Beyond RSS: A PRR aided RSS System to Localize Transceiver-free Target in Sparse Wireless Networks

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***Abstract*—Nowadays transceiver-free (also referred as Device-free) localization by using Radio Signal Strength (RSS) is a hot topic for researchers due to its wide applicability. But RSS is easily affected by indoor environment, resulting in dense deployment of reference nodes. Some hybrid systems have already been proposed to help RSS localization, but most of them require additional hardware support. In order to solve this problem, in this paper, we propose two algorithms, which leverage Packet Received Rate (PRR) to help RSS localization without additional hardware support. Specifically, when reference nodes are sparsely deployed and RSS is very weak, our approach is able to accurately localize the target. Based on sparsely wireless sensor network, the experiment results show that the localization accuracy of our approach outperforms the pure RSS based approach by about 12.8%.**

***Index Terms*—Transceiver-free localization; PRR; RSS; None-Line-Of-Sight**

I. Introduction

Transceiver-free (also referred as Device-free) localization is able to localize target without carrying any device. Radio Frequency (RF) based technologies remain a hot topic in research field, since they can be applied in various scenarios without too much limitation.

Such traditional technologies usually leverage the signal variance, effected by the target in localization. Radio Signal Strength (RSS) and Channel State Information (CSI) are two kinds of resources often used. Some WiFi-based positioning systems [1] - [4] using CSI can locate transceiver-free target with only two signal transceivers. However, CSI is physical layer information, which is not available in most common devices.

The greatest disadvantage of RSS-based localization is that the RSS signal is easy to be influenced by slight variation in environment. Therefore, most RSS-based localization methods require dense deployment of the reference nodes [5] [6] [7]. By and large, the traditional transceiver-free indoor localization methods require at least 3 communication nodes in a limited experimental area [5]. There are also some hybrid systems utilizing other resource, e.g. ultrasound, image, infrared sensors, in localization [8] [9] [10] [14] [15]. These systems not only reduce the number of RF transceivers, but also provide more information compared to pure RF-based system. But all these above systems usually require additional hardware support. Huang et al. [11] uses Packet Received Rate (PRR) to recognize human motion, but localization can not be realized.

In this paper, we propose a fine-grained localization approach BEYOND RSS, which leverages both PRR and RSS. Our work is able to localize transceiver-free target, without introducing additional hardware support. Specifically, our approach works better in those complex environments with a sparse node deployment, where Line-of-Sight (LOS) paths among reference nodes do not exist, or the RSS signal is very weak.

Our basic idea is to introduce Packet Received Rate (PRR) as an additional resource to traditional RSS technology. PRR is a free resource for any common wireless device. It represents the quality of wireless link. When the RSS signal is good, the PRR will stabilize at 100%, on the contrary, when the RSS signal is very week, the PRR value may vary, which is known as critical section [12]. Traditional RSS-based technologies usually cannot accurately localize the target when RSS is very weak. Our approach is able to solve this problem, as PRR can play a constructive role in localization and be the successful partnership for RSS in this situation.

Based on both RSS and PRR information, we propose two localization algorithms based on K-Nearest Neighbour(KNN) and Dynamic Time Warping (DTW). In our experiments with only 2 far away deployed TelosB [13] sensors, we find that the localization accuracy of our BEYOND RSS approach outperforms the pure-RSS based approach by 12.8%.

The main contributions of this paper are as follows. First, we introduce PRR in RSS transceiver-free localization. To the best of our knowledge, we are among the first group to comprehensively utilize PRR-aided RSS system in localization.

Second, our approach is able to potentially improve all the traditional RSS based localization technologies, without additional hardware support. Third, our approach only requires very few transmitters/receivers, even when the RSS signal is very weak. At last, the empirical analysis considered here is the subject to real experiments.

The rest of this paper is organized as follows. In the next methodology section, we introduce the KNN and DTW algorithms. The proposed scheme with experimental evaluations is validated in Section III. We finally draw conclusions in Section IV.

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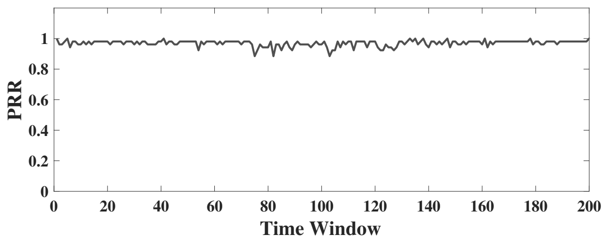
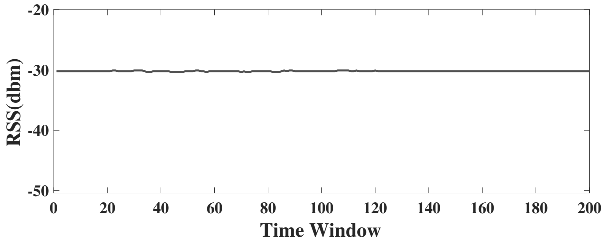
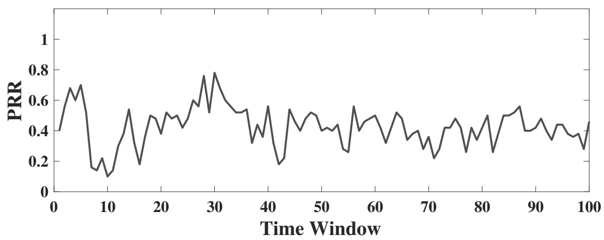


(a) PRR when no transceiver-free target appears.

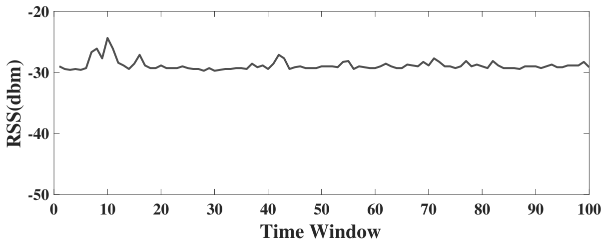


(b) RSS when no transceiver-free target appears.

Fig. 1: PRR vs. RSS when no transceiver-free target appears.



(a) PRR when transceiver-free target appears.



(b) RSS when transceiver-free target appears.

Fig. 2: PRR vs. RSS when transceiver-free target appears.

II. Related Work

Transceiver-free object localization usually utilizes two following resources: Radio Signal Strength (RSS) and Channel State Information (CSI). However, CSI information [1] - [4] is obtained from physical layer information. It is not available for most common devices. On the other hand, RSS information is easily obtained from common devices, making it popular in localization. Most RSS-based localization methods require dense deployment of the reference nodes, to avoid environmental influence to the signal. RASS system [5] deployed many sensor nodes on the ceiling as a regular triangle. In each such triangular area, RASS utilizes Support Vector Regression (SVR) model to locate transceiver-free object. The work by (J. Wang et al, 2014) proposed a Bayesian grid approach (BGA) to locate the target, which was suitable for resource-limited applications. The number of nodes they needed in an area of $8m \times 8m$ is 17 [6]. The work by (Y. Guo et al, 2015) could mitigate the multipath interferences by using the Exponential-Rayleigh (ER) model [7]. At least 17 sensors were required in the above experiment. By and large, the traditional transceiver-free indoor localization methods require at least 3 communication nodes in an experimental area [5]. The work by (L. Chen et al, 2012) could monitor and localize the transceiver-free target by using RFID technologies. They also require dense deployment of the tags with $1m$ apart.

Besides, there are also some hybrid systems utilizing other resource in localization. In 2012, Sverre Holm proposed an ultrasound RSS-based hybrid system for indoor positioning [8]. However, it covered limited area due to the inherent ultrasound characteristic. The work by (Lee et al, 2012) combined visible light communication (VLC) with Zigbee signal in localization [9]. The work by (Geng and Pahlavan, 2015) applied RF based and image processing based hybrid system into 3-dimensional localization [10] [15]. The work by (Bitew et al, 2014) proposed a hybrid localization method by utilizing Radio Frequency and pyro-electric infrared sensors [14]. The work by (Xiong et al, 2013) jointly utilized WSN and RFID technologies to positioning and tracking target at indoor environment [16]. All these above systems usually require additional hardware support. Huang et al. [11] used Packet Received Rate (PRR) to recognize human motion, but localization can not be realized.

III. Methodology

In this section, we first give the basic idea of how PRR can help RSS-based localization, then present the detail algorithm that we use to localize the target transceiver-free object.

A. Basic Idea

Traditional RSS-based transceiver-free localization usually deploy a number of reference nodes (consists of both transmitters and receivers) in advance, then leverage the RSS variance effected by the target to calculate the target position. However, we find that, besides RSS, the PRR of some wireless link will also be affected by the target. Especially in those scenarios where the reference nodes are sparsely deployed, or having no Line-Of-Sight (LOS) paths among reference nodes, this phenomenon is more prominent.

An example is shown below to further explain our basic idea. We deploy two wireless nodes in an indoor environment. One is the transmitter and the other is the receiver. The beacon interval is $15ms$. We arrange them in a Non-Line-Of-Sight (NLOS) environment (the two nodes are separated by a wall), which means no LOS path exists between the transmitter and receiver. We observe that, when in a static environment where no transceiver-free target appears, both RSS and PRR are stable, as Figure 1 shows. Each time window in the Figure 1 and Figure 2 is a time period (here is $0.75s$) during which we receive 50 received packets and calculate a PRR. However, when transceiver-free target object appears, both PRR and RSS

TABLE I: Notations used in this paper

Notation	Description
$l_i = (x_i, y_i)$	One transceiver-free target location on the ground
r	Total number of received packets
s	Number of received packets to compute one PRR value
q	Number of PRR values to calculate the target position
K	Number of nearest neighbors
γ	Vector length
T_i^k	The kth data of the vector for the ith location (store the radio map in the offline phase)
P^k	The kth data of the vector (received data) in the online phase
Seq_k	The sequence number of testing point
(x_t, y_t)	The coordinate of the target location
$D(P^\gamma, T_i^\gamma)$	The vector distance between P^K and each T_i^K

will change, but differently, as shown in Figure 2. In our example, the RSS has small changes while PRR information has prominent changes. In this scenario, PRR is more sensitive to the target.

Therefore, it is feasible for us to utilize PRR to help RSS-based localization.

B. Map Construction

Before introducing our algorithm in detail, we define the location space L as a set of n points on the ground (assume in a $2D$ area). L is denoted as

$$L = \{l_1 = (x_1, y_1), \cdots, l_n = (x_n, y_n)\} \tag{1}$$

where each tuple (x_i, y_i), $1 \leqq i \leqq n$, represents one transceiver-free target location on the ground.

During the offline phase, we arrange a person to represent the transceiver-free target to stand on each location on the ground to build a map which stores the RSS and PRR information during a fixed time period $\triangle H$ for each pair of transmitter and receiver.

During each fixed time period $\triangle H$, let r be the total number of received packets. We calculate PRR and average RSS for each s number of packets ($1 < s \leqq r$). Therefore, we will have $q = \ulcorner r/s \lrcorner$ number of average RSS value, and the same number as PRR values. In total, we will have $U = 2q$ number of RSS average and PRR values.

Suppose there are M pairs of transmitters and receivers (also referred as wireless links, we regard the symmetric links as one link) in the environment, we will have $\gamma = M \times U$ number of RSS average and PRR values. We can utilize a vector to define it as T_n^γ.

C. Localization Algorithm 1

In this subsection, we describe our algorithm based on K-Nearest Neighbor(KNN) [19]. After building the offline map as introduced in the previous subsection, in the online phase, when the transceiver-free target comes into the environment, for each fixed time period $\triangle H$, we can get the RSS and the PRR vector P^γ. Then we calculate the Euclidian distance between P^γ and each T_i^γ ($1 \leqq i \leqq n$) as follows

$$E_i = \sqrt{\sum_{j=1}^{n} (P^j - T_i^j)^2} \tag{2}$$

Then we select K number of locations with the smallest E values. The target location can be estimated as below

$$(X_t, Y_t) = \sum_{i=1}^{K} w_i (x_i, y_i) \tag{3}$$

w_i is a weight function, which can be estimated from the following equation

$$w_i = \frac{\frac{1}{E_i}}{\sum_{i=1}^{K} \frac{1}{E_i}} \tag{4}$$

D. Localization Algorithm 2

In this subsection, we will introduce our localization algorithm using DTW [18]. This algorithm is usually used in time series analysis. Since PRR potentially contains temporal information, we utilize this algorithm in localization.

When the target transceiver-free object appears, for each fixed time period $\triangle H$, we obtain the RSS and the PRR vector P^γ. Then we use Dynamic Time Warping (DTW) algorithm to calculate the vector distance between P^γ and each T_i^γ ($1 \leqq i \leqq n$). The calculation procedure is listed as follows.

At first, the initial value for each $D(P^j, T_i^k)$ is defined as

$$D(P^j, T_i^k) = \begin{cases} 0 & j = 1 \text{ and } k = 1 \\ +\infty & 1 < j \leqq \gamma \text{ and } 1 < k \leqq \gamma \end{cases} \tag{5}$$

Then we use the following equation to calculate the distance between P^γ and each T_i^γ. when j is larger than 1 or k is larger than 1

$$D(P^j, T_i^k) = |P^j - T_i^k| + \min \begin{bmatrix} D(P^{j-1}, T_i^k), \\ D(P^j, T_i^{k-1}), \\ D(P^{j-1}, T_i^{k-1}) \end{bmatrix} \tag{6}$$

For total n number of points on the ground, we define a vector Dist to store the n points' distance $D(P^j, T_i^\gamma)$ which is calculated by the above equation.

$$Dist_i = D(P^\gamma, T_i^\gamma), \quad 1 \leqq i \leqq n \tag{7}$$

At Last, we choose K number of locations (x_{c1}, y_{c1}),· (x_{cK}, y_{cK}) from L, which have smallest $Dist$ values. The coordinate of the target location (X_t, Y_t) can be calculated as

$$X_t = \frac{1}{K} \sum_{i=1}^{K} x_{ci}, \quad Y_t = \frac{1}{K} \sum_{i=1}^{K} y_{ci} \tag{8}$$

Some important notations used in this paper are listed in the Table I.

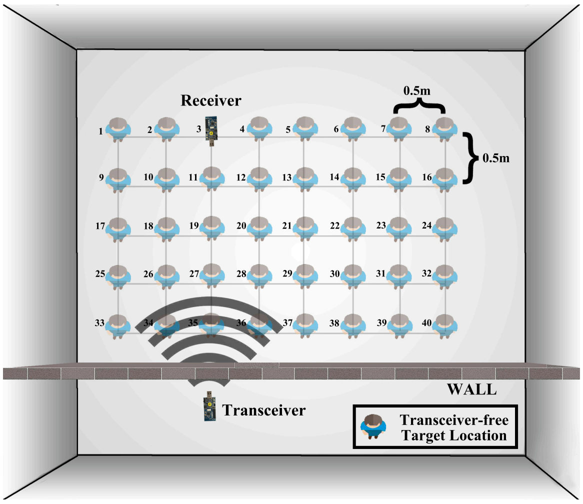


Fig. 3: Experimental environment.

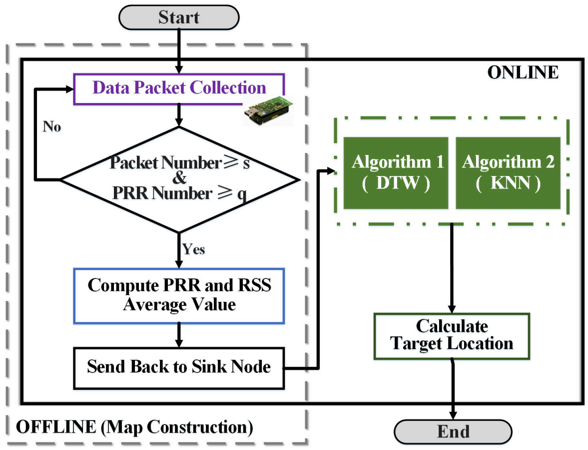


Fig. 4: Beyond RSS system flow.

IV. Experiment

A. Experiment Setting & System Flow

The experiment was conducted in an indoor environment, whose area is $5m \times 7m$, as shown in Figure 3. In our experiment, we set up the sparse deployment by only using two nodes. They are two popular TelosB sensor nodes [13] deployed and separated by a wall. One sensor acts as the transmitter while the other acts as the receiver. Therefore, there exists no LOS signal path between them. The default transmission power is set as $-25dBm$ (power level 3) and the radio frequency is $2.4GHz$. The beacon interval of the transmitter is defaulted at $15ms$. The parameter K is selected as 4 by default according to empirical study[19].

Our BEYOND RSS system flow chart is described in Figure 4. At first during the training phase, for each target location on the ground, we collect the received packets. Each receiver will compute the PRR value after receiving every s (in our experiment this value is default at 50) packets, then send back to the sink along with RSS information. After we get q (in our experiment this value is default at 6) number of PRR values, the collection procedure is completed and the map is constructed. We will discuss how to set the parameters of s and q in the later subsection.

Second during the online phase, when the transceiver-free target appears in the environment, similarly, each receiver will also collect the received packets and compute the PRR value every s packets, and send back to the sink along with the RSS information. After we get q number of PRR values, users can choose our algorithm 1 based on KNN or algorithm 2 based on DTW to perform at the server part to calculate the target location. When the procedure repeats, we can track the target transceiver-free object.

B. Impact of Parameter q

The value of q depends upon how many PRR values are considered to calculate the target location. It decides the input vector dimension and is one of the key parameters to the performance of our system. If this value is set very large, the time required to collect the packets will be longer, resulting in high system delay. On the contrary, if this value is set too small, the localization accuracy will be affected.

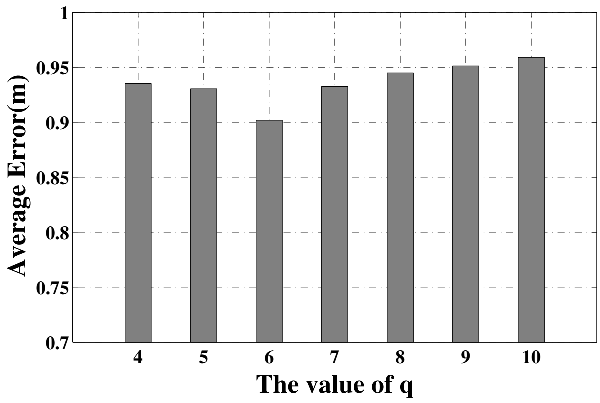
In order to test how the value of q will impact the localization accuracy, we test different values of q from 4 to 10 (other parameter s is randomly chosen), as shown in Figure 5. We find that, the localization error is smallest when the value of q is set to 6. For the other values of q smaller than 6 or larger than 6, the localization errors are larger. The reason may be attributed to the following: if the q is lower than 6, the time is too short to get enough PRR values for the localization algorithm. On the contrary, if the q is set higher, the time is too long and there is a possibility of introducing noise information in the localization algorithm.

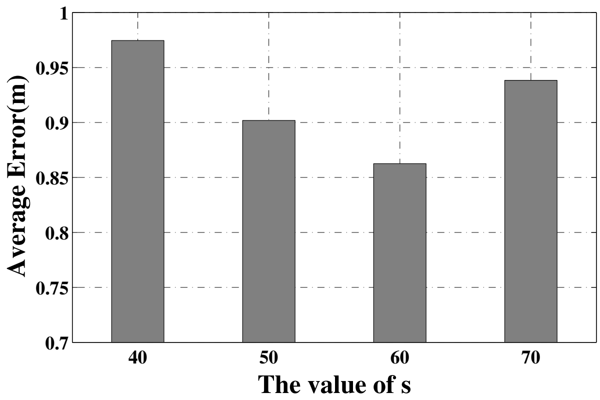
Therefore, in our later experiment, we consciously choose the value of q as 6.

C. Impact of Parameter s

The value of s depends on how many packets required to calculate one PRR value. It is also one of the key parameters which decides the localization accuracy and system performance. If this value is set very large, the time to receive all the required packets will be longer, resulting in high system delay. On the contrary, if this value is set too small, PRR value may not be well represented.

In order to test how the value of s will impact the localization accuracy, we test different values of s from 40 to 70, in steps of 10, as shown in Figure 7. We find that, the localization error is smallest when the value of s is set to 50 or 60, wherein the localization accuracy can reach about $0.9m$. For the values of s smaller than 50, the localization errors are larger. The reason is that, if the value of s is set too low, the time is too short to get a well-represented PRR. For the values of s larger than 60, the localization errors are larger. The reason may be attributed to the following: If we calculate one PRR value based on a large number of received packets, it increases the possibility of introducing more noise information. Moreover, the latency will increase.





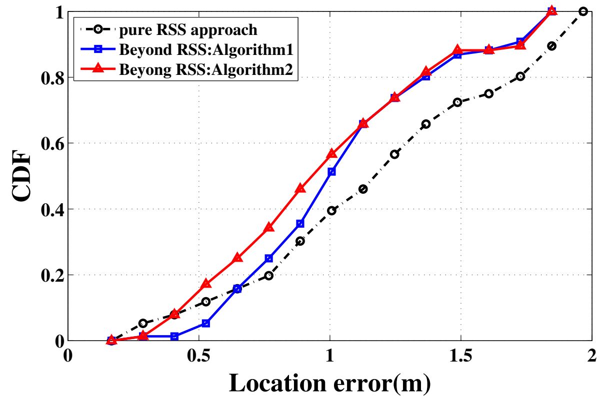


Fig. 6: Algorithm results based on all sample target positions.

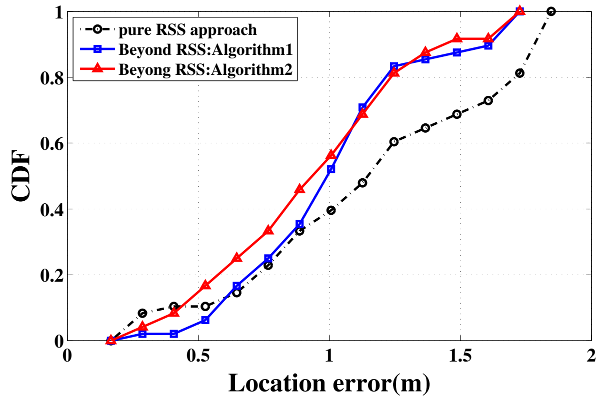


Fig. 8: Algorithm results based on non-border sample target positions.

Therefore, in our later experiment, in order to get a tradeoff between localization accuracy and system latency, we choose the value of s as 50 instead of 60, since 60 will increase the system latency. But this value can be decided by the users depending on their priority.

D. Localization Accuracy

In the subsection, we will test the localization accuracy of our BEYOND RSS system. In total, we have tested 38 sample target positions on the ground. Among the above sample target positions, there are 14 sample target positions on the border area.

The experiment results are shown in Figure 6 and Figure 8. Figure 6 is the algorithm results based on all sample target positions, while Figure 8 is the algorithm result based on non-border sample target positions.

For all the sample target positions including the border area, the localization accuracy of our BEYOND RSS system can reach about $0.95m$ by our algorithm 2. For algorithm 1, the localization accuracy can reach about $1.02m$. But the pure RSS-based localization accuracy is only about $1.09m$. It is noted that, for the non-border sample target positions, our localization accuracy can reach about $0.96m$ and $0.86m$, by algorithm 1 and algorithm 2 respectively, while the pure RSS-based localization accuracy is only about $1.03m$. The localization results for sample target positions are shown in Figure 9, the blue circle represents the real position, while red star represents the calculated position.

The reason why we have better localization accuracy for the target positions in non-border area is the following. In our system, we only have 2 sensor nodes which are sparsely deployed in the environment. There are no LOS signal path between the two nodes. Thus, the signal is very weak. If in the border area, the signal is too weak, even the PRR is hard to have a valid value for the localization algorithm.

In summary, our experiment results shows that, no matter the test samples include the border area or not, our BEYOND RSS always outperform the pure RSS-based approach by about 12.8%.

E. Latency

The latency of our BEYOND RSS system depends on how long the server (a sink is connect to it) to obtain all the PRR and RSS information. The running time of the localization algorithm on the server can be ignored.

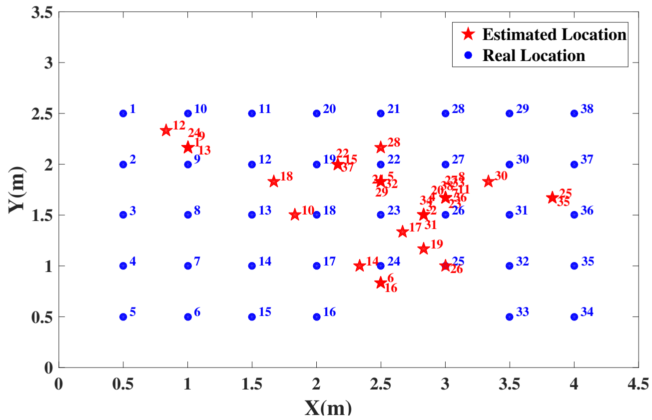


Fig. 9: Localization results.

Suppose the beacon interval for the transmitter to transmit a packet to receiver is T_I in our system, and again the number of collecting packets to compute a PRR value is s, and the number of PRR values to calculate a target position is q, the latency can be calculated as follows.

$$T_{latency} = q \times s \times T_I \tag{9}$$

In our system, the value of q is set as 6, the value of s is set as 50, and the beacon interval is set as $15ms$. Therefore, the total latency is $15ms \times 6 \times 50 = 4.5s$.

Although the latency is not very low, it is still a good choice for sparse wireless networks and can reduce the deployment cost. In real scenarios, users may get a tradeoff between system latency and localization to get a tolerated accuracy with lower latency.

V. Conclusion and Future Work

In this paper we propose an approach, which leverages PRR to help traditional RSS transceiver-free object localization. PRR can be obtained from common device without additional hardware cost. Moreover, it can be widely used in sparse wireless networks or complex indoor environments where LOS path often not existing among reference nodes. We propose two algorithms based on DTW and KNN algorithm, to accurately localize the transceiver-free target. In our experiment, we only use 2 wireless nodes in the indoor environment, the localization accuracy can outperform the pure RSS based approach by about 12.8%. Our approach is potential to improve almost all the RF-based localization using common hardware.

As future work, first, we may perform our experiment in a larger and more complicate indoor environment. Second, reference nodes with different sparse deployment should be tested. At last, we may try different algorithm to get a higher accuracy.

Acknowledgment

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References

[1] X. Wang, L. Gao, S. Mao and S. Pandey, "CSI-Based Fingerprinting for Indoor Localization: A Deep Learning Approach," IEEE Transactions on Vehiculat Technology. 60(1), pp. 763–776, 2017.

[2] M. Kotaru, K. Joshi, D.Bharadia and S. Katti, "SpoFi: Decimeter Level Localizatioin Using WiFi," ACM Special Interest Group on Data Communication, 45(4), pp. 269–282, 2015.

[3] Y. Du, D. Yang and C. Xiu, "A novel method for constructing a WiFi positioning system with efficient manpower," Sensors, 15(4), pp. 8358–8381, 2015.

[4] C. Yang, H. R. Shao, "WiFi-based indoor positioning," IEEE Communications Magazine, 53(3), pp. 150–157, 2015.

[5] D. Zhang, Y. Liu, X. Guo and L. M. Ni, "RASS: A Real-Time, Accurate, and Scalable System for Tracking Transceiver-Free Objects," IEEE Transactions on Parallel Distribution System. 24(5), p. 996–1008, 2013.

[6] J . Wang, Q. Gao, P. Cheng, Y. Yu,K. Xin and H. Wang, "Robust Devicefree Wireless Localization Based on Differential RSS Measurements," IEEE Transactions on Industrial Electronics, 60(10), p. 5681–5689, 2014.

[7] Y. Guo, K. Huang, N. Jiang, X. Guo, Y. Li and G. Wang, "An Exponential-Rayleigh Model for RSS-Based Device-Free Localization and Tracking," IEEE Transactions on Mobile Conputing, 14(3), p. 484–494, 2015.

[8] S. Holm, "Ultrasound positioning based on time-of-flight and signal strength," IEEE Indoor Positioning and Indoor Navigation (IPIN), International Conference on. IEEE, 1–6, 2012.

[9] Y. Lee, M. Kavehrad, "Two hybrid positioning system design techniques with lighting LEDs and ad-hoc wireless network," IEEE Transactions on Consumer Electronics, 58(4), 2012.

[10] Y. Geng and K. Pahlavan, "On the Accuracy of RF and Image Processing Based Hybrid Localization for Wireless Capsule Endoscopy," IEEE Wireless Conmunications and Networking Conference (WCNC), Track 1: PHY and Fundamentals, 2015.

[11] X. Huang, M. Da, "Indoor Device-Free Activity Recognition Based on Radio Signal," IEEE Transactions on Vehicular Technology, PP(99):1–1, 2016.

[12] M. Zuniga, B. Krishnamachari, "Analyzing the transitional region in low power wireless links," Sensor and Ad Hoc Communications and Networks. IEEE SECON 2004. 2004 First Annual IEEE Communications Society Conference on. IEEE, p.517–526, 2004.

[13] XBOW Corporation, "TelosB mote specifications," http://www.xbow.com/Products/productdetails.aspx?sid=252.

[14] M. A. Bitew, R. Hsiao, H. Lin and D. Lin, "Hybrid Indoor Human Localization System for Addressing the Issue of RSS Variation In Fingerprinting," International Journal of Distributed Sensor Networks, 2014(1), p.199–202, 2014.

[15] Y. Geng and K. Pahlavan, "Design, Implementation, and Fundamental Limits of Image and RF Based Wireless Capsule Endoscopy Hybrid Localization," IEEE Transactions on Mobile Computing, 15(8), p. 1951–1964, 2016.

[16] Z. Xiong, Z. Song, A. Scalera, E. Ferrera, F. Sottile, P. Brizzi, R. Tomasi and M. A Spirito, "Hybrid WSN and RFID indoor positioning and tracking system," EURASIP Joutnal on Embedded Systems, 2013(1): 6, 2013.

[17] Lei Chen, Yiyang Zhao, Yunhao Liu, Jian Pei, Jinsong Han, "Mining Frequent Trajectory Patterns for Activity Monitoring Using Radio Frequency Tag Arrays," IEEE Transactions on Parallel & Distributed Systems vol. 23 no. , p. 2138–2149, 2012.

[18] J. Wang, H. Jiang, J. Xiong, K. Jamieson, X. Chen, D. Fang, B. Xie, "LiFS: Little Human-Effort for Device-Free Localization with Fine-grained Subcarrier Information," International Conference on Mobile Computing and Networking (Mobicom), pp. 234–256, 2016.

[19] Altman N S. An Introduction to Kernel and Nearest-Neighbor Nonparametric Regression[J]. American Statistician, 1992, 46(3):175–185.