Proceedings of APCC2008 copyright (c) 2008 IEICE 08 SB 0083

TOA Localization using RSS Weight with Path Loss Exponents Estimation in NLOS Environments

Toshihiro Mogi
Faculty of Science and Technology
Keio University
3-14-1, Hiyoshi, Kohoku, Yokohama
223-8522 Japan

Tomoaki Ohtsuki
Faculty of Science and Technology
Keio University
3-14-1, Hiyoshi, Kohoku, Yokohama
223-8522 Japan
Email: ohtsuki@ics.keio.ac.jp

Abstract—**This paper proposes a localization algorithm that needs no priori knowledge about path loss exponents for non-line-of sight (NLOS) environments. The proposed algorithm utilizes both time-of-arrival (TOA) measurements and received-signal-strength (RSS) measurements. In the proposed localization algorithm the distances estimated with TOA measurements are weighted by the believable factor (BF) derived from the difference between the estimated distance with TOA measurements and that with RSS ones. In addition the path loss exponents are estimated for each node in a maximum likelihood (ML) manner. Simulation results show that the proposed algorithm can efficiently reduce the effect of NLOS error and achieve higher localization accuracy than the other conventional algorithms, TOA, RSS, and BF ones, without priori knowledge about the path loss exponents.**

I. Introduction

Target localization is one of the important applications of wireless sensor networks [1]. Smart disposable microsensors can be deployed on the ground, in the air, under water, on bodies, in vehicles, and inside buildings. A system of networked sensor nodes can detect and track threats and be used for targeting and monitoring. Each sensor node will have the embedded processing capability, and will potentially have multiple onboard sensors, operating in the acoustic, infrared, and magnetism. Current and potential applications of sensor networks include environmental monitoring, traffic control, food administration, tracking customers, and so on [2], [3].

A general technique of localizing a target is from measurements of time-of-arrival (TOA), time-difference-of-arrival (TDOA), angle-of-arrival (AOA), received-signal-strength (RSS), or a combination of these [4]. In TOA three or more sensor nodes measure the TOAs of the transmission from the target, each of which makes a circle, and the intersections of circles give the target location. Owing to errors in TOA measurements, the circles do not intersect at a unique point. Thus, it is necessary to find a location that best fits the measurements.

One of the other serious problems is the non-line-of-sight (NLOS) condition, where the signal arrives at a sensor node from reflections, and there is no direct or line-of-sight (LOS) path. Localization with an NLOS TOA can lead to large estimation errors [5].

There are two methods to cope with the NLOS condition. The first method localizes with all LOS and NLOS condition sensor nodes, but provides weighting or scaling to minimize the effects of the NLOS contributions [6]–[8]. The advantage of this method is that there is always an estimate, even when all the sensor nodes are NLOS. The problem is that the answer can be unreliable, because NLOS errors, though reduced, are always present.

The second method attempts to identify NLOS sensor nodes and localize with only the LOS sensor nodes. Identification of LOS sensor nodes is by a probabilistic model [9], residual information [10], and so on. If the identification is correct, the accuracy is what the localization algorithm can provide, however, there is always the possibility of wrong identification. The identification requires at least three LOS sensor nodes to localize. In ideal environments where there is no noise, the estimated point is decided by more than or equal to three sensor nodes, because each circle calculated by each sensor node's measurement intersects at a unique point. However, in real environments, using RSS localization, propagation environment (path loss exponent) would be changed for place or time because of AWGN, NLOS noise, and other kinds of noise.

An localization algorithm in NLOS named believable factor algorithm (BFA) was proposed in [8]. The BFA is a kind of weighting to minimize the effects of the NLOS contributions in cellular networks and is shown to achieve the better performance than the other conventional algorithms when the assumed channel models, that is, the assumed path loss exponents are perfectly matched to the real ones. However, as written above, we often have no priori knowledge about the path loss exponents. In addition the BFA needs some assumptions that are not favorable for wireless sensor networks. First is that the Mobile Station (MS) must be surrounded by three base stations (BSs). Second is that the BFA uses only three BSs to localize the MS.

In this paper, we propose a localization algorithm that needs no priori knowledge about the path loss exponents for NLOS environments. The proposed algorithm utilizes both TOA and RSS measurements. In the proposed localization algorithm the distances estimated with TOA measurements are weighted by the believable factor (BF) derived from the difference between the estimated distance with TOA measurements and that with RSS ones. In addition the path loss exponents are estimated for each node in a maximum likelihood (ML) manner. Simulation results show that the proposed algorithm can efficiently reduce the effect of NLOS error and achieve higher localization accuracy than the other conventional algorithms, TOA, RSS, and BF ones, without priori knowledge about the path loss exponents.

The remainder of the paper is organized as follows. The received measurement model is outlined in Section II. The proposed algorithm is outlined in Section III. The simulation results are discussed in Section IV, followed by some concluding remarks in Section V.

II. Received Measurement Model

We consider a two dimensional sensor field, where n sensor nodes and one target exist. At each sensor node, the TOA measurement determines a circle centered at the sensor node and the radius is equal to the TOA measurement multiplied by the light speed. If there is no NLOS errors and measurement noises, the target must locate on each circle, thus, the intersection of three such circles is its position.

The true distance between the sensor node i and the target is described as

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

where (x, y) is the real position of the target, (x_i, y_i) is the position of the sensor node i.

The TOA measurement for the sensor node i is described as [4]

$$t_i = \frac{R_i}{v_c} + w_d + u_i \tag{2}$$

where the sensor node i is contaminated with the TOA measurement noise w_d and the NLOS range error u_i. w_d is AWGN (additive white Gaussian noise), whose distribution is the normal probability distribution function $\mathcal{N}(0, \delta_d^2)$ with zero-mean and the variance of the TOA measurement noise δ_d^2. The sensor node i in NLOS condition is contaminated with not only w_d but also u_i. u_i is modeled as positive random uniform distribution variable, whose distribution is $\mathcal{U}(0, u_{\mathrm{MAX}})$ where u_{MAX} represents the maximum possible bias of NLOS range error [11].

Under NLOS condition, the estimation accuracy of the TOA estimation degrades. The obstacles block the direct path from the target to the sensor node, and the sensor node under NLOS condition gets larger measurement than that under LOS condition owing to the diffracted or reflected path. Fig. 1 shows an example of TOA measurements under LOS and NLOS conditions. In the figure, the estimated distances between the sensor nodes and the target are shown by the circles. In NLOS condition, the circles become larger than those in LOS condition owing to the obstacles block [8].

The RSS measurement for the sensor node i in dBm is described as [12]

$$P_i = P_0 - 10\kappa_i \log_{10} \frac{R_i}{r_0} + w_r \tag{3}$$

where P_0 is the RSS measurement at unit distance r_0 from the target. κ_i is the path loss exponent, which is set to the sensor node i. The κ_i takes generally, the value within the range from 2.0 to 4.0 and it may change according to the environments [4]. w_r is AWGN, whose distribution is $\mathcal{N}(0, \delta_r^2)$. δ_r^2 is the variance of the RSS measurement noise.

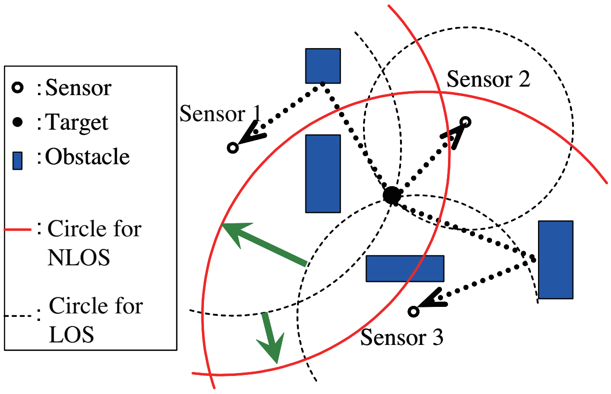

Fig. 1. An example of TOA measurements under LOS and NLOS conditions

III. Conventional Localization Algorithm in NLOS

In this section, we will introduce a conventional localization algorithm in NLOS condition [8].

A. Believable Factor Algorithm (BFA) [8]

BFA is the localization algorithm for cellular networks, where three stationary BSs (Base Stations) are used for localization. There are some assumptions need for the BFA algorithm: At any instant, not more than one BS is LOS; each pair of overlapping range circles intersects at two distinct points, thus, the three circles form an area where the MS (Mobile Station) location is.

Believable factor (BF) is calculated by the distances estimated with the TOA and RSS measurements, and it represents the degree of reliability for measurement.

In [8] the BFA is evaluated with COST231-Walfish-Ikegami model [13]. Given the received power and the path loss models under LOS and NLOS conditions, the estimated distance $r_{\mathrm{LOS}i}$ and $r_{\mathrm{NLOS}i}$ are calculated as

$$r_{\mathrm{LOS}i} = 10^{(L_i - C_1)/26} \tag{4}$$

$$r_{\mathrm{NLOS}i} = 10^{(L_i - C_2)/38} \tag{5}$$

where C_1, C_2 are the parameters dependent on the carrier frequency, antenna heights of MS and BS, signal incident angle, and MS moving direction,and so on. L_i (dB) is the estimated path loss converted from the received power.

The BF is given by [8]

$$\alpha_i = \begin{cases} 1 - \dfrac{|r_{\mathrm{NLOS}i} - d_i|}{d_i}, \\ (|r_{\mathrm{NLOS}i} - d_i| \ll |r_{\mathrm{LOS}i} - d_i| \ \&\ d_i \geq r_{\mathrm{NLOS}i}) \\ 1 - \dfrac{|r_{\mathrm{NLOS}i} - d_i|}{r_{\mathrm{NLOS}_i}}, \\ (|r_{\mathrm{NLOS}i} - d_i| \ll |r_{\mathrm{LOS}i} - d_i| \ \&\ d_i < r_{\mathrm{NLOS}i}) \\ 1 - \dfrac{|r_{\mathrm{LOS}i} - d_i|}{d_i}, \\ (|r_{\mathrm{LOS}i} - d_i| \ll |r_{\mathrm{NLOS}i} - d_i| \ \&\ d_i \geq r_{\mathrm{LOS}i}) \\ 1 - \dfrac{|r_{\mathrm{LOS}i} - d_i|}{r_{\mathrm{LOS}_i}}, \\ (|r_{\mathrm{LOS}i} - d_i| \ll |r_{\mathrm{NLOS}i} - d_i| \ \&\ d_i < r_{\mathrm{LOS}i}) \end{cases} \tag{6}$$

where $d_i = t_i v_c$. As long as the path loss model approximates the propagation condition quite well, the BFA will not deteriorate the optimizing result, and concluded to be

$$\begin{aligned}&\min_{\mathbf{X}} f(\mathbf{X}) = (1-\alpha_1) \parallel \mathbf{X}-\mathbf{X}_{\mathrm{A}} \parallel^2 + \\ &(1-\alpha_2) \parallel \mathbf{X}-\mathbf{X}_{\mathrm{B}} \parallel^2 + (1-\alpha_3) \parallel \mathbf{X}-\mathbf{X}_{\mathrm{C}} \parallel^2\end{aligned} \quad (7)$$

where $\mathbf{X}$ and $\mathbf{X}_{\mathrm{A,B,C}}$ are the two dimensional vectors, $\mathbf{X} = (x, y)$, $\mathbf{X}_{\mathrm{A,B,C}} = (x_{\mathrm{A}}, y_{\mathrm{A}}), (x_{\mathrm{B}}, y_{\mathrm{B}}), (x_{\mathrm{C}}, y_{\mathrm{C}})$. A, B and C are intersections of three circles. $\parallel \bullet \parallel$ indicates the distance norm.

The BFA is presented for mobile location estimation using only three BSs in the absence of LOS paths. Simulation results show that, for the cells of 1 km radius, the positioning accuracy of BFA is much higher than that of the conventional algorithm, if the assumed path loss models match the real ones.

IV. Proposed Algorithm

A. TOA Localization

We use n sensor nodes to localize a target. The sensor field is delimited like the grid, and likelihood, which represented by RMSE (root mean square error) is calculated at all the grid points. The grid point where the likelihood takes the largest is decided to be the estimated point. RMSE is calculated by the difference between the estimated distance and the distance between the candidate grid point and each sensor node position.

The TOA localization is described as

$$d_i = t_i \cdot v_c \quad (8)$$

$$\delta_{g,i} = \sqrt{(x_i - x_g)^2 + (y_i - y_g)^2} \quad (9)$$

$$e_t = \sqrt{\frac{\sum_{i=1}^{n} (\delta_{g,i} - d_i)^2}{n}} \quad (10)$$

$$\hat{\mathbf{X}}_t = \arg\min_{\mathbf{X}_t} \ e_t \quad (11)$$

where d_i is the estimated distance between the sensor node i and the target using TOA localization including errors. (x_g, y_g) is the candidate grid point. e_t is the RMSE using TOA localization, and $\hat{\mathbf{X}}_t$ is the estimated position vector using TOA localization.

If there are some sensor nodes under NLOS condition, estimated accuracy is greatly deteriorated.

B. RSS Localization and Attenuation Constants Estimation

The RSS localization and the attenuation constants estimation are described as

$$r_i = 10^{h(\kappa_i)} \quad (12)$$

$$h(\kappa_i) = \left(\frac{P_0 - P_i}{10\kappa_i} + 10\log_{10} r_0\right) \quad (13)$$

$$e_r = \sqrt{\frac{\sum_{i=1}^{n} (\delta_{g,i} - r_i)^2}{n}} \quad (14)$$

$$< \hat{\mathbf{X}}_r, \hat{\kappa} > = \arg\min_{\mathbf{X}_r, \kappa} \ e_r \quad (15)$$

where r_i is the estimated distance between the sensor node i and the target using RSS. κ_i is the attenuation constant, which is inherent to the sensor node i. κ_i takes generally the value within the range from 2.0 to 4.0 and may change according to the environments [4]. κ is $\kappa = \{\kappa_1, \kappa_2, \cdots, \kappa_n\}$. e_r is the RMSE using RSS localization, and $\hat{\mathbf{X}}_r$ is the estimated position vector using RSS localization.

TABLE I
SIMULATION PARAMETERS

Sensor field	13.0 × 14.0 m
Number of Targets	1 (random location)
Number of Sensor nodes	5, 7 (random location)
Path loss exponent [8]	LOS: 2.6, NLOS: 3.8
RSS measurement at unit distance	0 dBm
TOA NLOS uniform distribution noise	$\mathcal{U}$ (0, 1.60×10^{-8})
TOA normal distribution noise [14]	$\mathcal{N}$ (0, $(1.70)^2$)
RSS normal distribution noise [14]	$\mathcal{N}$ (0, $(6.1\times10^{-9})^2$)
Step size of field grid	1.0
Path loss exponent step size	0.2

C. Believable Factor (BF) and Objective Function

The proposed BF of the sensor node i is defined by

$$\alpha_i = \begin{cases} 1 - \dfrac{\mid r_i - d_i \mid}{d_i} & , \ d_i \geq r_i \\ 1 - \dfrac{\mid r_i - d_i \mid}{r_i} & , \ d_i < r_i \end{cases} \quad (16)$$

which shows how believable the measurement is. The BF nearer 1 is more reliable, and that nearer 0 is less reliable. In the proposed localization algorithm the signal attenuation constants are estimated so that the proposed BF is written in simple form, compared to the conventional one. Finally, the weighted BF objective function is described as

$$e_{tw} = \sqrt{\frac{\sum_{i=1}^{n} (\delta_{g,i} - \alpha_i d_i)^2}{n}} \quad (17)$$

$$\hat{\mathbf{X}} = \arg\min_{\mathbf{X}} \ e_{tw} \quad (18)$$

where e_{tw} is the RMSE using TOA localization of BF weight, and $\hat{\mathbf{X}}$ is the final estimated target position vector. In the conventional BFA, the objective function is defined as eq. (7), which needs intersections of circles. This assumption is disadvantage for sensor networks, because there are often the cases where no intersections exist so that the conventional BFA cannot be applied. The proposed algorithm with eqs. (17) and (18) can be applied to the cases where no intersections exist.

V. Simulation Results

The performance of the proposed algorithm is evaluated by computer simulation. Simulations are done in two cases. In the first case, we assume that there are five sensor nodes at random position. In the second case, we assume that there are seven sensor nodes at random position. We list simulation parameters in Table I.

Figs. 2 and 3 show the estimation error using 5 sensor nodes. Fig. 2 shows the results of using 2 LOS sensor nodes and 3 NLOS sensor nodes. Fig. 3 shows the results of using 5 NLOS sensor nodes. In all the figures, the abscissa axis shows the estimation error between the

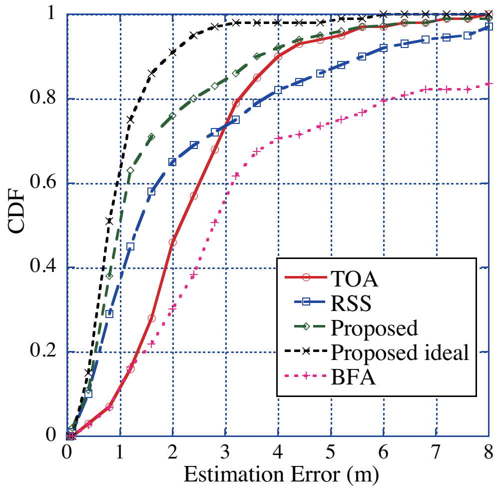

Fig. 2. Comparison of estimation error distribution, LOS sensor nodes: 2, NLOS sensor nodes: 3, number of sensor nodes: 5

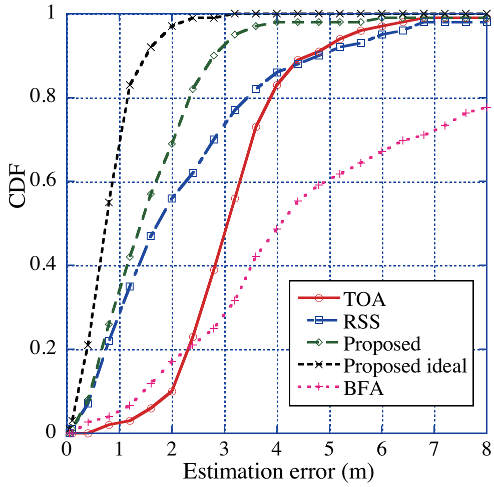

Fig. 3. Comparison of estimation error distribution, LOS sensor nodes: 0, NLOS sensor nodes: 5, number of sensor nodes: 5

real target position and the estimated one, the vertical axis shows the CDF (Cumulative Distribution Function) of estimation error. In all the figures, "TOA" uses only TOA localization, "RSS" uses only RSS localization with the estimated path loss exponent for each sensor node, "Proposed" represents the performance of the proposed scheme with the estimated path loss exponents, "Proposed ideal" represents the performance of the proposed scheme when the path loss exponents are perfectly known, "BFA" represents the performance of the conventional BFA with three sensor nodes and the estimated path loss exponents. In all the figures we can see that the proposed scheme achieves better performance than the other conventional schemes. This is because in the proposed scheme the TOA estimation is weighted by its reliability so that the effects of NLOS is reduced. In addition the proposed scheme can localize using more than three sensor nodes. Thus, the proposed scheme can achieve the better performance. The reason why the conventional BFA has worst performance is as follows. In the conventional BFA two intersections of two circles are calculated and one intersection nearer to the remaining sensor node is selected. If the target is not surrounded by three sensor nodes, the wrong intersection wrongly selected with higher probability and thus the estimation accuracy becomes worse. In addition the conventional BFA uses only three sensor nodes for localization. Thus, the conventional BFA has the worst performance. Note that the conventional BFA is for the cellular systems. The reason why TOA has worse performance than RSS is as follows. RSS in this paper uses the estimated path loss exponents so that the MSE of the distance becomes small. TOA in this paper uses no way to modify the NLOS error or AWGN error. Thus, TOA has worse performance than RSS.

Figs. 4 and 5 show the estimation error using 7 sensor nodes. Fig. 4 shows the result of using 3 LOS sensor nodes and 4 NLOS sensor nodes. Fig. 5 shows the result of using 5 LOS sensor nodes and 2 NLOS sensor nodes. Figs. 4 and 5 are similar to Figs. 2 and 3 about performances.

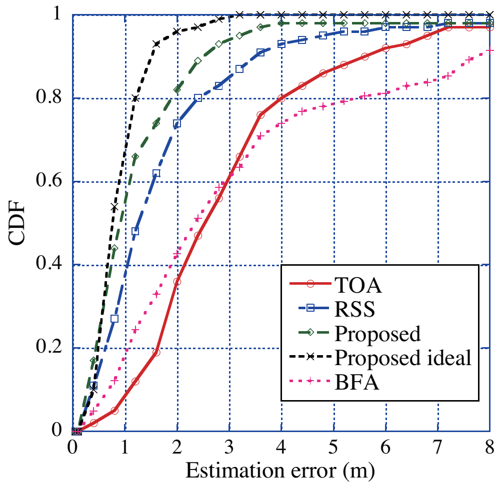

Fig. 4. Comparison of estimation error distribution, LOS sensor nodes: 3, NLOS sensor nodes: 4, number of sensor nodes: 7

VI. Conclusion

We propose a novel localization algorithm based on time-of-arrival (TOA) measurements, received-signal-strength (RSS) measurements, path loss exponents estimation, and believable factor (BF), which describes how believable a TOA range measurement is, for sensor networks in LOS and NLOS conditions. The proposed algorithm has no need to discriminate between LOS and NLOS range measurements. Simulation results show that the proposed algorithm can efficiently reduce the effect of NLOS error and can achieve higher localization accuracy than the other conventional algorithms, TOA, RSS, and BF algorithms in NLOS conditions. The proposed algorithm has high localization accuracy without the knowledge of path loss exponents, which is particularly important in practical situations.

References

[1] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," *IEEE Communications Magazine,* vol. 40, no. 8, pp. 102–114, Aug. 2002.

[2] C. Y. Chong and S. P. Kumar, "Sensor networks: evolution, opportunities, and challenges," *Proceedings of the IEEE,* Vol. 91, pp.1247–1256, Aug. 2003.

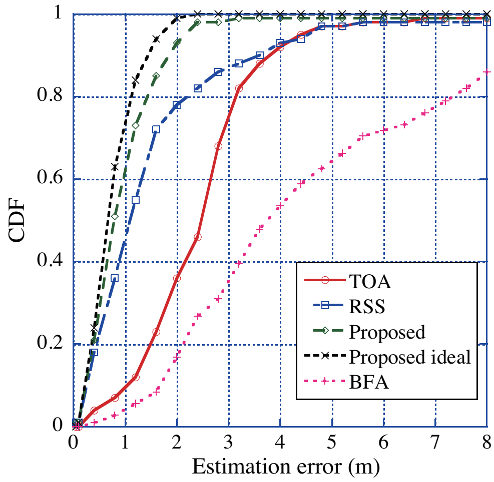

Fig. 5. Comparison of estimation error distribution, LOS sensor nodes: 5, NLOS sensor nodes: 2, number of sensor nodes: 7

[3] Wireless Sensor Network. Available: MOTE http://www.xbow.jp/motemica.html

[4] N. Patwari, J. N. Ash, S. Kyperountas, A. O. Hero III, R. L. Moses, and N.S. Correal, "Locating the nodes: cooperative localization in wireless sensor network," *IEEE Transactions Signal Processing Magazine.,* pp.54–69, July 2004

[5] A. H. Sayed, A. Tarighat, and N. Khajehnouri, "Network-based wireless location," *IEEE Transactions Signal Processing Magazine.,* pp.24–40, July 2005.

[6] W. Wei, X. J. Yu, and Z. Z. Liang, "A new NLOS error mitigation algorithm in location estimation," *IEEE Trans. on Vehicular Technology.,* Vol. 54, no. 6, pp. 2048–2053, Nov. 2005.

[7] C. H. Lin, J. Y. Cheng, and C. N. Wu, "Mobile location estimation by density-based clustering for NLoS environments," *IEEE AINA,* 2006.

[8] H. Yan, H. Han-ying, and Z. Shan, "A TOA based believable factor mobile location algorithm," *IEEE WCNC.* pp. 260–263, 2004.

[9] J. Borras, P. Hatrack, and N. B. Mandayam,"Decision theoretic framework for NLOS identification," *Proc. IEEE Vehicular Technology Conference*, 1998.

[10] Y. T. Chan, W. Y Tsui, H. C. So, and P. C. Ching, "Time-of-arrival based localization under NLOS conditions," *IEEE Transactions on Vehicular Technology*, vol. 55, no. 1, Jan. 2006.

[11] S. Slijepecevic, S. Megerian, and M. Potkonjak, "Location errors in wireless embedded sensor networks: sources, models, and effects on applications." ACM Mobile Computing and Communications Review, vol. 6, No. 3, pp. 67–78, 2002.

[12] N. Kitakoga and T. Ohtsuki, "Distributed EM algorithms for acoustic source localization in sensor networks," *IEEE Vehicular Technology Conf.,* Sep. 2006.

[13] L. Gordon and G. Stuber, Principles of mobile communication, *Kluwer Academic Publishers*, 1996.

[14] N Patwari, A. O. Hero III, M. Perkins, N. S. Correal, and R. J. O'Dea "Relative location estimation in wireless sensor networks," *IEEE Transactions Signal Processing*, vol. 51, no. 8, Aug. 2003.