RF-Based Location Determination in Heterogenous Sensor Networks Using Rayleigh Fading Channel

Sabit Ekin and Aly I. El-Osery
Department of Electrical Engineering
New Mexico Tech
Socorro, NM 87801
Email:elosery@ee.nmt.edu

Wael Abd-Almageed
Institute for Advanced Computer Studies
University of Maryland
College Park, MD 20742
Email: wamageed@umiacs.umd.edu

***Abstract*—Location determination is an essential component in large sensor networks. In those types of networks, sensors are data centric, and hence, the location of each sensor is critical. Furthermore, the need for a cost-effective means for sensor localization eliminates a variety of options including GPS. In this paper, we use particle filters for estimating the location of sensors assuming a noisy Rayleigh fading channel. Simulation results show that the algorithm converges to approximately two-meter error range.**

I. Introduction

In recent wireless sensor networks technology, localization of both mobile and stationary nodes gained a lot of interest [1]–[14]. Over the past few years researchers have investigated a variety of localization approaches which differ based on environment, cost, computational capabilities, etc. These approaches may be classified into few key subgroups such as indoor environment [5], [10], [14] or outdoor environment [4], [9] and calibration-free techniques [1], [14] or calibration-based techniques [5]. In addition, there are key methods used for any of the above subgroups or a combination thereof. RF-based methods for sensor localization are very popular because radio-frequency is employed in a faded channel, angle-of-arrival (AOA) [6], [10], time-of-arrival (TOA), time-difference-of-arrival (TDOA) [11], [12] and received-signal-strength (RSS) [1]–[3], [7]–[9], [13], [14].

Due to the proliferation of wireless transmitters with received signal strength indicators, The use of RF-based approaches provide a cost effective approach. On the other hand, other approaches, e.g., TOA, TDOA and AOA approaches need special hardware, such as synchronization devices and/or smart antennas [13], [14], hence, costing more.

In RF-based approaches, e.g. [1]–[3], [8], [9], [12]–[14], there is a direct proportion between the RSS and the distance between the transmitter and receiver nodes, and through triangulation the location may be determined. The main issue in RF channels is the channel fading effects that distort the signal making it very challenging to determine the distance (see Figure 1). The most realistic scenario for small-scale channel fading is when there is no direct line-of-sight component present in the received signal that is called Rayleigh fading [1]–[3], [7]–[9]. In this paper, we propose a calibration-free RF-based method to localize sensor nodes using particle filters and the RSS between mobile (anchor) and sensor nodes.

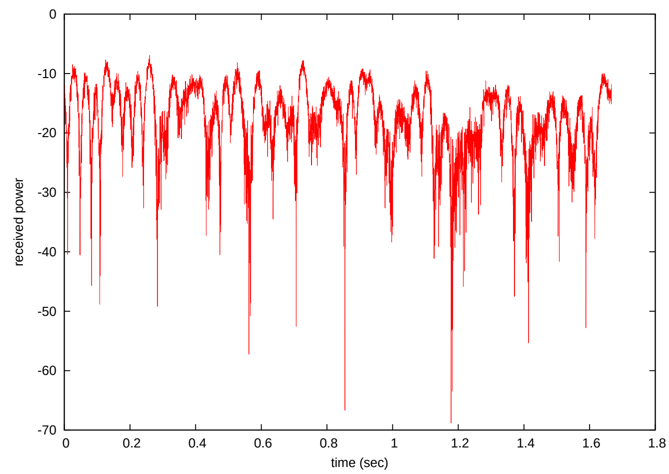


Fig. 1: Example of received power through noisy Rayleigh fading channel

In [1] we have presented an approach using importance sampling (also known as particle filters) that is capable of localizing nodes assuming Rician channel. In this paper we present an importance sampling approach to localization that uses received power prediction to tackle Rayleigh fading channels. Moreover, we design a received power level prediction algorithm. In our system we assume the use of a number of moving nodes, will be referred to as anchor nodes, with some computational capability that are used to localize stationary sensor nodes.

This paper is organized as follows. Our proposed approach is introduced in Section II. The channel model used in the simulation is discussed in Section III. The prediction algorithm used to predict the channel variation is presented in Section IV. In Section V, particle filter is introduced and our localization algorithm is developed. Results are provided in Section VI followed by conclusion in Section VII.

II. Proposed Approach

In our research we assume the use of very small sensor with limited computational capabilities along with anchor nodes (e.g. autonomous mobile robots) that have much higher

$$
\begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ \vdots \\ h_N \end{bmatrix} = \begin{bmatrix} R_{\beta^2}(0) & R_{\beta^2}(1) & R_{\beta^2}(2) & \cdots & R_{\beta^2}(N-1) \\ R_{\beta^2}(1) & R_{\beta^2}(0) & R_{\beta^2}(1) & \cdots & R_{\beta^2}(N-2) \\ R_{\beta^2}(2) & R_{\beta^2}(1) & R_{\beta^2}(0) & \cdots & R_{\beta^2}(N-3) \\ \vdots & \vdots & \vdots & & \vdots \\ R_{\beta^2}(N-1) & R_{\beta^2}(N-2) & R_{\beta^2}(N-3) & \cdots & R_{\beta^2}(0) \end{bmatrix}^{-1} \begin{bmatrix} R_{\beta^2}(1) \\ R_{\beta^2}(2) \\ R_{\beta^2}(3) \\ \vdots \\ R_{\beta^2}(N) \end{bmatrix} \tag{1}
$$

processing power. The motion of the anchor nodes will proof beneficiary in overcoming the channel limitations. Given this environment, the sensor nodes will transmit to the anchor nodes. The anchor nodes will measure the received signal strength and proceed with the localization algorithm that will be discribed shortly.

III. Channel Model

In a typical mobile-radio situation, there is a relative movement between the transmitter and the receiver. This movement is usually in such a way that the direct line between them may be obstructed. Therefore, the mode of propagation of the electromagnetic energy from the transmitter to the receiver will be largely by way of scattering, either by reflection from flat sides of the buildings or by diffraction around such buildings. Due to the relative motion between the transmitter and receiver, Doppler shift is introduced. Clarke's model [15] deduced the statistical characteristics of the fields and signals in the reception of radio frequencies by a receiver from a scattering propagation model. The random received signal envelope has a Rayleigh distribution given by

$$
p(r) = \begin{cases} \frac{r}{\sigma_r} \exp\left(-\frac{r^2}{2\sigma_r^2}\right) & (0 \le r \le \infty), \\ 0 & (r < 0), \end{cases} \tag{2}
$$

where σ_r is the rms value of the received voltage signal, and $r(t)$ is the complex envelope of the received signal.

For wideband fading channel, the baseband impulse response of the channel having L resolvable taps [16] is

$$
h(t) = \sum_{l=1}^{L} \xi(d,\alpha,\eta)\beta_l \delta(t-\tau_l)\exp(j\theta_l), \tag{3}
$$

where $\xi(d,\alpha,\eta)$ is a factor due to large-scale fading over the link between the transmitter and the receiver, β_l is the magnitude of the lth path of the small-scale fading channel response at time τ_l, and θ_l is phase shift of the lth path relative to the 0th path and is uniformly distributed between 0 and 2π. $\xi(d,\alpha,\eta)$ is defined as

$$
\xi^2(d,\alpha,\eta) = d^{-\alpha}10^{\eta/10}, \tag{4}
$$

where d is the distance between the transmitter and the receiver, α is the path loss exponent and η is the shadowing variable which is a normally distributed variable with zero mean and variance σ_s^2. Assuming the communication channel is of the form given in Equation (3) the average received power is given by

$$
p_r(n) = Gp_t, \tag{5}
$$

where G is the communication link and is defined as $\overline{\xi}^2(d,\alpha,\eta)\sum_{l=1}^{L}\overline{\beta_l}^2$, and p_t is the transmission power.

IV. Received Power Prediction

Taking advantage of the known spatial correlation of the received power we can derive a linear predictor that uses the past values to predict the future change of the channel. Since variations of $\bar{\beta}$ in Equation (5) is much faster compared to the other terms, we will concentrate on estimating it. Further, since large-scale fading varies much slower than small-scale fading, over a short period of time, it will be assumed constant. Consequently, we will estimate G using the autocorrelation of β^2 [17].

Assuming that we have N observations of received power, p_r, we can design a linear estimator that is optimal in the mean-square-sense as shown below.

$$
\hat{p}_r(t+1) = \sum_{i=1}^{N} h_i p_r(n-i), \tag{6}
$$

where $\hat{p}_r$ is the prediction of p_r, h_i is computed as shown in (1) [18] and

$$
R_{\beta^2}(\tau) = 1 + J_0^2(2\pi f_{md}\tau), \tag{7}
$$

where $J_0(\cdot)$ is the zero-order Bessel function of the first kind.

V. Particle Filter

The system may be modeled using discrete-time state-space representation. Using $\mathbf{x}_j^t$ as the system state at time t, which represents a column vector of the relative distances between sensor node j and each of the anchor nodes. The measurement, $\mathbf{y}_j^t$, represents the received signal strengths at each of the anchor nodes from sensor node j. The system model may be written as

$$
\mathbf{x}_j^t \sim P_j(\mathbf{x}_j^t|\mathbf{x}_j^{t-1},\mathbf{n}_j^{t-1}), \tag{8}
$$

and

$$
\mathbf{y}_j^t \sim P_j(\mathbf{y}_j^t|\mathbf{x}_j^t,\mathbf{v}_j^t), \tag{9}
$$

where $P_j(\mathbf{x}_j^t|\mathbf{x}_j^{t-1},\mathbf{n}_j^{t-1})$ is the probabilistic state-transition density function, $\mathbf{n}_j^{t-1}$ is the covariance of zero-mean process noise, $P_j(\mathbf{y}_j^t|\mathbf{x}_j^t,\mathbf{v}_j^t)$ is probabilistic measurement function representing the propagation channel and $\mathbf{v}_j^t$ is the measurement noise. Our aim is to estimate recursively in time the posterior distribution $p(\mathbf{x}_j^{0:t}|\mathbf{y}_j^{1:t})$ using particle filters.

Similar to Kalman filtering [19], the idea behind particle filtering [20] [21] is to estimate the state of a given system and track this state as it evolves over time. However, in contrast to Kalman filtering, the state of the system might follow a multi-modal, non-Gaussian probability density function (pdf).

In particle filters, each sample (also known as particle) may be described by

$$\{\mathbf{s}_i^t(j),\ \pi_i^t(j);\ i=1,\ \ldots,\ N^t;\ t=1,\ \ldots,\ \infty\}, \quad (10)$$

where $\mathbf{s}_i^t(j)$ and $\pi_i^t(j)$ represent particle i at time t and its weight, respectively, such that

$$\sum_{i}^{N^t} \pi_i^t(j) = 1, \quad (11)$$

where N^t represents the number of particles and the superscript t indicates that the number of particles may vary over time. Each particle $\mathbf{s}_i^t(j)$ represents the state of sensor j at time t with probability $\pi_i^t(j)$. In our localization algorithm, the state of each sensor node is defined as a vector representing the relative distances between sensor node j and each of the actuator (anchor) nodes.

The propagation of the particles over time follows the state-transition model of (8), and hence, the particles are generated according to

$$\mathbf{s}_i^t(j) \sim \mathcal{N}(\mathbf{x}_j^{t-1}, \mathbf{n}_j^{t-1}), \quad (12)$$

where $P_j(\mathbf{x}_j^t|\mathbf{x}_j^{t-1}, \mathbf{n}_j^{t-1}) = \mathcal{N}(\mathbf{x}_j^{t-1}, \mathbf{n}_j^{t-1})$.

The initialization of the algorithm to localize node j, is as follows.

1) A guess of the sensor location $\mathbf{y}_j^0$ is obtained by using a two dimensional uniform random number generator.
2) The initial set of particles $\mathbf{s}_i^0(j)$ is generated using a 2D uniform distribution in the known area where the sensors are located

We then use the prediction algorithm in the process of estimating the next received power level and use this information in the evaluation algorithm of each particle. The particle evaluation algorithm is as follows

1) A prediction of the next received power, at $t+1$, is obtained based on (6).
2) Estimate of the small-scale fading value at time instance $t+1$
$$\hat{\beta}(t+1) = \hat{p_r}(t+1)/\bar{p}_r, \quad (13)$$
where $\bar{p}_r$ is the mean of the received power p_r.
3) As the motion of the anchor nodes is known the distance between all of the particles and the anchor nodes are known. Using these distances an estimate of the next received power based on the new position of each anchor node and the location of the particles is computed as follows
$$\hat{p_j}(n+1) = \hat{\beta}(t+1) d_{ik}^{-1/\alpha}, \quad (14)$$
where d_{ik} is the distance between particle i and anchor node k.
4) Get new value of received power from anchor node k, compute the absolute value of the error between the received power and the estimated power at each particle as shown below
$$E_{ik} = |p - \hat{p}|. \quad (15)$$
5) Using a triangulation algorithm an estimate of the sensor position is made by using the mean of $\hat{p}$ corresponding to the particle with the minimum median of the error given above.
6) The inverse of the error between this estimate and the particle location is used as the importance weight to estimate the initial density $\hat{p}(\mathbf{s}_i^0(j))$.

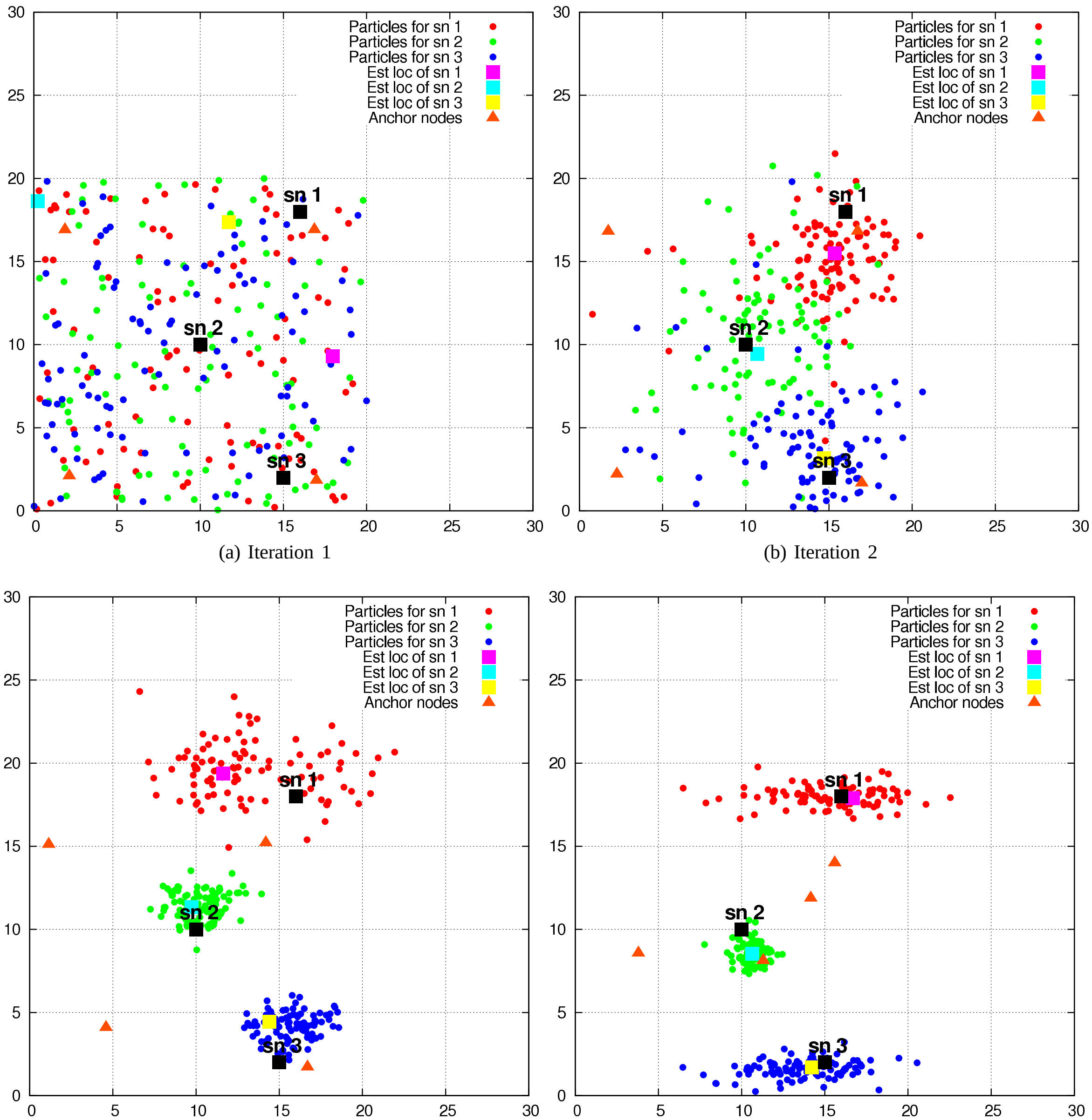
The main loop of the algorithm works in a similar fashion. At each time step, an estimate of the node location $\mathbf{y}_j^t$ is computed using the triangulation algorithm. A new set of particles $\mathbf{s}_i^t(j)$ is generated according to (12) where $\mathbf{n}_j^{t-1}$ is adaptive noise covariance. This selection step eliminates the particles having low importance weights and multiplying particles having high importance weights [20]. At each time step t, the node location is updated as shown in (16)

$$\mathbf{x}_j^t = \sum_{i=1}^{N^t} \pi_i^t(j)\ \mathbf{s}_i^t(j). \quad (16)$$

To summarize, the algorithm simply iteratively eliminates particles that exhibit high error with respect to the observed position $\mathbf{y}_j^t$ and samples more of the particles that consistently exhibit low error. Following is a pseudo-code of the localization algorithm.

ALGORITHM: LOCALIZE_SENSOR(j)

1) *Initialization*
   - Compute the initial node locations using the received signal strength and triangulation.
   - Sample $\mathbf{s}_i^0 \sim \hat{p}(\mathbf{s}_i^0); i=1,\ldots,N_0$, where $\hat{p}(\mathbf{s}_i^0)$ is a Gaussian probability density function.
2) *Importance sampling step*
   - For $i=1,\ldots,N_t$, sample $\mathbf{s}_i^t(j) \sim \mathcal{N}(\mathbf{x}_j^{t-1}, \mathbf{n}_j^{t-1})$,
   - For $i=1,\ldots,N_t$, evaluate the importance weights.
   - Normalize the importance weights.
3) *Selection step*
   - Resample according to importance weights.
   - Set $t \leftarrow t+1$ and go to step 2.



(a) Iteration 1

(b) Iteration 2

(c) Iteration 20

(d) Iteration 94

Fig. 2: Snapshots of the simulation at different iterations using 4 anchor nodes

TABLE I: Mean of distance error for various noise levels

Noise variance	3 anchor nodes (m)	4 anchor nodes (m)
0.01	2.7476	1.9963
0.05	2.5885	2.0097
0.10	2.6440	2.0697
0.15	2.6771	2.0837
0.20	2.6139	2.0721

TABLE II: Variance of distance error for various noise levels

Noise variance	3 anchor nodes (m)	4 anchor nodes (m)
0.01	0.43334	0.23434
0.05	0.40130	0.23498
0.10	0.41605	0.26605
0.15	0.41630	0.25832
0.20	0.40296	0.24563

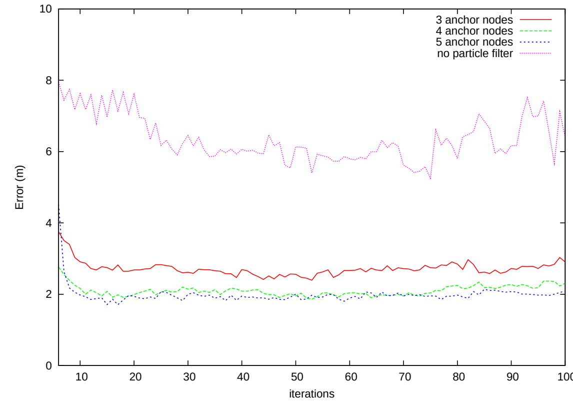


Fig. 3: Distance error results using particle filters with 3, 4, 5 anchor nodes, and using no particle filters with 4 anchor nodes.

VI. Simulation and Results

In order to demonstrate our algorithm several simulations have been designed. A random motion scenario is created where the nodes move in a random direction till they reach the edge of the simulation area then change to another random. A Rayleigh fading channel is implemented based on [22] using a Doppler shift $f_m = 20$.

Snapshots of the simulation and convergence of the particles is shown in Figure 2. The simulation was run for three, four and five anchor nodes. In order to get good statistical data, each simulation is run 100 times. The distance error for each of the cases of three, four and five anchor nodes is shown in Figure 3. These results are compared with the case when no particle filters is used and the received power is averaged. Tables I and II shows the mean and variance of the errors. It is important to point out that the variations shown in the table are very small even though the variance of the noise has been increased. This is attributed to the particle filters.

VII. Conclusion

Localization is a very critical problem in sensor networks. Several approaches are available to determine the location of the sensor nodes. Most of these algorithms require extra hardware resulting in higher costs which is not feasible for large networks. Due to advances in wireless technologies, most wireless transceivers provide received signal strength indicators. Consequently, developing RF-based localization algorithm provide a cost effective approach. On the other hand, due to the fast fluctuations in the propagation channel due to large- and small-scale fading, RF-based localization is very challenging.

In this paper we have presented a RF-based localization approach using particle filters. It was shown through simulation that localization with three anchor nodes results in an average error of approximately 2.5m and 2m using five anchor nodes. Furthermore, due to the use of particle filters the increase in the channel noise variance does not affect the results.

References

[1] A.I. El-Osery, W. Abd-Ablmageed, and M. Youssef, “Calibration-free rf-based localization algorithm for actuator sensor networks using particle filters,” *IEEE Antennas and Propagation Magazine*, vol. 48, no. 4, pp. 166–173, August 2006.

[2] D. Koutsonikolas, S.M. Das, Y.C. Hu, L. Yung-Hsiang, and C.S.G. Lee, “Cocoa: Coordinated cooperative localization for mobile multi-robot ad hoc networks,” in *26th IEEE International Conference on Distributed Computing Systems Workshops*, July 2006, pp. 9–9.

[3] Y. Kiran, K. Bhaskar, R. Sharmila, and S. Bhaskar, “Ecolocation: a sequence based technique for rf localization in wireless sensor networks,” *Fourth International Symposium on Information Processing in Sensor Networks*, p. 285292, 2005.

[4] W. Christian, M. Andreas, T. Hashem, and Z. Andreas, “Fast outdoor robot localization using integral invariants,” in *Proceedings of the 5th International Conference on Computer Vision Systems*, 2007.

[5] M. Ocaa, L. M. Bergasa, M.A. Sotelo, J. Nuevo, and R. Flores, “Indoor robot localization system using wifi signal measure and minimizing calibration effort,” *Proceedings of the IEEE International Symposium on Industrial Electronics*, vol. 2, pp. 1545–1550, June 2005.

[6] B. Jehoshua, G. Jie, and J. Anxiao, “Localization and routing in sensor networks by local angle information,” *Proceedings of the 6th ACM international symposium on Mobile ad hoc networking and computing*, pp. 181–192, 2005.

[7] P. Bergamo and G. Mazzini, “Localization in sensor networks with fading and mobility,” *The 13th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, vol. 2, pp. 750–754, 2002.

[8] S. Dezhen, Y. Jingang, and G. Zane, “Localization of unknown networked radio sources using a mobile robot with a directional antenna,” in *American Control Conference*, July 2007, pp. 5952–5957.

[9] M.L. Sichitiu and V. Ramadurai, “Localization of wireless sensor networks with a mobile beacon,” in *IEEE International Conference on Mobile Ad-hoc and Sensor Systems*, October 2004, pp. 174–183.

[10] D. Carrick, L. John, R. Daniela, and T. Seth, “Passive mobile robot localization within a fixed beacon field,” in *Seventh International Workshop on the Algorithmic Foundations of Robotics*, July 2006 2006.

[11] P. Bahl and V.N. Padmanabhan, “Radar: an in-building rf-based user location and tracking system,” in *INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies*, vol. 2, March 2000, pp. 775–784.

[12] C. Srdjan, C. Mario, and S. Mani, “Secure localization with hidden and mobile base stations,” in *INFOCOM 2006. 25th IEEE International Conference on Computer Communications. Proceedings*, April 2006, pp. 1–10.

[13] A. Dogandzic and P.P. Amran, “Signal-strength based localization in wireless fading channels,” in *Signals, Systems and Computers, 2004. Conference Record of the Thirty-Eighth Asilomar Conference*, vol. 2, November 2004, p. 21602164.

[14] L. Hyuk, K. Lu-Chuan, C.H. Jennifer, and L. Haiyun, "Zero-configuration, robust indoor localization: Theory and experimentation," in *INFOCOM 2006. 25th IEEE International Conference on Computer Communications*, April 2006, pp. 1–12.

[15] R. Clarke, "A statistical theory of mobile-radio reception," *Bell Sys. Tech. Journal*, vol. 47, pp. 957–1000, 1968.

[16] J. Proakis, *Digital Communications*. New York: McGraw-Hill, 1983.

[17] A. El-Osery, C. Abdallah, and M. Jamshidi, "Time Delay and Power Control in Spread Spectrum Wireless Networks," in *3rd IFAC Workshop on Time Delay Systems (TDS 2001)*. Santa Fe: Elsevier Science, December 2001.

[18] K. Shanmugan and A. Breipohl, *Random Signals: Detection, Estimation and Data Analysis*. New York: John Wiley & Sons, 1988.

[19] R. E. Kalman, "A new approach to linear filtering and prediction problems," *Transactions of the ASME - Journal of Basic Engineering*, vol. 82, pp. 35–45, 1960.

[20] A. Doucet, N. de Freitas, and N. Gordon, *Sequential Monte Carlo methods in Practice*, ser. Statistics for engineering and information science. New York: Springer, 2001, ch. 1, pp. 3–14.

[21] A. Doucet, C. Andrieu, and S. Godsill, "On sequential monte carlo sampling methods for bayesian filtering," *Statistics and Computing*, vol. 10, no. 3, pp. 197–208, 2000.

[22] K. E. Baddour and N. C. Beaulieu, "Autoregressive Modeling for Fading Channel Simulation," *IEEE Transactions on Wireless Communications*, vol. 4, no. 4, pp. 1650–1662, July 2005.