Modified RWGH and Positive Noise Mitigation Schemes for TOA Geolocation in Indoor Multi-Hop Wireless Networks

Young Min Ki, Jeong Woo Kim, Sang Rok Kim, and Dong Ku Kim

Yonsei University, Dept. of Electrical and Electronic Engineering
134 Shinchon-Dong, Seodaemun-Gu, Seoul 120-749, Korea
{mellow, c13664, khannury, dkkim}@yonsei.ac.kr
http://mcl.yonsei.ac.kr

Abstract. Time of arrival (TOA) based geolocation schemes for indoor multi-hop environment are investigated and compared to some of conventional geolocation schemes such as least squares (LS) or residual weighting (RWGH). The multi-hop ranging involves positive multi-hop noise as well as non-line of sight (NLOS) and Gaussian measurement noise, so that it is more prone to ranging error than one-hop range. In this paper, RWGH algorithm is modified by adapting weighted residual normalization considering the number of hops taken to measure each ranging. The iterative positive noise mitigation schemes are further developed by using distance enlargement test (DET) to mitigate the multi-hop ranging noise. Simulation results show that the proposed modified RWGH algorithms show 5 to 25% smaller average estimation error compared to LS and RWGH for both positive noise mitigation and no mitigation cases, and the positive noise mitigation schemes provide 28 to 42% error mitigation compared to no mitigation schemes.

1 Introduction

Rather recently, geolocation finding has attracted much attention in the indoor environments. Depending on environments and applications, ranging and geolocation measurements can be performed in a variety of ways, using angle of arrival (AOA), time of arrival (TOA), or Received Signals Strength (RSS) [1]. The TOA technique where range is determined by measured propagation delay between mobile node (MN) and sensor node (SN) is the most popular for accurate geolocation systems [1]. For TOA geolocation, a set of ranging information allow us to draw a multiple number of circles at each SN with radius of their measurement. The traditional geometrical approach for computing the position of MN is to solve for the intersection of the circular lines of position. The circles do not intersect at a point due to the measurement noise, requires more statistically adjustable methods, such as least squares (LS) or residual weighting (RWGH) location estimation [2-3].

The traditional geolocation approaches assumed a few fixed, powerful long range nodes, which is similar to base station for communicating with all other nodes in the network. However, if there is no direct communication link between MN and SN, the range must be measured by using multi-hop relaying [4-5]. It was found in [4] that larger number of hops of TOA based ranging makes raging measurement value more unreliable in the system of one-dimensionally placed nodes. This paper assumed the two-dimensional non-linearly arranged multi-hop cases, in which the sum of intermediate range measurements is always greater than the direct distance between source and destination. In this paper, RWGH algorithm is modified by adapting weighted residual normalization considering the number of hops taken to measure each ranging. The iterative positive noise mitigation schemes are further developed by using distance enlargement test (DET) to mitigate the multi-hop ranging noise.

The remainder of the paper is organized as follows. In Section 2, the system description of geolocation problem for multi-hop wireless network is introduced. The Section 3 represents the TOA-based geolocation schemes for one-hop ranging measurements. In Section 4, the proposed geolocation schemes for multi-hop ranging measurements are presented. The performances of the schemes are shown in Section 5. Finally, conclusions are made in Section 6.

2 System Description

2.1 Geolocation in Multi-hop Wireless Network

In wireless indoor network, the nodes have a limited energy supply and a very limited communication range, so that SNs often should route through other wireless nodes to communicate to remote MNs [4-5][8]. Fig. 1 shows a wireless multi-hop network example, where the positions of sensor nodes (SNs) are known but the positions of the remaining mobile nodes (MNs) are unknown. The question is how to get the reliable positions of the MNs by using the known positions of SNs. MN 1 can reach to all of three SNs with direct link, while MN 2 has two direct links to SN 1 and SN 2 and one relay link to SN 3 via MN 1. Since at least three ranging measurements are needed for 2-D geolocation, the position of MN 1 can be determined by three direct ranging measurements, but MN 2 has two direct ranging measurements and the third ranging information from SN 3 which is measured by relay link.

2.2 Multi-hop Ranging Measurement

The multi-hop ranging measurement consists of mobile node (MN), sensor node (SN), and R relay nodes (RNs) as shown in Fig. 2. It is assumed that the geolocation systems originally know the locations of SNs and the number of hops between SN to MN, but it does not know location of MN and RN. Therefore, the range measurement between MN and SN should be measured by sum of each hop range measurement. The range measurement between mobile node (MN) and the i-th sensor node (SN) at time instance t is modeled as:

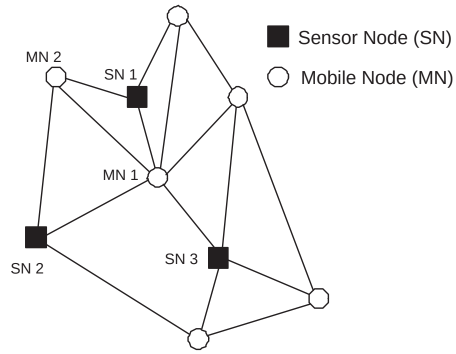

Fig. 1. A wireless multi-hop network example

$$r_i(t) = \sum_{j=0}^{R} d_{i,j}(t), \qquad i = 1, 2, ..., N, \tag{1}$$

where $d_{i,j}(t)$ is the range measurement between the $(j-1)$-th relay and the j-th relay node (RN). $d_{i,1}(t)$ is the range measurement between MN to RN 1 and $d_{i,R}(t)$ is the range measurement between RN R to SN, where R is the number of RNs. While the authors of [4-5] assumed the one-dimensional system in which all of nodes are linearly placed, we assume the non-linearly placed multi-hop cases, where sum of intermediate range measurements is always lager than the direct distance between source and destination.

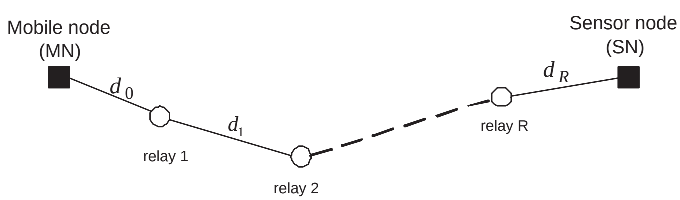

Fig. 2. A ranging example for wireless multi-hop network

2.3 Problem Formulation

The range measurement of the i-th SN is modeled as:

$$r_i(t) = L_i(t) + n_i(t) + NLOS_i(t) + MHR_i(t), \quad i = 1, 2, ..., N, \tag{2}$$

where $L_i(t)$ is the real line of sight (LOS) distance defined as:

$$L_i(t) = \sqrt{(x_M - x_i)^2 + (y_M - y_i)^2}, \qquad (3)$$

where (x_M, y_M) and (x_i, y_i) are the coordinates of the MN and the i-th SN respectively. $n_i(t)$ is a measurement noise modeled as zero mean Gaussian random variable. If the variance of one-hop range Gaussian random variable is σ^2, that of R-hop range is $R \cdot \sigma^2$ [4]. When direct LOS path is not detected, $NLOS_i(t)$ for one-hop range can be model as the positive Exponential distribution [2-3][6-7]. Therefore, NLOS error for R-hop range can be modeled as R-Erlang random variable. If multi-hop exists and relay nodes are not linearly placed, $MHR_i(t)$ is positive error. The geolocation problem is to determine the coordinates of the MN (x_M, y_M) by using range measurements of (2).

3 TOA-based Geolocation Schemes for One-Hop Ranges

3.1 Least Squares (LS)

The LS location estimation fundamentally focuses on minimizing the value of the least square objective function. The LS estimated location is determined as:

$$[\hat{x}_{LS}, \hat{y}_{LS}] = \arg\min_{x,y} \sum_{i=1}^{N} \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - r_i \right)^2, \qquad (4)$$

where (x_i, y_i) is the coordinate of the i-th SN and r_i is the range measurement. N is the number of SN. The square-root term is readily recognized as the distance between a point (x, y) and a SN located at (x_i, y_i). The difference in the parentheses is commonly called *residual* of the estimate [2-3][7].

3.2 Residual Weighting (RWGH)

The residual weighting (RWGH) [2-3] is a form of weighted least-squared algorithm which is a way of mitigating the effects of noise in ranging measurements on NLOS channel conditions. Since NLOS channel conditions introduce strictly positive noise, ranging measurements corrupted by NLOS noise would give location estimates having larger residuals than that of no NLOS case. Therefore, if the number of distance measurements is available, then various sub-groups of range measurements allow us to compute intermediate LS estimates using those sub-groups. Some of these intermediate estimates would have lower residual than the others. The final estimate of the location can be determined as a linear combination of these intermediate estimates weighted by the inverse of its associated residual. Specifically, given N $(N > 3)$ distance measurements, the algorithm calls for the formation of M different distance measurement combinations, where

$$M = \sum_{i=3}^{N} \binom{N}{i}, \tag{5}$$

with each combination being represented by an index set $\{S_k | k = 1, 2, ..., M\}$. For S_k, an intermediate LS estimate $(\hat{x}_k, \hat{y}_k)$ is computed as follows:

$$(\hat{x}_k, \hat{y}_k) = \arg\min_{x,y} R_{es}(x, y, S_k), \tag{6}$$

where the residual of the k-th SN set S_k is defined as:

$$R_{es}(x, y, S_k) = \sum_{i \in S_k} \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - r_i \right)^2. \tag{7}$$

A normalized residual is computed for every intermediate estimate, $(\hat{x}_k, \hat{y}_k)$ as:

$$\tilde{R}_{es}(\hat{x}_k, \hat{y}_k, S_k) = \frac{R_{es}(\hat{x}_k, \hat{y}_k, S_k)}{\text{size of } S_k}. \tag{8}$$

The final location estimate $(\hat{x}_{RWGH}, \hat{y}_{RWGH})$ can then be computed as:

$$\hat{X}_{RWGH} = \frac{\sum_{k=1}^{M} \hat{X}_k \cdot \left(\tilde{R}_{es}(\hat{x}_k, \hat{y}_k, S_k) \right)^{-1}}{\sum_{k=1}^{M} \left(\tilde{R}_{es}(\hat{x}_k, \hat{y}_k, S_k) \right)^{-1}}, \tag{9}$$

where $\hat{X}_k = [\hat{x}_k \ \hat{y}_k]^T$ and $\hat{X}_{RWGH} = [\hat{x}_{RWGH} \ \hat{y}_{RWGH}]^T$ [2-3].

4 Geolocation Schemes for Multi-Hop Ranges

4.1 Modified Residual Weighting (MRWGH)

Since the multi-hop ranging is likely to become inaccurate compared to one of direct path measure, each range measurement should be adopted into location estimation scheme in consideration of its number of hops. RWGH algorithm is modified by adapting weighted residual normalization considering the number of hops taken to measure each ranging, so that larger residual values put with smaller weight into final location estimation. We investigated two versions of modified residual weighting (MRWGH), one of which is given as:

$$\tilde{R}_{es}(\hat{x}_k, \hat{y}_k, S_k) = \frac{R_{es}(\hat{x}_k, \hat{y}_k, S_k)}{\text{size of } S_k} \cdot \prod_{i \in S_k} R_i, \tag{10}$$

where R_i is the number of RNs for the i-th SN to make ranging. The other modified one is given as:

$$\tilde{R}_{es}(\hat{x}_k, \hat{y}_k, S_k) = \frac{R_{es}(\hat{x}_k, \hat{y}_k, S_k)}{\text{size of } S_k} \cdot \sum_{i \in S_k} R_i. \tag{11}$$

Therefore, the modified normalized residual of the k-th SN set S_k having larger number of multi-hop range measurements gives smaller contribution to the final position determined by linear summation of (8) than that of SN set having smaller number of hops.

4.2 Positive Noise Mitigation with Distance Enlargement Test

This paper investigates the multi-hop ranging noise mitigation schemes by using distance enlargement test (DET) [8]. Once the location estimation $(\hat{x}, \hat{y})$ is determined, the distance enlargement test (DET) metric for range measurement of the i-th SN can be computed as:

$$DET_i = r_i - \sqrt{(\hat{x} - x_i)^2 + (\hat{y} - y_i)^2}, \qquad i = 1, 2, ..., N, \tag{12}$$

where r_i is the range measurement and (x_i, y_i) are the coordinates of the MN and the i-th SN. If $|DET_i| \leq \delta$, where δ is the allowable expected error, the location estimation $(\hat{x}, \hat{y})$ is valid. If not, it has some positive ranging noise such as multi-hop ranging noise or NLOS noise [8]. In the latter case, if $DET_i > \delta$, the range measurement has larger positive noise than other ranges. If $DET_i < -\delta$, the range has only Gaussian measurement noise or smaller positive noise than other ranges. We investigate the positive mitigation scheme given as:

$$r_{i,new} = \begin{cases} r_{i,old} - DET_i, & DET_i > \delta \\ r_{i,old}, & otherwise \end{cases}, \qquad i = 1, 2, ..., N, \tag{13}$$

where $r_{i,new}$ is the new range measurement for the i-th SN after positive noise mitigation and $r_{i,old}$ is the old range measurement prior to conduct positive noise mitigation. In our positive noise mitigation scheme, the location estimation such as LS, RWGH and MRWGH is followed by distance enlargement test (DET). Then if positive DET value is present the positive noise is mitigated by (13). Otherwise, noise mitigation is not performed. The location estimation and positive noise mitigation are iteratively performed until DET_i becomes less than δ for all range measurements.

5 Performance Evaluation

5.1 Simulation Setup

The performance of the geolocation algorithms described in Section 3 and 4 is evaluated through simulations. The example of node arrangement is shown in Fig. 3. The regular $L \times L$ grid arrangement of fixed four SNs is assumed and L is set to 30m. One MN and three RNs are uniformly placed in $L \times L$ area and their locations are generated more than 100 times. For each drop, RNs are fixed but MN moves straightly with maximum speed of 8.33m/s. The simulation time for each drop is 20msec, sampling time is set to 200nses, and the MN has a limited communication range of 20m. If SN is within first-hop coverage of the MN, the range measurement of the SN is determined by one-hop range. Otherwise, the range of the SN is measured by multi-hop relaying. The mixed line of sight (LOS)/non-line of sight (NLOS) scenario is simulated using a binomial random variable, such that the channel is likely to be NLOS with probability p, and LOS with probability $(1-p)$ [3]. Range measurements are generated by adding measuring noise of Gaussian random variable and NLOS noise of Exponential random variable to the true ranges. The probability density function of NLOS error d (in meters) can be written as:

$$D(d) = \begin{cases} \frac{1}{c \cdot \tau_{rms}} \cdot e^{-\frac{d}{c \cdot \tau_{rms}}}, & d > 0 \\ 0, & otherwise \end{cases}, \tag{14}$$

where c is the speed of light, and τ_{rms} is the delay spread and is set to 30nsec.

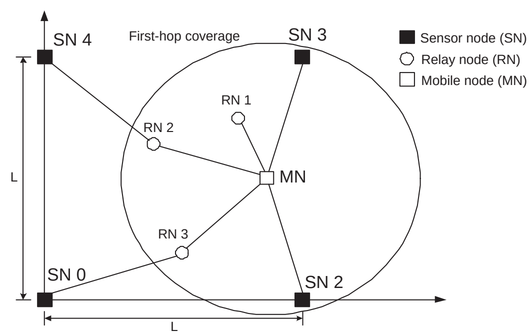

Fig. 3. The basic configuration example for a geolocation system simulation

5.2 Results on LOS Environment

We investigated the LS, RWGH, and two versions of MRWGH: MRWGH1 means the modified version of (10) and MRWGH2 is that of (11). The positive noise mitigation scheme is simulated for each geolocation algorithms in parallel with the simulation of the original algorithms with no mitigation. The positive mitigation threshold δ is set to 0.3m. The performance metric is the average estimation error E_{av}, defined as:

$$E_{av} = E\Big\{\big|X_M - \hat{X}\big|\Big\}, \tag{15}$$

where X_M and $\hat{X}$ are the actual and estimated locations of a MN. Also, the average number of iterations for mitigation is computed for positive noise mitigated schemes.

Fig. 4 shows the average estimation error as a function of standard deviation of measurement noise in LOS environment. It is shown that MRWGH algorithms show the smallest average estimation error among the simulated schemes, and both versions of MRWGH have little difference in error performance in either no mitigation or mitigation schemes. The average estimation error of MRWGH algorithms is 20 to 25% smaller than that of LS and 9 to 13% smaller than that of original RWGH. It is due to the fact that more uncertain multi-hop ranges give less affects to the final position than one-hop ranges in the MRWGH algorithms. The positive noise mitigated schemes show 28 to 30% smaller error than no mitigation scheme of LS and RWGH, and around 33% less than that of MRWGH algorithms. The RWGH with no mitigation provides almost same estimation error performance as positive error mitigated LS scheme. For all of schemes, the error performance degradation due to measurement noise is within 10%, even though standard deviation of Gaussian noise changes from 0.01m to 1.0m. Fig. 5 represents the average number of iterations for mitigation as a function of standard deviation of measurement noise for positive noise mitigation schemes in LOS case. It is shown that the necessary number of iterations of positive noise mitigation for MRWGH algorithms is around 18% smaller compared to that of LS, and 6% smaller compared to that of RWGH.

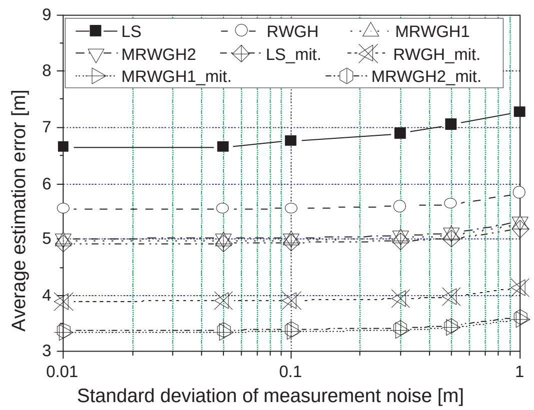

Fig. 4. Average estimation error as a function of standard deviation of measurement noise (LOS case)

5.3 Results on mixed LOS/NLOS Environment

Fig. 6 shows average estimation error as a function of standard deviation of measurement noise in mixed LOS/NLOS environment where the $p(NLOS)$ is set to 0.2. The average estimation error of MRWGH algorithms is 17 to 22% smaller

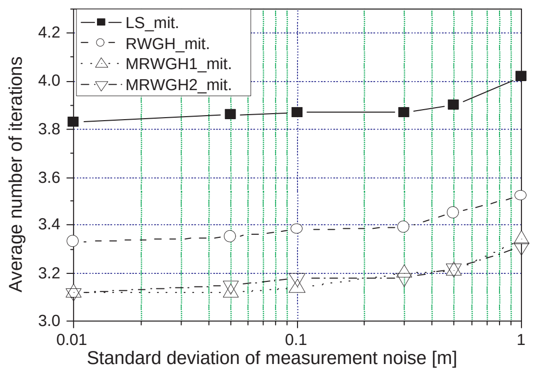

Fig. 5. Average number of iterations for mitigation as a function of standard deviation of measurement noise for positive noise mitigation schemes (LOS case)

than that of LS and 5 to 8% smaller than that of original RWGH. The positive noise mitigated schemes show around 37 to 42% smaller error than no mitigation schemes. Since positive noise mitigation schemes manage both NLOS and multi-hop ranging errors, the performance gain in NLOS case is much larger than in LOS case. Fig. 7 represents the average number of iterations for mitigation as a function of standard deviation of measurement noise for positive noise mitigation schemes in mixed LOS/NLOS environment in which the probability of a range measurement corrupted by the NLOS noise $p(NLOS)$ is set to 0.2. The number of iterations of positive noise mitigation for MRWGH algorithms is around 17% smaller compared to that of LS, and around 6% smaller compared to that of RWGH.

Fig. 8 represents the average estimation error as a function of $p(NLOS)$ when the standard deviation of measurement noise is 0.01m. It is shown that if the $p(NLOS)$ increases from 0.0 (LOS) to 1.0, the performance difference among the schemes become larger. Since positive noise mitigation schemes could manage both NLOS and multi-hop ranging errors, the performance gain in NLOS case increases when the $p(NLOS)$ becomes larger. Fig. 9 shows the average number of iterations for mitigation as a function of $p(NLOS)$ for positive noise mitigation schemes when the standard deviation of measurement noise is 0.01m. It is found that the number of iterations of positive noise mitigation for MRWGH algorithms is around 16 to 18% smaller compared to that of LS, and 4 to 6% smaller compared to that of RWGH. It is demonstrated that the MRWGH algorithms improve average estimation error performance compared to the LS and RWGH for both positive noise mitigation and no mitigation cases, and reduce the necessary number of iterations for positive noise mitigation case. Also, the positive noise mitigation schemes provide around 28 to 42% error mitigation effect compared to the no mitigation schemes.

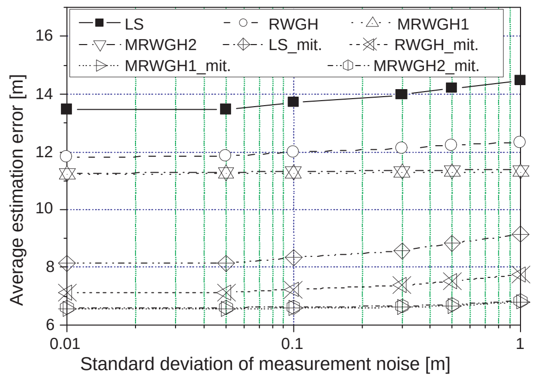

Fig. 6. Average estimation error as a function of standard deviation of measurement noise (mixed LOS/NLOS case, $p(NLOS)$ is 0.2)

6 Concluding Remarks

The multi-hop ranging often involves positive multi-hop noise as well as NLOS and Gaussian measurement noise, so that it is more prone to ranging error than one-hop range. In this paper, RWGH algorithm was modified by adapting weighted residual normalization considering the number of hops taken to measure each ranging. The iterative positive noise mitigation schemes were further developed by DET to mitigate the multi-hop ranging noise. The proposed schemes were compared to LS and RWGH algorithms in terms of average estimation error and the number of positive noise mitigations. It was demonstrated that the proposed MRWGH algorithms improve average estimation error performance compared to the LS and RWGH for both positive noise mitigation and no mitigation cases, and reduce the necessary number of iterations for positive noise mitigation case. Also, the positive noise mitigation schemes provide around 28 to 42% error mitigation effect compared to the no mitigation schemes.

Acknowledgment

This research was supported by the MIC(Ministry of Information and Communication), Korea, under the ITRC(Information Technology Research Center) support program supervised by the IITA(Institute of Information Technology Assessment) (IITA-2005-(C1090-0502-0030))

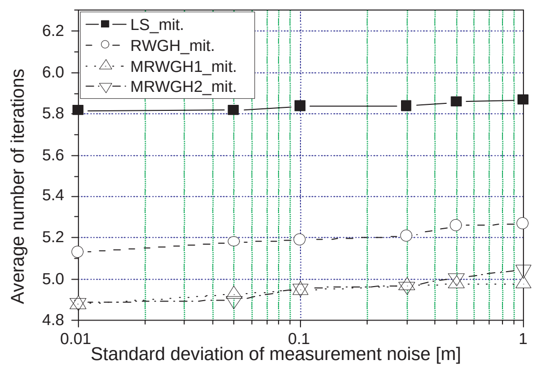

Fig. 7. Average number of iterations for mitigation as a function of standard deviation of measurement noise for positive noise mitigation schemes (mixed LOS/NLOS case, $p(NLOS)$ is 0.2)

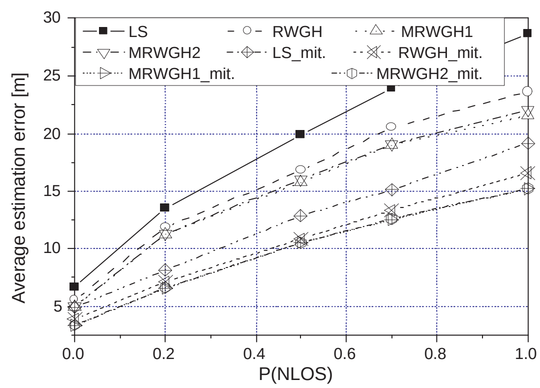

Fig. 8. Average estimation error as a function of $p(NLOS)$ (standard deviation of measurement noise is 0.01)

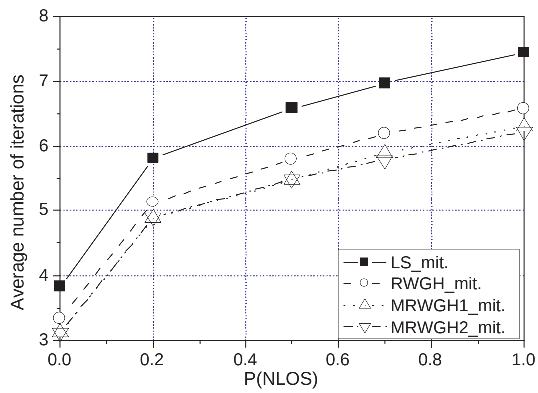

Fig. 9. Average number of iterations for mitigation as a function of $p(NLOS)$ for positive noise mitigation schemes (standard deviation of measurement noise is 0.01)

References

1. Pahlavan K., Li X., Makela J.-P.: Indoor Geolocation Science and Technology. IEEE Communications Magazine, Vol. 40. Issue 2. (2002) 112-118
2. Chen P.-C.: A Non-Line-of-Sight Error Mitigation Algorithm in Location Estimation. IEEE Wireless Communications and Networking Conference (WCNC 1999)
3. Chen P.-C.: A Cellular Based Mobile Location Tracking System. 1999 IEEE 49th Vehicular Technology Conference (VTC 99-Spring)
4. Shi Q., Correal N., Kyperountas S., Niu F.: Perofmrnace Comparison Between TOA Ranging Technologies and RSSI Ranging Technologies for Multi-hop Wireless Networks. 2005 IEEE 62nd Vehicular Technology Conference (VTC 2005-Fall)
5. Shi Q., Kyperountas S., Niu F., Correal N.: Location Estimation in Multi-Hop Wireless Networks. 2004 IEEE International Conference on Communications (ICC 2004)
6. Alavi B., Pahlavan K.: Bandwidth Effect on Distance Error Modeling for Indoor Geolocation. 14th IEEE Personal, Indoor and Mobile Radio Communications (PIMRC 2003)
7. Kannan M., Pahlavan K.: A Comparison of Wireless Geolocation Algorithms in the Indoor Environment. IEEE Wireless Communications and Networking Conference (WCNC 2004)
8. Capkun S., Hubaux J.-P.: Secure positioning of wireless devices with application to sensor networks. 24th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM 2005)
9. Wylie M.P., Holtzman J.: The non-line of sight problem in mobile location estimation. 1996 5th IEEE International Conference on Universal Personal Communications (ICUPC 96)
10. Chung W.C., Ha D.S.: An accurate ultra wideband (UWB) ranging for precision asset location. 2003 IEEE Conference on Ultra Wideband Systems and Technologies (UWBST 2003)