used for enhancing the results. Section V shows the position accuracy for sample scenarios. Our conclusions are drawn in Section VI.

2. RSS ranging in WiMAX Networks

WiMAX is a standards-based technology enabling the delivery of wireless broadband, which acts as an alternative to cable and DSL [10]. WiMAX networks are very similar to GSM networks from topological point of view; the two of them use base stations (BS) connect wirelessly to subscriber stations (SS); therefore, the positioning techniques which can be applied on GSM networks like triangulation, trilateration…etc., could also be applied on WiMAX networks taking into account the different technology aspects for each of the two technologies.

Ranging is the process of estimating the distance between two nodes. Localization algorithms may be divided into two main categories; *range-based* and *non-range-based*. The range-based localization using RSS is particularly attractive, as it doesn't need any additional hardware. In contrast, other range-based techniques such as TOA, AOA, and TDOA require specialized hardware and sometimes complex processing.

In WiMAX networks, estimating the range between BS and SS can be obtained by observing the RSS values then substituting in the path-loss model. The relationship between transmitted power and received power of wireless signals and the distance among them described by:

$$P_r = P_t \left(1/d\right)^m \tag{1}$$

Where: P_r is the received power of wireless signals, P_t is the transmitted power of wireless signal, d is the distance between the transmitter and receiver, and m is the path loss exponential factor whose value depends on the propagation environment.

Observing the RSS values can be done by reading the available RSS index (RSSI) in certain modems and then get the RSS values using the modem calibration table (convert RSSI values to RSS)or measuring directly the RSS values. The main advantage of reading RSSI values is the possibility of measuring this value for all the available base stations simultaneously. However, its drawback lies in limited measurement accuracy; it is slightly less accurate to obtain RSS values from RSSI than measuring the RSS values directly.

3. Path-loss model

Modeling the path-loss using deterministic models depends on calculating all the possible attenuation components and possible paths between transmitters and receivers. This requires accurate data (including the buildings, vegetation …etc.), and also requires high computing capacity to process all the data. In realistic propagation environments, it is very difficult to model all the physical phenomena that influence the propagation of the electromagnetic waves. Empirical models [11] have been developed to avoid the time consuming calculations required in the deterministic models. These empirical models are based on conducting extensive measurements in the area under study, for the required frequency, and then modeling the obtained data.

In this work, it was desired to obtain simulated RSS data, taking into account the non-deterministic nature of the propagation scenario, without the need to conduct real extensive measurements. The other alternative was to use a deterministic model, in the form of (2) which would falsely result in perfect localization every time. Since the same model would be used to get the RSS values and then used again to convert them back to distances.

Consequently, we used statistical multipath channel models to ensure more realistic scenarios, and superimposed the path loss model to put into account the signal attenuation according to distance. This was conducted as a separate experiment, and curve fitting was used to estimate the Okumura–Hata model parameters for the simulated multipath environments. The channel gains were fitted to a model of the form:

$$R_{ss} = a \ \log_{10}(d) + b \tag{2}$$

Where: R_{ss} is the received signal strength in dBm, d is the range between BS and SS in meters, a and b are constant depending on the simulation results. Figure (1) shows the simulated multipath channel gains as scattered dots and the curve resulting from the fitting process. The curve fitting results the parameters $a = -23.58$ and $b = -26.92$ for Rician channel with k-factor equal 2, the curve fitting shows that Root Mean Square Error (RMSE) equal 4.338, which means that there is a good matching between the model obtained and the estimated received signals.

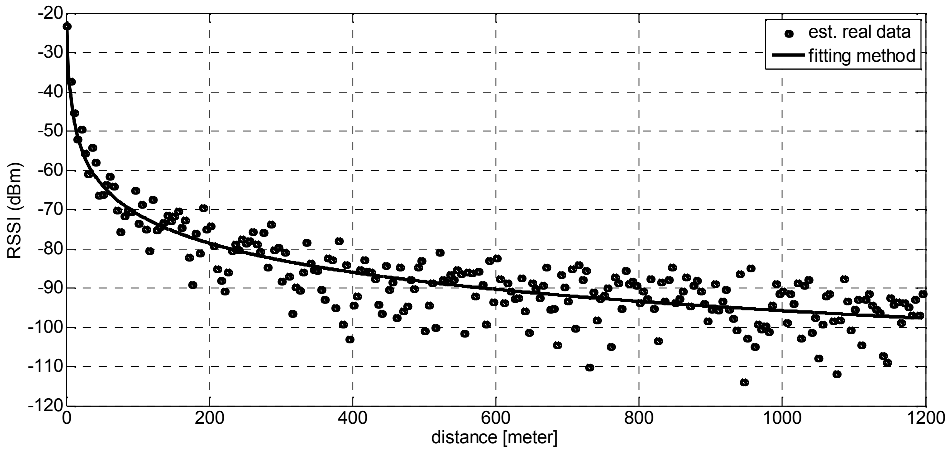

Fig.1. Estimated path loss model

We use in the simulation a Rayleigh channel with 20 taps [12], with curve fitting parameters $a = -23.91$, $b = -28.63$ and the RMSE calculated from curve fitting 5.438. The Rician channel used with 21 taps [12], table 1 shows the parameters obtained from the curve fitting for different k-factors, and RMSE calculated from curve fitting.

Table 1 Curve fitting parameters for Rician channel

k-factor	Curve fitting parameters		RMSE
	a	*b*	
k=1	-23.12	-25.84	4.834
k=2	-23.58	-26.92	4.338
k=3	-22.18	-24.18	4.056
k=4	-22.77	-25.35	3.892
k=5	-23.81	-26.08	3.768
k=6	-23.91	-25.24	3.661
k=7	-22.12	-26.71	3.561
k=8	-23.58	-24.28	3.252
k=9	-22.58	-26.24	3.012
k=10	-23.62	-26.74	2.973
k=11	-23.25	-24.15	2.754
k=12	-22.81	-25.84	2.568
k=13	-24.02	-26.12	2.361
k=14	-22.52	-27.21	2.238
k=15	-23.41	-26.75	2.063
k=16	-22.48	-27.25	1.831
k=17	-23.14	-23.67	1.854
k=18	-23.72	-26.71	1.781
k=19	-23.72	-25.28	1.497
k=20	-22.92	-26.24	1.416

The range between BS and SS may be estimated using the above path-loss model that converts the energy of the received signal to a distance. To estimate the position in three dimensions (3D) the system needs at least four or more transmitters with known coordinates, while three transmitters or more are needed to estimate the position in the case of 2D. By using the triangulation technique, as shown in Figure (2), each transmitter is considered to be in a center of the circle at which the user lies on the circumference of it. The distance between the center of the circle (transmitter) and the user is the radius of the circle, and the intersection of these three circumferences is the position of the user.

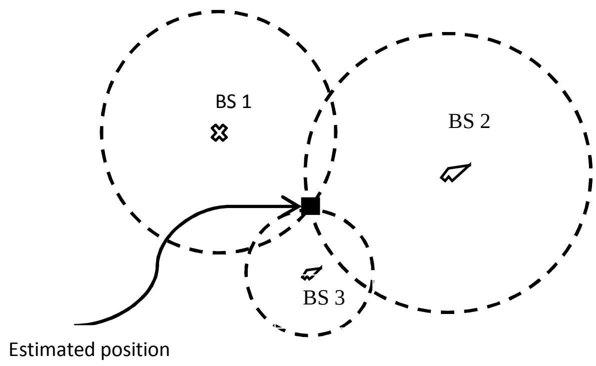

Fig.2. Triangulation technique

4. Tracking enhancement using KF

The Kalman filter is essentially a predictor-corrector type estimator. It minimizes the estimated error covariance when some presumed conditions are met. Kalman filter has been used for many applications, particularly in the area of autonomous or assisted navigation [13].

Herein, consider the coordinate of the moving receiver and its velocity are presented by (x, y) and (x', y') respectively. The coordinate of the transmitters are presented by (x_i, y_i); where i is the transmitter number. Therefore, the Euclidian distance between transmitter i and the receiver at instance n is given by:

$$d_i(n) = \sqrt{(x(n) - x_i)^2 + (y(n) - y_i)^2} \tag{3}$$

Using equation (2), the received signal strength at instant n for transmitter i is defined by:

$$R_{ss} = a \log_{10}\left(\sqrt{(x(n) - x_i)^2 + (y(n) - y_i)^2}\right) + b \tag{4}$$

Now, Assume a state vector X_n , which represents both the position and the velocity components of the receiver and the corresponding measurement vector Z_n for a receiver moving with constant velocity, for an interval of time, while its direction may change at any time. Thus the system is modeled as:

$$\begin{bmatrix} x(n) \\ \dot{x}(n) \\ y(n) \\ \dot{y}(n) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(n-1) \\ \dot{x}(n-1) \\ y(n-1) \\ \dot{y}(n-1) \end{bmatrix} = \mathbf{A}\mathbf{X}_{n-1}$$

$$\begin{bmatrix} z_1(n) \\ z_2(n) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x(n) \\ \dot{x}(n) \\ y(n) \\ \dot{y}(n) \end{bmatrix} + \begin{bmatrix} w_{xn} \\ w_{yn} \end{bmatrix} = \mathbf{H}\ \mathbf{X}_n + \mathbf{w}_n \tag{5}$$

Where: $\boldsymbol{A}$ is the state transition matrix, $\boldsymbol{H}$ is the observation matrix, $\boldsymbol{w}$ is the observation noise vector, and Δt is the sampling period. The Kalman filter equations are responsible for projecting forward the current state and error covariance estimates to obtain the a priori estimates for the next step. We shall not repeat here the standard Kalman equations, which can be found in [13] ref. However, specific to our application, the measurement update equations are responsible for the feedback to obtain an improved a posteriori position estimate. The newest estimate for the average error, which represents the covariance prediction, is given by:

$$\mathbf{E}_n = \mathbf{A}\mathbf{E}_{n-1}\mathbf{A}^T + \mathbf{Q} \tag{6}$$

Where: $\mathbf{Q}$ is the covariance matrix of the state vector, and the innovation covariance which compares the real error against prediction is given by:

$$\mathbf{S} = \mathbf{H}\ \mathbf{E}_n\mathbf{H}^T + \mathbf{R} \tag{7}$$

Where: $\mathbf{R}$ is the covariance matrix of the observation noise vector. Equations (5-7), when combined with the remaining standard Kalman filter equations [13], are used to obtain the enhanced location estimates presented in next Section.

5. Simulation Results

In this section, we present a sample scenario based on the above method. Assume the receiver is moving with constant velocity (20 km/hr), and 3 WiMAX base stations are located at (-200,-200), (-200,800) and (300,900) respectively. Assume further that we use the previous logarithmic path loss model for different channel models. Assuming the process variance matrix (error due to process) was *0.001I*, and the measurement variance matrix (error from measurements) was *I*, for the Kalman filter, where *I* is identity matrix, and $\Delta t = 0.1 sec.$ In the next sub-sections, we first discuss the effect on Rayleigh channel and then shows the effect on Rician channel with different k-factors.

A. Rayleigh channel

Herein, we discuss the effect of Rayleigh channel on the estimated position error using the above positioning method; there is no line of sight between the transmitter and the receiver. Figure (3) shows the estimated path when there is no line of sight between the transmitter and the receiver, with the pre-calculated path loss model parameters. The RMSE for the overall estimated path was 275m and after using KF the RMSE enhanced by about 25% to be 210m.

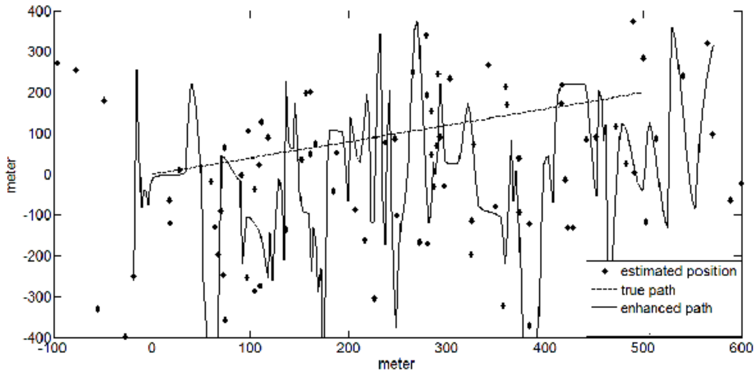

Fig. 3. Enhanced path for the Rayleigh channel

B. Rician channel

Herein, we discuss the effect of the k-factor on the estimated positions, path loss parameters for each scenario obtained from table 1. Figure (4) shows the estimated path when k-factor equal 1, which means the receiver located in weak line of sight environment, we found the RMSE for the overall estimated path after before KF equal 210m and after using KF the RMSE enhanced by about 25% to be 160m. When k-factor increased to be 5, the RMSE for the overall estimated path equal 80m, and KF decrease the RMSE with about 40% to be 49m, figure (5) shows the estimated path for k-factor =5.

Figure (6) shows the estimated path when k-factor =10, the calculated RMSE was 35m, and KF enhanced it to be 20m, which means the KF enhanced RMSE with about 45%. Figures (7) and (8) show the estimated path for *k*=15 and *k*=20 respectively, the RMSE when k=15 equal 25m, and equal 13.5m for k=20 which represent the rural area, KF enhanced RMSE to be 15.5m and 12m respectively. All the above results summarized in figure (9), which shows the RMSE for the estimated positions for different k-factor, and the enhancement due to KF, the figure proved that KF has less RMSE than ordinary technique without KF, for all k-factors. However, its effect may be ignored when $k > 20$.

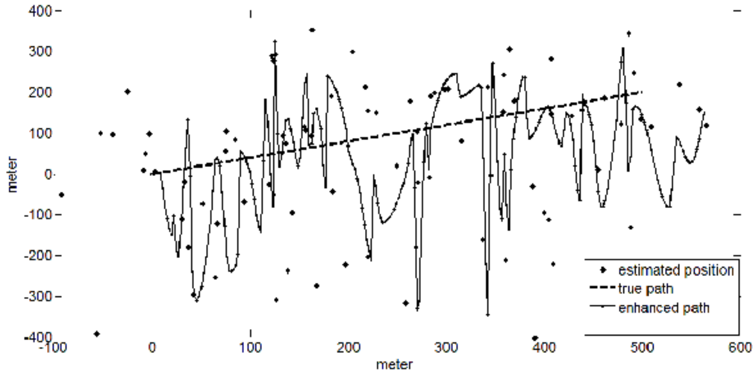

Fig.4. Enhanced path when k=1

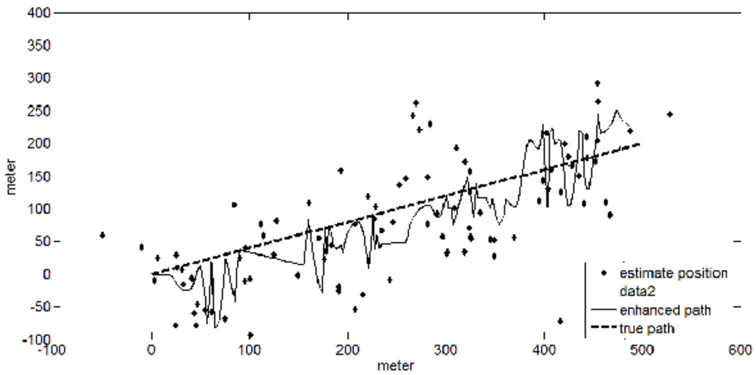

Fig. 5. Enhanced path when k=5

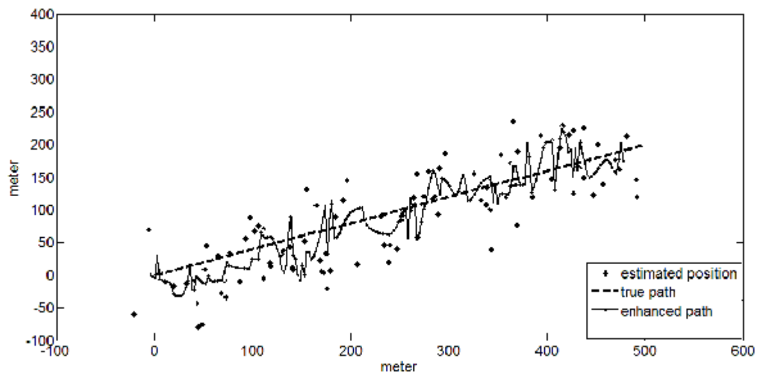

Fig.6. Enhanced path when k=10

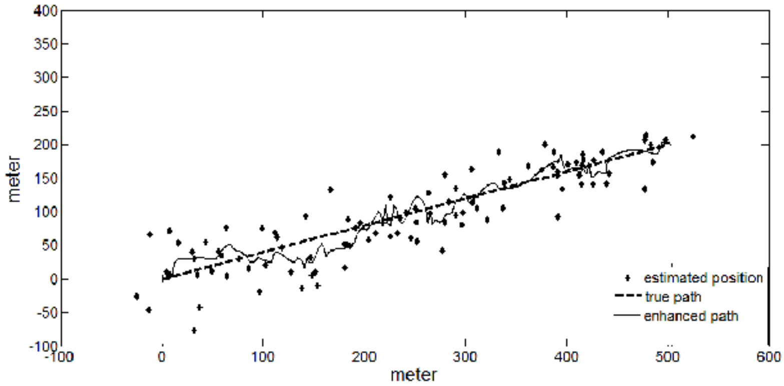

Figure 7 Enhanced path when k=15

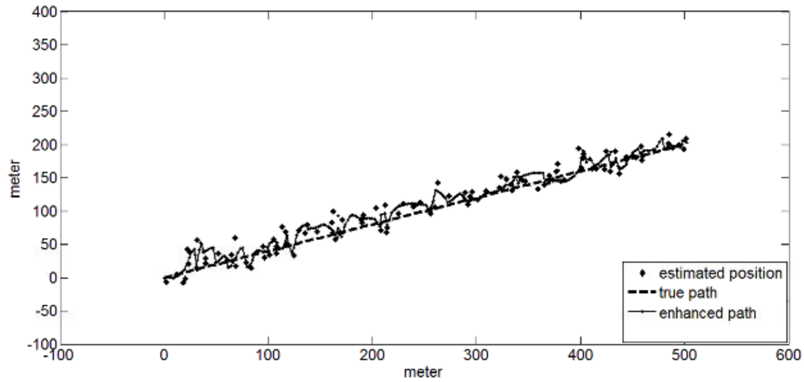

Fig.8. Enhanced path when k=20

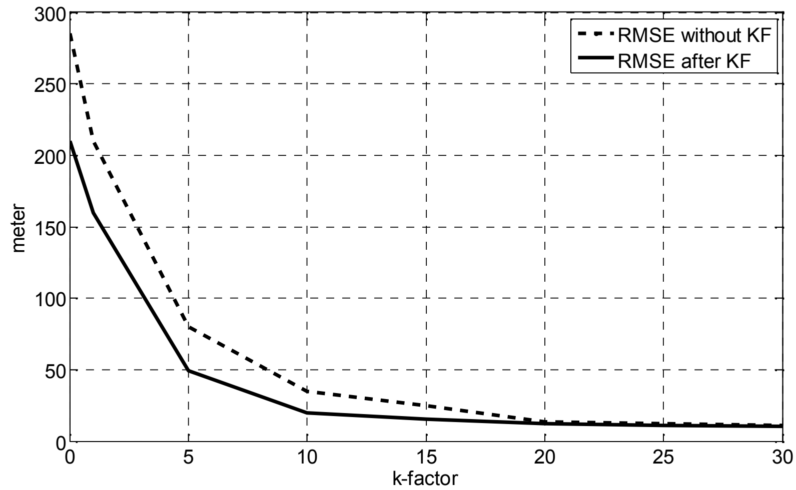

Fig. 9. RMSE for estimated positions

6. Conclusions

This paper discusses the possibility for using WiMAX signals as SoOP for position estimation. A relatively simple and proven algorithm based on received signal strength has been applied. It was found that, this positioning technique was not applicable when there is no line of sight between the transmitter and the receiver. The Kalman filter has been applied for better position estimation, under the assumption of linear motion. Otherwise; changing direction of the receiver may lead to filter divergence. The used Kalman filter, was able to decrease the RMSE by 25% compared to simple technique that is used in [9] for certain channels. Kalman filter has small effect for the Rician channels with k-factor more than 20. Further enhancement of this work can consider the use Constrained Unscented Kalman Filter to incorporate the non-linearity of the measurements [14].

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