Device-free Localization using Received Signal Strength Measurements in Radio Frequency Network

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Abstract

Device-free localization (DFL) based on the received signal strength (RSS) measurements of radio frequency (RF) links is the method using RSS variation due to the presence of the target to localize the target without attaching any device. The majority of DFL methods utilize the fact the link will experience great attenuation when obstructed. Thus that localization accuracy depends on the model which describes the relationship between RSS loss caused by obstruction and the target’s position. The existing models is too rough to explain some phenomenon observed in the experiment measurements. In this paper, we propose a new model based on diffraction theory in which the target is modeled as a cylinder instead of a point mass. The proposed model can well fits the experiment measurements and well explain the cases like link crossing and walking along the link line. Because the measurement model is nonlinear, particle filtering tracing is used to recursively give the approximate Bayesian estimation of the position. The posterior Cramer-Rao lower bound (PCRLB) of proposed tracking method is also derived. The results of field experiments with 8 radio sensors and a monitored area of 3.5m*3.5m show that the tracking accuracy of proposed model is improved by at least 36% with the single target case and 25% with the two targets case compared to other models.

Index Terms

DFL, RSS, diffraction, particle filtering, PCRLB.

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I. INTRODUCTION

Device-free localization (DFL) which enables the target attach no tags is important in many applications like security, law enforcement and rescuing operations. Conventional methods of DFL utilize video cameras, radar sensors and infrared sensor to passively localize the target. The applications of these method are restricted by the privacy concern, cost or capability of the penetration. In recent year, DFL techniques using received signal strength (RSS) measurements \cite{1}, \cite{2} have attracted great attention because RSS measurements are available in most wireless equipment like WiFi access points (APs) or easily obtained in some low-cost wireless transceivers. Therefore, RSS-based methods can be easily extended to deployed network without extra hardware. Moreover, radio signals can penetrate walls and other non-metallic structures \cite{3}. Currently, RSS-based DFL methods have already successfully demonstrated for applications such as residential or monitoring \cite{4}–\cite{6}, roadside surveillance \cite{7}, cooperative mapping \cite{8}, \cite{9}, fall detection for elder persons \cite{10}.

The concept of RSS-based DFL is originally proposed and tested in \cite{1}, \cite{11} which compares the RSS samples collected online with the radio map constructed offline. The procedure is very similar to WiFi fingerprinting for mobile user localization \cite{12}. The disadvantage is that it is time consuming to build the radio map for large-scale deployment of sensors and the method is vulnerable to the change of the environment. \cite{13} exploited the RSS dynamics due to the reflection of the target and the RF sensors were mounted on the ceiling of the room. The experiments conducted in \cite{13} achieved about 1 meter tracking accuracy. Most DFL methods use the fact the link will be greatly attenuated when the link is obstructed by the target. Inspired by X-ray tomography, Wilson formulated a method termed as radio tomographic imaging (RTI) to scan the monitored area by employing the shadowing loss of the links \cite{14}. The brightest spot in the generated image corresponds to the position of the target. The accuracy of RTI can be further improved in cluttered environments by channel diversity \cite{15}, \cite{16}, antenna diversity \cite{17} and compressive sensing \cite{8}, \cite{9}, \cite{18}. Another category of DFL method is grouped by modeling the RSS variation of the link as a function of the position of the target and the position estimation is given by Bayesian filtering which maximizes the posterior distribution of the states of the target \cite{19}–\cite{21}. Since the models are usually nonlinear, particle filtering (PF) should be employed to approximate the posterior distribution by weighted particles.

The challenge of the DFL is to accurately model the RSS variation by the presence of target. In the most literature of DFL, the target is treated as a point mass for simplicity. In \cite{19}, \cite{20}, an exponential model is formulated intuitively by fitting the experimental measurements. The exponential model is easy
to use but lack of solid theoretic foundation. Moreover, the model cannot explain the phenomenon that the link is more affected when moves closer to transmitter or receiver. [14], [21] use the elliptical model based on the LOS propagation assumption, which is too rough to accurately model the RSS variation.

The contribution of the paper is three fold. First, the target is modeled as a cylinder [22], [23] instead of a point mass. In fact, the RSS loss due to obstruction can be explained by diffraction theory [24]. Therefore, we use the knife-edge diffraction theory to model the RSS loss. Different from the one side knife-edge method in [24], the received signal is the combination from two diffraction paths passing through two lateral sides of human body. The diffraction model better matches the experiment measurements and explain the phenomenon appeared the measurements than other models. Second, since the model is highly nonlinear, a PF tracking scheme is proposed [25], [26]. For all estimation problems, the mean square error (MSE) of estimation is bounded by the Cramer-Rao lower bound (CRLB) [27] if the estimator is unbiased. For nonlinear dynamic systems where the prior distribution is known, posterior CRLB (PCRLB) can better describe the lower bound [28]. To evaluate the tracking performance, the PCRLB of the proposed tracking method is also derived. Third, real experiments are conducted to verify the effectiveness of the proposed model. Compare to other models, the proposed model achieves better tracking accuracy. In addition to a single target case, the experiment of multiple targets is also conducted. Compared to the multiple target tracking methods in [29], [30], the proposed methods still outperforms.

II. Problem Formulation

Considering $K$ wireless sensor nodes with known Cartesian coordinate $(\alpha_k, \beta_k)$, $k = 1, 2, \ldots, K$ are uniformly deployed around the perimeter of a 2-dimensional region and mounted on the strands with same height from the ground, as illustrated in Fig. 1. The 2-dimensional region is referred as monitored area. The sensors only working in half-duplex mode can transmit or receive radio signals at each time instant. The sensors can also measure the RSS and send the RSS measurements to the fusion center. $K$ sensors can constitute $L = K (K - 1) / 2$ unidirectional links. Suppose that a target (or person) with coordinate $(x_t, y_t)$, $t \in \mathbb{N}$ is moving within the monitored area. Unlike some active localization methods which require the target to wear a tag, the target is free of any kinds of tags. The presence of the target will alter the propagation environment of the radio signals, resulting in the variation of the RSS of the links, for example, diffracting or reflecting the radio signals. The most dramatic effect of the target on the link is occurred when the target passes through or moves in the vicinity of the light of sight (LOS) of the link. The RSS of affected link will be observed great attenuation due to the obstruction of the target. Suppose the RSS of the $l$th link is $\bar{r}_l$ when the target is absent and $r_{l,t}$ when the target is located
at \((x_t, y_t)\), where the unit of the RSS measurement is dBm. Thus that the measurement of RSS change of link \(l\) at time instant \(t\) is \(z_l(x_t, y_t) = r_{l,t} - r_{l,t}^l\). We hope to estimate the position of the target from the measurements \(z_l(x_t, y_t), l = 1, 2, ..., L\) of all links.

III. MODEL FORMULATION

In DFL, the major problem is to accurately characterize the relationship between the RSS variation induced by the presence of the target and the position of the target. Obviously, the model should at least satisfies the following two properties: (1) when the target walk through the link, the attenuation of RSS increases gradually and (2) the link observes larger loss the target move closer to the transmitter or the receiver.

In the papers, two empirical models have been proposed to model the target’s effect, i.e., exponential model (EM1) \[14\] and elliptical model (EM2) \[19\], \[20\] which both treat the target as a point mass. Considering a link is constituted by transmitting sensor 1 with coordinate \((\alpha_1, \beta_1)\) and receiving sensor 2 with coordinate \((\alpha_2, \beta_2)\). EM1 and EM2 assume that the RSS variation is related to the excess path length of the link which is defined as

\[
\Delta d = d(1) + d(2) - d
\]

where \(d(1) = \sqrt{(x - \alpha_1)^2 + (y - \beta_1)^2}\), \(d(2) = \sqrt{(x - \alpha_2)^2 + (y - \beta_2)^2}\) are the distances from the centroid of the target to the sensor 1 and sensor 2 respectively and \(d = \sqrt{(\alpha_1 - \beta_1)^2 + (\alpha_2 - \beta_2)^2}\) is the path length of the link. Here the subscript \(t\) in the coordinate \((x_t, y_t)\) is dropped for simplification of notation.

EM1 model is obtained by fitting experimental measurements which assumes the RSS exponentially
decays as the excess path length $\Delta d$ increases. If $f(x, y)$ represents the loss due to obstruction of the target, the EM1 model can be written as

$$f(x, y) = \phi e^{-\kappa \Delta d}$$

(2)

where $\phi$ is the maximum loss observed at $\Delta d = 0$ and $\kappa$ is the decaying factor. The parameters $\phi$ and $\kappa$ can be determined by experimental measurements.

EM2 model is established under the LOS propagation assumption which expects that the influence of the target on the link is limited within the ellipse with focus at the transmitting sensor and receiving sensor. Within the ellipse, the loss is identical for each location and the influence of the target can be neglected when the target is outside the ellipse. Thereby, the EM2 model can be expressed by

$$f(x, y) = \begin{cases} \varphi, & \Delta d < \delta \\ 0, & \text{otherwise} \end{cases}$$

(3)

where $\delta$ is a tunable parameter which adjusts the size of the ellipse and $\varphi$ is the loss constant. Usually the ellipse is considered to be first Fresnel zone of the link [24]. Thus that $\delta = \frac{\lambda^2}{2}$, where $\lambda$ is the wavelength of the radio signals. For example, when we use the 2.4G radio signals, $\delta = \frac{\lambda^2}{2} = 0.0625m$.

Fig. 2 displays the RSS attenuation of the link when the target locates different positions of the monitored area for EM1 model and EM2 model respectively. The brightness of the pixel represents the level of the attenuation. We can see from Fig. 2 (a), the brightness of the pixels are the same within the ellipse. That means when the target walk through the link (see the line $X = 0$ in Fig. 2 (a)) or the target moves along the link (see the line $Y = 0$ in Fig. 2 (a)), the RSS loss is unchanged. Therefore, EM2 cannot satisfy the two requirements of the models. EM1 meets the first property (see the line $X = 0$ in Fig. 2 (b)) but the second property is still not satisfied (see the line $Y = 0$ in Fig. 2 (b)).

In fact, the target holds a certain volume instead of a point mass. Usually, the target can be modeled as a cylinder with radius $R$, which is frequently employed in the literature [22], [23]. Similarly, we consider the link comprised of sensor 1 and sensor 2, the link line can be represented as

$$[\beta_2 - \beta_1, \alpha_1 - \alpha_2] \begin{bmatrix} x \\ y \end{bmatrix} = \alpha_1 \beta_2 - \alpha_2 \beta_1$$

(4)

If we denote $a = \beta_2 - \beta_1$, $b = \alpha_1 - \alpha_2$ and $e = \alpha_1 \beta_2 - \alpha_2 \beta_1$, (4) can be rewritten as $ax + by = e$. 
Fig. 2. Attenuation map of the two models: (a) EM2 model (b) EM1 model. The coordinates of the two sensors are (-2.4m, 0) and (2.4m, 0).

Thus the perpendicular distance from the centroid of target to the link is

\[ h = \frac{|ax + by - c|}{\sqrt{a^2 + b^2}} \]  

(5)

It is well known that 2/3 of the human body is composed of water, which can be seen as a good conductor. Thus that radio signals usually cannot penetrate human tissue but can arrive at the receiver by diffraction of the target. As shown in Fig. 3 the target diffracts the radio waves by two diffraction points which occurs at the two lateral sides of the human body. The two diffraction path are numbered as path 1 and path 2. If the perpendicular distance from the target to the link is \( h \), then the distances from the
Fig. 3. Radio waves diffraction by the target.

Fig. 4. Two scenarios of diffraction: (a) LOS path is obstructed \( h \leq R, v_1 > 0 \) and (b) LOS path is not obstructed \( h > R, v_1 < 0 \).

diffraction points to the link are \( |h - R| \) and \( h + R \). Denote \( d_i(j), i = 1, 2; j = 1, 2 \) is the distance from diffraction point of path \( i \) to sensor \( j \), which can be written as

\[
\begin{align*}
\ d_{1}^{2}(1) &= (x - \alpha_{1})^{2} + (y - \beta_{1})^{2} - h^{2} + (R - h)^{2} \\
\ d_{1}^{2}(2) &= (x - \alpha_{1})^{2} + (y - \beta_{1})^{2} - h^{2} + (R + h)^{2} \\
\ d_{2}^{2}(1) &= (x - \alpha_{2})^{2} + (y - \beta_{2})^{2} - h^{2} + (R - h)^{2} \\
\ d_{2}^{2}(2) &= (x - \alpha_{2})^{2} + (y - \beta_{2})^{2} - h^{2} + (R + h)^{2}
\end{align*}
\]  

Then the excess path length of the two diffraction path are

\[
\begin{align*}
\Delta d_{1} &= d_{1}(1) + d_{1}(2) - d, \\
\Delta d_{2} &= d_{2}(1) + d_{2}(2) - d
\end{align*}
\]  

The diffraction can be seen as the knife edge diffraction which is popular used to predict the path
loss in radio wave propagation. Diffraction loss is closely related to the Fresnel-Kirchhoff diffraction parameter $v_i$ [24] which is defined as

$$|v_i| = 2 \sqrt{\frac{\Delta d_i}{\lambda}}, i = 1, 2$$ (8)

The diffraction parameter can be positive or negative. As shown in Fig. 4(a), if $h \leq R$, which means the LOS path is blocked by the target, the diffraction parameters $v_1$ and $v_2$ are both positive. However, as shown in Fig. 4(b), if $h > R$, the diffraction points are located the same side of the LOS path, the diffraction parameter for the path closer to the LOS path is negative while the other diffraction parameter is always positive. If we always denote the diffraction path closer to the LOS path is the first path, the diffraction parameter can be rewritten as

$$v_1 = 2 \text{sgn}(R - h) \sqrt{\frac{\Delta d_1}{\lambda}}, v_2 = 2 \sqrt{\frac{\Delta d_2}{\lambda}}$$ (9)

According to Fresnel-Huygens principle [24], the electric field strength of the diffraction signal is given by

$$E_D(v_i) = \frac{1}{2} E_0 (1 + j) \int_{v_i}^\infty \exp\left(-j \frac{\pi v^2}{2}\right) dv, i = 1, 2$$ (10)

where $E_0$ is the field strength when the target is absent. The above formula is called Fresnel integration which has no closed form expression. Fresnel integration is usually evaluated by numerical approximation [31]. In fact, we frequently use $C(v) = \int_0^v \cos\left(\frac{\pi v^2}{2}\right) dv$ and $S(v) = \int_0^v \sin\left(\frac{\pi v^2}{2}\right) dv$. Then $E_D(v_i)$ can be rewritten as

$$E_D(v_i) = \left\{ \begin{array}{ll}
E_0 \frac{1}{2} (1 + j) \left( \int_0^\infty \exp\left(-j \frac{\pi v^2}{2}\right) dv - \int_{v_i}^\infty \exp\left(-j \frac{\pi v^2}{2}\right) dv \right) \\
E_0 \frac{1}{2} (1 + j) \left( \int_0^{v_i} \exp\left(-j \frac{\pi v^2}{2}\right) dv - \int_0^\infty \exp\left(-j \frac{\pi v^2}{2}\right) dv \right) \\
E_0 \frac{1}{2} (1 + j) \left( \int_0^{v_i} \exp\left(-j \frac{\pi v^2}{2}\right) dv + \int_0^{-v_i} \exp\left(-j \frac{\pi v^2}{2}\right) dv \right) \\
E_0 \frac{1}{2} (1 + j) \left( \frac{1 - j}{2} + (C(v_i) - jS(v_i)) \right) \text{ if } v_i > 0 \\
E_0 \frac{1}{2} (1 + j) \left( \frac{1 - j}{2} + (C(v_i) - jS(v_i)) \right) \text{ otherwise}
\right.$$ (11)

The deviation of (11) uses two properties about the functions $C(v)$ and $S(v)$. One is that $C(\infty) = \int_0^\infty \cos\left(\frac{\pi v^2}{2}\right) dv = \frac{1}{2}$, $S(\infty) = \int_0^\infty \sin\left(\frac{\pi v^2}{2}\right) dv = \frac{1}{2}$. The other property is that $C(v)$ and $S(v)$ are all odd functions about $v$. The curves of $C(v)$ and $S(v)$ versus $v$ are plotted in Fig. 5. We can see as $C(v)$ and $S(v)$ oscillates around 0.5 when $v > 2$. 
The power of the diffraction signal is

\[
|E_D(v_i)|^2 = \begin{cases} 
\frac{1}{2}|E_0|^2 \left[ \left( \frac{1}{2} - C(v_i) \right)^2 + \left( \frac{1}{2} - S(v_i) \right)^2 \right] & \text{if } v_i > 0 \\
\frac{1}{2}|E_0|^2 \left[ \left( \frac{1}{2} + C(v_i) \right)^2 + \left( \frac{1}{2} + S(v_i) \right)^2 \right] & \text{otherwise}
\end{cases}
\] (12)

We can see that as \( v_i \to \infty \), \( C(v_i) = S(v_i) = \frac{1}{2} \), \( |E_D(v_i)|^2 \) will be 0 and as \( v_i \to -\infty \), \( C(-v_i) = S(-v_i) = \frac{1}{2} \), \( |E_D(v_i)|^2 \) will approach 1. The result well matches the real situations: if the target has infinite size, \( v_i \to \infty \), the diffraction signal is be very weak and if the target is far away from the LOS path, \( v_i \to -\infty \), the radio signal is almost unaffected.

The electric field strength \( E_D \) at the receiver is the sum of the two diffraction signals. Thus that the power of the received signal can be represented as

\[
|E_D|^2 = |E_D(v_1) + E_D(v_2)|^2 = |E_D(v_1)|^2 + |E_D(v_2)|^2 + 2|E_D(v_1)||E_D(v_2)|\cos \theta
\] (13)

where \( \theta \) is the relative phase between the two diffraction signals. Considering that the target is not a perfect cylinder because of the rough surface of the target, the phase \( \theta \) can be assumed to be a random variable uniformly distributed within interval \((0, 2\pi)\). Then the average power of received signal is

\[
E\left(|E_D|^2\right) = |E_D(v_1)|^2 + |E_D(v_2)|^2
\] (14)
The diffraction loss \( f(x, y) \) due to the presence of the target is

\[
f(x, y) = 10 \log_{10} \frac{E\left(|E_D|^2\right)}{E_0} = 10 \log_{10} \left( \frac{|E_D(v_1)|^2}{|E_0|^2} + \frac{|E_D(v_2)|^2}{|E_0|^2} \right)
\]  

(15)

If we substitute (12) into (15), \(|E_0|^2\) will be canceled. Thus the diffraction loss \( f(x, y) \) only depends on \( v_1 \) and \( v_2 \). The model proposed above is named by diffraction model or DM for short.

IV. Model Assessment

To verify the proposed model and compare the proposed model with the EM1 and EM2, we collect RSS samples of a link from real experiments. In the experiments, a pair of sensors are placed apart with 4.8m with coordinates \((-2.4m, 0)\) and \((2.4m, 0)\). One sensor transmits the radio signals while the other sensor receives the signals, measures the RSS and sends the RSS readings to the base station node. To test whether the DM satisfies the properties mentioned above, two special case are considered, as illustrated in Fig. 6. The first special case is that the target crosses the link line from one side of the link to the other side of link. The measurements and curves of three models versus the vertical coordinate \( y \) are shown in Fig. 7. The parameters of the models are \( \phi = \varphi = 10dB, \kappa = 20, R = 0.20m \). We can see from the measurements the RSS loss increases when the distance reduces if \( h < 0.6m \) and reaches to peak at \( h = 0m \). Moreover, it is interesting to note that when \( h > 0.6m \) the loss is not zero but oscillates around 0. EM2 can model the blockage effect but cannot reflect the gradual change of the RSS when crossing. EM1 can model the gradual process but is unable to explain the oscillation behavior. However, the curve of DM well fits the measurements. The oscillation behavior are also be explained by the property of function \( C(v) \) and \( S(v) \), as depicted in Fig. 5.

The other special case is that the target walks along the LOS path from the transmitter sensor to the receiver sensor. In this case, the distance from the target to the link is \( h = 0 \) and excess path length for EM1 and EM2 is \( \Delta d = 0 \). Thus that RSS loss \( f(x, y) \) is constant for EM1 and EM2. For DM model, the distance from the target to the transmitter is \( d_T = \sqrt{(x - \alpha_1)^2 + (y - \beta_1)^2} \). Due to symmetry, the
The excess path lengths for two diffraction paths are the same, which can be written as
\[
\Delta d_1 = \Delta d_2 = d_1 (1) + d_1 (2) - d = \sqrt{d_T^2 + R^2} + \sqrt{(d - d_T)^2 + R^2} - d
\]
\[
= \sqrt{d_T^2 + R^2 - d_T} + \sqrt{(d - d_T)^2 + R^2 - (d - d_T)}
\]
\[
= R^2 \left( \frac{1}{\sqrt{d_T^2 + R^2 + d_T}} + \frac{1}{\sqrt{(d - d_T)^2 + R^2 + (d - d_T)}} \right)
\]
\[
\approx R^2 \left( \frac{1}{2d_T} + \frac{1}{2 (d - d_T)} \right) = \frac{R^2d}{2d_T (d - d_T)}
\]

The diffraction parameters are \(v_1 = v_2 = R \sqrt{\frac{2d}{d_T (d - d_T) x}}\), which are the functions of \(d_T\). We can see when \(0 < d_T \leq \frac{d}{2}\), \(v_1\) and \(v_2\) decreases as \(d_T\) increases. However, in the interval \(\left[ \frac{d}{2}, d \right]\), \(v_1\) and \(v_2\) increases as \(d_T\) gets larger. Thus that minimum of \(v_1\) and \(v_2\) are observed when \(d_T = \frac{d}{2}\).

Experimental measurements and the modeling results of three models are shown in Fig. 8. We can see from the measurements, the loss increases when the target walks closer to the transmitter and receiver. However, the curves of EM1 and EM2 are presented as straight lines and overlapped. Therefore, the EM1 and EM2 fail to explain the measurements while DM well fits the measurements.

Fig. 9 shows the variation of RSS obtained by DM when the target is located different positions. We can see clearly from the image the RSS loss changes gradually when the link is crossed by the target and also the RSS loss in larger is the region around the transmitter and receiver than other regions.

V. MEASUREMENT AND MOTION MODEL

Suppose \(z_t(x_t, y_t)\) is the RSS variation of link \(l\) and \(f_t(x_t, y_t)\) is the diffraction loss evaluated by DM model at time instant \(t\). In fact, in addition to the diffraction, the target can also reflect the radio
signals during motion and there may be also some perturbations in the monitored area, which make the RSS change rapidly. The variation of RSS due to refection or the disturbance of the environments can be modeled as additive noise. Thus the measurement model of link $l$ is

$$z_l (x_t, y_t) = f_l (x_t, y_t) + n_l (x_t, y_t), \ l = 1, 2, ..., L$$

(17)

where $n_l (x_t, y_t)$ is assumed to be Gaussian distributed with variance $\sigma^2$.

In this paper we use a linear motion model to describe the dynamics of the target. The states of the model consists of position and velocity of the target and it is denoted by $x_t = [x_t, y_t, \dot{x}_t, \dot{y}_t]^T$, where $\dot{x}_t$
and \( \dot{y}_t \) are the velocities in \( X \) and \( Y \) directions. Suppose \( \Delta t \) is the time duration from \( t \) to \( t + 1 \), the motion model can be written as
\[
x_t = Fx_{t-1} + \varepsilon_t
\]  
(18)
where \( \varepsilon_t \) is Gaussian noise with covariance matrix \( Q \) and \( F \) is given by
\[
F = \begin{bmatrix}
1 & 0 & \Delta t & 0 \\
0 & 1 & 0 & \Delta t \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}
\]  
(19)
If we stack all the \( L \) measurements into a column vector \( z_t = [z_1(x_t), z_2(x_t), ..., z_L(x_t)]^T \), the measurement models for \( L \) links can be simplified as
\[
z_t = f(x_t) + n_t
\]  
(20)
where \( f(x_t) = [f_1(x_t), ..., f_L(x_t)]^T \) is the nonlinear function of \( x_t \) and \( n_t = [n_1(x_t), ..., n_L(x_t)]^T \) is the noise vector. Suppose the measurements of \( L \) links are independent, the covariance of noise vector \( n_t \) is \( R = \sigma^2 I_{L \times L} \).

VI. PARTICLE FILTERING TRACKING

Denote \( z_{1:t} \) are all the measurements up to the current time instant \( t \). Given measurements \( z_{1:t} \) to estimation the position of target at time instant \( t \) is called filtering. The optimal filtering is given.
by Bayesian filtering which maximizes the posterior distribution \( p(x_t | z_{1:t}) \), i.e., \( \hat{x}_t = \max_{x_t} p(x_t | z_{1:t}) \). Bayesian filtering can be divided into two steps: prediction and updating [25]. In the prediction step, the distribution up to time instant \( t \) can be predicted by Chapman-Kolmogorov equation

\[
p(x_t | z_{1:t-1}) = \int p(x_t | x_{t-1}) p(x_{t-1} | z_{1:t-1}) \, dx_{t-1}
\]

(21)

In the second step, given current measurement \( z_t \), the predicted distribution can be updated by Bayes rule

\[
p(x_t | z_{1:t}) = \frac{p(z_t | x_t) p(x_t | z_{1:t-1})}{p(z_t | z_{1:t-1})}
\]

(22)

For linear measurement model, Bayesian filtering is identical to Kalman filtering (KF) which the above two steps can be simplified by linear equations. However, in this paper, the measurement model is highly nonlinear, the prediction and updating steps are computationally intractable. Extended Kalman filtering (EKF) linearizes the measurement model by Taylor series expansion but it is the suboptimal method.

In the last two decades, a sequential Monte Carlo (SMC) based method or also called particle filtering (PF) is successfully used for nonlinear filtering [25], [26]. PF attempts to approximate the posterior distribution \( p(x_t | z_{1:t}) \) by weighted particles. Suppose that \( x^i_t, i = 1, 2, ..., N \) denotes the state of \( i^{th} \) particle at time instant \( t \) and its associated weight is \( w^i_t \), where \( N \) is the number of particles, the \( p(x_t | z_{1:t}) \) can be approximated by

\[
p(x_t | z_{1:t}) = \sum_{i=1}^{N} w^i_t \delta(x_t - x^i_t)
\]

(23)

where \( \delta(\cdot) \) is the Dirac function. The random particles are drawn from the proposal distribution \( q(\cdot) \), i.e,

\[
x^i_t \sim q(x^i_t | x^i_{t-1}, z_t)
\]

(24)

The weight can be recursively computed according to

\[
w^i_t \propto w^i_{t-1} \frac{p(z_t | x^i_t) p(x^i_t | z_{1:t-1})}{q(x^i_t | x^i_{t-1}, z_t)}
\]

(25)

Usually it is difficult to determine the optimal proposal distribution. The commonly used proposal distribution is the state transitional prior, i.e., \( q(x^i_t | x^i_{t-1}, z_t) = p(x^i_t | x^i_{t-1}) \). Thus that the (25) can be greatly simplified to

\[
w^i_t \propto w^i_{t-1} p(z_t | x^i_t) = w^i_{t-1} \prod_{l=1}^{L} N([z_l - f(x^i_t)], \sigma^2)
\]

(26)

The weights of particles should be normalize to ensure the sum of the weights is 1. The normalization
of particle $x_i^t$ can be performed by
\[ w_t^i = \frac{1}{N} \sum_{i=1}^{N} w_t^i \] (27)

One problem of PF is the degeneracy, where almost all the weights of particles are zero except some particles. The degeneracy can severely degrades the performance of PF. One benchmark to measure the degeneracy problem is the effect particle size defined by $N_{eff} = \frac{1}{\sum_{i=1}^{N} (w_t^i)^2}$. If $N_{eff}$ is larger than a predefined threshold $N_{th}$, the degeneracy can be thought to be occurred. Resampling can be used to overcome the degeneracy problem by dropping particles with small weight and replacing the particle with large weight by several equally weighted particles.

After having done those steps, state estimation by PF can be computed as
\[ \hat{x}_t = \sum_{i=1}^{N} w_t^i x_i^t \] (28)

The steps of PF tracking algorithm is listed in Algorithm 1.

**Algorithm 1 Particle Filtering Tracking**

**INITIALIZATION:**
Draw particle $x_0^i \sim p(x_0)$ and initialize the weight $w_t^i = \frac{1}{N}$, $i = 1, 2, ..., N$, where $p(x_0)$ is the prior distribution of the state.

**TRACKING:**
for $t = 1, 2, ..., $ perform the following steps:
1) Draw new particles from the proposal distribution $x_t^i \sim p(x_t|x_{t-1}^i)$, $i = 1, ..., N$.
2) Update the weight according to $w_t^i \propto w_{t-1}^i \prod_{l=1}^{L} \mathcal{N} \left( \left[ z_l(x_t) - f(x_t^i) \right], \sigma^2 \right)$ using the measurements of $L$ links.
3) Normalize the weight by $w_t^i = 1 / \sum_{i=1}^{N} w_t^i$.
4) Resample if $N_{eff} = \frac{1}{\sum_{i=1}^{N} (w_t^i)^2} < N_{th}$.
5) Output state estimation $\hat{x}_t = \sum_{i=1}^{N} w_t^i x_t^i$.

**VII. POSTERIOR CRAMER-RAO LOWER BOUND**

The PCRLB provides a lower limit for the accuracy of tracking in terms of mean squared error (MSE). If $\hat{x}_t$ is an unbiased estimator about target state, the MSE of $\hat{x}_t$ is bounded by
\[ \mathbb{E} \left[ (\hat{x}_t - x_t) (\hat{x}_t - x_t)^T \right] \geq J_t^{-1} \] (29)
where \( J_t^{-1} \) is the posterior Fisher information matrix (FIM) at time instant \( t \), which can be recursively computed as (the deviation can be seen in Appendix)

\[
J_t = (Q + FJ_{t-1}F^T)^{-1} + H_t^T R^{-1} H_t
\]

(30)

where \( H_t \) is the Jacobian matrix which is evaluated when the true target state is \( x_t \). Because the measurement model only depends on the position of the target, partial derivatives of \( f_l(x_t) \) with respect to velocities are zero. Thus the Jacobian matrix \( H_t \) can be computed by

\[
H_t = \nabla f (x_t) = \begin{bmatrix}
\frac{\partial f_1(x_t)}{\partial x_t} & \frac{\partial f_1(x_t)}{\partial y_t} & 0 & 0 \\
\frac{\partial f_2(x_t)}{\partial x_t} & \frac{\partial f_2(x_t)}{\partial y_t} & 0 & 0 \\
\vdots & \vdots & \vdots & \vdots \\
\frac{\partial f_L(x_t)}{\partial x_t} & \frac{\partial f_L(x_t)}{\partial y_t} & 0 & 0 \\
\end{bmatrix}
\]

(31)

Considering the covariance of measurement noise is \( R = \sigma^2 I_{L \times L} \), \( H_t^T R^{-1} H_t \) can be calculated as

\[
H_t^T R^{-1} H_t = \frac{1}{\sigma^2} \begin{bmatrix}
\sum_{l=1}^{L} \left( \frac{\partial f_l(x_t)}{\partial x_t} \right)^2 & \sum_{l=1}^{L} \frac{\partial f_l(x_t)}{\partial x_t} \frac{\partial f_l(x_t)}{\partial y_t} & 0 & 0 \\
\sum_{l=1}^{L} \frac{\partial f_l(x_t)}{\partial x_t} \frac{\partial f_l(x_t)}{\partial y_t} & \sum_{l=1}^{L} \left( \frac{\partial f_l(x_t)}{\partial y_t} \right)^2 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
\end{bmatrix}
\]

(32)

It is obvious that the recursion requires the initial FIM to be known. When \( t = 0 \), the initial FIM can be computed as \( J_0 = P_0^{-1} \) if the initial target state is assumed to be Gaussian distributed with zero-mean and covariance \( P_0 \).

In the context of target tracking, the most interested is the position of the target and not its velocities. Thus that the first two elements on the diagonal of \( J_t^{-1} \) can be used to compute the lower bound of root MSE (RMSE) of position error, which is given by

\[
PCRBL_t = \sqrt{\sum_{i=1}^{2} [J_t^{-1}]_{ii}}
\]

(33)

VIII. EXPERIMENTAL RESULTS

A. Setup

In the experiments, the size of the monitored area is 3.52m*3.52m. 8 TI CC2530 radio sensors are placed on the perimeter of the monitored area and mounted on the tripods at a height of 1m. The distance
between two adjacent sensors on each side of the area is 1.76m to reduce ground reflection. TI CC2530 radio sensors can be fully compatible with IEEE 802.15.4 protocol and provide quantized RSS with range from 0 to 255. The maximum transmitting power of the sensor is 4.5dBm, which is high enough to cover the whole monitored area.

The experiments are conducted in the hallway on the second floor of NO.10 Teaching Building in Beijing Institute of Technology (BIT), as shown in Fig. 10. We can see that there are many reflectors causing multipath fading outside the monitored area such as walls, doors and pedestrians walking nearby. If the antennas installed on the radio sensors are omnidirectional, the links might be corrupted by the multipath and the tracking performance will degrade. To mitigate the multipath, we use directional antennas instead of omnidirectional antennas. In this experiment, patch antennas with horizontal angle of 110 degrees and vertical angle of 30 degrees are employed, which can effectively reduce the interference outside the monitored area. Theoretically speaking, the link comprised a pair of sensors will be more robust to interference if the two sensor use directional antenna with narrower horizontal angle like the antenna used in [34]. However, if the angle is too narrow, full coverage cannot be guaranteed which means that the number of available links decreases.

To rapidly measure the RSS of the links, we use the communication protocol similar to the protocol developed by [14]. In the protocol, to avoid collision, each sensor is assigned by a unique ID and the sensors transmit signals in turn according to their ID. When one sensor transmits signals, other sensors measure the RSS. Thus that after all the sensors have transmitted signal once, the RSS of all links can be updated. In the experiment, the time required for completing one round measurement is 10ms. As a result, the RSS of links can be considered to be updated at the same time. Moreover, to conserve battery power of sensors, the time interval between two rounds of measurement is \( \Delta t = 0.2s \), which is fast enough to track the motion of a person. The RSS measurements are sent to a base station sensor which
feds the measurements to a local PC for real-time processing.

Note the RSS measurements should be subtracted by the static measurements which are obtained when
the target is absent in the monitored area. Static measurements can be measured in advance before the
target enters the area or estimated from online measurements [35]. In this paper, the former method is
used because the focus of the paper is to verify the proposed model and the corresponding tracking
results.

B. Performance Metrics

The most important metric to evaluate tracking performance is the root mean squared error (RMSE)
which is defined as

$$RMSE = \sqrt{\frac{1}{N_T} \sum_{t=1}^{N_T} e_t^2}$$

(34)

where $N_T$ is the number of time instants and $e_t = \sqrt{(x_t - \hat{x}_t)^2 + (y_t - \hat{y}_t)^2}$ is the localization error
at time instant $t$. Another metric which describes the statistical property of localization error is the
cumulative distribution function (CDF) of the localization error, defined as

$$CDF (Error) = Pr (Error < \varepsilon)$$

(35)

where $\varepsilon$ is the localization error level.

C. Results

A person walks along the zigzag trajectory as shown in Fig. 11 with a speed of 0.4m/s. The covariance
of noise in the motion model is chosen as $Q = diag (0.01, 0.01, 1, 1)$ and the variance of measurement
noise is $\sigma^2 = 2$. The parameters of the three models are the same with the parameters used in the model
assessment section.

The number of particles is chosen as $N = 400$. Because the particles are generated randomly, the
processing results can be different for each run for the same tracking method. Thus that the RMSE
should be averaged by 100 Monte Carlo runs for PF tracking methods.

For comparison, four tracking results are presented. Apart from the PF tracking methods with associated
the three models, the tracking results of RTI is also presented. In fact, RTI is formulated based on EM2
model.

Fig.12 shows the tracking results of the 4 methods respectively in a Monte Carlo run. We can see
PF using the proposed model outperforms the other three methods. The localization error of RTI with
Fig. 11. The ground truth of the target.

Kalman filtering is the largest among the 4 methods. We can see from Fig. 12 (a) the estimated positions greatly deviate the true positions in some instants, partly because the position estimation given by RTI is not robust to noise. Using the same EM2 model, the tracking results given by PF is much better than RTI. Moreover, tracking results of EM1 is smoother than EM3 when PF is used for tracking. The tracking results given by proposed model best fits the ground truth in the three models.

The tracking error versus time instant over 100 Monte Carlo runs is depicted in Fig. 13. We can see the tracking accuracy of DM is closest to the PCLRB. Note at some instants, the tracking error of DM is below the PCRLB which is about centigrade level. It does not mean the tracking error of DM violates the PCRLB. It occurs because the true position of the target is not accurately calibrated (centimeter-level accuracy is very difficult to achieve).

The RMSEs of the 4 tracking methods are listed in Table. I. We can see that the RMSE of the DM is only 0.09m and its tracking accuracy is improved by 57%, 36% respectively compared to the other two models. The CDF of the tracking error is plotted in Fig. 14. It is shown that the tracking error of proposed method is lower than 0.2m with 100% and 0.1m with 67%.

All the data processing is performed in a PC using MATLAB routines. The PC has 4GB RAM and 32bit Inter Core-i3 processor. The average time consumed by four methods is 4.5ms, 101ms, 108ms, 26ms with stand deviation 0.86ms, 7.9ms, 4.4ms, 2.2ms. Although the time required for PF is much longer than KF, but it is fast enough to track the target.

In the above results, only one target is considered. Next we will investigate the performance of tracking when there are more than one target present. For simplicity, we consider the case of two targets and
the number of targets is fixed during experiment. Before tracking, we have to modify the measurement model to adapt to multiple targets. We assume that RSS variation due to the two targets are independent. Therefore, for link \( l \), the measurement model is

\[
z_l(x_{1,t}, x_{2,t}) = \sum_{m=1}^{M} f_l(x_{m,t}) + \sum_{m=1}^{M} n_l(x_{m,t})
\]

where \( z_l(x_{1,t}, x_{2,t}) \) is the observed RSS variation, \( M = 2 \) is the number of the targets, \( x_{1,t} \) and \( x_{2,t} \) are
the states of two targets respectively.

Similar to the single target case, the measurement model is still nonlinear and PF should be used to perform tracking. The only difference is that the number of states increases to 8. Therefore, the number of particles increases to $N = 1000$ and the other parameters are the same with the single target case. In the experiment, two targets move along the opposite directions with the same speed. In Fig. 15, the red dashed line and blue dashed line represent the ground truth of two targets respectively.

The tracking results of one Monte Carlo run using 4 methods are plotted in Fig. 15 and the corre-
TABLE I
RMSE OF TRACKING RESULTS

| Method      | EM2+KF | EM2+PF | EM1+PF | DM+PF |
|-------------|--------|--------|--------|-------|
| RMSE        | 0.32m  | 0.21m  | 0.14m  | 0.09m |

The corresponding RMSE is listed in Table. We can see the tracking results of RTI method is slightly worse than the other methods. The PF tracking results using EM1 and EM2 are comparable and the DM shows the best performance with RMSE 0.15m and 0.14m for two targets respectively.

From the Fig. we can see the tracking results of two targets is a little worse than those of single target, especially for PF tracking methods. Note that when the two targets block the same link, the tracking error is very large, as shown in Fig. This occurs because of the superposition assumption in the measurement model. In the measurement model of two target case, we simply assume the observed RSS variation is the sum of the RSS variation due to the every target independently, which is too optimistic. However, in real scenarios, the two targets are not independent but coupled, causing that the measurement model for multiple targets does not satisfy the superposition assumption.

TABLE II
RMSE OF TRACKING RESULTS

| Method    | EM2+KF | EM2+PF | EM1+PF | DM+PF |
|-----------|--------|--------|--------|-------|
| RMSE (target 1) | 0.28m  | 0.27m  | 0.20m  | 0.15m |
| RMSE (target 2) | 0.30m  | 0.22m  | 0.19m  | 0.14m |

IX. CONCLUSION

In this paper, the problem of device-free target localization using RSS measurements of radio frequency link is addressed. A new measurement model between RSS measurements and the position of the target is proposed. In the model, the target is assumed to be a cylinder rather than a point mass. The model is formulated based on the diffraction theory and better fits the experiment measurements compared to other models. Since the measurement model is nonlinear, a PF tracking method is also presented. The experiment results show that tracking accuracy is improved by using the proposed method. Future work about DFL is to modify the measurement model for multi-target case to improve the localization accuracy.
The FIM at time instant $t$ is defined by

$$J_t = -E \left[ \Delta x_t^T \log p(z_t, x_t) \right]$$

(37)

where $\Delta x_t = \nabla x_t, \nabla x_t^T$ and $\nabla$ and $\Delta$ are the fist and second order operator of partial derivative respectively.
According to [28], the FIM can be recursively calculated as

$$\mathbf{J}_{t+1} = \mathbf{D}_{t}^{22} - \mathbf{D}_{t}^{21}(\mathbf{J}_{t} + \mathbf{D}_{t}^{11})^{-1}\mathbf{D}_{t}^{12}$$

(38)

where

$$\mathbf{D}_{t}^{11} = E[-\nabla_{x_{t+1}}^{x_{t}} \log p(x_{t+1}|x_{t})]$$

$$\mathbf{D}_{t}^{12} = E[-\nabla_{x_{t+1}}^{x_{t}} \log p(x_{t+1}|x_{t})]$$

$$\mathbf{D}_{t}^{21} = E[-\nabla_{x_{t+1}}^{x_{t}} \log p(x_{t+1}|x_{t})]$$

$$\mathbf{D}_{t}^{22} = E[-\nabla_{x_{t+1}}^{x_{t}} \log p(x_{t+1}|x_{t})] + E[-\nabla_{x_{t+1}}^{x_{t}} \log p(z_{t+1}|x_{t+1})]$$

(39)

From the motion model we can obtain

$$p(x_{t+1}|x_{t}) = \frac{1}{\sqrt{2\pi \det (Q)}} \exp \left[ -\frac{1}{2}(x_{t+1} - Fx_{t})^{T}Q^{-1}(x_{t+1} - Fx_{t}) \right]$$

(40)

and

$$p(z_{t}|x_{t}) = \frac{1}{\sqrt{2\pi \det (R)}} \exp \left[ -\frac{1}{2}(x_{t} - f(x_{t}))^{T}R^{-1}(x_{t} - f(x_{t})) \right]$$

(41)

Then the log-likelihood functions are

$$\ln (p(x_{t+1}|x_{t})) = -\frac{1}{2}(x_{t+1} - Fx_{t})^{T}Q^{-1}(x_{t+1} - Fx_{t}) - \ln (2\pi \det (Q))$$

$$\ln (p(z_{t}|x_{t})) = -\frac{1}{2}(x_{t} - f(x_{t}))^{T}R^{-1}(x_{t} - f(x_{t})) - \ln (2\pi \det (R))$$

(42)

Thus that $$\mathbf{D}_{t}^{11}, \mathbf{D}_{t}^{12}, \mathbf{D}_{t}^{21}$$ and $$\mathbf{D}_{t}^{22}$$ can be derived by

$$\mathbf{D}_{t}^{11} = \mathbf{E}\left[ \frac{1}{2}\nabla_{x_{t+1}}^{x_{t}} \left( (x_{t+1} - Fx_{t})^{T}Q^{-1}(x_{t+1} - Fx_{t}) \right) \right] = \mathbf{F}^{T}\mathbf{Q}^{-1}\mathbf{F}$$

$$\mathbf{D}_{t}^{12} = \mathbf{E}\left[ \frac{1}{2}\nabla_{x_{t+1}}^{x_{t}} \left( (x_{t+1} - Fx_{t})^{T}Q^{-1}(x_{t+1} - Fx_{t}) \right) \right] = -\mathbf{F}^{T}\mathbf{Q}^{-1}$$

$$\mathbf{D}_{t}^{21} = \mathbf{E}\left[ \frac{1}{2}\nabla_{x_{t+1}}^{x_{t}} \left( (x_{t+1} - Fx_{t})^{T}Q^{-1}(x_{t+1} - Fx_{t}) \right) \right] = -\mathbf{Q}^{-1}\mathbf{F}$$

$$\mathbf{D}_{t}^{22} = \mathbf{E}\left[ \frac{1}{2}\nabla_{x_{t+1}}^{x_{t+1}} \left( (x_{t+1} - Fx_{t})^{T}Q^{-1}(x_{t+1} - Fx_{t}) \right) \right] + \mathbf{E}\left[ \frac{1}{2}\nabla_{x_{t+1}}^{x_{t+1}} \left( z_{t+1} - f(x_{t+1}) \right)^{T}R^{-1}(z_{t+1} - f(x_{t+1})) \right]$$

$$= \mathbf{Q}^{-1} + \mathbf{H}_{t+1}^{T}\mathbf{R}^{-1}\mathbf{H}_{t+1}$$

(43)

Substituting (43) into (38) and using the Sherman-Morrison formula \((\mathbf{Q} + \mathbf{FJ}_{t}^{T}\mathbf{F})^{-1} = \mathbf{Q}^{-1} - \mathbf{Q}^{-1}\mathbf{F}(\mathbf{J}_{t}^{-1} + \mathbf{F}^{T}\mathbf{Q}^{-1}\mathbf{F})^{-1}\mathbf{F}^{T}\mathbf{Q}^{-1}$$ [36] we can get

$$\mathbf{J}_{t+1} = (\mathbf{Q} + \mathbf{FJ}_{t}^{T}\mathbf{F})^{-1} + \mathbf{H}_{t+1}^{T}\mathbf{R}^{-1}\mathbf{H}_{t+1}$$

(44)
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