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MODLoc: Localizing Multiple Objects in Dynamic Indoor Environment

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Abstract—Radio frequency (RF) based technologies play an important role in indoor localization, since Radio Signal Strength (RSS) can be easily measured by various wireless devices without additional cost. Among these, radio map based technologies (also referred as fingerprinting technologies) are attractive due to high accuracy and easy deployment. However, these technologies have not been extensively applied on real environment for two fatal limitations. First, it is hard to localize multiple objects. When the number of target objects is unknown, constructing a radio map of multiple objects is almost impossible. Second, environment changes will generate different multipath signals and severely disturb the RSS measurement, making laborious retraining inevitable. Motivated by these, in this paper, we propose a novel approach, called Line-of-sight radio map matching, which only reserves the LOS signal among nodes. It leverages frequency diversity to eliminate the multipath behavior, making RSS more reliable than before. We implement our system MODLoc based on TelosB sensor nodes and commercial 802.11 NICs with Channel State Information (CSI) as well. Through extensive experiments, it shows that the accuracy does not decrease when localizing multiple targets in a dynamic environment. Our work outperforms the traditional methods by about 60 percent. More importantly, no calibration is required in such environment. Furthermore, our approach presents attractive flexibility, making it more appropriate for general RF-based localization studies than just the radio map based localization.

Index Terms—Multiple objects, dynamic environment, localization

1 Introduction

Localization is highly in demand and essential in many applications [1], [2], [3]. Among various technologies, radio map based technologies seem very promising. This is because the radio map technique can be easily implemented without additional hardware support and the localization accuracy is high.

A large number of works have been written based on the technologies [5], [6], [4], [7]. In general, only several wireless nodes are required in localization [8], [9]. Therefore, their hardware cost is low. However, these methods have two great challenges for real application: The first is that it is hard to localize multiple objects and multiple objects scenario is usual in practical application. The reasons are as follows. The process of radio map technique has two stages: offline training and online localization. At the first stages, we need to survey the site by dividing the target area into cells and measuring the signal strength one by one. However, when multiple objects exist and the number of target objects is unknown, it is impossible to measure the signal strength at different permutations in advance, since the positions of the objects are independent, the RSS of an object at a specific position depend on the other objects [10]. Second, environment changes (e.g., more target objects appear or layout changes) will generate different multipath signals and severely disturb the RSS measurement, making laborious calibration inevitable. In a real environment in particular indoors, signal propagation suffers from severe multipath fading effect subject to signal reflection, diffraction and absorption by humans or structures [8]. As a result, a transmitted signal can reach the receiver through different paths and these different components are combined to reproduce a distorted version of the original signal [11], [12]. Thus, radio map based technologies usually require a labor-intensive calibration procedure, which limit their usage in real applications.

Traditionally, there are usually two ways to handle this problem. The first is to utilize densely deployed nodes as a reference (e.g., LANDMARC [13]) to localize the targets. However, this approach is costly. Also, if the multiple objects are close to each other, it is very hard to find the correct nearest reference nodes and thus the accuracy may dramatically reduced. The second way is to localize the target based on the radio map of single object [9], [8]. As a result, the localization of multiple objects is far from accurate. Moreover, once the environment changes, the RSS signals are usually different. Therefore, many systems have to rebuild the radio map between the RSS and distance by repeating the training process [8], [14], [15]. Although some works try to reduce such overhead by using various methods, such as adaptive training [16], they cannot fully eliminate such overhead.

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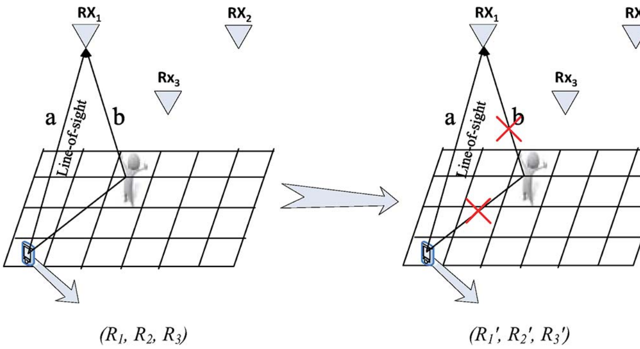

Fig. 1. Illustrate basic idea by collecting RSS of LOS.

To solve the above problems, in this paper, we propose a novel approach, called Line-of-Sight (LOS) map matching. It is able to accurately localize multiple objects without rebuilding the radio map in dynamic environments (the environment often changes). Our basic idea is triggered by the following observations. The target objects or other environmental changes often generate or change some non-line of sight (NLOS) paths (reflection, diffraction and absorption of the original signal). If we could build a radio map based on LOS signal, the multipath signal influence by the target objects or environmental changes will be eliminated.

Looking at Fig. 1, suppose we have three anchor nodes acting as the receiver and a person hold a mobile device is the target object acting as the transmitter. R_1, R_2, R_3 denote the RSS value received from the three anchor nodes, a person appearing in this environment will cause an additional signal reflection path for A, changing the RSS. If we are able to construct a radio map that only reserves the RSS of LOS path, the appearing person will not affect the LOS signal. As shown in Fig. 1, R_1', R_2', R_3' denote the RSS at LOS path from three anchor nodes. Since the LOS signal is not blocked by the person, the value of R_1', R_2', R_3' will not change after introducing the person. Therefore, such a map is more stable in a dynamic environment, and it is denoted as LOS radio map. To the best of our knowledge, we are the first to accurately localize multiple objects by using radio map based technologies. In order to realize the LOS radio map construction and valid map matching for localization, a key issue is to identify the LOS signal from different paths. Our approach is to leverage the frequency diversity to help RSS provide phase information indirectly. We find that RSS values are significantly different when the nodes are in different spectrum channels (the other setting is the same). Such RSS differences on different channels carry valuable phase information. By analyzing these RSS, we can identify the amplitudes and phases of signals from each path. We may then derive the RSS of the LOS path by solving the optimization problem. As a result, we can eliminate the multipath behavior, making RSS more reliable than before. These reliable RSS signals can be leveraged to construct the LOS radio map instead. Such map only reserves the LOS signal among nodes. By careful pre-deployment (e.g., the reference nodes are deployed on the ceiling of the floor and the targets are on the ground), the environment changes and the number of objects do not affect the LOS signal between the targets and the reference nodes. This LOS radio map is easily constructed and requires no training if reference nodes are carefully pre-deployed.

We have also implemented our approach on commercial 802.11 NICs with CSI information, which describes how a signal propagates from the transmitter to the receiver and represents the combined effect of, for example, scattering, fading, and power decay with distance.

Compared with other traditional radio map based localization methods, our approach has the following advantages:

- We are able to accurately localize multiple objects in dynamic environment without calibration on the map. Our approach is based on collecting RSS of LOS path. Thus we may achieve a more reliable RSS value, and fundamentally solve the traditional problem and achieve good localization result.
- Our approach is adaptive to environmental changes. The LOS radio map we build reserves only the LOS signal among nodes, so if the environment changes, we do not need to rebuild it.
- Our solution is able to eliminate the multipath effect of RSS signal without additional hardware support. Through solving the related optimization problem, we may identify the signal along the LOS path.
- Our work is not only suitable for the radio map based localization. Many current RSS based approaches may need a revisit. We identify the LOS signal among nodes, making RSS more reliable. This presents promising generality which enable it be applied in a much broader scope of application.
- Our work utilizes CSI to improve the localization accuracy. We could obtain such information from 802.11 NICs with OFDM technology and relatively high accuracy result is achieved compared with use only RSS information.

We implement a real time tracking system based on TelosB platform with only three anchor nodes and three 802.11 NICs. Experimental results show that localization accuracy of multiple objects in dynamic environments outperform the traditional approaches by 60 percent.

The rest of this paper is organized as follow. In the next section, we introduce the theoretical background. Section 3 describes our methodology in details. Section 4 presents our localization system implementation and evaluates the performance. Related work is presented in Section 5. Finally, we conclude this work and point out some possible future work directions.

2 Theoretical Background

In this section, we first introduce the radio propagations in free space and multipath environment. Then we will discuss the limitation of radio map based localization on multiple objects.

2.1 Radio Propagation in Free Space and Multipath Environment

Radio propagation is the behavior of radio waves when they are transmitted from transmitters to receivers. Radio

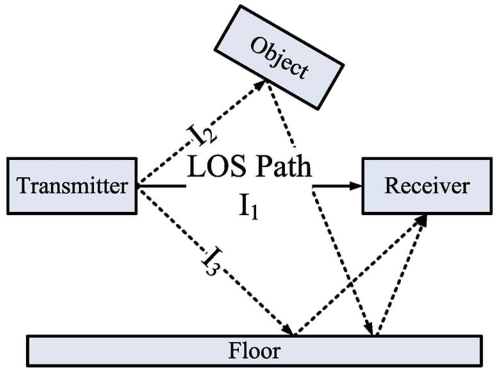

Fig. 2. Multipath effect.

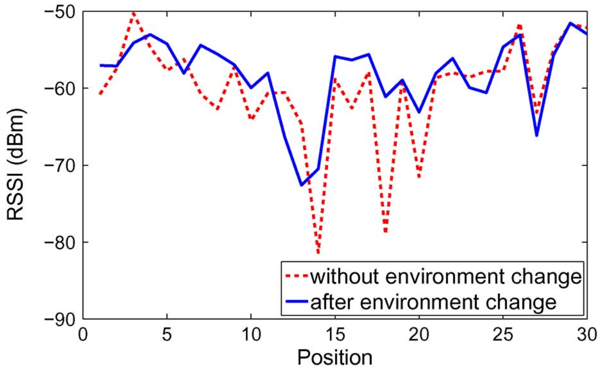

Fig. 3. Impact of environmental change.

propagation along the LOS path can be expressed as follows according to Friis model [17] in free space:

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

Here P_r, P_t represents received radio strength and transmitted signal strength in Watts respectively. G_t is antenna gain of transmitter and G_r is antenna gain of receiver. λ is the signal wavelength. d is the path length of the LOS path (the physical distance between the transmitter and receiver). $\overrightarrow{p} = \{|\overrightarrow{p}|, \theta\}$ is the signal wave vector, $|\overrightarrow{p}|$ is its path power (amplitude) and θ is the path phase at the receiver. Suppose the sender has the phase zero, the path phase of the signal at the receiver is:

$$\theta = 2\pi \cdot \left(\frac{d}{\lambda} - \left\lfloor \frac{d}{\lambda} \right\rfloor\right). \tag{2}$$

However, in real environments, many NLOS paths exist. Such paths are caused by the radio reflection and refraction by surroundings. In each reflection or refraction, only partial energy will be transmitted [17]. These parts can be measured by a reflection (refraction) coefficient, which is denoted as γ, $\gamma \in (0, 1)$. As a result, for a given NLOS path, the path power is:

$$|\overrightarrow{p}| = \gamma \frac{P_t G_t G_r \lambda^2}{(4\pi d)^2}. \tag{3}$$

It is noted here that d is no longer equal to the physical distance between the transmitter and receiver. Eq. (3) is the same as Eq. (1) when the path is LOS path ($\gamma = 1$).

The multipath effect refers to a signal that arrives at the receiver by more than one path. For example, in Fig. 2, there are three paths from the transmitter to the receiver. l_1 is the LOS path, l_2 and l_3 are the reflection paths by the surroundings. As a result, the signal strength at the receiver is the signal combination of all the paths. It can be denoted as:

$$|\overrightarrow{p}| = \left|\sum_{i=1}^{n} \overrightarrow{p_i}\right|. \tag{4}$$

2.2 Radio Map Based Technology and Its Limitations When Localizing Multiple Objects

The radio map technique (also referred as fingerprint technique) is to construct a mapping between the RSS (e.g., from Aps or sensors) and location information of the target in advance. The target object then can be localized by matching its received RSS information with it in the radio map. The mapping construction part is known as the *off-line training phase* and the matching part is know as the *online localization phase*.

However, the localization accuracy suffers from localizing multiple objects and environment changes. Since in the off-line training phase, it has to put the target in advance to stay at all the possible locations and collect the corresponding RSS information. Once the environment changes (e.g., a new target object appears or layout changes), the RSS may change significantly. As shown in Fig. 3, based on 2 TelosB sensor platform (one is transmitter at fixed position, the other one is the target acting as the receiver, the transmission power is fixed at 0 dBm), we test the RSS of the receiver at different locations in our lab. The result shows that the RSS is sensitive to the environment changes (A person walking around act as the new object). It is easy to understand such behavior due to the multipath effect introduced by the new object.

Consider a scenario of multiple objects, it is too costly to build such a map. For example, suppose for one object we have to build a radio map of n locations. For two objects we have to build a radio map of $n \times n$ locations. If we do not know how many objects in advance, it is almost impossible for us to build such a map. Traditional radio map based technology only localizes objects based on the radio map of single object. The localization accuracy is dramatically reduced when multiple target objects exist. Moreover, if the environment layout changes, we have to rebuild to the radio map. It is a very laborious work which limits its application in the real use.

3 METHODOLOGY

In this section, we first explain our basic idea by showing the framework of MODLoc. Then, we explain how to construct our LOS radio map. We describe our algorithm of leveraging frequency diversity to identify the LOS signal from multipath. Finally the localization method of our LOS map matching is proposed.

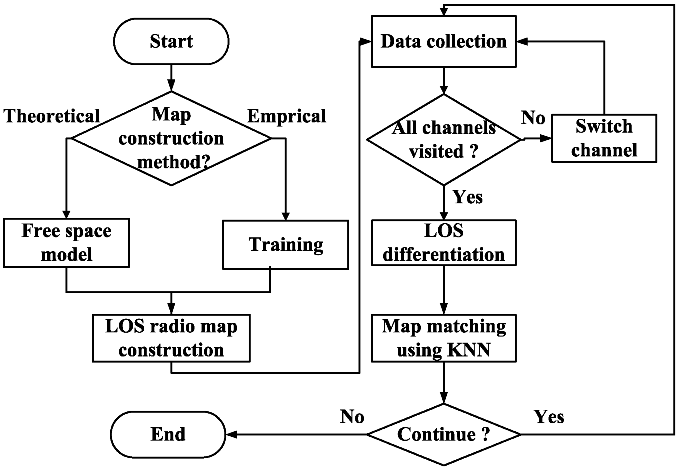

Fig. 4. System workflow of RSSI.

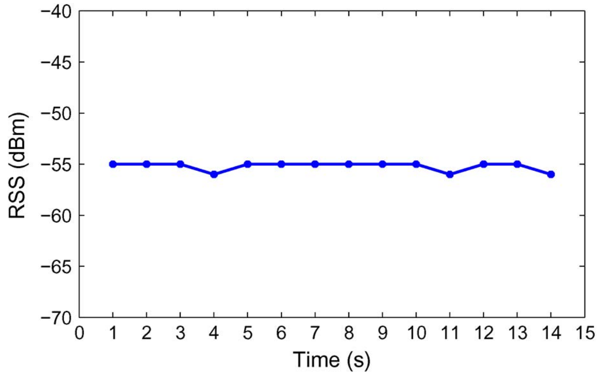

Fig. 6. RSS over time.

3.1 Framework of MODLoc

The Framework of our TelosB based system is demonstrated in Fig. 4. The whole localization process is divided into two phases: LOS radio map construction and localization. In the map construction phase, we are able to construct LOS radio map either by the theoretical approach or by training as detailed in the last section. Once the map is constructed, no calibration is required. When the localization phase begins, we collect RSS information from each target node at different channels. After all the channels have been visited, we differentiate RSS of LOS path by leveraging frequency diversity. Then we apply the KNN algorithm to estimate each target node's position. This procedure is repeated until the users terminates it.

For the use of CSI, the workflow is similar. As shown in Fig. 5. The key difference lies in collecting the CSI information when constructing the radio map, and the phase information could be obtained directly.

3.2 LOS Radio Map Construction

It is known that RSS is a signal combination of all the paths in a real environment. If we are able to learn the phase information of signal along each path, we may easily get the LOS signal. However, RSS itself has no phase information and we find that the RSS is different at different operating frequencies. Such a difference is potentially able to give us information to infer the phase information of signal. As a result, we may filter out the LOS signal from multipath signals between transmitter and receiver pair, based on just the RSS information.

This idea is triggered by an interesting observation from experiments of two TelosB sensors. One of the sensors acts as the transmitter and the other one is the receiver. The transmission power is fixed at 0 dBm and The default channel is 13. We find that if the environment does not change, the RSS is stable as shown in Fig. 6. However, in such an environment, if we only change the channels, the RSS tend to vary, as shown in Fig. 7. Such a difference is due to the different radio wave length on different channels. For a fixed path with the same radio propagation distance, the path phase will be different when radio arrives at the receiver. Therefore such RSS difference potentially gives us phase information. We could eliminate the multipath effect and get the LOS signal accordingly. Note that when the difference of radio wave length is extremely small when we change the channel (only several millimeters between different channels for TelosB nodes), the existing radio propagation paths are unlikely to change.

Our radio map and localization method are all based on the LOS signal. Since the LOS radio map only keeps the LOS signal between the transmitter and receiver, we may easily construct it through using the free space model without training. In the following localization, frequency diversity method is used to eliminate the multipath signal

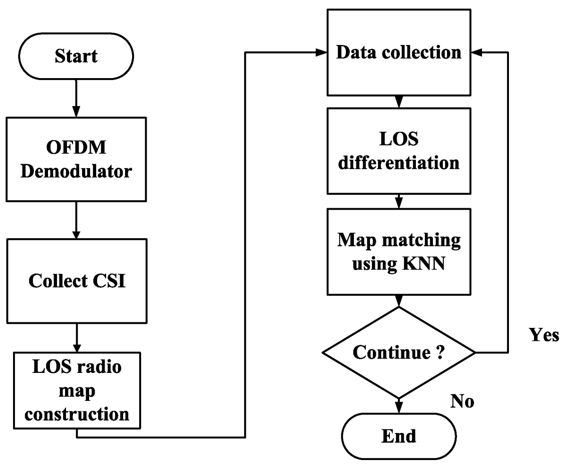

Fig. 5. System workflow of CSI.

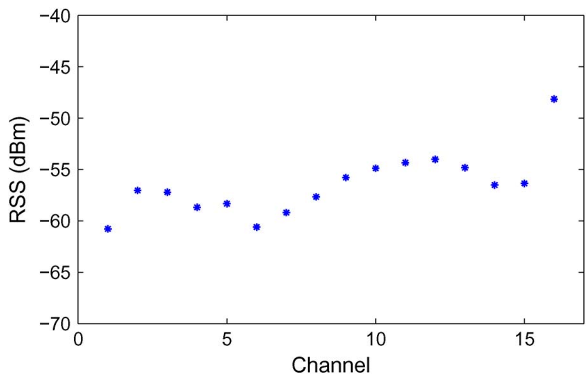

Fig. 7. RSS with different channel.

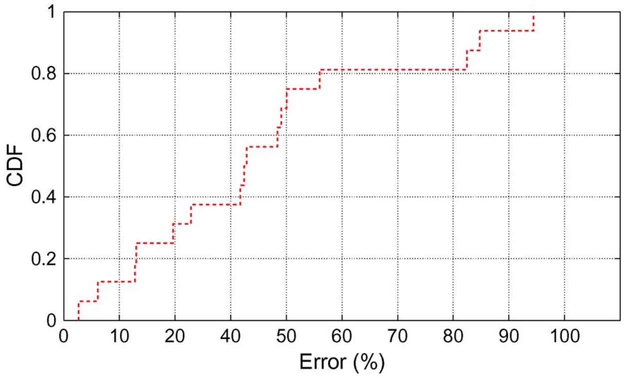

Fig. 8. LOS accuracy by training methods.

between the anchor nodes and target. The details are listed in the following subsections.

In our system, the whole tracking area is divided into cells. Suppose we have anchor nodes acting as the receivers and the target nodes as the transmitters. The first fundamental step is to construct a LOS radio map. We offer two methods to construct such a map. The first one is to construct it from theory, while the second one is from the training results.

In the first method, we can easily construct the map by using the Friis free space model. In each cell, we are able to estimate the received power by using Eq. (1). In this equation, the transmission power P_t is configured by users, the transmitter and receiver antenna gain G_t, G_r can be obtained from the hardware specification manual [18]. Also since the anchor nodes are fixed deployed, the length of LOS path d between each anchor node and transmitter can be estimated. The main advantage for building such a map is that we do not require the laborious offline training to construct the radio map and the LOS signal can be accurately modeled.

In the second method, we build the LOS radio map from training. The procedure is similar to traditional radio map construction, except that we should measure RSS in different channels, then we identify the LOS signal by using the frequency diversity, which is introduced in the next subsection. To compare the estimate distance with the true distance, we use training methods to compute distance between a anchor node and the target node and we show the accuracy of LOS path in Fig. 8,

After the LOS radio map is constructed, it can leverage the localization. As long as the environment changes do not block the LOS signal between transmitter and receiver, the map does not need to be rebuilt. We may realize it by carefully deploying the anchor nodes in advance. For example, we may deploy the anchor nodes on the ceiling of the floor and the target nodes are supposed on the ground. Therefore, most environment changes will not affect the LOS signal. Only if the transmission power of the anchor nodes change (P_t changes) or the nodes themselves change (G_t, G_r change), or the anchor nodes are redeployed, the map needs to be rebuilt.

3.3 Eliminate Multipath Effect by Using Frequency Diversity

Suppose there are n radio propagation paths between transmitter and receiver. According to Eq. (4), we use orthogonal decomposition on each path, i.e., every path is transformed to a combination of sine and cosine, the received power could be represented a combination of each path. The total received power at the receiver is:

$$\begin{aligned} |\overrightarrow{p}| = &\left(\left(\sum_{i=1}^{n}\left(\gamma_i \frac{P_t G_t G_r \lambda^2}{(4\pi d_i)^2}\sin\left(\frac{d_i}{\lambda}\right)\right)\right)^2 \right.\\ &\left. + \left(\sum_{i=1}^{n}\left(\gamma_i \frac{P_t G_t G_r \lambda^2}{(4\pi d_i)^2}\cos\left(\frac{d_i}{\lambda}\right)\right)\right)^2\right)^{\frac{1}{2}} \\ = &f(\gamma_1, \ldots, \gamma_n, d_1, \ldots, d_n). \end{aligned} \tag{5}$$

In Eq. (5) P_t, G_t, G_r, and π are all constant values. Transmit power P_t is configured by users. The output power level is from 3 to 31 with the corresponding output power from -25 dBm to 0 dBm. The antenna gain of transmitter and receiver is 3.1 dBi.

Suppose we measure up to m channels, the wavelengths of the radio at these channels are $\lambda_j, j \in [1, m]$. For different radio wave lengths we have different received power, therefore we could have the following equation:

$$\begin{cases} \varepsilon_1 = f_{\lambda_1}(d_1 \ldots, d_n, \gamma_1 \ldots, \gamma_n) - |\overrightarrow{p_{\lambda_1}}|, \\ \varepsilon_2 = f_{\lambda_2}(d_1 \ldots, d_n, \gamma_1 \ldots, \gamma_n) - |\overrightarrow{p_{\lambda_2}}|, \\ \vdots \\ \varepsilon_m = f_{\lambda_m}(d_1 \ldots, d_n, \gamma_1 \ldots, \gamma_n,) - |\overrightarrow{p_{\lambda_m}}|. \end{cases} \tag{6}$$

Here ε_m is the individual fitting error. Our goal is to find proper $d_1, \ldots, d_n$, $\gamma_1, \ldots, \gamma_n$, which can minimize such errors. As such, the problem is transferred into the following non-linear optimization problem:

$$\text{Minimize}\left(\sum_{j=1}^{m}(\varepsilon_j)^2\right). \tag{7}$$

We have proved that when the number of used channels is larger than $2n$, we can solve the optimization problem and obtain the numerical result by using Newton and Simplex approach [19]. Due to limited space, we skip this part. Our goal is to accurately find d_1 and estimate the LOS path power, the accuracy of the other parameters is trivial.

In addition, we use a similar idea to implement our system based on WiFi devices, that is to use frequency diversity to eliminate the multiple phenomenon. We could obtain the physical layer information by using the commodity NICs. With this rich information we extract the phase. The CSI of a single subcarrier is mathematically represented as

$$h = |h| e^{j sin\{\angle h\}} \tag{8}$$

where $|h|$ is the amplitude and $\angle h$ is the phase of each subcarrier and j represents the imaginary unit.

Since the multipath effect will introduce inter symbol interference, a cyclic prefix (CP) is added to each symbol to combat the time delay in OFDM systems. However, the CP technique is useless for the multiple reflections within a symbol time.

For narrow-band systems, these reflections will not be resolvable by the receiver when the bandwidth is less than the coherence bandwidth of the channel. Fortunately, the bandwidth of 802.11n waveforms is 20 MHz (with channel bonding, the bandwidth could be 40 MHz), which provides the capability of the receiver to resolve the different reflections in the channel. We propose a multipath mitigation mechanism that can distinguish the LOS signal or the most closed NLOS from other reflections in the expectation of reducing the distance estimation error. The commonly used profile of the multipath channel in the time domain is described as:

$$h(\tau) = \sum_{k=0}^{L_P-1} \alpha_K \delta(\tau - \tau_K), \tag{9}$$

where L_p is the number of multipath channel components. α_k and τ_k are the amplitude and propagation delay of the k-th path. In practice, OFDM technologies are efficiently implemented using a combination of fast Fourier Transform (FFT) and inverse fast Fourier Transform (IFFT) blocks. The 30 groups of CSI represent the channel response in the frequency domain, which is about one group per two subcarriers. With IFFT processing of the CSI, we can obtain the channel response in the time domain, i.e., $h(t)$. Then we reconstruct the CSI using FFT.

Since the channel bandwidth of an 802.11n system is larger than the coherence bandwidth in a typical indoor environment, the fading across all subcarriers are frequency-selective. To combat such fading of wireless signals, multiple uncorrelated fading subchannels (multiple frequency subcarriers) are combined at the receiver.

3.4 Path Number Selection

In order to solve Eq. (7), we have to set the number of paths in advance. However, in a the real indoor environment, it is almost impossible to know how many paths existing between a transmitter and receiver pair for several reasons. First, the signal radiation is evenly distributed in the directions. Second, the environment is so complex that the layout may add more surfaces. So in this subsection, we discuss the impact of multipath and conclude with a reasonable result of path selection without sacrificing too much accuracy.

As introduced in the last section, given a radio propagation path between a fixed transmitter and receiver (G_t, G_r are fixed) with fixed transmission power (P_t is fixed) and wavelength (λ_i is fixed), there are two parameters deciding the signal power of each path: (refraction) coefficient γ_i and the distance between transmitter and receiver d_i. Then we will discuss how to determine these two parameters.

The first one actually depends on the surface of the reflection (refraction) materials. For common materials, this value is around 0.5 [20]. Therefore, if the radio is reflected (or refracted) multiple times, its contribution to the total received power is minimal. For example, a reflection more than three times results in only $(0.5)^3 = 0.125$ times the original energy. Since there is no reflection or refraction, the LOS path value is 1. Therefore, in practice, though some accuracy is sacrificed, we may skip those signal propagation paths having many reflections (refractions), e.g., larger than three. The second parameter is d_i, including the LOS path and the other Non-LOS paths. The received power is is inversely proportional to $(d_i)^2$ according to Eq. (1). Therefore, if the length of the Non-LOS paths is large, its influence on the total received power is also minimal. For example, if the path is longer than two times the LOS path, the remaining energy is smaller than $\frac{1}{2}^2 = 0.25$ of the original energy. Therefore we also skip the signal reflection paths whose path length is very large, say twice the length of the LOS path length.

Furthermore, since all the multipath signals have at least one reflection (refraction) and their length are all longer than the LOS path, most of their influence on the total received power is limited. For example, if one path is twice as long as the LOS path and with one reflection, it remaining energy will be $0.5 \times \frac{1}{2^2} = 0.125$ of the original energy.

After discussion of these two parameters, recall that in order to solve the non-linear optimization problem stated as Eq. (9), we should find proper di and i according to Eq. (8). Therefore we easily get the result of those Non-LOS path length returned by algorithm easily.

We further show the impact of the different number of paths to the total received power at the receiver through simulation on TelosB sensor nodes. For a fixed transmitter and receiver, we set the transmission power to 0 dBm. The distance between the transmitter and receiver (also the length of the LOS path) is 4 m. We perform six test rounds to observe the signal combination effect when different numbers of paths combine. These are: just one LOS path, LOS path with on multipath (8 m), LOS path with two multipaths (4 m and 8 m), LOS path with three multipaths (4 m, 8 m, 12 m), LOS path with four multipaths (4 m, 8 m, 12 m, 16 m), LOS path with five multipaths (4 m, 8 m, 12 m, 16 m, 20 m), LOS path with four multipaths (4 m, 8 m, 12 m, 16 m, 20 m, 24 m). We assume each multipath signal is reflected (refracted) only once. At each round of tests, all 16 channels on TelosB are tested. From Fig. 9, we can see that, when path length is longer than twice the LOS path length, its influence on the combined signal at the receiver is very small, no matter which channel is selected. An interesting observation is that when the number of path exceed a certain value (in this example is 3), the RSS in each channel becomes stable. In other words, the RSS does not change a lot with more paths introduced. Thus, we could utilize a limited number of paths to represent the influence of the multipath with minimal loss of accuracy.

Therefore, the number of paths we use is limited through to the above reasons. We skip those paths whose path length is long or having many reflection (refraction) times, say two times of the LOS path length. Therefore in practice, we suppose the path number is no larger than 5, though some accuracy is sacrificed.

3.5 802.11 NICs with CSI

As commercial 802.11 NICs could provide additional information CSI, which could not be obtain from the sensor node, we also implement our basic idea with WiFi devices. Eq. (8) shows that the CSI of a single subcarrier can be mathematically represented in terms of amplitude and phase. therefore we could treat the CSI in the same way. The amplitude in this equation represents the transmission power of a single subcarrier, which can be applied directly

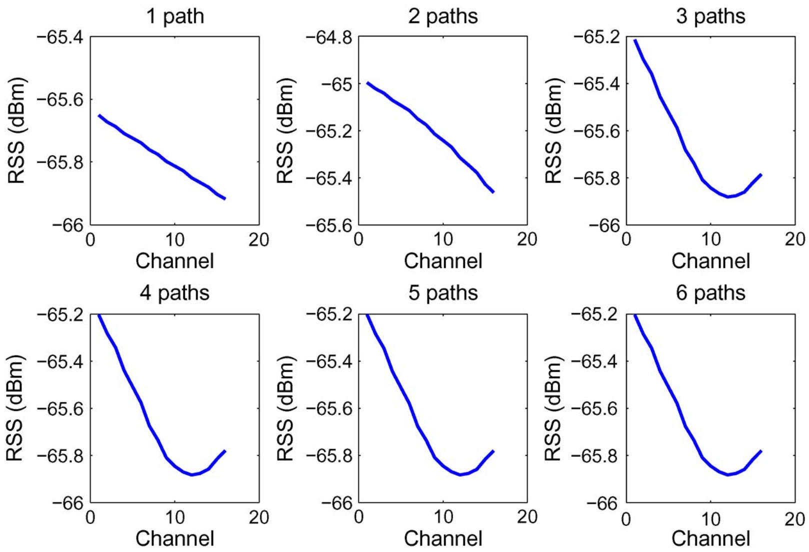

Fig. 9. Simulation result for different number of paths.

into the equation array with the phase information in Eq. (5). Then, we could solve a similar optimization problem and obtain the signal strength of The LOS path.

4 Performance Evaluation

In this section, we show the system architecture and evaluate the proposed methods under different environments. We estimate the localization accuracy of a single object in both a static and a dynamic environment. Then we show the impact of the number of targets. At last, we compare two different LOS construction approaches and show the latency analysis.

4.1 Impact of Environmental Changes on Different Maps

In this part, we investigate how environmental changes affect different radio maps.

At first, we collect RSS data from all the 50 training points. After that, we change the environment by introducing more people and alter some of the interior layout. We then collect the RSS data again. The RSS difference after the environmental change is demonstrated in Fig. 10. Each cell represents a training point and the cell with dark area means its RSS difference is big, otherwise it is small. This figure well illustrates that traditional radio maps can be significantly affected by the environmental change. Furthermore, the impact is irregular and it is hard to find a pattern, making multiple objects tracking a challenging task for traditional map matching. Fig. 11 illustrates differences in the RSS at the LOS path under such an environmental change. We can see that, the RSS difference is very small (paler) compared with the traditional one. From these two figures we find that our LOS radio map is more stable under environmental changes than the traditional map.

4.2 Comparison of Different Map Construction Methods

In this section, we compare the localization accuracy based on different map construction methods. 24 target locations have been tested in our experiment area and the results are shown in Fig. 12. We find that using training to construct the LOS radio map, results in slightly better localization accuracy than using theory to construct the map. This is because different nodes may have different variance on the hardware parameters. Therefore, if users prefer higher accuracy, they may choose training to construct the LOS radio map. Otherwise, using theory to construct the map will save more cost. We use training to construct the map in in the following experiments.

4.3 Impact of Path Number Selection

In this section, we show the impact of number of a path on the localization accuracy. We test different numbers of paths from 2 to 5, based on 24 different target positions on the ground. Fig. 13 shows the experiment result, where n denotes the number of path. We find that when $n = 2$, its average localization accuracy is only about 2 m. When we take more path into consideration, say $n = 3, 4, 5$, we obtain better localization accuracy. However, we also observe that when $n \geq 3$, the improvement in accuracy is marginal with a localization accuracy of about 1.5 m. Therefore in our later experiments, we set this value as 3.

4.4 Impact of Number of Channel

TelosB nodes can adjust to 16 different channels. In our system, we leverage frequency diversity by transmitting data through all the possible channels. In this part, we would like to examine the impact of different number

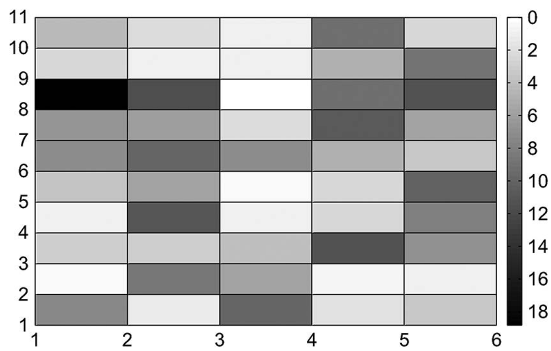

Fig. 10. Change of RSS.

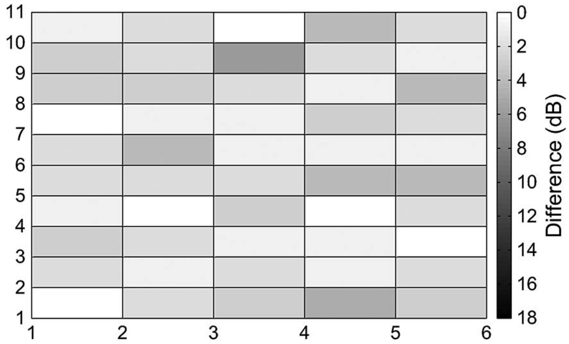

Fig. 11. Change of LOS RSS.

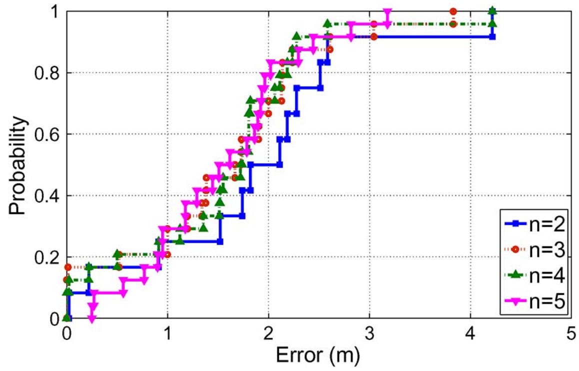

Fig. 13. Accuracy of different number of path.

of channel in use. we compares the normalized ranging accuracy with different channel numbers with $m = 8, 11, 16$ respectively. In Fig. 14. The experiment shows that for $m = 8$, the averaged range error is about 32 percent. When we use the maximum number of channels 16, the accuracy is at best 25 percent on average. From this, we could draw the conclusion that when latency and measurement overheads are not a concern, we should use more channels.

In this section, we evaluate the localization accuracy of a single object in a dynamic environment, where we arrange some people walking around. Based on 24 different target locations, we compare the accuracy of our algorithm with Horus [9], which has the best localization accuracy in the traditional work. The localization results are shown in Fig. 15. We may see that, in a dynamic environment, the localization accuracy of Horus is around 3 m while our LOS map matching has the accuracy of 1.5 m. The localization accuracy is improved by 50 percent.

4.5 Accuracy of Multiple Objects in Dynamic Environment

In this experiment, we evaluate the system performance of multiple objects in a dynamic environment, where we arrange for some people to walk around. We have two target objects, named O_1 and O_2. These two objects are TelosB nodes held by two people. In the experiment, both people try to keep the target node at a fixed height and direction to minimize the effect of other factors. For each target object, 40 locations on the ground are tested. From Fig. 16 we can observe that, by using Horus, the localization accuracy is about 4.4 m, which is much worse than the localization accuracy of a single object. Our LOS map matching method, however, has a localization accuracy of about 1.8 m and outperforms traditional radio map based technologies by 60 percent.

Second, to better understand the impact of multiple objects, we introduce another person known as O_3 while keeping the other environmental factors stable. We show the impact of the third object O_3 on the localization of the other two target objects O_1 and O_2. The experiment result by using the traditional radio map is shown in Fig. 17. The top figure demonstrates an absolute localization error of O_1 with and without O_3 presents, and the bottom figure demonstrates the impact of object O_3 on O_2. However, the extra object O_3 has little impact on RSS of LOS path and the experiment result is shown in Fig. 18. By using LOS map matching, both O_1 and O_2 have an average localization error of around 1.8 meters.

The experiment results have indicated that, without calibration, the LOS map matching has high accuracy for multiple objects in a dynamic environment.

4.6 Performance of CSI Information

In this part, we implement our basic idea with 802.11 NICs, which is manufactured by TP-LINK technologies CO.Ltd. we use a laptop with 2.4 Ghz dual-core CPU as the transmitter and three WiFi devices are deployed on the ceiling as receivers. In Fig. 19, we show the CDF of the amplitude change of CSI between two successive packets in 5 mobile traces and the amplitude variance of CSI is within 15 percent. The temporal variance of RSSI in corresponding traces is much larger within 30 percent

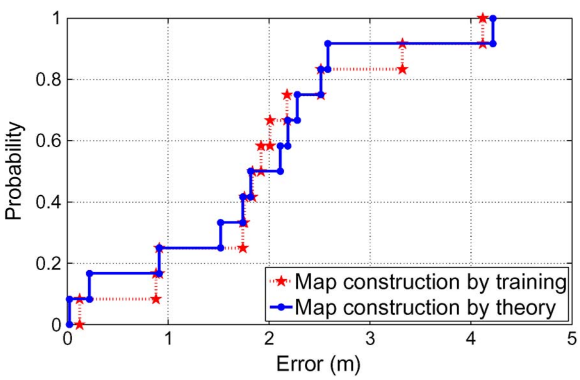

Fig. 12. Localization accuracy by using two different map construction approaches.

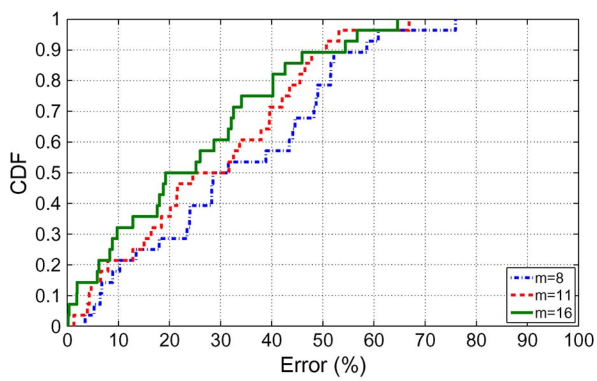

Fig. 14. Impact of number of channel.

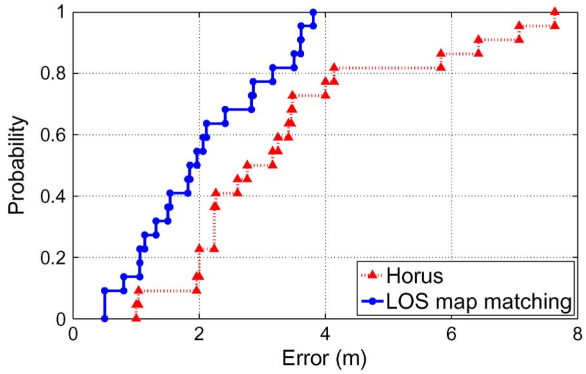

Fig. 15. CDF of localization accuracy in dynamic environment.

as presented in Fig. 20. Therefore, the relative stability for CSI is an essential advantage for a higher accuracy gain compared with the use of only RSSI information.

In addition, we compare the CSI based localization result with an RSSI based localization result. In Fig. 21, the experiment showss that, with this additional information from the physical layer, we could obtain more accurate location information.

4.7 Latency

The latency of a TelosB based system mainly depends on how much time it takes for each node to finish visiting all the channels. In our system, we transmit beacon messages through all the 16 channels and at each channel, 5 packets are transmitted. TelosB node takes approximately 7 ms to transmit a single packet and 0.3 4 ms for channel switching. In order to avoid beacon collision when multiple objects exist, the target nodes transmit packets every 30 ms. Therefore, for each node, the minimum time spend on visiting all the channels is $(37 + 0.34) \times 16 \approx 0.59$ s. Since we transmit 5 packets in each channel, the total latency will be $(37 \times 5 + 0.34) \times 16 \approx 2.9$s The total latency can be expressed as:

$$T_l = (T_t + T_s) \times N, \tag{10}$$

where T_t denotes the time interval between packet transmission, T_s represents the channel switch time and N denotes the number of channels.

Furthermore, 802.11 NICs with OFDM technology could provide information of all the subcarriers simultaneously, thus, there is no such latency issue.

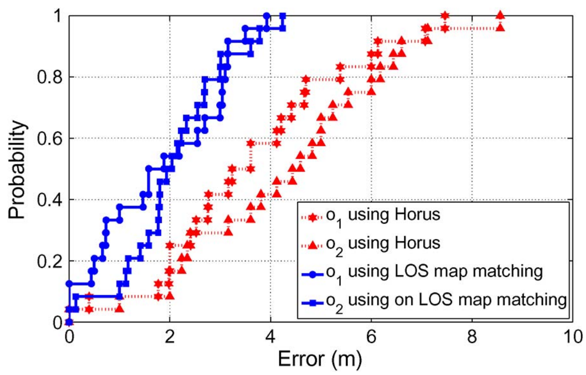

Fig. 16. CDF of localization accuracy of multiple objects.

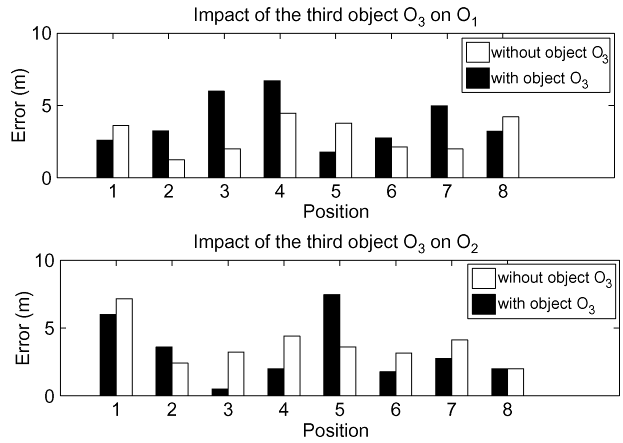

Fig. 17. Accuracy with original map.

5 Related Work

There are some video-based technologies that track multiple objects, such as [21], [22], [23]. Their computation complexity is relatively high and it is hard to track objects in a dark area. In [10], a RF-based method has been proposed for multiple objects localization. However, this approach is sensitive to environment change.

Significant work has been done in the area of indoor localization by using RSS information. These works can be roughly divided into two categories: radio map based technology and non-radio map based technology.

In radio map based technology, some works use adaptive learning approaches such as found in [24]. This work utilizes the RSS information of some reference points to help reconstruct the radio map. Thus, reducing the calibration cost. However, calibration on the map is still required if the environment changes. A large number of probabilistic approaches [9], [4] have also been proposed. Their main idea is to construct a probabilistic model to represent the behavior of the linked RSS values. Many parameters still need to be trained in real environments, which also suffer from environmental changes. One work [14] built multiple radio maps in advance under various environmental conditions and selected the most appropriate radio map to localize an object by using sensors to identify the current environment.

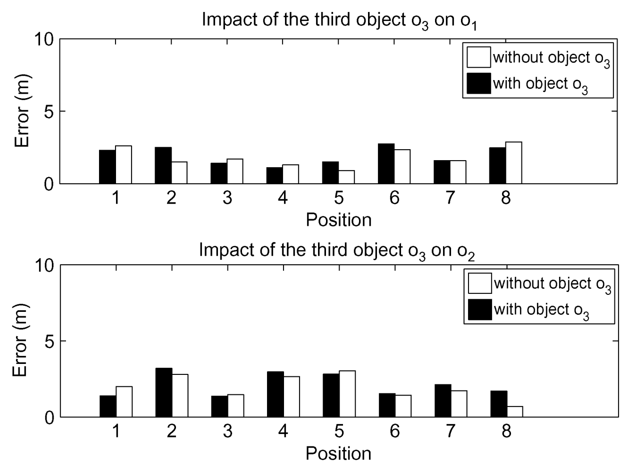

Fig. 18. Accuracy with LOS map.

However, if environments or the number of targets changes often, it is hard to construct all possible maps. Another work [7] assumes positions of access points (anchor nodes) are unknown. Their proposed algorithm does not rely on knowledge of the placement of the access points. [25] considered the NLOS issue by leveraging the prior probabilities and distribution of the NLOS errors. However, these performances also suffer from environment change. In our previous work [26], though we could achieve relatively high accuracy in localizing multiple objects in a dynamic environment, we only leverage the RSS information, which will introduce latency for switching channel. In this work, we consider leveraging CSI information to improve the localization accuracy and reduce the latency as well.

In non-radio map based technologies, RIPS [27], [28] utilized the interference behavior between two nodes with slightly frequency difference to localize target. This is improved in [29], [30] used Doppler effect work to track mobile target and improve the system accuracy. Although these work have excellent positional accuracy and sensing range in outdoor environments, they are unsuitable for indoor environment due to severe multipath effect indoors. LANDMARC [13] used RFID technology to localization object inside building by finding similar RSS value between reference nodes and the target nodes. However, the accuracy of this approach relies on dense deployment of the reference nodes. Its extended work [31] is able to localize target by using less reference nodes. However, its density is still high. In [3], [32], it leverages vector network analyzer to obtain the channel impulse response (CIR) and improve the accuracy by adopting the neural networking training algorithm.

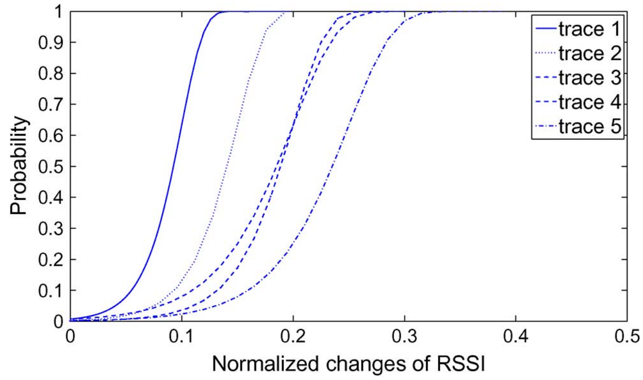

Fig. 20. Temporal stability of RSSI.

6 Conclusion and Future Work

In this paper, we proposed a novel localization system called MODLoc and we implement it on TelosB sensor nodes and 802.11 NICs respectively. This system is able to accurately localize multiple targets in a dynamic environment without any calibration procedure making it totally different from traditional approaches. Moreover, it presents promising generality which enables it to be applied in a much broader scope of application. With this new approach, many of the existing RF-based localization approaches may need a revisit.

Our radio map construction and localization methods are both based on the LOS path information among nodes. The LOS signal is identified from the original signal by utilizing frequency diversity of wireless nodes to eliminate multipath behavior. During the multipath elimination procedure, each wireless node only needs to visit different channels to transmit. Then, the elimination problem is transferred into an optimization problem. Our system shows that the number of targets and environmental changes do not affect the LOS map and no calibration is required. Through extensive experiments, compared with traditional radio map based technologies, the accuracy of localizing multiple objects in a dynamic environment (e.g., the target number changes or layout changes) can be dramatically improved by 60 percent and more gain with CSI provided by 802.11 NICs. Our method can be widely used and benefit all the RF-based localization methods.

Future work can be conducted in the following directions. First, based on this new technology, some fundamental radio map based localization problems become open. For example, based on the new LOS radio map, other appropriate map matching methods should be further investigated. Second, we only conduct our experiments in an area of 15×10 meters. A larger experiment area is expected in our future work. Third, in our experiment, the number of target nodes is at most three. The localization results of more target objects will be given in our ensuing work. Finally, the parameter of path number selection in frequency diversity is from our empirical results and its theoretical foundation calls for further investigation.

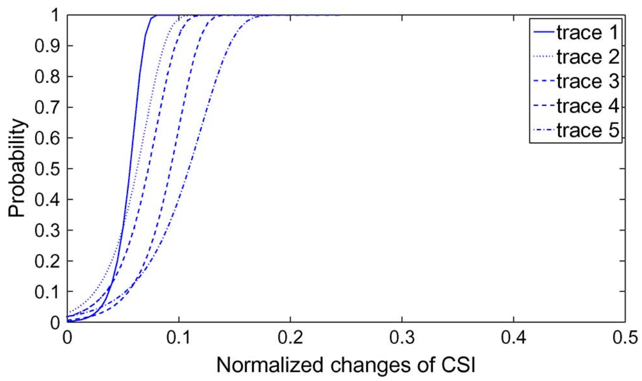

Fig. 19. Temporal stability of CSI.

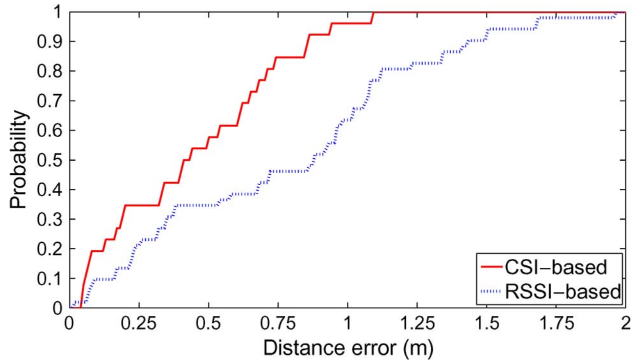

Fig. 21. CSI VS. RSSI.

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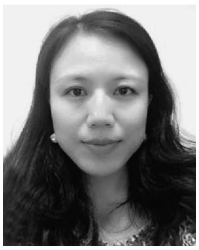

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