Effects of Shadow Fading in Indoor RSSI Ranging

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Abstract— **Received signal strength indication method enables flexible positioning without additional hardware installation and modification from communication resources. The expectation value of distance is changed due to the shadow fading. The effects of shadow fading in indoor RSSI ranging and convergence with pedestrian dead reckoning by using Extended Kalman Filter are presented. The fusion of pedestrian dead reckoning and RSSI ranging simulation shows that the compensation Shadow Fading effect has slightly less errors.**

Keywords— **Indoor Positioning, RSSI Ranging, Pathloss Mod el, Shadow Fading, Pedestrian Dead Reckoning**

I. INTRODUCTION

One of the Global Navigation Satellite System (GNSS), Global Positioning System (GPS) can satisfy outdoor positioning requirements in most cases. Because not only the vehicle navigation system but also GPS-equipped smartphone comes into wide use, the area of the navigation has been extended to individuals. However, GPS system cannot be used in GPS shadow area like indoor.

Ultrasonic wave ranging technology or positioning support communications infrastructure can support indoor positioning. However, this method must have the infrastructure in advance, positioning in areas where infrastructure is not installed is not possible. Thus, using communication resources installed in many buildings such as Wi-Fi can provide more flexible indoor positioning.

By received signal strength indication (RSSI) method, flexible positioning is possible without additional hardware installation and modification from communication resources such as Wi-Fi. But positioning with RSSI does not get the high accuracy due to the indoor radio propagation characteristics.

To improve the positioning accuracy, there are many recent studies on sensor fusion. In order to apply sensor fusion, the uncertainty of the measurement data is crucial. In this paper, we examine models of the received radio signal strength and factors that influence on RSSI ranging.

According to IEEE802.11TGn Channel Model, the wireless signal strength follows the Log-distance path loss model and log-normal shadow fading. So the effects of shadow fading in indoor RSSI ranging and convergence with pedestrian dead reckoning by using Extended Kalman Filter are presented.

This paper is organized as follows. In section II, theoretical analysis of RSSI Ranging in log-distance path loss and log-normal shadow fading is presented. In section III, positioning with inertial measurement unit is presented. In section IV, simulation results are presented. Finally, the conclusions are given in section V.

II. RSSI RANGING

The principle of the RSSI Ranging describes the relationship between transmitted power and received power of wireless signals and the distance between transmitters and receivers. If we know the received power which is a function of the distance between tx and rx, RSSI Ranging is done by using the inverse of this function.

A. RSSI-based Ranging Model

Free-space model is applicable to the following occasions:

- The transmission distance is much larger than the antenna size and the carrier wavelength λ.
- There are no obstacles between the transmitters and the receivers.

The received power can be determined by follow

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \tag{1}$$

where P_t and P_r are transmitted power and received power respectively, d is distance, G_t and G_r are antenna gain, and L is system loss factor. G_t=1, G_r=1 and L=1 are usually taken.

$$PL(dB) = 10\log\frac{P_t}{P_r} = -10\log\left[\frac{\lambda^2}{(4\pi)^2 d^2}\right] \tag{2}$$

Equation (2) is the signal attenuation formula using a logarithmic expression.

Log-normal shadow model is a more general propagation model. It provides a number of parameters which can be configured according to different environments. The pathloss of log-normal shadow model can be determined by follow

$$PL(d)(dB) = \overline{PL}(d) + X_\sigma = \overline{PL}(d_0) + 10\eta \lg\left(\frac{d}{d_0}\right) + X_\sigma \quad (3)$$

where d_0 is the near-earth reference distance which depends on the experiential value, η is a path loss index which depends on specific propagation environment, X_σ is zero-mean Gaussian random variable.

IEEE802.11TGn Channel Model using this log-normal shadow model with $\overline{PL}(d_0)$ is free-space model and other parameters as in TABLE 1.

TABLE 1. IEEE802.11TGN CHANNEL MODEL PATH LOSS MODEL PARAMETERS

New Model	d_{BP} (m)	Slope before d_{BP}	Slope after d_{BP}	Shadow fading std. dev. (dB) before d_{BP} (LOS)	Shadow fading std. dev. (dB) after d_{BP} (NLOS)
A (optional)	5	2	3.5	3	4
B	5	2	3.5	3	4
C	5	2	3.5	3	5
D	10	2	3.5	3	5
E	20	2	3.5	3	6
F	30	2	3.5	3	6

B. Log-normal Distribution

A log-normal distribution is a probability distribution of a random variable whose logarithm is normally distributed. The notation of log-normal distribution can be represented by follow

$$\ln N(\mu, \sigma^2) \quad (4)$$

Two log-normal parameters, μ and σ^2 means that the logarithm of this log-normal distributed random variable's mean and variance respectively. We can call these as the location parameter and the scale parameter respectively.

Mean and variance of the log-normal distribution can be determined by follows

$$E[X] = e^{\mu+\sigma^2/2} \quad (5)$$

$$Var[X] = (e^{\sigma^2} - 1)e^{2\mu+\sigma^2} \quad (6)$$

where $X \sim \ln N(\mu, \sigma^2)$.

C. Effects of Log-normal Shadow Fading in RSSI Ranging

Since the pathloss is linear in decibels when the distance is the log-distance, the distance measurement error due to the shadow fading is greater when the distance is farther with same shadow fading variance.

While the log-normal shadow model has Gaussian shadow fading in decibel, distance vary with the shadow fading is log-normal distribution. As shown in equation (5), expectation value of distance is changed due to the shadow fading. In this case, what we want to know is median, not mean of log-normal distributed distance. The median m can be determined by follow

$$P(X \le m) \ge \frac{1}{2} \quad \text{and} \quad P(X \ge m) \ge \frac{1}{2} \quad (7)$$

In log-normal distribution case, median m can be calculated by follow

$$m = e^{\mu} \quad (8)$$

From equation (5) and (8), relationship between mean and median of log-normal distribution can be represented by follow

$$\frac{m}{E[X]} = \frac{e^{\mu}}{e^{\mu+\sigma^2/2}} = \frac{1}{e^{\sigma^2/2}} \quad (9)$$

Ranging result from measured RSSI needs to be multiplied with equation (9). Once the shadow fading parameters are selected, this is multiplied with a constant number. In decibel, just adding a constant number is enough.

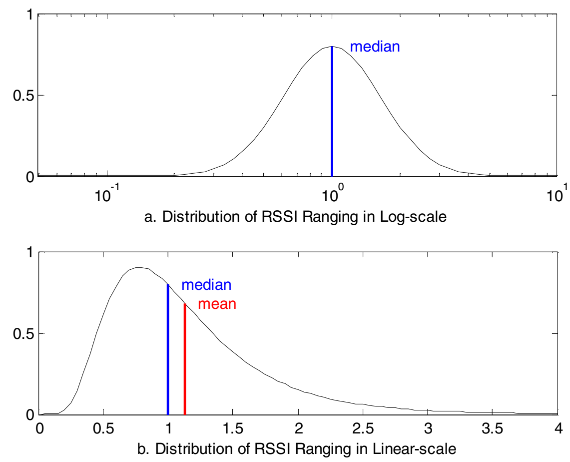


Figure 1. Ranging Variation in Log-scale and Linear-scale

III. POSITIONING WITH INERTIAL MEASUREMENT UNIT

When the pedestrian is moving, information of the location change can be linked between the past and the future positioning information.

Latest Smartphones have Gyroscope, Accelerometer and Digital Compass. These allow of executing the Pedestrian Dead Reckoning. Location change information obtained through the PDR has the measurement errors and these errors are accumulated as time goes. Thus, Extended Kalman Filter is needed to combine PDR and RSSI ranging.

A. Measured Heading & Travel Distance

We use the heading model and travel distance model by applying the Gaussian noise on each measurements. The measured heading and the measured travel distance can be represented by follows

$$\Delta\theta = \Delta\theta_{real} + n_\theta, \quad n_\theta \sim N(0, \sigma_\theta^2) \quad (10)$$

$$\Delta d = \Delta d_{real} + n_d\,, \quad n_d \sim N(0, \sigma_d^2) \tag{11}$$

where $\Delta\theta$ and $\Delta\theta_{real}$ are the measured angle change and real angle change respectively, Δd and Δd_{real} are the measured distance and real distance respectively, n_θ and n_d are measurement noise of angle change and distance respectively.

B. Extended Kalman Filter

To define the problem of tracking, consider the evolution of the state sequence $\{x_k, k \in \mathbb{N}\}$ of a target given by

$$x_k = f_k(x_{k-1}, v_{k-1}) \tag{12}$$

The objective of tracking is to recursively estimate x_k from measurements

$$z_k = h_k(x_k, n_k) \tag{13}$$

The Kalman filter assumes that the posterior density at eve time step is Gaussian and, hence, parameterized by a mean and covariance.

- v_{k-1} and n_k are drawn from Gaussian distributions of known parameters.
- $f_k(x_{k-1}, v_{k-1})$ is known and is a linear function of x_{k-1} and v_{k-1}.
- $h_k(x_k, n_k)$ is a known linear function of x_k and n_k.

That is, (12) and (13) can be rewritten as

$$x_k = F_k x_{k-1} + v_{k-1} \tag{14}$$

$$z_k = H_k x_k + n_k \tag{15}$$

F_k and H_k are known matrices defining the linear functions. The covariances of v_{k-1} and n_k are Q_{k-1} and R_k respectively.

If equation (12) and (13) cannot be rewritten in the form of (14) and (15) because the functions are nonlinear, then a local linearization of the equations may be a sufficient description of the nonlinearity. The EKF is based on this approximation. $p(x_k|z_{1:k})$ is approximated by a Gaussian

$$p(x_{k-1} \mid z_{1:k-1}) \approx N(x_{k-1}; m_{k-1|k-1}, P_{k-1|k-1}) \tag{16}$$

$$p(x_k \mid z_{1:k-1}) \approx N(x_k; m_{k|k-1}, P_{k|k-1}) \tag{17}$$

$$p(x_k \mid z_{1:k}) \approx N(x_k; m_{k|k}, P_{k|k}) \tag{18}$$

where

$$m_{k|k-1} = f_k(m_{k-1|k-1}) \tag{19}$$

$$P_{k|k-1} = Q_{k-1} + \hat{F}_k P_{k-1|k-1} \hat{F}_k^T \tag{20}$$

$$m_{k|k} = m_{k|k-1} + K_k(z_k - h_k(m_{k|k-1})) \tag{21}$$

$$P_{k|k} = P_{k|k-1} - K_k \hat{H}_k P_{k|k-1} \tag{22}$$

and where now, $f_k(\cdot)$ and $h_k(\cdot)$ are nonlinear function, and $\hat{F}_k$ and $\hat{H}_k$ are local linearizations of these nonlinear functions (i.e., matrices)

$$\hat{F}_k = \left.\frac{df_k(x)}{dx}\right|_{x=m_{k-1|k-1}} \tag{23}$$

$$\hat{H}_k = \left.\frac{dh_k(x)}{dx}\right|_{x=m_{k|k-1}} \tag{24}$$

$$S_k = \hat{H}_k P_{k|k-1} \hat{H}_k^T + R_k \tag{25}$$

$$K_k = P_{k|k-1} \hat{H}_k^T S_k^{-1} \tag{26}$$

The EKF as described above utilizes the first term in a Taylor expansion of the nonlinear function. A higher order EKF that retains further terms in the Taylor expansion exists, but the additional complexity has prohibited its widespread use.

IV. SIMULATION RESULTS

A. Scenario

The simulation scenario is presented in Figure 2. Pedestrian is walking from (0, 0) to (40, 0). RF Tag is located at (20, 5). The step length is 0.5m. The std. deviation of step length measurement noise is 0.1 std. deviation of heading measurement noise is 0.2. Std. deviation of shadow fading is 3dB.

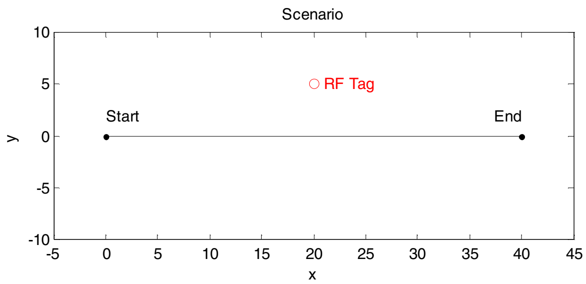
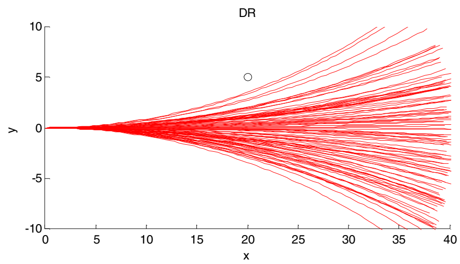


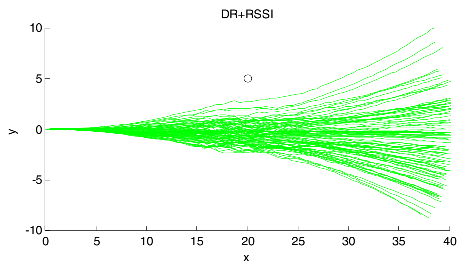
Figure 2. Simulation Scenario

B. Results

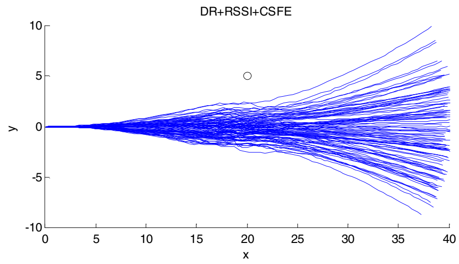
Figure 3-a. shows the simulation result of dead reckoning algorithm. It shows the errors are increasing constantly. Figure 3-b. is the simulation result of DR with RSSI Ranging. The errors are being accumulated but near the RF Tag, errors do not increased due to the RSSI ranging information. Figure 3-c. is the simulation result of DR + RSSI Ranging + Compensation SF Effect(CSFE). The errors are slightly more reduced than Figure 3-b.



a. Dead Reckoning



b. DR+RSSI Ranging



c. DR+RSSI+CSFE

Figure 3. Simulation Results

Figure 4. shows the RMS Errors of each algorithms and TABLE 2 shows the RMS Errors at travel distance 10, 20, 30 and 40 in decibel.

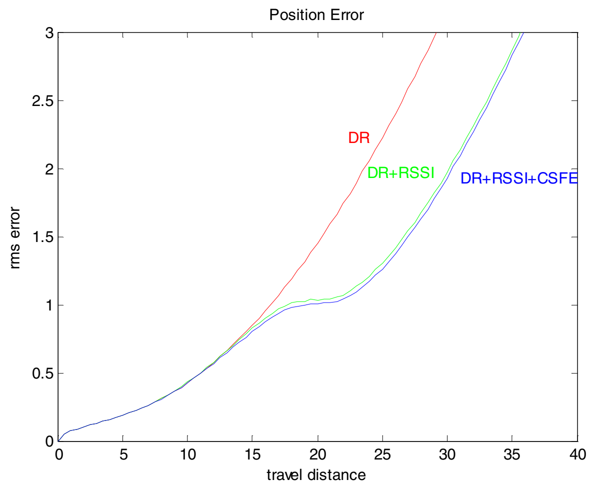


Figure 4. RMS Errors of each Algorithm

TABLE 2. RMS ERRORS OF EACH ALGORITHM

Algorithm \ Travel Distance	10	20	30	40
DR	-3.70 dB	1.61 dB	5.00 dB	7.44 dB
DR+RSSI	-3.66 dB	0.14 dB	2.95 dB	5.96 dB
DR+RSSI+ CSFE	-3.71 dB	0.02 dB	2.85 dB	5.92 dB

V. CONCLUSIONS

The RSSI Ranging error due to the Log-normal Shadow Fading is presented. The expectation value of distance is changed due to the shadow fading. The fusion of pedestrian dead reckoning and RSSI ranging simulation shows that the compensation Shadow Fading effect has slightly less errors.

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