A novel motion tracking system with sparse Radio-Frequency sensor network

Aidong Men, Guang Zhao, Yun Zhou, and Yi Zheng
Multimedia Technology Center
Beijing University of Posts and Telecommunications
Email: {menad, guang1988juv, zhouyun, yizheng}@bupt.edu.cn

***Abstract*—This paper presents a novel device-free motion tracking (DFMT) system using an RF sensor network with very few nodes. The system includes a newly designed measurement model and corresponding tracking algorithm. Based on the uniform theory of diffraction (UTD), we prove that the received signal strength (RSS) measurements can be separated into two parts, the long-term one and the short-term one, reflecting the shadowing and scattering effects of the target. Then a model considering both the two effects is proposed to obtain positions of target using RSS measurements, which expands the sensing range of each wireless link. Particle filtering algorithm is applied to perform tracking. Experiment results illustrates that the system works well with very few nodes in different settings.**

***Index Terms*—sparse, measurement model, device-free**

I. Introduction

Using received signal strength (RSS) to perform device-free motion tracking (DFMT) is an emerging technology in wireless sensor networks. The RSS measurements are taken on the links which connect different sensor nodes in the network. In the region covered by links, the existence of a moving person or object will shadow or scatter the radio waves on links intersecting or nearby its path. The incurred variations of RSS are used to estimate the positions of target. Taking advantage of this feature, the tracking system collects RSS measurements continuously and tracks target locations using corresponding models and algorithms. In RSS-based DFMT, the targets need not carry any devices or tags, while the RF waves used by sensors have strong penetrability and do not depend on lighting conditions. These features make it have wide applications in the fields like rescue, military and security, where you can not expect all targets to wear a radio tag [1].

In an RF sensor network, when more links pass through a common area, more RSS information can be collected to reconstruct the attenuation occurring in that area. The information can be used to average out noises and other corruptions, which is helpful to improve the accuracy of localizing and tracking. Therefore, in most existing works [2] [3], sensor nodes are placed close to ensure that sufficient links travel through the area of interest. Although they achieved high tracking accuracy, the high complexity of deployment and maintenance must be taken into account. In most applying fields of this technology, we cannot expect to spend a long time in node deployment or have sufficient existing RF infrastructure.

In this paper, we present a novel DFMT system which is able to perform accurate motion tracking with sparse RF sensor networks. With fewer nodes and links in the same area, the RSS measurements that can be utilized are also insufficient. To alleviate this problem, we separate the components of radio waves into two parts, named long-term waves and short-term waves, based on the uniform theory of diffraction (UTD) [4] and derive their relationships with properties of the RSS value. Then, a measurement model considering the effects of the two parts of waves respectively is proposed. This novel model expands the sensing range of single link as far as possible. Afterwards, the particle filtering algorithm combining the posterior and prior information is applied to perform tracking.

The rest of the paper is organized as follows. Section II gives a brief evaluation of several main DFMT methods. Section III presents theoretical demonstration of the relationships between properties of RSS measurements and two parts of radio waves. Section IV describes the novel measurement model. Section V introduces the applied tracking algorithm. The experiments are presented in Section VI, and Section VII makes conclusion remarks.

II. Related works

Existing works for RSS-based DFMT can be classified into three major categories, namely, fingerprint matching, grid sensor array, and radio tomography imaging. Fingerprint matching method [5] [6] uses relatively few wireless devices to track targets based on a pre-trained database. This database is a "radio map" constructed manually by recording RSS with a person standing at known locations. The positioning process is virtually a comparison between measured RSS and the database. This shows the feasibility of the DFMT technology in sparse RF sensor networks.

Grid sensor array is a method placing sensor nodes on the ceiling [7]. When the variation of RSS on a link succeeds a threshold, this link is seen as an "influential link". As the scattering effect, the "influenced links" tend to cluster around the target position. Then corresponding algorithms are used to perform estimation. The experimental results verify the feasibility of using the scattering effect of an object for DFMT.

Radio tomography imaging (RTI) [2] presents a measurement model to transfer the attenuation of RSS on the links to an attenuation image. Every "pixel" of the image indicates the attenuation in a unit area. Algorithms like Kalman filtering [8] are used to perform tracking and update parameters. The basic idea of our system is derived from RTI.

III. Analysis of RSS measurements

A person inside the sensor network area will absorb, reflect, diffract or scatter the radio waves on some links. Previous works [2] [9] have shown that the human body can be approximated by a conducting cylinder at microwave frequencies. It is too complicated for a DFMT system to use UTD directly. Here we present a simplified fading model based on it.

Consider a single wireless link and a moving person as depicted in Fig. 1. $\boldsymbol{x_t}$ and $\boldsymbol{x_r}$ are the positions of two nodes, respectively. The line from transmitting node to receiving node is called the line-of-sight (LOS) path. At time t_1, the LOS path is not shadowed. At time t_2, the person has moved and shadowed the LOS path. So the multipath components arriving at the receiver can be classified into two categories: some waves travel in LOS path at time t_1 and are shadowed by the person at time t_2, we call them "diffracted waves" in this paper; the other waves are reflected or scattered by the human body or travel through it, we call them "scattered waves", as past studies often use the scattering model to describe them [1].

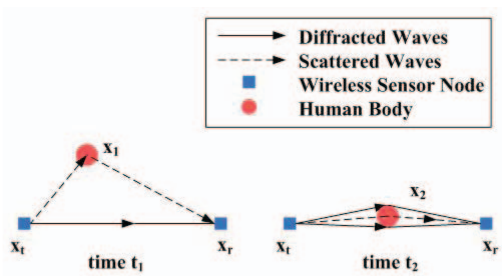


Fig. 1. The change of radio waves along with motion.

Considering $s_0(t)$ is the carrier radio signal, it can be expressed in the following complex form:

$$s_0(t) = a_0 e^{j(\omega_0 t + \phi_0)}$$

where a_0 represents amplitude, ω_0 represents the angular frequency and ϕ_0 the phase. We denote the set of diffracted waves as W_d, the set of scattered waves as W_s. The summed received signal $s(t)$ can be expressed as:

$$s(t) = \sum_{i \in W_d} a_i s_0(t - \tau_i) + \sum_{i \in W_s} a_i s_0(t - \tau_i) \qquad (1)$$

where a_i and τ_i are the amplitude attenuation and propagation time of the i th wave. For simplicity, we may assume that there are only two waves: the diffracted wave (the sum of diffracted waves) and the scattered wave (the sum of scattered waves). Then $s(t)$ can be written as:

$$s(t) = A_d a_0 e^{j\omega_0 t + \Phi_d} + A_s a_0 e^{j\omega_0 t + \Phi_s}$$

where A_d and A_s represent the amplitude attenuations, Φ_d and Φ_s are corresponding phases. The RSS we normally used is the decibel measurement of received power which is defined as the squared amplitude of signal. So the RSS measurement R_{dB} can be expressed as:

$$R_{dB} = 10 \lg(P_d + P_s + 2\sqrt{P_d P_s} \cos\Phi) \qquad (2)$$

where $P_d = A_d^2$ and $P_s = A_s^2$ are power attenuations; $\Phi = \Phi_d - \Phi_s$ is the phase difference. Since the scattered wave suffers a significant scattering loss and a higher path loss, we consider that $P_d \gg P_s$. Then Eq. (2) can be expanded by a Taylor series, retaining the two leading terms, as follows:

$$R_{dB} = 10(\lg P_d + 2\sqrt{\frac{P_s}{P_d}} \cos\Phi) \qquad (3)$$

In a finite period of time T, P_d and P_s can be considered constant, while Φ changes rapidly and randomly. So the RSS measurement can be treated as a random process $R_{dB}(t)$, its mean and variance $\mu_R(t)$ and $\sigma_R^2(t)$ can be calculated then,

$$R_{dB}(t) = 10[\lg P_d + 2\sqrt{\frac{P_s}{P_d}} \cos(\omega t + \Phi)] \qquad (4a)$$

$$\mu_R(t) = E[R_{dB}(t)] = 10 \lg P_d \qquad (4b)$$

$$\sigma_R^2(t) = E[R_{dB}(t) - \mu_R(t)]^2 = \frac{2P_s}{P_d} \qquad (4c)$$

where Φ is a random variable which is uniformly distributed within the $[-\pi, \pi]$ interval. It can be easily proved that this random process is ergodic. So the statistical averages are equivalent to the unbiased time averages. However, in RF sensor networks, the RSS measurements are sampled at a constant time interval T_s, resulting in a discrete-time signal $R(n)$:

$$R(n) = R_{dB}(nT_s)$$

Hence, the mean and variance of RSS can be approximated by arithmetical averages of a finite number of samples, which are expressed as follow:

$$\mu_R(n) = 10 \lg P_d = \frac{1}{2N_s + 1} \sum_{p=-N_s}^{N_s} R(n+p) \qquad (5a)$$

$$\sigma_R^2(n) = \frac{2P_s}{P_d} = \frac{1}{2N_s + 1} \sum_{p=-N_s}^{N_s} [R(n+p) - \mu_R(n)]^2 \quad (5b)$$

where $\mu_R(n)$, $\sigma_R^2(n)$ are the mean and variance at time nT_s; N_s is the buffer size, the number of samples used for calculation is $2N_s + 1$. $\mu_R(n)$ and $\sigma_R^2(n)$ represent the long term and short term variations of RSS, respectively. So we call them "long-term measurement" and "short-term measurement" in this paper. The model based on them will be presented in Section IV.

IV. Measurement model

This section proposes a novel measurement model based on the long-term and short-term measurements, which can be expressed as:

$$\mu_R(n) = \phi_d(\boldsymbol{x_n}) + \omega_{d,n}$$

$$\sigma_R^2(n) = \phi_s(\boldsymbol{x_n}) + \omega_{s,n}$$

where $\boldsymbol{x_n}$ is the location of the person at time interval n. $\phi_d(\boldsymbol{x_n})$ and $\phi_s(\boldsymbol{x_n})$ represent the models for long-term and short-term measurements $\mu_R(n)$ and $\sigma_R^2(n)$, respectively. $\omega_{d,n}$ and $\omega_{s,n}$ are mutually independent zero-mean Gaussian white noise with variances $\sigma_{W_d}^2$ and $\sigma_{W_s}^2$. We refer to $\phi_d(\boldsymbol{x_n})$ as "diffraction model", and $\phi_s(\boldsymbol{x_n})$ as "scattering model". They will be introduced in the next two subsections.

A. Diffraction model

Long-term measurement mainly reflects the shadowing effects caused by the person. In previous studies, several models have been proposed for describing the shadowing effects, like the "pixel-free model" in our previous work [3]. The diffraction model we use is an extension of it. In pixel-free model, $\phi_d(\boldsymbol{x_n})$ can be expressed as follow:

$$\phi_d(\boldsymbol{x_n}) = R(\boldsymbol{x_n}) + R_e \tag{6}$$

where R_e is the average RSS when no target is present; $R(\boldsymbol{x_n})$ is the attenuation of RSS caused by the person located at $\boldsymbol{x_n}$, which is defined as:

$$R(\boldsymbol{x_n}) = c_d \exp\left(\frac{\|\boldsymbol{x_t} - \boldsymbol{x_r}\| - \|\boldsymbol{x_n} - \boldsymbol{x_t}\| - \|\boldsymbol{x_n} - \boldsymbol{x_r}\|}{\sigma_d}\right) \tag{7}$$

where $\boldsymbol{x_t}$ and $\boldsymbol{x_r}$ are the locations of transmitting node and receiving node. c_d is the attenuation when the person is in directly obstructing the link, i.e. when $\|\boldsymbol{x_t} - \boldsymbol{x_r}\| - \|\boldsymbol{x_n} - \boldsymbol{x_t}\| - \|\boldsymbol{x_n} - \boldsymbol{x_r}\| = 0$. σ_d controls the decaying rate of the attenuation.

Based on the definition of diffracted waves in Section III, when link distance is very short, the human body will obstruct more diffracted waves than a link with longer distance, and cause larger attenuation on long-term measurement. Hence, the attenuation is modified by us as:

$$R_a(\boldsymbol{x_n}) = \frac{R(\boldsymbol{x_n})}{\|\boldsymbol{x_t} - \boldsymbol{x_r}\|} \tag{8}$$

For simplicity of measuring, we use Friis' free space pass loss formula to calculate the value of R_e, replacing the method of averaging the RSS measured when no target is present. R_e is expressed as:

$$R_e = -10 n_e \lg \|\boldsymbol{x_t} - \boldsymbol{x_r}\| - R_1 \tag{9}$$

where n_e is the propagation exponent, R_1 is the average RSS measured when the distance of two nodes is 1 meter. Finally, combining Equs. (7) and (8), the diffraction model can be written as:

$$\phi_d(\boldsymbol{x_n}) = R_a(\boldsymbol{x_n}) + R_e \tag{10}$$

B. Scattering model

The short-term measurement mainly reflects the scattering effects. In classical wireless theories like radar literature [10] and indoor propagation models [11], it is typically assumed that the scattered waves only change in direction when traveling in new paths created by the presence of obstruction. When the antenna of node radiates uniformly in all horizontal directions, the power attenuation of scattered wave $P_s(\boldsymbol{x_n})$ can be expressed as:

$$P_s(\boldsymbol{x_n}) = \frac{c_s}{\|\boldsymbol{x_n} - \boldsymbol{x_t}\|^{n_s} \|\boldsymbol{x_n} - \boldsymbol{x_r}\|^{n_s}} \tag{11}$$

where c_s is a constant; n_s is the propagation exponent. Based on the Friis freespace pass loss formula, the power attenuation of diffracted wave $P_d(\boldsymbol{x_n})$ can be expressed as:

$$P_d(\boldsymbol{x_n}) = \frac{c_d}{\|\boldsymbol{x_t} - \boldsymbol{x_r}\|^{n_d}} \tag{12}$$

where c_d is a constant, n_d is the propagation exponent. We set different propagation exponents for then two sets of waves for better adjustments of different environments. From Eqs. (5b), (11) and (12), the scattering model can be finally written as:

$$\phi_s(\boldsymbol{x_n}) = \frac{c_h \|\boldsymbol{x_t} - \boldsymbol{x_r}\|^{n_d}}{\|\boldsymbol{x_n} - \boldsymbol{x_t}\|^{n_s} \|\boldsymbol{x_n} - \boldsymbol{x_r}\|^{n_s}} \tag{13}$$

where $c_h = 2c_s/c_d$.

V. Algorithm

The measurement model in itself does not provide the positions of the person. The particle filtering algorithm [12] provides a framework to track such position estimations. Particle filtering algorithm is a numerical method for solution of optimal estimation problems in non-linear and non-Gaussian scenarios. Compared with standard approximation methods like the Kalman filter [8], the particle filtering algorithm does not rely on any local linearization or any crude functional approximation. This property is fit for our tracking system. In our system, the algorithm utilizes the long-term and short-term measurements as posterior information, and target positions at the previous time interval as prior information. Estimation results are derived by a large collection of random samples, which are termed "particles". We model the target dynamic using the autoregressive gaussian(ARG) model. i.e. $\boldsymbol{x_{k+1}} = \boldsymbol{x_k} + \sigma_v \boldsymbol{v}$, where $\boldsymbol{x_k}$ is the target position at the kth time interval, σ_v is a constant and $\boldsymbol{v} \sim N(0,1)$. The tracking process can be described by following steps:

1. Set N particles with random positions $X = [\boldsymbol{x_1}, ..., \boldsymbol{x_N}]$;
2. Compute the weights of particles $\omega(X)$ according to the measurement model and normalize them as W;
3. Resample $\{W, X\}$ to obtain N equally-weighted particles $\{\frac{1}{N}, \bar{X}\}$;
4. Compute the estimated position $X_{est} = \frac{1}{N}\sum_{i=1}^{n} \bar{X}^i$;
5. Update the positions of particles as the ARG model, $X = \bar{X} + \sigma_v V$, where $V = [\boldsymbol{v}, ..., \boldsymbol{v}]$ is an 1×1000 vector;
6. Jump back to step 2 and repeat.

For information on the derivation of this algorithm, there are many textbooks on the topic of particle filtering [12].

VI. Experiment results

A. Testbed Setup

We build a sparse RF sensor network with only 4 sensor nodes along the perimeter of a 4×4 meter square, as seen in Fig. 2, 5 and 6. Each node consists of a TI CC2530

TABLE I
PARAMETER SETTINGS OF THE MEASUREMENT MODEL

Parameter	Equation	Value	Parameter	Equation	Value
N_s	(6)	35	R_1	(10)	-35dBm
c_d	(8)	30	c_s	(14)	1.5
σ_d	(8)	0.04	n_d	(14)	1.8
n_e	(10)	1.8	n_s	(14)	2

radio transceiver chip, an omnidirectional antenna and two 1.2V rechargeable batteries. The chips use the IEEE 802.15.4 standard for communication in the 2.4GHz frequency band. A base station node receives all transmissions and feeds the data to a laptop computer via a USB port. The network is placed in an outdoor area about 6m apart from nearest tall building.

A simple token-ring transmission protocol is developed to avoid network transmission collisions. Each node is assigned a fixed node ID at the compile time. The time interval between two measurements is set to 20ms. In particle filtering algorithm, the number of particles, N, is set to 1000 and σ_v is set to 0.15. The parameters of the model are set as presented in Table I.

B. Motion Tracking

Firstly, we place the four nodes at the midpoints of the four edges of square, with the target moving along a square trajectory. Fig. 2 shows the tracking results superimposed on the true tracks. As shown in Fig. 2, we see that the estimated positions successfully agree with the ground truth.

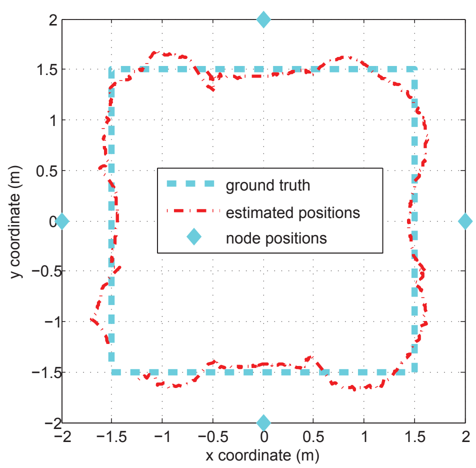


Fig. 2. Motion tracking when the person moved along squared path: position estimates superimposed on ground truth

To quantify the tracking accuracy of system, we calculate the root mean square error(RMSE) of the estimated results. Fig. 3 is a plot of RMSE as a function of time. The average RMSE is 0.1157m. As shown in Fig. 2 and Fig. 3, there are relatively higher RMSE values at the corners of the square trajectory. As an abrupt turn is a much less likely event in the ARG model, fewer particles are able to track the trajectory when the target changes direction at the corners [3].

For detailed analysis, we present the RSS measurements on a single link. The chosen link is the link from the node at (0,2)

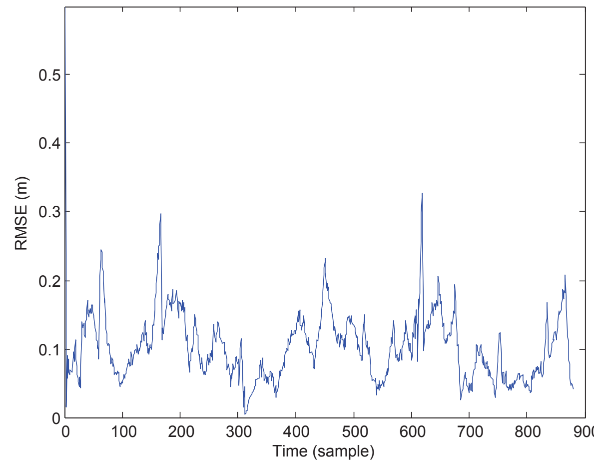


Fig. 3. Plot of RMSE as a function of time

TABLE II
PERFORMANCE COMPARISON OF OUR SYSTEM AND TRACKING SYSTEM IN [3]

	Size of network area(m)	Number of nodes	RMSE(m)
Our system	4×4	4	0.1157
System in [3]	7×7	24	0.3214

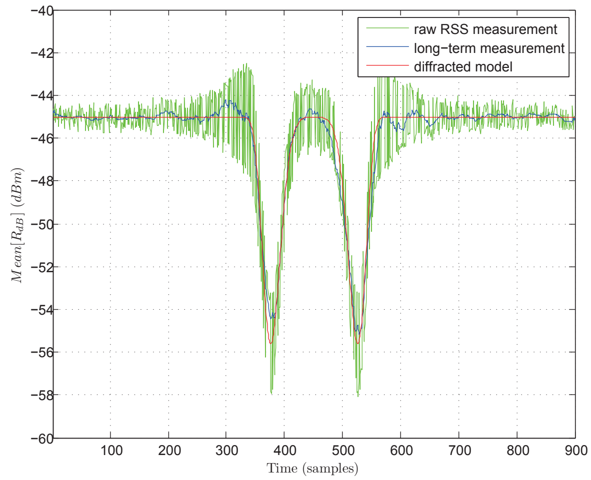
to the node at (2,0). From Fig. 4, we can see that the value of RSS changes rapidly when the person moves. As seen in Fig. 4(a), the value of long-term measurement is roughly constant when the LOS is not shadowed, and decreases sharply when the person moves towards the LOS path. Similarly, in Fig. 4(b), the short-term measurement increases as the person gets closer to the LOS path. The red lines in Fig. 4(a) and 4(b) are theoretical values of RSS based on the measurement model and ground truth. We can see the theoretical values reveal an excellent agreement with the measurements.

We also carried out experiments in other scenarios. Fig. 5 shows the motion tracking result when the person moves along a zigzag path. The average RMSE of this scenario is 0.1332m. Fig. 6 shows the motion tracking result when sensor nodes are arranged irregularly. The average RMSE is 0.1193m. The results demonstrate that the system is adaptive to changes in motion path and sensor deployment.

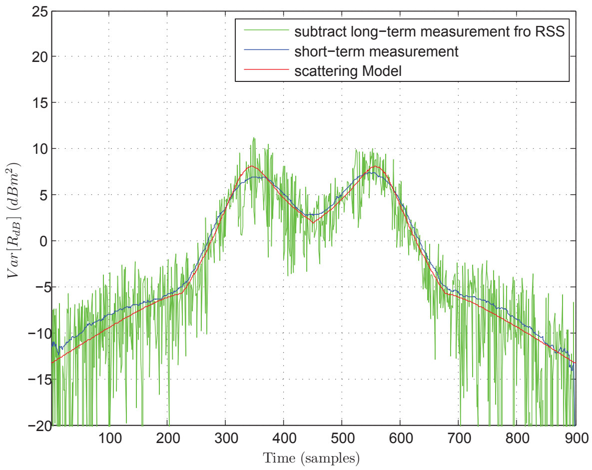
We compare the performance of our system and widely accepted motion tracking system in [3], which also uses SMC to perform tracking and is also deployed in an open outdoor area. As shown in Table II, with novel measurement model, our system achieves much better accuracy with fewer nodes.

VII. CONCLUSION

This paper presents a novel system using sparse RF sensor network to track a person without carrying any device. The system do not need any training phases. New measurement, model, algorithm, and testbed are designed. By theoretical analysis of the multipath fading phenomenon in RF sensor networks, we extend the sensing range of each wireless link to the maximum. Experimental results show that the system achieves high accuracy with much fewer nodes. These features



(a) Comparison of raw RSS measurement, long-term measurement and theoretical value of diffracted model



(b) Comparison of the value subtracted long-term measurement from RSS, short-term measurement and and theoretical value of scattering model

Fig. 4. RSS Measurement on link (0,2) to (2,0)

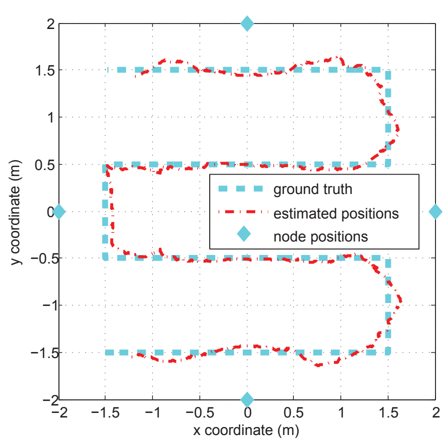


Fig. 5. Motion tracking when the person moved along zigzag path: position estimates superimposed on ground truth

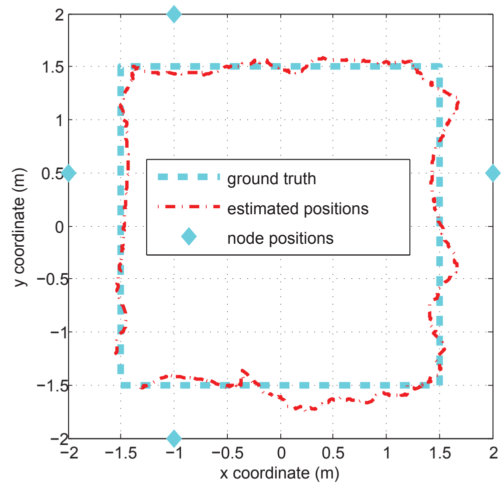


Fig. 6. Motion tracking when the nodes are arranged asymmetrically: position estimates superimposed on ground truth

will enable several new applications that are otherwise impractical, such as perimeter surveillance and fire rescue. Our future work will focus on tracking in more challenging scenarios and tracking of multiple targets.

References

[1] N. Patwari and J. Wilson, "Rf sensor networks for device-free localization: Measurements, models, and algorithms," *Proceedings of the IEEE*, vol. 98, no. 11, pp. 1961–1973, 2010.

[2] J. Wilson and N. Patwari, "Radio tomographic imaging with wireless networks," *Mobile Computing, IEEE Transactions on*, vol. 9, no. 5, pp. 621–632, 2010.

[3] Y. Li, X. Chen, M. Coates, and B. Yang, "Sequential monte carlo radio-frequency tomographic tracking," in *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*. IEEE, 2011, pp. 3976–3979.

[4] R. Kouyoumjian and P. Pathak, "A uniform geometrical theory of diffraction for an edge in a perfectly conducting surface," *Proceedings of the IEEE*, vol. 62, no. 11, pp. 1448–1461, 1974.

[5] M. Youssef, M. Mah, and A. Agrawala, "Challenges: device-free passive localization for wireless environments," in *Proceedings of the 13th annual ACM international conference on Mobile computing and networking*. ACM, 2007, pp. 222–229.

[6] M. Seifeldin and M. Youssef, "Nuzzer: A large-scale device-free passive localization system for wireless environments," *Arxiv preprint arXiv:0908.0893*, 2009.

[7] D. Zhang, J. Ma, Q. Chen, and L. Ni, "An rf-based system for tracking transceiver-free objects," in *Pervasive Computing and Communications, 2007. PerCom'07. Fifth Annual IEEE International Conference on*. IEEE, 2007, pp. 135–144.

[8] G. Welch and G. Bishop, "An introduction to the kalman filter," *Design*, vol. 7, no. 1, pp. 1–16, 2001.

[9] M. Ghaddar, L. Talbi, T. Denidni, and A. Sebak, "A conducting cylinder for modeling human body presence in indoor propagation channel," *Antennas and Propagation, IEEE Transactions on*, vol. 55, no. 11, pp. 3099–3103, 2007.

[10] E. Paolini, A. Giorgetti, M. Chiani, R. Minutolo, and M. Montanari, "Localization capability of cooperative anti-intruder radar systems," *EURASIP Journal on Advances in Signal Processing*, vol. 2008, no. 17, 2008.

[11] O. Norklit and J. Andersen, "Diffuse channel model and experimental results for array antennas in mobile environments," *Antennas and Propagation, IEEE Transactions on*, vol. 46, no. 6, pp. 834–840, 1998.

[12] A. Doucet and A. Johansen, "A tutorial on particle filtering and smoothing: Fifteen years later," 2009.