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Double Free: Measurement-free Localization for Transceiver-free Object

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***Abstract*—Transceiver-free object localization is essential for emerging location-based service, e.g., the safe guard system and asset security. It can track indoor target without carrying any device and has attracted many research effort. Among these technologies, Radio Signal Strength (RSS) based approaches are very popular because of their low-cost and wide applicability. In such work, usually a large number of reference nodes have to be deployed. However, if in a very large area, many labor work to measure the positions of the reference nodes have to be performed, result in not practical in real scenario. In this paper, we propose Double Free, which can accurately track transceiver-free object without measuring the positions of the reference nodes. Users may randomly deploy nodes in a $2D$ area, e.g., the ceiling of the floor. Our Double Free contains two steps: reference node localization and target localization. The key to achieve the first step is to utilize the RSS difference in different channel to distinguish the Line-Of-Sight (LOS) signal from combined multiple paths' signal. Thus, the reference nodes can be accurately localized without additional hardware. In the second step, we propose two algorithms: Influential Link $\&$ Node (ILN) and MultiPath Distinguishing (MD). ILN is simple to implement, while MD can accurately model the additional signal caused by the target, then accurately localize the target. To implement this idea, 16 TelosB nodes are placed randomly in a $25\times10m^2$ laboratory. The experiment results show, the average localization error is only round 2 meters without requiring to measure the positions of reference nodes in advance. It shows enormous potential in those localization areas, where manual measurement is hard to perform, or hard labor work want to be saved.**

I. Introduction

Transceiver-free object localization can localize the target without carrying any device (transmitter or receiver or both). It is an emerging research area and attracts many researchers' attentions [21], [17]. It can be widely used in many indoor localization fields. For example, in the safeguard system or asset security system, the thief will definitely not carry any device to be tracked. Another scenario is in an indoor disaster area, e.g., an indoor fire or Poisonous gas leak place. The trapped people cannot carry any device in advance to be tracked.

Among various technologies in transceiver-free object localization, Radio Frequency (RF)-based approaches are very popular [23], [15], [12], [24], due to their low cost and wide applicability. But such technologies are apt to be affected by the environmental factors. In order to gain well localization accuracy, a typical approach is to deploy a large number of reference nodes. Usually a large number of reference nodes have to be deployed in advance. Each reference node will act as both transmitter and (or) receiver. If the target enters such environment, it will cause the Radio Signal Strength (RSS) of some wireless links among the reference nodes to change. Since such wireless links are clustered around the target [23], such RSS change information plus the reference nodes' positions can to be leveraged for localization.

However, such traditional RF-based transceiver-free object localization approaches have to manually measure the accurate coordinates of reference nodes before localization. If in a very large indoor area, a large amount of labor work have to be performed in advance. Furthermore, measuring locations of reference nodes is hard to put into practice in some real scenario, such as the underground coal mine area. To overcome this drawback, we put forward Double Free, which can accurately localize transceiver-free object without manually measuring the position of each reference node. Users only randomly deploy some wireless nodes in the specified area. They can localize the target accurately. So a large amount of labor work are reduced.

Our localization approach contains two basic steps: reference node localization and target object localization. In the first step, all the randomly deployed reference nodes (assumed in a $2D$ area) can be accurately and automatically localized. In the process of localizing reference nodes using RF-based technologies, some traditional approaches may be applied. For example, the

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radio map approaches [5], [20] usually profile a radio environment map and refer to it while localizing. Some other approaches can accurately localize the reference nodes [7], [10], [13], [15]. However, these approaches are easily affected by the environmental changes. If in the complex indoor environment, various objects in the indoor environment will cause the radio refraction and reflection, result in radio reaching the receiver by two or more paths (referred to *multipath phenomenon*). The localization accuracy is dramatically affected. Therefore, such technologies cannot be applied to localize the reference nodes, since the position of each reference node should be precisely known. Our approach can overcome this drawback and localize the reference nodes accurately. We can calculate the accurate distance before each pair of Transmitter-Receiver (T-R) reference nodes. Since we find that, for a pair of T-R reference nodes, different spectrum channels will cause different RSS. We can leverage such RSS difference to distinguish the RSS along the Line-Of-Sight (LOS) path. So the accurate distance between each pair of T-R reference nodes is obtained. Only three reference nodes are selected as anchor nodes whose absolute position is known, we can have the absolute position of each reference node by trilateration.

In the second step, under the reference nodes infrastructure, we propose two transceiver-free object localization algorithms: ILN and MD. ILN utilizes the RSS influenced by the target object for localization. It is simple to implement. MD can comprehensively model the additional radio signal caused by the target, and accurately localizes the transceiver-free target. The key idea is to utilize the different RSS value at different spectrum channel. Through solving a Curvature Fitting Problem, we may distinguish the radio signal caused by the target and obtain the length of the additional path. So such information plus the reference nodes' positions can be used to calculate the target position.

Compared with traditional RSS-based transceiver-free localization approaches, this paper has the following key advantages. 1)It can localize transceiver-free target without requiring to measure the positions of each reference node in advance. So many labor work can be saved. 2) It can adapt to the dynamic environment. That is, the localization of each reference nodes will not be affected by the environment changes, since only the LOS signal of each T-R pair of reference nodes is utilized for localization. 3) It has high localization accuracy without additional hardware support. We may comprehensively model the additional radio signal caused by the transceiver-free target. Therefore, the localization is high and the cost is very low, especially in those complex indoor environments.

To demonstrate the effectiveness of our idea, we implement a tracking system based on TelosB [4] platform. 16 sensor nodes are hung on the ceiling randomly acting as the reference nodes. Experimental results show that the average error to localize each reference node is around 1 meter, and the average tracking error of the target transceiver-free object (person) is round 2 meters and the tracking latency is $0.9s$. Compared with traditional RSS-based approaches, the accuracy is improved by 2 times.

The rest of this paper is organized as follows: Section 2 will discuss the relevant work. We will introduce our approaches to localize each reference node and transceiver-free target object in section 3. Section 4 will show the experimental results and evaluation of the performance. Finally, we will conclude this work and list our future work in section 5.

II. Related Work

In transceiver-free object localization, since the target doesn't carry any device, traditional transceiver-free object localization approaches usually are required to carefully deploy a large number of reference nodes. The positions of the reference nodes also have to be manually measured in advance. For example, Device-free [21] illustrated the feasibility to track target with no device, through processing changes in the received physical signals to detect changes in the environment. It requires to know the positions of access points and wireless sniffers in advance. Tag-free [11] used RFID tag array to well obtain the target trace. It also requires to densely deploy the reference tag array with $1m$ apart. ILight [12] use light sensors to accurately track transceiver-free object, but it also requires dense deployment and cannot work in dark place. Our previous work [23], [22] can achieve high accuracy without sacrificing latency during tracking transceiver-free object, but it is based on the exact location of reference nodes. Measuring the coordinates of all nodes is a huge work in a large area with massive nodes. Our current work may randomly deploy the reference nodes without know their positions in advance. Laser-based [9] technology can reach high accuracy , but the cost is very high, preventing it from for widely usage. Technologies using infrared [3] and pressure [17] require very dense and careful deployment. Its cost is very high. Viani et.al [18] can track moving object without carrying any device. It works well outdoor, it also requires amount of work for training.

Since the first step of our Double Free is reference node localization. Its goal is similar to traditional localization approaches requiring each object to carry a device. However, the way to realize and accuracy is very different. Our approach can accurately localize each reference node in a dynamic indoor environment, where multipath phenomenon occurs often. Basically, traditional work can be divided into two categories. One is profile-based techniques, RADAR [5], LANDMARC [15] are two typical ones. RADAR built a radio map for the environment, then referred it in localization. LANDMARC got the location of nodes by matching the received RSS to that of the reference nodes. All these methods can't adapt to dynamic environment (e.g., people walking round or environment changes). Furthermore, they require a large number of work to be done before localization, e.g., building the radio map or manually measuring most reference nodes. For the second model-based techniques, there are many propagation models, such as free space path loss (Friis [16]) model, the log-distance path loss (LDPL) model [8] and etc. Friis got distance by mapping directly from the RSS into distance of a pair of T-R nodes without considering the multiple paths propagation phenomenon. LDPL obtained the target location by referring to the measured RSS. The accuracy of these methods is not high, and they are vulnerable to the environment dynamics. RIPS and related systems [7], [10], [13] can achieve high accuracy when obtaining the distance between a pair of T-R nodes, but it is susceptible to the multipath environments, especially indoor.

III. Methodology

In this section, we first introduce the background of radio propagation, then describe how to accurately localize the randomly deployed reference nodes without manually measurement. In the following, we will give two localization methods to track transceiver-free target. At last, we will give some problems that we meet in our method and the treatment of the problems.

A. Background of Radio Propagation

For a pair of T-R nodes, radio will propagate from the transmitter to the receiver. In theory or in free space, there is only one propagation path. The radio signal vector at the receiver $\vec{p}$ is

$$\vec{p} = \{|\vec{p}|, \theta\} \tag{1}$$

Where $|\vec{p}|$ is the amplitude of the radio signal and θ is the signal phase. The amplitude of the radio signal (also referred as RSS) is consistent with Friis model [16]. This model is expressed as

$$|\vec{p}| \quad = \quad \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{2}$$

here d is the path length (here is LOS path length, which is the distance between the transmitter and receiver). P_t is the transmission power. G_t, G_r are the antenna gain of the transmitter and the receiver. λ is the radio wavelength.

We can see that, the received RSS is inversely proportional to the square of the path length. Also, if the T-R nodes and the transmission power are fixed, G_t, G_r and P_t are constant values.

The path length d and wavelength λ have effect on the radio signal phase θ. As the phase at the sender is 0, the signal phase at receiver is

$$\theta \quad = \quad (\frac{d}{\lambda} - \lfloor\frac{d}{\lambda}\rfloor)2\pi \tag{3}$$

So we can get different $\vec{p}$ by changing the λ with the same distance d.

In practice, except the LOS propagation path, there are many other propagation paths from the transmitter to the receiver. Since radio will be reflected or refracted by the surroundings. Such path are named as Non-Line-Of-Sight (NLOS) paths. The behavior of NLOS is similar with that of LOS. The behavior is as

$$|\vec{p}| \quad = \quad \Gamma\frac{P_t G_t G_r \lambda^2}{(4\pi d)^2} \tag{4}$$

Where Γ is the reflection coefficient, where $\Gamma = \frac{E^-}{E^+}$ where E^+, E^- are the radio wave energy before and after reflection. d is also the path length (here is the NLOS path length).

The RSS of each path also contains the information of signal phase θ and path length d. We may decompose the RSS of each path with trigonometric. The RSS received at the receiver is the combination of the decompositions on all paths. Decomposition on each path can be expressed as

$$\begin{aligned}(|\vec{p}|)^2 \quad &= \quad (\Gamma\frac{P_t G_t G_r \lambda^2}{(4\pi d)^2}\cos\theta)^2 \\ &\quad + (\Gamma\frac{P_t G_t G_r \lambda^2}{(4\pi d)^2}\sin\theta)^2\end{aligned} \tag{5}$$

where $|\vec{p}|$ is the RSS of each path, d is path length, θ is the signal phase on the path.

If we change the radio wavelength, the signal phase θ at the receiver will be different. Therefore, RSS may be different. The other background details and proof can be referred to our previous work [22].

B. Reference Node Localization

After users randomly deploy the reference nodes on the ceiling (in a $2D$ area) in the specified indoor environment, each reference node will act as both transmitter and receiver. Thus, there are many wireless links among these reference nodes. The reference node localization contains the following two steps. 1). Calculate the distance (also referred as ranging) between each pair of T-R reference nodes. That is, for each wireless link, we will calculate the distance between the transmitter and receiver. 2). Localize each reference nodes. That is, when we have all the distance between each pair of reference nodes, each reference node can be localized. In the following, we will introduce them in detail.

1) Calculate the Distance (Ranging) between Each pair of T-R Reference Nodes:

Our basic idea is as follows. For each pair of T-R reference nodes (wireless link), we filter out the NLOS signal and only get the signal along the LOS path. Therefore, the distance between transmitter and receiver can be accurately calculated. As illustrated in $Fig.1$, $Node1$ and $Node2$ are two reference nodes. When radio is sent out from $Node1$ to $Node2$, except the LOS radio propagation path p_1, there are also other path, e.g., the ground reflection path p_2. Usually the received signal at the receiver $Node2$ is the combination signals of all the paths, result in very hard to build an accurate relation between the T-R distance and the RSS. Our idea is to filter out the signal along the other paths, only obtain the signal along path p_1. Thus, distance between $Node1$ and $Node2$ can be accurately estimated. The detail is to utilize that, different frequency (different λ values) will cause different RSS value, indicating different signal phase, as introduced in the previous subsection. Through transforming the problem with trigonometric model functions into non-linear curvature fitting problem, the distance between each T-R reference nodes among the reference nodes can be calculated.

Without loss the generality, suppose there are n radio path between a pair of T-R reference nodes, their length are $d_1, d_2, \ldots, d_n$ respectively where d_1 is the length of LOS path and the others are the length of NLOS paths. Their reflection co-efficiency is $\Gamma_1, \Gamma_2, \ldots, \Gamma_n$, respectively . Γ_1 is the co-efficiency of LOS path and its value is 1. Suppose there are m channels to be utilized. Their radio wavelengths are $\lambda_1, \lambda_2, \ldots, \lambda_m$, respectively. The total RSS at receiver can be expressed as

$$\begin{aligned} P(x,\lambda_j) &= |\sum_{i=1}^{n} \vec{p_i}| \\ &= ((\sum_{i=1}^{n} c\lambda_j^2 d_i^{-2} \sin(d_i\lambda_j^{-1}))^2 \\ &\quad +(\sum_{i=1}^{n} c\lambda_j^2 d_i^{-2} \cos(d_i\lambda_j^{-1}))^2)^{\frac{1}{2}} \end{aligned} \quad (6)$$

Where $c = \frac{P_t G_t G_r}{(4\pi)^2}$, the value of c is a fixed unknown can be derived in advance through the method we introduced in our previous work [22]. $P(x, \lambda_j)$ is the total RSS at receiver when the radio wavelength is λ_j and $x = (c, \Gamma_2, \ldots, \Gamma_n, d_1, \ldots, d_n)$. There are $2n$ unknown parameters, so the problem may be solved when the number of channel is larger than $2n, m \geq 2n$. Now our task is to find an x to satisfy m measurements (P_j, λ_j) with the model function $P(x, \lambda_j)$ as close as possible. Here P_j is the measurement strength when the wavelength is λ_j . That is to find an x to make the sum of fitting error minimum. This problem is a Curvature Fitting Problem (CFP):

$$given \quad r_j(x) : \Re^{2n} \rightarrow \Re, j = 1, \ldots, m$$

$$min_{x\epsilon\Re^{2n}} f(x) \quad = \quad \sum_{j=1}^{m} r_j(x)^2 \quad (7)$$

here $r_j(x) = P(x, \lambda_j) - P_j, P_j$ is the real measurement value with λ_j and $P(x, \lambda_j)$ is the calculated value with the $Equ.(6)$. By tradition $\Re$ is the set of real numbers. $x = (c, \Gamma_2, \ldots, \Gamma_n, d_1, \ldots, d_n) \in \Re^{2n}$ will be obtained when the problem is solved, so is d_1.

2) Localize Each Reference Node:

After having the distance of each T-R reference nodes, if we want to calculate the absolute position of each reference node, we may choose three reference nodes as the anchor nodes (For example, the reference nodes colored in grey in $Fig.1$) and get their absolute positions. our approach is based on Trilateration to get the coordinate of each reference node. Trilateration [9], [14], [2] is the process of determining absolute or relative locations of points by measurement of distances, using the geometry of circles, spheres or triangles. But our approach performs better than traditional ones, when the Trilateration circles have no intersection point.

Suppose the coordinates of three anchor nodes, $1, 2, 3$, are(x_1, y_1), (x_2, y_2), and (x_3, y_3), respectively. r_{1X}, r_{2X}, r_{3X} are the distance from three anchor nodes to the unknown reference node $X = (x, y)$ respectively. r_{1X}, r_{2X}, r_{3X} are calculated from the previous subsection. So we have

$$r_{iX} \quad = \quad ((x - x_i)^2 + (y - y_i)^2)^{\frac{1}{2}} \quad (8)$$

where $i = 1, 2, 3$, r_{iX} is the distance from $i-th$ anchor node to the unknown node. In theory, (x, y) is unique by solving the $Equ.(8)$. However, while calculating the distance of the each pair of T-R nodes (here is r_{iX}), it may result in no intersection of three circles. So we transform this problem into CFP and find (x, y) to minimize the sum of fitting error.

$$given \quad d_i(x, y) : \Re^2 \rightarrow \Re, i = 1, 2, 3$$

$$min_{x\epsilon\Re, y\epsilon\Re} F(x, y) \quad = \quad \sum_{i=1}^{3} d_i(x, y) \quad (9)$$

where $d_i(x, y) = \sqrt{(x - x_i)^2 + (y - y_i)^2 - r_{iX}^2}$, r_{iX} is the calculated distance from anchor node i to the unknown node X, (x_i, y_i) is the coordinate of anchor node i. As long as the problem is solved, the coordinate of unknown node X is solved.

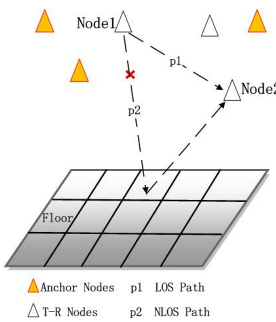

Fig. 1. Basic Idea of Localizing Reference Nodes by Distinguishing LOS path

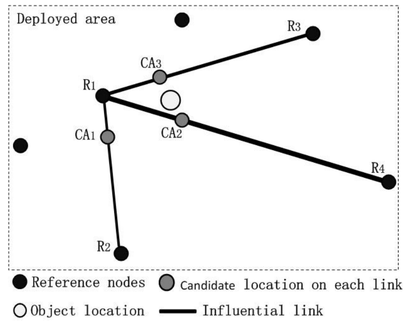

Fig. 2. An Example for ILN Algorithm

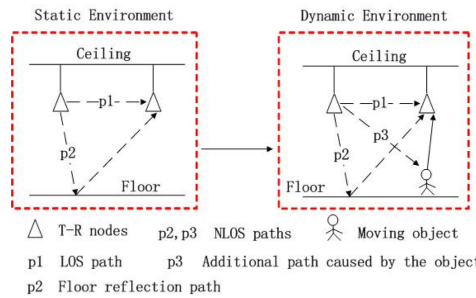

Fig. 3. Basic Idea of MD Algorithm

C. Transceiver-free Object Localization under the Reference Node Infrastructure

After obtaining the position of each reference node on the ceiling, we can localize the transceiver-free target on the ground. Since each reference node acts as both transmitter and receiver, we have may wireless links among these references. Each wireless link will measure the RSS at the receiver periodically. If in *static environment*, which has no target, the RSS is relatively stable. When target appears (*dynamic environment*), the RSS of some wireless links will change. Such change is referred as *RSS dynamic*. When the RSS dynamic is greater than the threshold (detail defined in the later subsection), we call them *influential links*. Those reference nodes, which are involved in the influential links, are called *influential nodes*. If the target appears, the influential links will cluster around the target [23].

Our proposed localization algorithms are based on the information of influential links and influential nodes. They are Influential Link & Node (ILN) and Multipath Distinguishing (MD). The first one leverages RSS Dynamics of each influential link and location of influential nodes to localize the target. The latter one can model the signal caused by the target by distinguishing multipath signal, for each influential link.

1) Influential Link & Node (ILN) Algorithm:

Since target can cause the RSS of some wireless links to change, the basic idea of this algorithm is to utilize the RSS dynamics of those influential links and the locations of influential nodes to calculate the target position. The detail procedure is as follows. First, for each influential link, we will estimate the *candidate object position* on this link. Such link connects two influential nodes. If one of the influential nodes appears more times than the other influential node among all the influential links, the candidate object position is more likely closer to it. When finishing all the candidate object position calculation on all the influential links, we may weight average all the candidate object positions, then get the target location. The weight value is the RSS dynamic of its corresponding influential link.

An example is shown in $Fig.2$. There are 6 reference nodes in the figure. The target causes 3 influential links, R_1R_2, R_1R_3 and R_1R_4. Here influential nodes are R_1, R_2 and R_4. We can see, R_1 appear 3 times among all the influential links. Similarly, R_2, R_3 and R_4 all appear 1 times. So for influential link R_1R_2, the candidate object position (CA_1 in $Fig.2$) is close the node R_1. Similar is for influential link R_1R_3 and R_1R_4. Then we weight average all the candidate object positions, the target object location can be estimated. The weight value of each candidate object position is the RSS dynamic value of its standing influential link. For example, the weight of candidate object position CA_3 is the RSS dynamic value of link R_1R_3.

Assuming we have m influential links and n influential nodes that the object causes. The coordinates of the n influential nodes are $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$. The number of times that the n influential nodes appear in the m influential links are $N_1, N_2, \ldots, N_n$, respectively. For one influential link, suppose the influential nodes it connects are i and j (here $1 \leq i, j \leq n$), the candidate object position (x_{ij}, y_{ij}) of such influential link ij is calculated as follows.

$$\begin{aligned} x_{ij} &= \frac{x_i N_i + x_j N_j}{N_i + N_j} \\ y_{ij} &= \frac{y_i N_i + y_j N_j}{N_i + N_j} \end{aligned} \tag{10}$$

So the target location (x, y) is calculated from all the candidate object positions as follows.

$$\begin{aligned} x &= \sum_{i=1,j=2,i<j}^{n} \frac{x_{ij} v_{ij}}{\sum_{i=1,j=2,i<j}^{n} v_{ij}} \\ y &= \sum_{i=1,j=2,i<j}^{n} \frac{y_{ij} v_{ij}}{\sum_{i=1,j=2,i<j}^{n} v_{ij}} \end{aligned} \tag{11}$$

where v_{ij} is the RSS Dynamic of influential link ij, and (x_{ij}, y_{ij}) is the candidate object position on the influential link ij. The positions of node i and node j are calculated by $Equ.(8)$.

Algorithm 1 Influential Link & Node (ILN) Algorithm

Input:

All links influenced by the object L_{array};
threshold array T_{array};

for each threshold t in T_{array} **do**
  the emerging times of all nodes $N_1, N_2, \ldots, N_n \leftarrow 0$;
  the total RSS dynamic at the threshold t: $v_{total} \leftarrow 0$;
  influential links array $I_{array} \leftarrow null$;
  the location of object $(x, y) \leftarrow 0$;
  for each link $l(i, j, v_{ij})$ in L_{array} **do**
    if $v_{ij} \geq t$ **then**
      put $l(i, j, v_{ij})$ into I_{array};
      $N_i \leftarrow N_i + 1$;
      $N_j \leftarrow N_j + 1$;
      $v_{total} \leftarrow v_{total} + v_{ij}$;
    end if
  end for
  for each link $l'(i, j, v_{ij})$ in I_{array} **and** (x_i, y_i), (x_j, y_j) in coordinates of all reference nodes R_{array} **do**
    the candidate object position $(x_{ij}, y_{ij}) \leftarrow 0$ on link l';
    $x_{ij} \leftarrow \frac{x_i N_i + x_j N_j}{N_i + N_j}$;
    $y_{ij} \leftarrow \frac{y_i N_i + y_j N_j}{N_i + N_j}$;
    $x \leftarrow x + x_{ij} \frac{v_{ij}}{v_{total}}$;
    $y \leftarrow y + y_{ij} \frac{v_{ij}}{v_{total}}$;
  end for

Output:

  display the object location (x, y);

end for

2) MultiPath Distinguishing (MD) Algorithm:

The basic idea of MD algorithm is as follow. For each pair of T-R reference nodes, according to the RSS dynamic values in different channel, we simulate the additional signal and its propagation path caused by the target, then calculate the path length of the additional signal. Since there are many pair of T-R reference nodes, a lot of additional radio propagation paths will occur. Thus, We may utilize them to localize the target.

$Fig.3$ shows one pair of T-R reference nodes. In static environment, suppose there are 2 paths between them. One is the LOS path, the other is the ground reflection path. In dynamic environment, the transceiver-free target appears,it will cause another reflection path $p3$. Through switching channels, the RSS dynamics are different. They potentially contain signal phase information [22]. Therefore, the length of $p3$ can be calculated. Because we have already finished localizing each reference node, through using Euclidean distance [1] and transforming such information into a CFP problem, we may solve it and get the target location.

Suppose there are n' paths between each pair of T-R reference nodes in static environment, and $n' + 1$ paths in dynamic environment. The new one is caused by the target. Their length are $d'_1, \ldots, d'_{n'}, d'_{n'+1}$, respectively. $\Gamma'_2, \ldots, \Gamma'_{n'}, \Gamma'_{n'+1}$ are the corresponding reflection coefficients. the reflection coefficient Γ'_1 of LOS path d'_1 is equal to 1 as introduced before. $d'_{n'+1}, \Gamma'_{n'+1}$ are the length of additional path and its reflection coefficient. Suppose there are m' channels, $\lambda'_1, \ldots, \lambda'_{m'}$ are the corresponding wavelength of the radio. The total RSS at receiver can be expressed as

$$\begin{aligned} P'(x', \lambda'_j) &= |\sum_{i=1}^{n'+1} \vec{p'_i}| \\ &= ((\sum_{i=1}^{n'+1} c{\lambda'_j}^2 {d'_i}^{-2} \sin(d'_i {\lambda'_j}^{-1}))^2 \\ &\quad + (\sum_{i=1}^{n'+1} c{\lambda'_j}^2 {d'_i}^{-2} \cos(d'_i {\lambda'_j}^{-1}))^2)^{\frac{1}{2}} \end{aligned} \quad (12)$$

Where $P(x', \lambda'_j)$ is the total RSS at receiver in dynamic environment when the radio wavelength is λ'_j and $x' = (\Gamma'_{n'+1}, d'_{n'+1})$. The $(c, d'_1, \ldots, d'_{n'}, \Gamma'_2, \ldots, \Gamma'_{n'})$ can be obtained in static environment with the method of $Equ.$(6). So there are 2 unknown parameters, the problem may be solved when $m' \geq 2$. Here we also need to find an x to fit m' measurement (P'_j, λ'_j) with model function $P'(x', \lambda'_j)$ as close as possible. This is also a CPF.

$$given \quad r'_j(x') : \Re^2 \rightarrow \Re, j = 1, \ldots, m'$$

$$min_{x' \epsilon \Re^2} f'(x') = \sum_{j=1}^{m'} r'_j(x')^2 \quad (13)$$

Where $r'_j(x') = P'(x', \lambda'_j) - P'_j$, P'_j is the real measurement value with λ'_j and $P'(x', \lambda'_j)$ is the calculated value with the $Equ.$(12). $d'_{n'+1}$ will be obtained when the problem is solved.

After getting the lengths of all additional paths of all nodes, we will get the location of the object with Euclidean distance [1]. Our method is based on $2D$ localization. Suppose there are q' influential links caused by the object, so totally there are q' additional paths. Their corresponding information of all influential links are $(x_{11}, y_{11}, x_{12}, y_{12}, d''_1), \ldots, (x_{i1}, y_{i1}, x_{i2}, y_{i2}, d''_i), \ldots,$ $(x_{q'1}, y_{q'1}, x_{q'2}, y_{q'2}, d''_q)$, where $(x_{i1}, y_{i1}, x_{i2}, y_{i2})$ are the coordinates of the two reference T-R nodes on the $i-th$ influential link and d''_i is the length of additional

Algorithm 2 Multipath Distinguishment (MD) Algorithm

Input:

all links in static environment L_{Sarray};
all links in dynamic environment L_{Darray};
threshold array T'_{array};
the coordinates of all nodes R'_{array};

for each threshold t' in T'_{array} **do**
  the location of target is $w \in \Re^2$;
  influential link array $I'_{array} \leftarrow null$;
  all additional path and corresponding coordinates array $A_{array} \leftarrow null$;
  $H(w) \leftarrow 0$;
  for each link $l(i,j,p'_{ij})$ in L_{Sarray} **and** $l'(i,j,p''_{ij})$ in L_{Darray} **do**
    $count \leftarrow 16$;
    $flag \leftarrow 0$;
    while $count$ **do**
      if $|p'_{ij}(\lambda_{count}) - p''_{ij}(\lambda_{count})| \geq t'$ **then**
        $flag \leftarrow flage + 1$;
      end if
      $count \leftarrow count - 1$;
    end while
    if $flag == 16$ **then**
      find $x = (d'_1, d'_2, \ldots, d'_{n'}, \Gamma'_2, \ldots, \Gamma'_{n'}) \in \Re^{2n-1}$ minimizing sum of $|P'(x, \lambda_{count}) - p''_{ij}(\lambda_{count})|, count = 1, \ldots, 16$;
      find $x' = (d'_{n'+1}, \Gamma'_{n'+1}) \in \Re^2$ minimizing sum of $|P(x', x, \lambda_{count}) - p'_{ij}(\lambda_{count})|, count = 1, \ldots, 16$;
      put x' and the corresponding coordinates of nodes (x_i, y_i),(x_j, y_j) in R_{array} into A_{array};
    end if
  end for
  for each additional path $a(d_{ij}, x_i, y_i, x_j, y_j)$ in A_{array} **do**
    $H(w) \leftarrow H(w) + |R(w, x_i, y_i, x_j, y_j) - d_{ij}|$;
  end for
  find w minimizing $H(w)$;

Output:

  display the object location w;

end for

path on $i-th$ influential link. The coordinate of the object location is (x, y). So we have

$$d''_i = ((x - x_{i1})^2 + (y - y_{ki1})^2 + h^2)^{\frac{1}{2}} + ((x - x_{i2})^2 + (y - y_{i2})^2 + h^2)^{\frac{1}{2}} \quad (14)$$

where h is the height between the T-R reference nodes and the object. $Equ.(14)$ is a function with 2 unknown parameters, which are $(x, y) \in \Re^2$. To solve the $Equ.(14)$, the number of influential links have to be larger than 2, $q' \geq 2$. We should find a pair of (x, y) to fit the information of q' influential links with $Equ.(14)$. we also transform it into a CFP. The problem will be solve by minimizing sum of fitting error

$$given \quad g_i(x, y) : \Re^2 \rightarrow \Re, j = 1, \ldots, q'$$

$$min_{x \epsilon \Re, y \epsilon \Re} F'(x, y) = \sum_{j=1}^{q'} g_i(x, y)^2 \quad (15)$$

Where $g_i(x, y) = \sqrt{(x - x_{i1})^2 + (y - y_{i1})^2 + h^2} + \sqrt{(x - x_{i2})^2 + (y - y_{i2})^2 + h^2} - d''_i$, d''_i is the calculated value of additional paths on $i-th$ influential link, it is obtained with $Equ.(12)$. $(x_{i1}, y_{i1}), (x_{i2}, y_{i2})$ are the coordinates of nodes on the $i-th$ influential link. We will get object location (x, y) when the problem is solved.

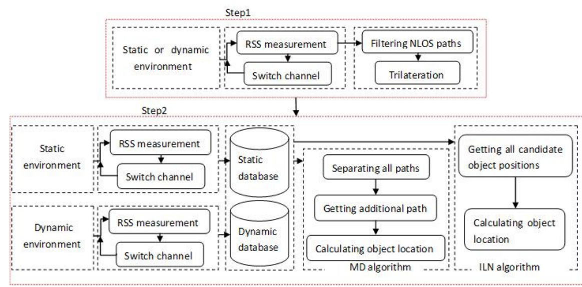

Fig. 4. Architecture of Double Free System

D. Problems and Their Treatments

While calculating the distance of each pair of T-R reference nodes, we find that the result is not stable. We can see that every item in $Equ.(6)$ contains $\frac{c}{d_i^2}$ where c and d_i are both unknown parameters. Only one of the two unknown parameters is known, the other is stable. So the result is not stable. To solve this problem, we find that c is unknown parameter only depending on the hardware, that is the c is a constant value when a pair of T-R nodes are fixed. So the problem will be solved when we get the value of c. There are three approaches to get the c, such as chamber training, specification manuals and online training [22].

Another problem is how to set the number of paths between a pair of reference nodes. Actually in different environments, this value is quite different and hard to know. Since we have already proved that NLOS paths with three or more reflections or refractions can be ignored [22], we set the number of path as 5 (not sacrificing too much accuracy) in our later experiment.

IV. Experimentation And Evaluation

In this section, we first introduce the implementation and architecture of our Double Free localization system, then we will show the performance evaluation.

A. Implementations of Double Free System

Our Double Free system is based on TelosB sensor platform [6]. By the $802.15.4$ standard, TelosB sensor have 16 channels. Each channel is spaced $5MHZ$ apart. The channel number is from 1 to 16. The spectrum frequency is from $2.4G$ to $2.4835G$. Accordingly, the radio wavelengths are from $0.1153m$ to $0.1189m$. The default transmission power of all sensor is fixed at $-10dBm$ in our system. For those algorithms that do not need to visited all the channel, the default channel number is default at 11.

We performed our experiments in a $25 \times 10m^2$ laboratory, as show in $Fig.5$. 16 TelosB sensor nodes are randomly deployed on the ceiling with the same height (here in our experiment is $1.93m$), as the reference nodes. Each reference node acts as both transmitter and receiver. All the reference nodes are synchronized so that they may switch channel at the same time. The beacon interval of each node is $14ms$ in our system. We introduce a person as the transceiver-free target for localization in our system. $Fig.6$ is a snapshot of tracking moving object.

B. Architecture of Double Free System

As $Fig.4$ shows our localization system architecture. Our localization system has 2 steps. The first step is reference node localization. The second step is transceiver-free target object localization . The first step is performed in the static environment. At the beginning, we calculate the hardware-dependent parameters c for each pair of T-R reference nodes, as introduce in the previous section. In the following, for each channel, we collect the RSS values of each T-R nodes, and switch to the next channel. Such procedure repeats until all the channels are visited. At last, we randomly choose 3 reference nodes as the anchor nodes (with known positions), then use our algorithm to calculate the absolute positions of all the reference nodes.

After all the reference nodes are positioned, our system enters the second step. In this step, different transceiver-free target localization algorithms have different procedure. At first, in the static environment, we construct a static table to store the RSS values of each pair of T-R reference nodes (the 16 different channels should be visited by turns for MD algorithm, ILN will stay at the default channel). Then, our system enters the target localization state. The system will construct a dynamic table to record the RSS values and calculate the RSS dynamics, for each pair of T-R reference nodes(the RSS information on different channels should also be collected for MD algorithm). If the RSS dynamic is larger than the defined threshold, the ILN or MD algorithm is performed to localize the target. Otherwise, the static table is updated.

C. Comparison of Different Ranging Algorithms

In the reference node localization, first we should calculate the distance between each pair of T-R reference nodes (also referred as ranging). We compare our ranging method with the traditional method which doesn't distinguish the LOS radio signal from multiple radio propagation paths and map the RSS into distance directly. We test 120 pairs of T-R reference nodes in the indoor environment. $Fig.7$ shows the Cumulative Density of Function (CDF) of ranging error in percentage and $Fig.8$ gives their CDF in absolute errors. We can see that the averaged ranging error with our method is $2m$ and the averaged error with traditional method is $22m$. Their averaged ranging errors in percentage are 36% and 365% respectively. In a word, the accuracy has been improved more than 10 times.

D. Comparison of Different Reference Node Localization Algorithms

In this experiment, we will compare our reference node localization algorithm with traditional Linearized System of Equations (LES) algorithm [14]. Our localization algorithm depends on our ranging results, while the LES algorithm depends on the result of the traditional ranging method. $Fig.9$ shows the CDF of comparison result in absolute value. The real deployment and calculated reference node positions in a bird view are shown in $Fig.10$. the red five-point stars are the calculated positions with our algorithm. The blue circles are the real locations of all the reference nodes. We can see that the averaged localization errors of our localization method and LES are $1.4m$ and $90m$, respectively. The accuracy has been improved more than 64 times.

E. Comparison of Different Transceiver-free Object Localization Algorithms

In this subsection, we will compare our ILN and MD algorithms with Midpoint algorithm [23]. Based on 40 target locations, $Fig.11$ shows the cumulative density function (CDF) of normalized error in absolute with different localization algorithms. We can see that, the accuracy of our MD algorithm are much better than the ILN and Midpoint in the $Fig.11$. Their averaged error are $2.2m$, $4.2m$ and $4.8m$ respective. To sum up, the accuracy has improved more than 2 times. It is noted that, such localization accuracy includes the localization error of reference nodes.

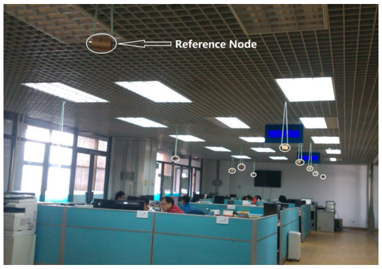

Fig. 5. Environment of Localizing Reference Nodes

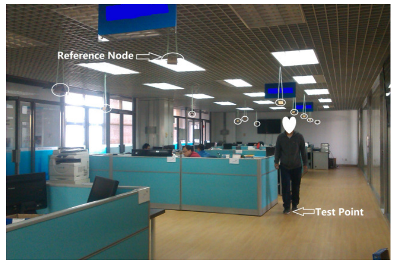

Fig. 6. A Snapshot of Tracking Moving Object

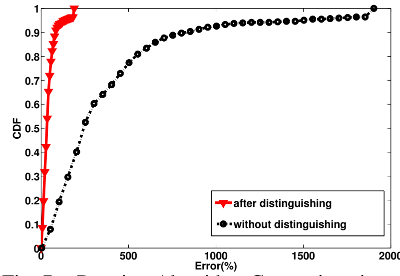

Fig. 7. Ranging Algorithm Comparison in Percentage

We also perform experiments to track moving target. In total, we test 20 target traces. One of the examples is shown in Fig.12. In this figure, the red line is the real target trace and the blue one is the estimated trace with MD algorithm. In this example, the average tracking error is $2.1m$. The speed of moving object is very slow, eg., $0.5m/s$. We will improve the speed whit Channel State Information (CSI) in our future work.

F. The Impact of Different Threshold

In this subsection, we will investigate the impact of different threshold. We conduct our experiments under 7 different thresholds ranging from $1dB$ to $4dB$ with 0.5 apart. In order to show it clearly, we only give 5 of them in Fig.13. We find that, the averaged errors are $2.7m$ and $3.0m$, when the threshold is $= 1.0dB$ and $4.0dB$, respectively. When threshold is set to $3.5dB$, the transceiver-free target localization accuracy is the best, it is $2.2m$ in average. The value of this threshold is similar to the RSS variance in the static environments. By analyzing the RSS dynamic values of each T-R reference nodes, we find that, there are too many influential links when the threshold is $1.0dB$ and too few influential links when the threshold is $4.0dB$. That is why the accuracy is relative low for the other threshold. Therefore, in the experiment, we all use $3.5dB$ as the threshold of the RSS dynamic.

G. Latency

The latency of our MD method for localizing object depends on the number of influential links. In dynamic environment, for one influential link, we should collect RSS at each channel for obtaining the additional path, (there are 16 channels). The related work [23] shows that channel switching costs $0.34ms$ each time . The study [19] shows that a TelosB sensor nodes takes $7ms$ on averaged to transmit a packet with 51 bytes. Here, we set the beacon interval of each node as $14ms$. Thus, calculating the length of additional path on one influential link should be at least $(14 + 0.34) \times 16 \times 2 \approx 458.88ms$, it is the same with calculating LOS path. So the latency of localizing reference nodes is $458.88 \times 3 \approx 1.37s$ derived from Equ.(8). Derived from Equ.(14), we need to calculate at least 2 influential links, as there are 2 parameters in the Equ.(14). Therefore, it need $458.88 \times 2 \approx 917.76ms$. The latency of MD can be expressed as

$$T_t = (T_{switch} + T_{trans}) \times 16 \times N_{influ} \tag{16}$$

Where T_{switch} is the channel switch time for each node. T_{trans} is the time for one node to transmit a packet. N_{influ} is the number of influential links. Our method can reach latency as fast as about $0.9s$.

V. Conclusion And Future Work

In this paper, we proposed Double Free, which can localize transceiver-free target object indoors without requiring to measuring the positions of all reference nodes. It contains two basic steps: reference node localization and transceiver-free target localization. The key idea of the first step is to utilize the RSS difference in different channel to distinguish the Line-Of-Sight (LOS) signal from the combined multiple paths signal. So accurate ranging and localization among all the reference nodes can be realized. In the second transceiver-free target localization step, we proposed two algorithms: ILN and MD. ILN is simple to implement, while MD can have better accuracy. The reason is that, MD can accurately model the signal caused by the target. The experimental results shows that the average reference node localization error is round $1m$, its accuracy has improved more than 64 times compared with traditional method. Under such reference node infrastructure, the averaged transceiver-free object localization error is round $2m$.

As future work, first we will try our approach in a larger indoor area. Furthermore, the randomly deployed reference nodes are assumed in a $2D$ area on the ceiling. We may try it in a $3D$ area for better application. At last, since this work is our first attempt to localize transceiver-free target under the unknown reference node infrastructure, we only conduct experiment for single target object. In the future, we may test the performance when multiple objects appear.

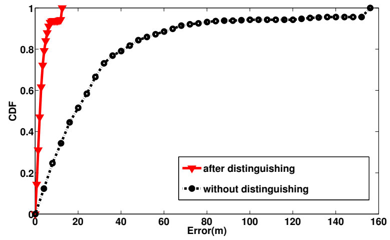

Fig. 8. Ranging Algorithm Comparison in Absolute

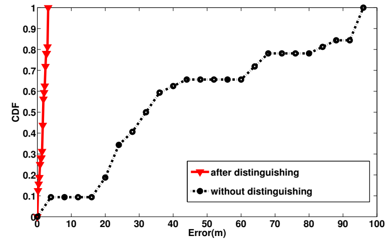

Fig. 9. Algorithm Comparison of Localizing Reference Nodes in Absolute

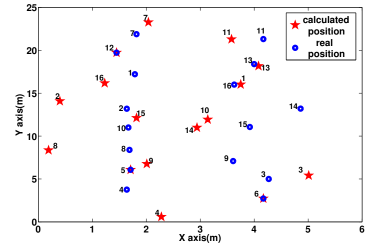

Fig. 10. Results of Localizing Reference Nodes

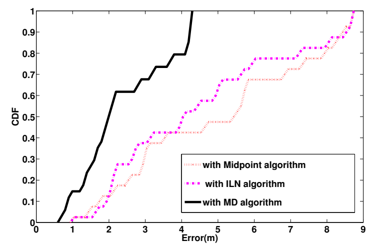

Fig. 11. Accuracy of Tracking with Different Tracking Methods (CDF)

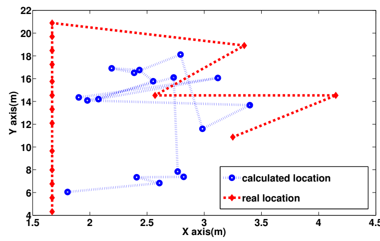

Fig. 12. Results of Tracking Moving Object

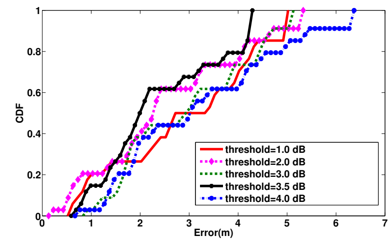

Fig. 13. Accuracy of Tracking Object with Different Threshold (CDF)

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