Towards Cognitive Device-Free Localization in Wireless Networks

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Abstract—Device-free localization (DFL) is a promising technology which could realize localization without equipping the target with a wireless device. It realizes location estimation by monitoring the changes of the radio signal attenuation with a wireless network. One vital problem of the DFL is that its performance will drop significantly when some wireless devices nearby work on the same channel with the DFL system. Motivated by the cognitive radio technique which could realize spectrum sensing efficiently, a novel cognitive DFL (CDFL) scheme is proposed. Different from the traditional DFL system which selects one channel offline and works on this channel online, the CDFL approach could evaluate and detect good channels online and work on the best channel all the time. The experimental results demonstrate that the CDFL could achieve a mean tracking error of only 0.44m, which reduces 52% compared the traditional DFL.

Keywords—Wireless localization, wireless networks, device-free localization, cognitive

I. INTRODUCTION

Device-free localization (DFL) has become a hot area of research due to its potential value in military and commercial applications. Most traditional wireless localization technologies [1]–[5] require each target being tracked to carry a wireless device to participate in localization. However, for some special applications, such as emergency rescue, battlefield surveillance, elderly care and security, etc., it is impractical to equip the target with a wireless device. The DFL technique solves the above problem. It could realize location estimation by utilizing the wireless measurements between wireless nodes. With the rapid spread and popularity of wireless networks, wherever we are, it is unavoidable that wireless signals are in the environment around us, and these wireless signals offer fundamental measurement information for the DFL.

A target within the deployment area of a wireless network will shadow some wireless links inevitably, affect the propagation of radio frequency (RF) signal, which induces the variation of these links’ received signal strength (RSS). Meanwhile, these shadowed links would be different when the target locates at different locations. Benefit from these differences, it is possible to realize DFL with these information. The DFL technique was originally proposed by Youssef et al. [6]–[8] and Zhang et al. [9]–[11], respectively, and further explored by Wilson, Patwari, and Zhao [12]–[16]. Youssef et al. [6]–[8] proposed the concept of device-free passive localization. They discovered that the location of an intruder could be determined with the information of the changes of wireless links in the monitoring area, and realized DFL with a fingerprint matching method. Zhang et al. [9]–[11] proposed schemes to find out the shadowed links, and developed a geometric method to solve the DFL problem. Wilson and Patwari et al. [12]–[16] modeled the DFL as a radio tomography imaging (RTI) problem, and realized location estimation by reconstructing the shadowed image generated by the shadowing effect of the target. Above DFL methods achieve reasonable performance and confirm the possibility of realizing DFL with RSS measurements. However, due to the sensitive nature of RSS, it is susceptible to various environmental factors, such as the variation of temperature or humidity of the environment. To improve the robustness of the RSS based DFL, Zhao et al. [15] proposed a subspace decomposition method to reduce the impact of environmental noise. We [17], [18] proposed a robust differential RSS based DFL scheme to adapt to the time-varying environment.

Despite these advancements, one vital problem still to be solved is that the performance of the DFL system may drop significantly when some wireless devices nearby work on the same channel with the DFL system. This is the so-called co-channel or adjacent channel disturbance problem. O. Kaltiokallio et al. [19] have evaluated that a disturbance channel could severely influence the link RSS, induce the fluctuation of the link RSS, and disturb the process of signal demodulation which could cause packages losing. Hence, they adopted the packet reception rate (PRRs) as a criterion to select a good channel offline, and let the DFL system work on this channel all the time. However, the noise is randomly distributed in the frequency domain. With the turn on/off the nearby wireless device, the frequency domain noise is time-varying. Hence, the scheme of finding out good channels offline could not guarantee that the DFL system would not be disturbed by the wireless devices nearby. In addition, the PRRs drops only when the noise is greater than a threshold power level, which makes it not sensitive to disturbance.

Motivated by the cognitive radio technique which could realize spectrum sensing efficiently, a robust channel evaluation and selection strategy is introduced into the traditional DFL framework. We observed that the variation of the link RSS measurement will be severely fluctuated when some wireless devices nearby work on the same channel with the DFL system. The more severe the fluctuation of the link RSS is, the greater the variance of the link RSS will be, and the worse the localization performance can be achieved. By comparing the variance of the link RSS measurements with a predefined threshold, we could judge whether the channel is disturbed. The above detection process is concise, thus, it could realize real-time detection. The cognitive DFL (CDFL)
system could be self-adaptive to the environment and work on the best channel all the time. Hence, the co-channel or adjacent channel disturbance problem is solved. Therefore, the location estimation performance can be improved significantly.

The main contributions of the paper can be summarized as follows:

1) To address the problem of time-varying channel disturbance, we introduce the cognitive capability into the DFL system, and propose a novel CDFL system which could evaluate channel performance online and work on a good channel all the time.
2) A robust and lightweight channel selection strategy based on the RSS variance is presented to evaluate the quality of each channel.
3) We build an experimental testbed and evaluate the proposed scheme with detailed evaluations.

The rest of the paper is organized as follows. Section II presents the motivation behind the CDFL system. Section III introduces the channel selection scheme. Section IV presents the location estimation algorithm. Section V validates the proposed approach with experimental evaluations. Finally, the conclusion is drawn in section VI.

II. MOTIVATION

A DFL system is illustrated in Fig. 1 with all the wireless nodes uniformly distributed in a square perimeter. When a target moves into the deployment area of the wireless networks, it will shadow some wireless links unavoidable, and the RSS measurements of these shadowed links must be different with the non-shadowed scenario. Hence, we can judge whether a link is shadowed. If a link is shadowed, the target must intersect with or nearby to the link. Otherwise, the target must be away from the link. With sufficient link measurement information, the location of the target could be estimated accordingly. The difference between the DFL and the CDFL is that the working frequency of the CDFL system is dynamically assigned.

From Fig. 1, we know that the essence of DFL is to utilize the change of RSS measurement to realize location estimation. However, when some wireless devices nearby work on the same channel with the DFL system, the signal to noise ratio (SNR) of the RSS signal will drop significantly, and the RSS measurement will fluctuate severely, which incurs erroneous judgement of shadowed links and degradation of location estimation performance. With the popularization of wireless devices, the random frequency domain noise from the co-channel or adjacent channel will become more and more serious. The real spectrum environment of the frequency band from 2.4GHz to 2.5GHz which is generally used by DFL systems is shown in Fig. 2. We can see that the spectrum power levels of some channels are very high which indicates that they are occupied. Meanwhile, we can see that the occupied channels are time-varying. Therefore, if we use a constant channel to perform the DFL task, it will be disturbed by the high power level noise with a high probability.

III. CHANNEL SELECTION SCHEME

To solve the afore mentioned problem, it is better to find out a good channel in real time for the DFL system. Motivated...
by the fact that the more severe the fluctuation of RSS is, the greater the variance will be. Therefore, we can judge whether a channel is disturbed by comparing the variance with a predefined threshold. The channel selection strategy can be seen as a binary hypothesis problem as follows

\[ \begin{cases} H_0 : y(t) = z(t) + n_1(t), \\ H_1 : y(t) = z(t) + n_1(t) + n_2(t), \end{cases} \]

where \( y(t) \) denotes the received signal at the receiver, \( n_1(t) \) represents the background noise, \( n_2(t) \) represents the noise caused by co-channel or adjacent channel disturbance, \( z(t) \) is the ideal received signal. The statistical property of the RSS measurements can be estimated as follows

\[ \bar{y}(t) = \frac{1}{T} \sum_{i=1}^{T} y(t), \]

\[ \sigma = \sqrt{\frac{1}{T} \sum_{i=1}^{T} (y(t) - \bar{y}(t))^2}, \]

where \( T \) is the number of samples during the test time, \( \bar{y}(t) \) represents the mean value of the sequence signal \( y(t) \), \( \sigma \) denotes the variance of the sequence signal \( y(t) \). Then, the channel state \( C \) can be calculated as

\[ C = \begin{cases} 1, & \text{if } \sigma \leq \gamma, \\ 0, & \text{else}, \end{cases} \]

where \( C = 1 \) indicates that the channel is undisturbed, and \( \gamma \) is a pre-defined threshold value.

On the online stage, the DFL system could select a good channel from the non-disturbed channels, so as to eliminate the negative effect of co-channel and adjacent channel noise. For simplicity, the CDFL scheme selects the channel with minimum RSS variance as the working channel. The channel selection strategy is a concise, yet robust scheme. The method can be implemented with a series of lightweight calculations, which makes it especially suitable for real-time implementation.

IV. PARTICLE FILTER-BASED LOCALIZATION ALGORITHM

In this section, we present the method that judges the shadowed links, the model that represents the relationship between the shadowed links and target location, and the PF-based algorithm to realize location estimation.

It has been shown in Fig. 1 that the presence of a target can shadow some wireless links and cause the variation of the link RSS measurements. Hence, we can utilize the shadowing state of a link to indicate the presence of the target, and the shadowing state of a link can be estimated by monitoring the change of RSS measurements. The change of RSS measurement \( \nabla R^j_t \) can be calculated as

\[ \nabla R^j_t = R^j_t - R^j_{t-1}, \]

where \( R^j_{t-1} \) and \( R^j_t \) represent the RSS measurement of link \( j \) at time \( t-1 \) and time \( t \), respectively.

Then, the link shadowing state \( S^j_t \) can be calculated as

\[ S^j_t = \begin{cases} 1, & \text{if } \nabla R^j_t \geq \beta, \\ 0, & \text{else}, \end{cases} \]

where \( \beta \) is a pre-defined threshold, \( S^j_t = 1 \) indicates that the \( j \)th link is shadowed.

As shown in the Fig. 1, if a link is shadowed, the target must intersect with or nearby to the link. Hence, we define an ellipsoid observation model to describe the relationship of the shadowed links and target location as follows

\[ z_{ij} = \min \left\{ \frac{1}{\lambda} \sqrt{d_{ij}^2 - d_j^2}, \lambda \right\}, \quad \text{if } d_{ij} < d_j + \lambda, \]

\[ 0, \quad \text{otherwise}, \]

where \( d_{ij} \) represents the sum of distances from the location \( i \) to the two nodes of link \( j \), \( d_j \) is the length of the link \( j \), \( \lambda \) is a tunable parameter. When \( z_{ij} \) is larger, it indicates that the location \( i \) is closer to the link \( j \), and vice versa.

By utilizing equation (7) as the observation model, we adopt a particle filter [17] algorithm to estimate the location of the target. The particle set \( \{ x^i_t, w^i_t | i = 1, \ldots, N \} \) is adopted to represent the probability distribution of the target, with \( x^i_t \) and \( w^i_t \) representing the location and weight of \( i \)th particle, and \( N \) representing the total number of particles. With the particle set, the estimated target location \( \hat{x}_t \) can be calculated as

\[ \hat{x}_t = \sum_{i=1}^{N} w^i_t \times x^i_t, \]

Now, the question is how to realize particle location prediction and particle weight calculation. Suppose the particle set at time \( t-1 \) is \( \{ x^i_{t-1}, w^i_{t-1} | i = 1, \ldots, N \} \), the particle location is predicted as

\[ x^i_t = x^i_{t-1} + \tau \times v_{\text{max}}, \]

where \( \tau \subset [0, 1] \) is a random variable, and \( v_{\text{max}} \) represents the maximum possible velocity of the target.

Then, the particle weight \( w^i_t \) can be updated as

\[ w^i_t = \frac{w^i_{t-1} \times \prod_{j=1}^{J} \left( \frac{1}{(\nabla R^j_t)^2 + z_{ij}} \right)}{\sum_{i=1}^{N} \left( w^i_{t-1} \times \prod_{j=1}^{J} \left( \frac{1}{(\nabla R^j_t)^2 + z_{ij}} \right) \right)}, \]

where \( J \) represents the number of shadowed links detected in the current time instant, \( z_{ij} \) represents the observation model which can be calculated with equation (7).

With the above particle location prediction and particle weight update operations, the particle set is updated with the available new RSS measurements, so as to come up with the moving target. The procedure of the proposed CDFL scheme is summarized in Algorithm 1.

V. EXPERIMENTAL EVALUATION

A. Validation of RSS Measurement and Channel Selection Scheme

To evaluate the effect of co-channel and adjacent channel noise, we placed 2 nodes in a hallway with 4.5m apart, and...
Disturbed channels accurately. The variation of the RSS measurement is very significant. When there is some disturbance, it is hard or even impossible to judge whether a target is there. However, when there is some disturbance in channel 13, the RSS variance increases significantly, no matter a target is near to the link or not. Hence, we need to make a compromise between the PD and PFA. When the predefined RSS variance threshold is set as 0.3, the PD is more than 0.9, and the PFA is less than 0.18. The proposed channel selection scheme based on the RSS variance is ideal for finding out better channels to participate in the DFL process.

B. Performance Evaluation of CDFL

We evaluated the proposed CDFL system in an outdoor scenario which is the same as above. The photograph and layout of the deployment area are shown in the Fig. 5. We deployed a wireless networks prototype containing 17 Zigbee nodes in an 8m×8m deployment area to evaluate the performance of the proposed scheme. The nodes are equipped with the chipset CC2520, and each node could work in 16 different channels, from 2.405GHz to 2.48GHz with 5MHz apart. The nodes are placed on the tripod which is 1.25 meters high. Nodes 1 to 16 are normal nodes placed 2m apart to perform wireless scanning sequentially, and node 17 is the central node that collects all the RSS measurements. One extra node that used to generate disturbance on channel 13 is placed inside the deployment area. We compare the performance of CDFL system with the traditional DFL system. The traditional DFL system works on the disturbance channel 13. The CDFL system works on a good channel which is selected cognitively and automatically. To improve the speed and accuracy of channel selection scheme, we use 4 links, i.e., nodes 1, 5, 9 and 13, to perform the channel selection task. When more than 3 links report that one channel is undisturbed, we judge that the channel is pure. The channel selection strategy is cognitive and automatic. The default parameters are as follows: the transmitted power of the normal node is +1dBm, the disturbance power of the disturbance node is -2dBm, the predefined RSS variance $\gamma = 0.3$, the number of samples during

Algorithm 1: Cognitive DFL

```plaintext
1 while $t = 0$ do
2     Initialize the particle set $\{x_i^0, w_i^0| i = 1, \ldots, N\}$.
3 end
4 while $t \geq 1$ do
5     Acquire the change of RSS measurement $\nabla R'_t$ with equation (5).
6     Estimate link shadowing state with equation (6).
7     Particle location prediction with equation (9).
8     Particle weight update with equation (10).
9     Resample particle set adaptively.
10    Channel state estimation with equations (2) and (3).
11 if the current channel is disturbed then
12      Change to a good channel.
13 end
14 end
```

![Fig. 3: RSS measurement under different conditions.](image)

(a) w/o target and w/o disturbance. (b) w/ target and w/o disturbance. (c) w/o target and w/ disturbance. (d) w/ target and w/ disturbance.

measured the RSS measurement under the conditions w/ and w/o an extra node nearby to transmitting signal in the same channel, and w/ and w/o a target standing close to the link. The measurement results are shown in Fig. 3. It can be seen that the variation of the RSS measurement caused by the presence of a target is significant when no disturbance is nearby. However, it is hard or even impossible to judge whether a target is there when the link is disturbed. Hence, it is of vital importance to select a good channel for the DFL system. Meanwhile, from the figure we can see that when there is some disturbance, the variation of the RSS measurement is very significant. Hence, the proposed variance-based scheme could find out the disturbed channels accurately.
the test time $T = 100$, the threshold value $\beta = 1$, maximum moving speed of target $v_{\text{max}} = 1\text{m/s}$, the width of the ellipse $\lambda = 0.1\text{m}$, the number of particles $N = 50$, the initial particles distribute uniformly within the deployment area.

One visualized tracking scenario is shown in the Fig. 6, where a target moves along the rectangular trace anticlockwise. We can see that when there is some disturbance, the estimated positions of CDFL are close to the true positions, while the estimated positions of traditional DFL scheme deviate from the true position seriously. The CDF of the localization errors is shown in the Fig. 6(b), with more detailed statistical character of tracking errors shown in Table I. We can see that compared with the traditional DFL, the mean tracking error of CDFL reduces from 0.92m to 0.44m. Hence, to perform DFL task in the cluttered environment where some channels are occupied by some wireless devices, we can use the proposed channel selection scheme to evaluate channel state cognitively online, so as to avoid the disturbance channels effectively and improve the location estimation performance significantly.

VI. CONCLUSION

In this paper, we introduce a novel CDFL system. It introduces the cognitive capability into the DFL framework, so as to work on a good channel all the time. The disturbance caused by the co-channel or adjacent-channel wireless devices working nearby will be eliminated. The experiments on a prototype wireless networks indicate that the CDFL scheme could achieve a location estimation error of only 0.44m, which reduces 52% compared the traditional DFL scheme. It should be mentioned that there are still some problems to be solved, such as how to realize multi-target DFL, how to develop more efficient and fast schemes to realize channel detection. We will try to solve these problems in our future work.

ACKNOWLEDGMENT

This work was supported by National Natural Science Foundation of China under grant 61190113 and 61172058, the Fundamental Research Funds for the Central Universities.
under grant DUT13JS09, and the Specialized Research Fund for the Doctoral Program of Higher Education of China under Grant 2012004110011.

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