SUMMARY Radio Frequency based Device-Free Localization (RFDFL) is an emerging localization technique without requirements of attaching any electronic device to a target. The target can be localized by means of measuring the shadowing of received signal strength caused by the target. However, the accuracy of RFDFL deteriorates seriously in environment with WiFi interference. State-of-the-art methods do not efficiently solve this problem. In this paper, we propose a dual-band method to improve the accuracy of RFDFL in environment without/with severe WiFi interference. We introduce an algorithm of fusing dual-band images in order to obtain an enhanced image inferring more precise location and propose a timestamp-based synchronization method to associate the dual-band images to ensure their one-one correspondence. With real-world experiments, we show that our method outperforms traditional single-band localization methods and improves the localization accuracy by up to 40.4% in real indoor environment with high WiFi interference.

key words: device-free localization, WiFi interference, dual-band, sensor networks

1. Introduction

Recently, indoor localization techniques have become crucial constituent in many applications. Localization systems can be classified into device-based and device-free localization. Compared with device-based localization system, Device-Free Localization (DFL) [1], [2], [4] does not require to attach any electronic device on the target. Among DFL methods, Radio Frequency based DFL (RFDFL) is the most widely used one. In RFDFL, location information can be extracted based on the path loss of radio frequency (RF) signal caused by the targets. RFDFL is a promising technique for many practical applications such as locating survivors during fires or earthquakes [1], helping police to locate terrorists through wall [3] and saving energy by controlling household appliances automatically via detecting occupancy at home. Comparing with other device free localization techniques, RFDFL is much cheaper than ultrawideband radar systems [4], while having no privacy problem compared with video cameras and being able to monitor larger area than infrared systems.

RFDFL techniques fall into two categories: WiFi-based and sensor network based approach. For WiFi-based methods [2], [5], radio maps are collected when the target stands on different predetermined locations and then the system maps the estimated location to one of the trained locations based on the changes of radio signals. However, its topology highly depends on the positions of Ethernet sockets and electric outlets, which cannot be easily changed. It is difficult to densely deploy Access Points (APs) to cover the whole monitoring areas, and therefore, the accuracy of this method is limited. In addition, the price of an AP is much higher than that of a sensor node. Sensor network based RFDFL, on the other hand, has the advantages of low price and easy deployment (battery-powered), which make it more practical for real applications [1]. Radio Tomography Image (RTI) [1], [3], [6], [7], [9] is a typical method to do RFDFL. By visualizing the RF propagation field, changes of RF are highlighted in the image, which is used to infer the location of the target. Most DFL systems adopt IEEE 802.15.4 sensor networks operating at 2.4 GHz band to localize human targets, because this frequency band has the same resonant frequency with water, which forms more than 70% parts of human body [24]. However, WiFi uses the same frequency band. Interference from WiFi has disastrous influence on the performance of IEEE 802.15.4 [10]–[12] such as packet drops, transmission delay and Received Signal Strength (RSS) value changes of communication links, which will severely reduce the localization accuracy of RFDFL.

Sensor networks can also use 433 MHz to do DFL [22]. 433 MHz band suffers less from environment interference because of the existence of fewer systems operating on this band [23]. Another advantage of 433 MHz band is that 433 MHz is a true ISM Band and requires no license worldwide, compared with 868/915 MHz and 2.4 GHz. However, its longer signal wavelength, it can easily penetrate the wall and human body with less attenuation compared with 2.4 GHz band, which makes it difficult to accurately infer the...
location of the target using RTI method.

As discussed above, for RDFDFL in an indoor environment it is very difficult (if not impossible) to find a suitable frequency band that has radio signal change very sensitive to the target’s movement and meanwhile suffers no environment interference. On the one hand, 2.4 GHz band is sensitive to human targets but is easily interfered by other high power 2.4 GHz devices (e.g. WiFi, bluetooth and microwave-oven, etc.). On the other hand, 433 MHz band has fewer issues regarding environment interference, but does not allow for localization as accurate as 2.4 GHz. In this paper we propose a novel dual-band method to solve this problem. The basic idea is to combine the advantages of both 2.4 GHz and 433 MHz band to establish a RDFDFL system that is robust to WiFi interference and allows for accurate indoor localization even with severe interference. The procedure works as follows. First, two RTI matrices are obtained from 433 MHz and 2.4 GHz. Then, we propose an algorithm for fusing the two images based on a weighting model. Through assigning different weights to 433 MHz and 2.4 GHz image matrices according to the packet received rate of 2.4 GHz band, the overlapped elements are fused to a new image matrix, from which we can achieve a more accurate estimation of the target’s location. In addition to the environment with severe WiFi interference, we can also benefit from this method for localization in a clean environment. Localization accuracy is also improved by means of the proper fusion of redundant information. Also, in a heterogeneous network, our device with extra 433 MHz can be used as a gateway communicate with both 433 MHz sensor nodes (e.g. BTnode, Mica2, Mica2Dot, iMote2) and 2.4 GHz sensor nodes (e.g. MICAz, TelosB) simultaneously. In an environment with crowded 2.4 GHz signals, 433 MHz can be employed to increase communication efficiency.

The rest of the paper is organized as follows: In Sect. 2, we discuss the related work. In Sect. 3, shadowing-based RTI is introduced. Section 4 analyses the influence factors to the accuracy of RDFDFL. Then our new dual-band localization method is presented in Sect. 5. Section 6 describes the experiment setup and shows the experimental results. Finally, the paper is concluded in Sect. 7.

2. Related Work

Most previous work on DFL for indoor localization is either WiFi based or sensor network based. Examples of WiFi based DFL [5], [8] use a fingerprint approach, which requires an offline training phase. During the training, a radio map is generated for each possible location of the target and stored in the database. During the online localization, the obtained radio map is compared with the stored radio maps. The closest matching is used to infer the target’s location. The scalability of this method is very limited. When the topology of the WiFi network is changed, the offline phase must repeat, which is a very time consuming process. What’s more, its topology highly depends on the position of power supply and Ethernet sockets. These are the limitation of all WiFi based approaches.

For sensor network based RDFDFL, Chen et al. [6] propose to use Sequential Monte Carlo for DFL. This method suffers from intensive computation and is not suitable for real-time localization. Radio Tomography Image (RTI) based methods [9], [13]–[15] are more effective. They localize the target in the RF propagation area using attenuation of RSS values caused by the target. However, all these methods are based on 2.4 GHz band and their accuracy is highly influenced by WiFi interference, which is not well-addressed in the previous work. In [13], the channel-diversity mechanism is proposed to improve the RTI accuracy. With this method, according to the fade level, each communication link chooses the best channel. The channel is fixed at the beginning and will remain the same in the later localization process, therefore cannot be adapted according to the changing interference level. Zhao et al. [14] use the subspace decomposition method to improve the accuracy of RDFDFL by reducing the impact of the environment noise including (such as tree branches moving, rotary machine) on the RSS value. However, packet loss caused by WiFi interference is still not addressed. Their later work in [9] proposes a method to improve the localization accuracy by calculating kernel distance. In this method, with the kernel distance between a long-term histogram and a short-term histogram, it is able to obtain the temporal RSS changes caused by the target. However, they only use channel 26 of 2.4 GHz sensor network for RDFDFL which is assumed not to be interfered with WiFi network. A multi-scale spatial weight model is proposed in [15]. To improve accuracy, different spatial weight is assigned to each link based on fade level. However, the problem of WiFi interference is not taken into account in that paper.

Dual-band techniques also used in device-based localization system [16], which employ 2.4 GHz band and 433 MHz band to estimate distance according to log-distance path loss model. In contrast, we target on improve the accuracy of RDFDFL with WiFi interference and the localization method is totally different.

3. Background of Radio Tomography Imaging

In RTI-based DFL, a radio tomography image is used to measure the attenuation of RSS due to signal absorption, diffraction, scattering or reflection caused by the target. Assuming we have $n$ sensor nodes, the total number of directional links is $M = n \times (n-1)$ in the RDFDFL system. The RSS value of link $i$ at time $t$ is denoted by $\gamma_i(t)$. Mathematically, it can be calculated as shown in [1].

$$\gamma_i(t) = P_i - L_i - S_i(t) - n_i(t).$$

(1)

where $P_i$ denotes the transmission power, $L_i$ is large scale path loss due to distance, $S_i(t)$ is shadowing attenuation caused by targets and $n_i(t)$ expresses the sum of measurement noise and multipath fading.

The RTI method quantizes the monitoring area into pixels with the number of $N$. The shadowing attenuation
$S_j(t)$ of RSS can be the approximate sum of attenuation in each pixel. Each pixel has different impact to different links depending on the distance from the pixel to the link. The shadowing attenuation for a link is defined as the integral of attenuation in pixels.

$$S_j(t) = \sum_{j=1}^{N} w_{ij} x_j(t).$$

(2)

where $w_{ij}$ is the weight of pixel $j$ on link $i$ and $x_j(t)$ is the attenuation in pixel $j$ at time $t$. An elliptical model is used to calculate the weight matrix according to the geometrical relationship between pixels and the links.

Assuming a time window $[0, t_b]$ while no one is in the monitoring area, the mean RSS value of link $i$ can be calculated during this calibration time, which is denoted by $\bar{\gamma}_i$. The attenuation between RSS value at time $t_b$ and calibration time ($t_a$) is calculated as following:

$$\Delta \gamma_i = \gamma_i(t_b) - \gamma_i(t_a) = \gamma_i(t_b) - \bar{\gamma}_i = S_i(t_a) - S_i(t_b) + n_i(t_a) - n_i(t_b)$$

$$\approx \sum_{j=1}^{N} w_{ij} (x_{i_a} - x_{i_b}) + n$$

$$= \sum_{j=1}^{N} w_{ij} \Delta x_i + n.$$

(3)

where $n = n_i(t_b) - n_i(t_a)$. Considering all communication links, the above formula can form a linear model [1], [17], [21].

$$\Delta \mathbf{y} = \mathbf{W} \Delta \mathbf{x} + \mathbf{n}.$$  

(4)

where $\Delta \mathbf{y}$ is RSS attenuation vector with size $M \times 1$, $\Delta \mathbf{x}$ is the attenuation value of all pixels with size $N \times 1$, and $\mathbf{n}$ is the measurement noise on all links with size $M \times 1$. $\mathbf{W}$ is the weight matrix with dimension $M \times N$. Each column of the weight matrix represents a single pixel and each row means the weight of each pixel for the corresponding link.

$$\Delta \mathbf{y} = [\Delta \gamma_1, \Delta \gamma_2, \ldots, \Delta \gamma_M]^T.$$  

$$\Delta \mathbf{x} = [\Delta x_1, \Delta x_2, \ldots, \Delta x_N]^T.$$  

$$\mathbf{n} = [n_1, n_2, \ldots, n_M]^T.$$  

(5)

For link $i$, the transmitter and the receiver are two focuses of the ellipse [17]. Only pixels in the ellipse affect the link, with weight $w_{ij}$, which is inversely proportional to the square root of the link length. The weights of the other pixels out of the ellipse are zero.

$$w_{ij} = \frac{1}{\sqrt{d_{ij}^p}} \begin{cases} 1, & \text{if } d_i^p(x_j) + d_j^p(x_i) < d_i^r + \lambda \cr 0, & \text{otherwise}. \end{cases}$$

(6)

where $d_i^p(x_j), d_j^p(x_i)$ are the distances from the center of pixel $j$ to the transmission node and receive node, respectively, for link $i$, $d_i^r$ is the length of link $i$, and $\lambda$ is the width of the ellipse, which can be adjusted according to the requirement of accuracy of RFDFL as shown in Fig. 1.

The RTI model takes elements of vector $\Delta \mathbf{x}$ as pixel values and estimates the image of $\Delta \mathbf{x}$ from formula $\Delta \mathbf{y} = \mathbf{W} \Delta \mathbf{x} + \mathbf{n}$. However, the same $\Delta \mathbf{y}$ can lead to multiple images due to the measurement and the noise $\mathbf{n}$ [1]. Here, we use the least-square approach to regularize this problem [14].

$$\hat{\mathbf{x}} = \Pi \Delta \mathbf{y}.$$  

(7)

$$\Pi = (\mathbf{W}^T \mathbf{W} + \delta_n^2 \mathbf{C}_x^{-1})^{-1} \mathbf{W}^T.$$  

(8)

$$[\mathbf{C}_x]_{jk} = \delta_n^2 e^{-d_{jk}^2/\delta_n^2}.$$  

(9)

where $d_{jk}$ is the Euclid distance between pixel $j$ and pixel $k$, other parameters’ definitions in Eqs. (7), (8), (9) are shown in Table 1. These parameters depend on a specific experimental scenario. In the following experiments, we choose them in accordance with [1], [13].

As an example, Fig. 2 shows a radio tomography image with a person in the RF propagation area. The pixel with maximum value is elected as the coordinator.

![Fig. 2 Relationship between actual location and estimated location. (Actual location represented by a white cross).](image1)

![Fig. 1 Weight model.](image2)
4. Problem Statement

4.1 Without WiFi Interference

As discussed in the previous section, the same link measurement might have different image solutions. Although least squares estimators are used [14], [17] to find the most proper image matrix and the element with the maximum value in the image matrix is selected as the estimated target’s location, this approximation even introduces error in a clean environment without WiFi interference. As a result, there is a high probability that the actual location of the target is in one of the surrounding high value pixels, which are very close to the maximum value.

Figure 2 shows a RTI from our experiment. An error can be seen between the estimated location and the actual location.

4.2 With WiFi Interference

Nowadays, WiFi signals are very common in most indoor environments. Figure 3 shows the distribution of WiFi network in our office building. There are almost 40 APs in the environment. WiFi network itself has already been very crowded with more than one APs on several WiFi channels. It becomes worse when the channels of IEEE 802.15.4 sensor network overlaps with IEEE 802.11 WiFi network. This overlapping is shown in Fig. 4. Therefore, interference becomes inevitable when IEEE 802.15.4 sensor network coexists with IEEE 802.11 WiFi network.

To show the impact of WiFi interference on the RFDFL system, we conducted a series of measurements. In Fig. 5, we pick channel 18 of IEEE802.15.4 to show the influence of WiFi interference on the RSS value and packet drop rate (PDR). As shown, WiFi interference does not lead to significant change of received RSS value, within 10 dBm, but cause severe packet drops. Due to the increased PDR, the measured RSS has large deviation from the actual value, leading to misjudgement of the target and reduce the localization accuracy. Hence, the increased PDR is the main cause of the degradation of localization accuracy. With the WiFi interference increasing, the accuracy of RFDFL becomes worse because of severe packet drops. In other words, the correct real-time measurement of RSS, which are used to extracted the target’s location in this moment cannot be obtained, because of packet drops. When packets are dropped, RFDFL uses the previous RSS values (real-time measurements of RSS are lost) to calculate the target’s location in this moment, which results in larger location error. Our measurement of packet drops as well as localization errors caused by WiFi interference is shown in Fig. 6. For example, WiFi interference with 1 Mbps transmission rate leads to a PDR of 50%, which makes the localization error in Root Mean Square Error increase by 79.4%, from 0.5571 m to 0.9895 m.

5. Dual-Band Localization Method

As discussed in Sect. 4, the accuracy of the state-of-the-art RFDFL method that uses 2.4 GHz band in a clean environment needs further improvement, while in an environment with WiFi, the serious interference problem needs to be addressed. To achieve these requirements, we propose here a novel dual-band method.

The idea of our method is to combine the advantages of both 2.4 GHz band and 433 MHz band to get a RFDFL system that is robust to WiFi interference and allows for accurate indoor localization even with severe interference. Two
RTI matrices are obtained from 433 MHz and 2.4 GHz as shown in Fig. 7. In a clean environment, the RTI from 2.4 GHz band can provide more accurate information of the target because 2.4 GHz RF signal is more sensitive to the target. However, additional localization information obtained from 433 MHz can be used to adjust the estimation to a more accurate result. Therefore, when fusing the two RTIs a higher weight is assigned to the matrix element values from 2.4 GHz. In contrast, in an environment with WiFi the location information from 433 MHz RTI is more accurate when the WiFi interference is severe. Therefore, a higher weight is assigned to the matrix element values from 433 MHz. The weight increases with increasing WiFi intensity. Therefore, a method is needed here to decide a proper weight value for a specific scenario. The dual-band fusion model as well as the associated weighting method are described in detail in Sects. 5.1 and 5.2.

Considering the complexity of dual-band algorithm, the sensor nodes deployed around the monitoring area are mainly responsible for sampling the RSS values and sending them to the base station. The sensor nodes do not need to keep extra data and do not have any calculation task. Therefore, there is no extra calculation/storage cost for the additional band (433 MHz). The dual-band algorithm runs on the base station, which can be a laptop, a desktop computer or a tablet and has enough resource.

Another important issue is the synchronization of sensor nodes. In our method, both 2.4 GHz sensor nodes and 433 MHz sensor nodes measure RSS values of all communication links and generate a RTI periodically. This period is called a sampling round. The sampling round of 2.4 GHz sensor nodes and 433 MHz sensor nodes must be synchronized so that the two RTIs reflect the target at exactly the same location. If the sensor nodes are not well synchronized and the target is moving fast, there will be a large error because of this synchronization issue. Assume that one RTI is taken time t later than the other RTI and the target is moving at velocity of v, an error of \( \Delta T = v \cdot t \) is introduced. To address this issue, a synchronization method is proposed. In addition, during a sampling round the sensor nodes must also be scheduled for measuring the data. These issues are discussed in Sect. 5.3 in detail.

5.1 Dual-Band Data Fusion Method

Figure 8 shows our dual-band fusion flow, where \( y \) and \( \hat{x} \) represent the RSS attenuation vector and the attenuation value of all pixels, respectively (in Eq. (4) \( \Delta y \) and \( \Delta x \) are used). All notions used in Fig. 8 are explained below:

- \( \hat{x}_H \): the image matrix of 2.4 GHz band;
- \( \hat{x}_L \): the image matrix of 433 MHz band;
- \( y_H \): the measurement vector of RSS attenuation from 2.4 GHz band;
- \( y_L \): the measurement vector of RSS attenuation from 433 MHz band;
- \( \Pi_H \): 2.4 GHz regularized least-square coefficient;
- \( \Pi_L \): 433 MHz regularized least-square coefficient;
- \( \hat{x}_F \): the image matrix generated by fusing \( \hat{x}_H \) and \( \hat{x}_L \);
- \((x_f, y_f)\): the coordinate of the finally estimated location.

Mathematically, the image fusion dual-band method is expressed as follows:

\[
\hat{x}_F = f(g_1(\hat{x}_H), g_2(\hat{x}_L)).
\]  

(10)

where \( g_1(\bullet) \) and \( g_2(\bullet) \) are two functions for normalizing the elements of \( \hat{x}_H \) and \( \hat{x}_L \), respectively. The reason for normalization is that the elements of the 2.4 GHz image matrix have much higher value than those of the 433 MHz image matrix and in addition, variance among the elements of the 433 MHz image matrix is also lower because of the low sensitivity of 433 MHz RF signal to the target. This can be observed in the RTIs in Fig. 17 obtained from our experiments. If \( \hat{x}_H \) and \( \hat{x}_L \) are directly fused, this will make the impact of data from 433 MHz band very low. Hence, normalization is needed to make data from 2.4 GHz band and 433 MHz band have comparable impacts. The two functions are defined as:

\[
g_1(\hat{x}_H) = \frac{\hat{x}_H - \min[\hat{x}_H]}{\max[\hat{x}_H] - \min[\hat{x}_H]},
\]

\[
g_2(\hat{x}_L) = \frac{\hat{x}_L - \min[\hat{x}_L]}{\max[\hat{x}_L] - \min[\hat{x}_L]}.
\]

(11)

where \( \min[\hat{x}_H] \) and \( \max[\hat{x}_H] \) are minimum and maximum values of matrix \( \hat{x}_H \), respectively. The minimum and maximum values of \( \hat{x}_L \) are denoted as \( \min[\hat{x}_L] \) and \( \max[\hat{x}_L] \), respectively. Where \( f(\bullet) \) is the fusing function. It operates on the two normalized matrices, \( g_1(\hat{x}_H) \) and \( g_2(\hat{x}_L) \). The function is defined as follows:

\[
\hat{x}_F = \arg\max_{(x_f, y_f)} \left( \sum_i g_i(\hat{x}_i) \right)
\]

Fig. 8 Dual-band fusion model.
Fig. 9 An example of dual-band fusion. A person at the coordinate \((1.5, 1.5)\) in the environment with 800 Kbps WiFi interference.

\[
f(\bullet) = \left\{ \frac{w_1}{w_1 + w_2} g_1(\hat{x}_H) + \frac{w_2}{w_1 + w_2} g_2(\hat{x}_L) \right\}.
\] (12)

where \(w_1\) and \(w_2\) are the respective weights added to data from 2.4 GHz band and 433 MHz band. The method for deciding the weight value is introduced in Sect. 5.2. \(\hat{x}_f\) is the new image generated by fusion. In \(\hat{x}_f\) the element with the largest value is identified as the target’s location:

\[
(x_f, y_f) = \arg \max_N (\hat{x}_f).
\] (13)

where \((x_f, y_f)\) is the coordinate of the finally estimated location.

Figure 9 shows an example of fusing two image matrices from the two bands in an environment with 800 Kbps WiFi interference. The figure shows part of the original 433 MHz matrix (left top) and part of the original 2.4 GHz matrix (left bottom). Part of the dual band matrix (right) is from the matrices after fusion. The weights for fusion are: \(w_1 = 53.5\%\); \(w_2 = 46.5\%\) (refer to Sect. 5.2). As shown in the figure, if only 433 MHz band is used the element with the value 1.747 is estimated as the target’s location, while if only 2.4 GHz band is used the element with the value 2.859 is selected. Using our dual-band method, the element with the value 0.895 is identified as the target’s location. In the figure, the actual location is also marked in every matrix, respectively. It is obvious that the estimation by the dual-band method is more accurate.

As described in Sects. 3 and 4.1, because of the measurement and environment noise \(n\), the least-square approach can only be approximated the solution of \(\Delta x\) roughly, result in an area, where each pixel could be the target’s location, as shown in Fig. 17. If we just select the pixel with maximum value to be the final estimated location, it will lead to large errors. For example, as shown in 2.4 GHz and 433 MHz matrix in Fig. 9, the pixel with the maximum value is not the actual location of the target.

Our method is to make use of location redundancy to improve localization accuracy. For example, in a clean environment, we can get more accurate estimation by fusing two measurement results, both from 2.4 GHz, than that uses only one measurement result from 2.4 GHz. In the same way, we improve the localization accuracy by fusing two measurement results from 433 MHz, if the WiFi interference is extremely high. With an inference in between, we cannot say for sure the result from which band is absolutely “good”, and therefore we fuse the results from both bands. However, when the interference is low, the result from 2.4 GHz has a higher probability to be good. Otherwise, the result from 433 MHz has a higher probability. Hence, we assign corresponding weights to the results from the two bands, to reflect their impact on the final result.

### 5.2 Weighting Model

As discussed before, In order to optimize the localization accuracy, suitable weights should be added to data from 2.4 GHz band and 433 MHz band according to the intensity of WiFi interference. The weight value should be determined by the accuracy of the two bands. The band with higher accuracy is assigned a higher weight. Since the accuracy of 2.4 GHz band depends on the intensity of WiFi interference, we can establish a correspondence between WiFi interference and weight value. Table 2 shows such a correspondence obtained by our measurements. We defined 5 levels of interference, from 0 Kbps (clean) to 20 Mbps (severe). Then, for each interference level, we measured the localization accuracy of RFDFL using only 2.4 GHz and only 433 MHz band. We first assigned initial weights to data from the two bands and then adjusted the weights with further measurements until a satisfying accuracy is achieved. Table 2 shows the final weights with respect to different interference level. These data are stored in a lookup table to be used at runtime for data fusion.

Therefore, to obtain the right weights at runtime, we need to know the intensity of interference of the current environment. Here, the packet of drop rate (PDR) of 2.4 GHz band is used to indicate the intensity of WiFi interference. PDR not only reflects the WiFi interference strength but also takes other important factors into account: the WiFi traffic volume and the distance from the interference source. It is clear that high WiFi transmission rate causes high PDR of 2.4 GHz band as shown in Fig. 6. Regarding the distance to the interference source, it is also taken into account, because we measure the average PDR of all nodes. A node that is closer to the interference source suffers from stronger WiFi interference and therefore has higher PDR. Although WiFi interference not only results in severe PDR, but also leads to variance of RSS value, deterioration of localization accuracy is mainly due to PDR rather than the variance of RSS value. This is because the packets interfered by WiFi are dropped[12], and the packets correctly received are almost

<table>
<thead>
<tr>
<th>Parameter</th>
<th>0 Kbps</th>
<th>400 Kbps</th>
<th>800 Kbps</th>
<th>1 Mbps</th>
<th>20 Mbps</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.4 GHZ PDR</td>
<td>0.13%</td>
<td>15.82%</td>
<td>28.42%</td>
<td>51.08%</td>
<td>60.06%</td>
</tr>
<tr>
<td>433 MHz PDR</td>
<td>0.17%</td>
<td>0.55%</td>
<td>1.04%</td>
<td>1.08%</td>
<td>0.04%</td>
</tr>
<tr>
<td>2.4 GHZ RMSE</td>
<td>0.3517</td>
<td>0.661</td>
<td>0.8602</td>
<td>0.9895</td>
<td>1.1355</td>
</tr>
<tr>
<td>433 MHz RMSE</td>
<td>0.7474</td>
<td>0.7533</td>
<td>0.7653</td>
<td>0.7851</td>
<td>0.7342</td>
</tr>
</tbody>
</table>

Table 2 Weight parameters.

\(w_1\) and \(w_2\) are the respective weights added to data from 2.4 GHz band and 433 MHz band according to the intensity of WiFi interference. The weight value should be determined by the accuracy of the two bands. The band with higher accuracy is assigned a higher weight. Since the accuracy of 2.4 GHz band depends on the intensity of WiFi interference, we can establish a correspondence between WiFi interference and weight value. Table 2 shows such a correspondence obtained by our measurements. We defined 5 levels of interference, from 0 Kbps (clean) to 20 Mbps (severe). Then, for each interference level, we measured the localization accuracy of RFDFL using only 2.4 GHz and only 433 MHz band. We first assigned initial weights to data from the two bands and then adjusted the weights with further measurements until a satisfying accuracy is achieved. Table 2 shows the final weights with respect to different interference level. These data are stored in a lookup table to be used at runtime for data fusion.
with insignificant variance of RSS as shown in Fig. 5. Lau et al. [18] showed the same results as ours and concluded that the PDR is the main reason causing the degradation of localization accuracy. Consequently, we establish a correspondence between PDR of 2.4 GHz band and weight value in the offline phase and then obtain the weight value at runtime by measuring the current PDR. As shown in Fig. 6, the PDR of 2.4 GHz can be used to reflect the trend of WiFi interference, and has tight relationship with localization accuracy. Hence, we measured the PDR under each interference level, as shown in Table 2. For example, at runtime, if the measured 2.4 GHz PDR is around 50%, $w_1 = 15\%$ and $w_2 = 85\%$ are used as the weights.

5.3 Dual-Band Data Synchronization

Sampling cycle is the time interval required for all nodes on one channel to complete the transmission as shown in Fig. 10. Sampling round is defined as the time interval needed for all nodes on all available channels to complete the transmission. If there are $k_n$ channels available, a sampling round consists of $k_n$ sampling cycles as shown in Fig. 10(a). In our work, for 433 MHz band only one channel is used, i.e. $k_n = 1$, while for 2.4 GHz band the channel-diversity method [13] is employed and multiple channels are used. After each sampling round, a serial number as well as a timestamp is added to each data record. For the two different bands, the data records are stored to two separate data bases as shown in Fig. 10.

The node transmission interval is 2.9 ms [13] for 2.4 GHz band and 24 ms for 433 MHz band, and these values are fixed. Therefore, the sampling round of 433 MHz band is $(\frac{24\times n}{320\times k_n} \div \lfloor \frac{5}{k_n} \rfloor)$ times longer than 2.4 GHz band, where $n$ is the number of nodes and $k_n$ is the number of channels used on 2.4 GHz band. For each data record of 433 MHz the corresponding 2.4 GHz data record can be found using the following equation:

$$j - 1 \times \left\lfloor \frac{8}{k_n} \right\rfloor + F.$$  \hspace{1cm} (14)

where $j$ is the serial number of the current 433 MHz data record and $F$ is the serial number of the first 433 MHz data record in the database. For example, if 4 channels are used in 2.4 GHz band. The sampling round of 433 MHz band is twice as long as that of 2.4 GHz band. Assume that the first 433 MHz data record has the serial number of 2. We can establish a correspondence of data records as shown in Fig. 11.

For example, the third 433 MHz data record should be fused with 6th 2.4 GHz data record. Although no 100% matching can be achieved with this method, many experiments proved that the time deviation between $t_H$ and $t_L$ is no more than 20 ms on average, where $t_L$ is the timestamp of $j$th 433 MHz data record, $t_H$ is the $((j - 1) \times \left\lfloor \frac{8}{k_n} \right\rfloor + F)$th 2.4 GHz data. Assuming the average walking speed of a person is 1m/s, so there is a deviation of less than 2 cm between the two estimated coordinators which is negligible for localization.

6. Experiments

6.1 Experiments Setup

In our experiment, we focus on human targets. We setup our experiments in a badminton hall in Karlsruhe, where no WiFi interference exists. At the beginning of the experiment, 40-second calibration time is needed to obtain the mean RSS value on each communication link, without any person in the monitoring area. During the experiments, a person stands at 10 pre-marked locations as shown in Fig. 12. Figure 12 (a) also shows the distribution of 26 USB dongles operating at 2.4 GHz band [29] and 26 Betty nodes operating at 433 MHz band [25] around the monitoring area. The Betty nodes and the USB dongles have the same range of IDs, from 0 to 25. The Betty node and the USB dongle with the same ID are put together on a tripod, as shown in Fig. 13 (b). Figure 12 (b) gives a picture of the experimental environment.
Fig. 12  Experiment layout and environment. (a) Experiment layout, distance between two node is set to 1 m, nodes (2.4 GHz dongle and 433 MHz Betty) with same node ID are fastened on same tripod. (b) Experiment environment.

Fig. 13  Hardware platform in our experiment. (a) Base station with a 433 MHz and a 2.4 GHz module. (b) A 433 MHz Betty node and a 2.4 GHz USB dongle.

Each Betty node is composed of a LPC2220 microcontroller and a CC1100 radio chip, which works at 433 MHz. Their transmission power is 10 dBm. They all run the Spin protocol [1] for communication. The procedure of Spin is that all nodes in network take turns to transmit data according to their node IDs, which is programmed beforehand. At any particular time, only one node is transmitting while the others are listening. When a packet is dropped or a node fails to transmit, a timer will fire to make sure the next node moves on. Each USB dongle working at 2.4 GHz is composed of a CC2531 micro-chip. Their transmission power is 4.5 dBm. Currently, state-of-the-art methods use channel-diversity [13] to improving the accuracy of RFDFL. In order to compare with it, here we also use the multi-spin communication protocol [13], on USB dongles. It works the same as the Spin protocol during each communication cycle.

Fig. 14  The impact of different intensities of WiFi interference on accuracy of 2.4 GHz band, 433 MHz band and dual-band RFDFL system, respectively.

The difference is that at the end of each sampling cycle all nodes synchronously switch to the next channel. The available channels are pre-defined. Channels 11, 18, 21 and 26 are used in our experiment.

In order to receive the packets sent at both 2.4 GHz and 433 MHz bands, we designed a base station consisting of two radio transceivers, as shown in Fig. 13 (a). It is composed of a reconfigurable system on chip (SmartFusion2 from Microsemi [27]), as well as a CC2420 and a CC1100 transceiver for communication at 2.4 GHz and 433 MHz, respectively. Both transceivers are connected through two dedicated Serial-Peripheral-Interface (SPI) buses and the collected data can be sent to a PC through two dedicated serial ports for analysis.

To generate WiFi interference with different intensities we followed the same approach as in [12]. We used two laptops and one WiFi access point to build a WiFi network. One laptop acted as the server, while the other one used the iperf tool [28] to produce different intensities of WiFi interference by requesting different transmission rates from the server.

6.2 Results and Discussion

In this subsection, we evaluate the performance of our dual-band method with the experiment setup described above. The experimental results prove that our method outperforms the channel diversity method [13] (for simplicity, it is referred to as “2.4 GHz band” in the following discussion) or 433 MHz band in both clean environment and the environment with WiFi interference of different intensities. Localization error is measured in Root-Mean-Square Error (RMSE), which is defined as the square root of the mean square error [9].

We generate WiFi interference in four levels including clean (0 Kbps), normal (800 Kbps), high (1 Mbps) and severe (20 Mbps). Figure 14 shows the influence of different intensities of WiFi interference to the accuracy of RFDFL using 2.4 GHz band, 433 MHz band and dual-band. The accuracy of RFDFL using 2.4 GHz band de-
creases significantly with the increase of WiFi interference. The RMSE under 0 Kbps WiFi interference (clean environment) is 0.5517 m, while the RMSE under 20 Mbps WiFi interference is 1.1595 m, increased by 79.4%. We can also see from the figure that the performance of RFDFL using 433 MHz band is relatively stable, because the different intensities of WiFi signals have almost no influence on this frequency band. The maximum and minimum RMSEs are 0.7851 m and 0.7342 m, respectively. It is interesting to see that, in these four scenarios that we tested, RFDFL using 2.4 GHz outperforms that using 433 MHz only in the clean environment. In the other three scenarios with WiFi interference, the performance of 433 MHz are always better. These results are consistent with our analyses described in Sect. 4 that the 2.4 GHz band is more sensitive to human body than 433 MHz but can easily be interfered by WiFi signals, while 433 MHz band is more robust to WiFi interference.

Our dual-band method outperforms RFDFL using 2.4 GHz band and 433 MHz band in all scenarios as shown in Fig. 14. In the environment with high WiFi interference, the RMSE of the dual-band method is 0.6481 m, while the RMSE of using 2.4 GHz is 0.9895 m. There means an improvement around 34.5%. As shown in Fig. 15, compared with RFDFL using 2.4 GHz, the improvement increases from 1.7% to 40.4% with WiFi interference increasing from clean to severe. In contrast, when comparing with RFDFL using 433 MHz, the improvement of accuracy by using the dual-band method decreases with the increase of WiFi interference, from 27.3% (clean environment) to 4.29% (severe WiFi interference environment). This is because accuracy of 433 MHz band is more stable than 2.4 GHz band in the environment with severe WiFi interference, therefore with increasing WiFi interference, higher weight is assigned to 433 MHz band in our dual-band fusion algorithm.

WiFi interference of 1 Mbps is very common in our daily life. Therefore, for this scenario we present more detailed views of the localization data in Figs. 16 and 17. Figure 16 shows all estimated and actual locations. The dual-band method is compared with RFDFL using 2.4 GHz. Then, in Fig. 16, we pick one location at coordinate (1.5, 1.5) as an example and show the radio tomography images, where the dual-band method is compared with both reference methods.

![Fig. 15](image) Improvement of dual-band method compared with 2.4 GHz band and 433 MHz band under different intensities of WiFi interference.

![Fig. 16](image) Relationship between actual and estimated location in the environment with 1 Mbps WiFi interference. (a) Only using 2.4 GHz band. (b) Using dual-band in WiFi interference environment.

![Fig. 17](image) RTI with a person at the coordinate (1.5, 1.5) in the environment with 1 Mbps WiFi interference. (Black triangle denotes the estimated coordinator and white cross is the actual coordinator) (a) using 433 MHz band image. (b) using 2.4 GHz band image. (c) using dual-band image.
7. Conclusion

In this paper, we introduced a novel dual-band method to improve the accuracy of RFDFL, particularly for environments with WiFi interference. We first proposed a dual-band data fusion method based on a weighting model to fuse two image matrices from 2.4 GHz and 433 MHz band, in order to localize the target more accurately. Then, a timestamp-based synchronization method is proposed to ensure that the fused images from the two bands are taken simultaneously for the target at a specific position. Extensive experimental results show that our dual-band method outperforms methods only using 2.4 GHz or 433 MHz band in both clean environment and environment with WiFi interference. Compared with the method only using 2.4 GHz band, we achieved up to 40.4% accuracy improvement in an environment under high WiFi interference. In a clean environment, there is still an improvement of 1.5%. Compared with the method using only 433 MHz band, an improvement of 27.3% is achieved. In the future work, we are going to integrate a 2.4 GHz and 433 MHz transceivers into a single node in order to save the hardware cost.

Acknowledgments

The authors thank the financial support of the National Science and Technology Support Program of China, grant No.2012BAH12B01. They also would like to thank Chih-Ming Hsieh, Sammer Srouji and Farzad Samie Ghahfarokhi from Chair for Embedded Systems in Department of Computer Science of KIT - Karlsruhe Institute of Technology Germany, for their contributions to this work.

References

[29] 2.4GHz IEEE 802.15.4 and ZigBee applications, http://www.ti.com/ lit/ds/symlink/cc2531.pdf
Manyi Wang received the B.S. degree and the M.S. in Signal and Information Processing from China University of Mining and Technology (CUMT), Xuzhou, China, in 2007 and 2010, respectively. He is working toward the Ph.D. degree in CUMT under Prof. Dr. Enjie Ding and is an intern research at the Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany in the Chair for Embedded Systems (CES) under Prof. Dr. Jorg Henkel. His research interests are in device-based and device-free localization based on wireless sensor networks and reconfigurable sensor networks.

Zhonglei Wang received his M.Sc. and Ph.D degrees in Electrical Engineering from the Technical University of Munich (TUM), Germany, in 2006 and 2010, respectively. He received two B.Eng. degrees in Biomedical Engineering and Electrical Engineering from the Zhejiang University, China, in 2004. Currently, he is a senior researcher at the Chair for Embedded Systems (CES) at the Karlsruhe Institute of Technology, leading the group System Simulation and Cyber Physical Systems. Before he joined CES, he was with the Institute for Integrated Systems, TUM, as a scientific staff member, from 2006 to 2010.

Enjie Ding received his M.S. and Ph.D. degrees both in information and communication engineering from China University of Mining and Technology. He is currently a professor at the Internet of Things Research Center of China University of Mining and Technology. His research interests include wireless sensor networks and their application in coal mines.

Yun Yang received the B.S. degree in electronic engineering department and the M.S. degree in microelectronic engineering department from Fudan University, Shanghai, P.R. China, in 1998 and 2004, respectively, and the Ph.D. (Eng.) degree in graduate school of information, production and systems from Waseda University, Kitakyushu, Japan, in 2008. From 1998 to 2000, he worked as the software engineering for Chuwa Software Company together with Fujitsu Co., Ltd. in MPEG chip design and audio compression research. He also worked as Research Associate in Information, Production and Systems Research Center (IPSRC), Waseda University, Kitakyushu, Japan in 2008. And he worked as Postdoctoral Researcher in Tohoku University, Sendai, Japan from 2009 to 2011. Then he works as JST CREST Special Researcher in Osaka University, Osaka, Japan. Now he is visiting research scientist in CNRS/CEA/UMR/INAC in Grenoble, France, and works as research cooperation with Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany. His research interests include 3D VLSI SoC design, EDA physical design, reconfigurable SoC design, magnetic memory research, analog-digital mixed-signal VLSI design, dependable VLSI system, MEMS/NEMS research, network-on chip research, image processing system, and computer pipeline architecture. He received the “Excellent Student Award of IEEE Fukuoka Section” in 2005.