Calibration-Free Wireless Indoor Localization (CAFLOC)

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***Abstract*— Indoor localization is a very promising field in the era of Internet of things (IoT) and has a large number of potential applications. Due to the popularity of mobile devices in recent years, using the Received Signal Strength (RSS) of Wi-Fi signals and a fingerprint database (a.k.a radio map) for indoor localization becomes quite attractive. One obstacle is that the RSS values on the reference device (the one used to build the radio map) and the target device (the one whose location needs to be determined) are not identical, resulting in localization errors. To reduce the errors, a costly and time consuming calibration process is often used. In this paper, we propose a novel CAlibration Free LOCalization (CAFLOC) approach that utilizes relative RSS information to locate target devices and does not require any calibration. Our method relies on the linear relationship between the RSS values on the reference and target devices, which has been reported by many papers in the literature and also verified in our LAB. We first show mathematically why such a linear relationship exists. We then present CAFLOC and prove that in ideal situations, it is able to precisely identify locations without errors. To verify its performance in real-world scenarios, we run extensive localization tests on CAFLOC and the Nearest Neighbor (NN) approach. Our results consistently show that CAFLOC is much more accurate than NN.**

***Index Terms*— indoor localization; wireless networks**

I. INTRODUCTION

Accurate indoor localization has the potential to transform the way people navigate indoors in a similar way that GPS transformed the way people navigate outdoors. Many exciting applications in the era of Internet of Things (IoT) can be built upon accurate indoor localization. To name a few, turn-by-turn directions will make people never get lost again in large shopping malls; vendors may push ads and promotions to customers' mobile devices based on their locations; indoor monitoring and tracking for little children and seniors will become a breeze. Therefore, indoor localization is a crucial component of IoT infrastructures for smart cities.

Because satellite signals are attenuated severely in indoor environment, the GPS technology, which has been very successful in outdoor localization, does not work well in indoor environment. For this reason, researchers have been looking for alternatives. In [1], Huang et. al. used acoustic signals to differentiate the spatial difference between different locations; visible light is used in [2]; UWB signal is used in [3]; FM radio signal is used in [4]; and sensors are used in [5] and [6]. Among all these alternatives, Wi-Fi signals perhaps are the most ideal choice, due to its two major advantages over other options: *(i)* most mobile devices have built-in Wi-Fi modules and *(ii)* no significant changes to the infrastructure are required.

There exists many different techniques for wireless indoor localization. A review can be found in [7]. In a nutshell, these techniques map physical measurements derived from wireless signals into either geometric parameters such as relative distance and direction from the reference points, or pre-labeled landmarks directly. In terms of physical measurements, there are three commonly used quantities: power, time, and angle. Time and angle based approaches often rely on either high bandwidth or costly signal generators. As a result, power based approaches are gaining popularity in recent years.

To convert physical measurements into actual locations, mapping methods are required. Geometric mapping is one approach, and a representative way is distance-based mapping (a.k.a ranging). Because indoor environment is often complex and it is difficult to differentiate line-of-sight paths from none-line-of-sight paths, fingerprinting based mapping becomes a good alternative to geometric mapping.

In fingerprinting methods, a site survey of the Received Signal Strength (RSS) values (fingerprints) on a *reference device* at all known locations needs to be done beforehand in order to build a database, using which a pattern-matching is performed to match the RSS values of a *target device* at an unknown location to that of an entry in the database. In Wi-Fi networks, the RSS values are readily available in the 802.11 protocols, making fingerprinting approaches very easy to implement on off-the-shelf devices. However, one significant drawback of fingerprinting based approaches is the added overhead of site survey. To avoid often tedious and time consuming site survey, crowd-sourcing based methods emerged in recent years to automatically populate the fingerprint database using mobile devices (smart phones, tablets, etc.)

To locate a device using the fingerprinting database, both deterministic and probabilistic methods can be utilized. High accuracy has been reported when the same wireless device is used for both site survey and localization. However, if one device is used for site survey and another is used for localization, i.e., the reference and target devices are different, then the aforementioned solutions may be inaccurate. The reason is that different wireless devices use different wireless modules and different antennas with different gains. As a result, the RSS values returned by different devices will vary. In addition, the 802.11 protocols do not precisely define how the RSS values should be reported. Thus, different vendors have their own interpretation of the protocol, causing

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The author's work is supported in part by Middle Tennessee State University under FRCAC Grant 16-16-215.

differences between reference and target RSS values. A common solution to this problem is calibration, in which the RSS values of the target device are converted to those of the reference device. Calibration can be done manually, quasi-automatically, or automatically. Regardless of how calibration is done, it adds computational overhead to the localization system and also inevitably incurs calibration errors. When crowd-sourcing is used to obtain the fingerprinting database, more sophisticated calibration is often required. Yet another problem with fingerprinting based approaches is that the RSS values of the same device at the same location change over time. This temporal variation adds another layer of complexity to the algorithm design, as the fingerprinting database also needs to be calibrated periodically.

In this paper, we propose a novel RSS fingerprinting based Calibration Free Localization (CAFLOC) method. Compared with the existing ones in the literature, our approach is truly calibration free, i.e., no calibration is ever needed for any target device.

The organization of the paper is as follows: in Section II, we summarize related work; in Section III, we introduce our system model and provide justifications; in Section IV, we present CAFLOC and show mathematically why it is truly calibration free; in Section V, we show experimental results obtained from real-world scenarios; finally, we conclude and discuss future work in Section VI.

II. Related Work

To the best of our knowledge, the first work that utilizes RF-based fingerprint database (a.k.a radio map) for indoor localization is RADAR [8]. In this pioneer work, Bahl et al. uses a deterministic method known as the Nearest Neighbor (NN) to infer the target device's location. In their approach, the nearest neighbor is determined by finding the smallest Euclidean distance in the signal space between the signal strength of the target device and the signal strength of the reference device in the fingerprint database. Although the authors use average RSS values of various combinations of orientation and position, RADAR was only able to achieve accuracy up to meter level, due to the variations of the RSS values. To reduce localization error, RADAR also proposes the k nearest neighbors approach, in which k, instead of 1, nearest neighbors in the signal space are used to calculate the localization of the target device. Note that the fingerprint database can be built using the data from either the access points (APs) [8] or the clients [9]. The latter approach is more scalable when the number of target devices is large.

In contrast to deterministic methods where only the average RSS values are used in localization, Bayesian probabilistic fingerprint approaches utilize more statistical information such as histogram to identify the location. In particular, Bayes' theorem is used to maximize the probability of successful localization. It has also been shown in [10] that Bayesian probabilistic approaches are more accurate than deterministic ones. However, in order to apply Bayes' theorem, some assumptions about the prior probabilities are required. In the context of indoor wireless localization, the prior probabilities are the probabilities of the target device appearing at each location. Such prior probabilities are often hard to be estimated accurately; in the literature, they are often assumed to be equal to each other. A representative work along this line is [11], in which Youssef et al. derived that the location that has the maximum probability of success is essentially the one with maximum probability of generating the measured RSS values.

Regardless of using deterministic NN or Bayesian probabilistic approaches, calibration has been an essential part in all practical and high accuracy wireless indoor localization systems [12] [13]. The goal of calibration is to eliminate the gap between the RSS values returned by the reference device and the target device. The drawback of calibration is that it is often time consuming, tedious, and impractical for real-world applications. See a recent work in [14], in which Laoudias et al. develop an automatic calibration algorithm that finds the relationship between the reference and target RSS values using the signal strength histograms and the inverse cdf functions of the two devices.

There also exists calibration-free localization approaches. The RSS difference between any AP pair is used to build relative fingerprint databases [15] [16]. The problem with this approach is that the size of the fingerprint database grows dramatically when the number of APs is large. Mahtab et al. [17] build the fingerprint database using the so called Signal Strength Difference: the relative RSS values between a reference AP and other APs. Although their method has less computational overhead and fewer entries in the database, it is not always easy to select the reference AP, since the locations may be covered by different sets of APs. Rank based calibration-free algorithms are proposed in [18] and [19], in which the ranking information of the RSS values is used for localization purposes. The problem with rank based approaches is that the ranking information alone is often insufficient for accurate localization. In [20], Yang et al. propose FreeLoc, a calibration-free crowd-sourced indoor localization algorithm. Instead of using the average value of all observed RSS values, their approach uses the average value of the most commonly seen RSS values to build the fingerprint database. This is based on the observation that most-recorded RSS values in the case of the short-duration measurements is very close to that in the long-duration measurement case. In addition, the authors also use relative signal levels in the fingerprint database. In particular, a location's entry contains key-value combos where the key is the BSSID of an AP and the values are other APs whose RSS values are within δ dB.

III. System Model

We first introduce some notations:

N : the total number of locations in the building.

L_i : the *i-th* location in the building, $i \in \{1, \ldots, N\}$

D_r : the reference device that is used to build the fingerprinting database

D_t : the target device whose location needs to be identified.

M : the total number of access points (APs) in the system.

M_i : the total number of access points (APs) detected by both D_t and D_r at location L_i. We introduce M_i because depending on the sensitivity of the reference and target devices, not all APs can be detected. The M_i APs are essentially the union of the sets of APs detected by the reference and target devices, respectively.

AP_i^j : the *j-th* AP in an ordered list of M_i APs, $j \in \{1, \ldots, M_i\}$. For example, the APs can be ordered based on their MAC addresses.

$d_{i,j}$: the distance between location L_i and AP_i^j.

$\overline{R}_{i,j}^r$: the average RSS value of AP_i^j received by the reference device at location L_i.

$\overline{R}_{i,j}^t$: the average RSS value of AP_i^j received by the target device at location L_i.

Note that the bar in $\overline{R}_{i,j}^r$ and $\overline{R}_{i,j}^t$ indicates that they are the average RSS values. Also note that although the RSS values received by a target device does not depend on L_i, M_i and AP_i^j do. Therefore, we have subscript i in $\overline{R}_{ij}^t$ to indicate the dependency.

We now derive the relationship between $\overline{R}_{i,j}^r$ and $\overline{R}_{i,j}^t$. To model the signal path loss between a particular transmitter-receiver pair in indoor environment, the log-normal shadowing model [21] is often used:

$$PL(d)_{[dB]} = \overline{PL}(d_0) + 10n\log(\frac{d}{d_0}) + X_\sigma$$

where d is the distance between the transmitter and the receiver, $\overline{PL}(d_0)$ is the average pass loss at reference distance d_0, n is the pass loss exponent, and X_σ is a zero-mean Gaussian distributed random variable (in dB) with standard deviation σ (also in dB). If we only use average power, the last term in the above equation can be eliminated and we get:

$$\overline{PL}(d)_{[dB]} = \overline{PL}(d_0) + 10n\log(\frac{d}{d_0})$$

The average RSS value is the difference between the transmission power and the average pass loss:

$$\begin{aligned}\overline{R}(d)_{[dBm]} &= P_{Tx[dBm]} - \overline{PL}(d)_{[dB]} \quad (1)\\ &= P_{Tx[dBm]} - \overline{PL}(d_0)_{[dB]} - 10n\log(\frac{d}{d_0})_{[dB]}\\ &= \overline{R}(d_0)_{[dBm]} - 10n\log(\frac{d}{d_0})_{[dB]}\end{aligned}$$

Note that $\overline{R}(d_0)_{[dBm]}$ above is the received signal strength at reference distance d_0 and can be represented using the Friis free space propagation model [21]:

$$\overline{R}(d_0)_{[dBm]} = 10\log(\frac{P_{AP}G_{AP}G_D\lambda^2}{16\pi^2 d_0^2 L})_{[dBm]} \quad (2)$$

where P_{AP} is the transmission power of an AP, G_{AP} is the gain of the AP's antenna, G_D is the gain of the receiving device's antenna, λ is the wavelength of the wireless signal, and L ($L \geq 1$) is the system loss factor related to hardware.

Combining (1) and (2), we have

$$\overline{R}(d)_{[dBm]} = 10\log(\frac{P_{AP}G_{AP}G_D\lambda^2}{16\pi^2 d_0^2 L}) - 10n\log(\frac{d}{d_0})_{[dB]}$$

Note that, n, the pass loss exponent, is determined by the indoor environment [21] and can be considered as a constant for each transceiver pair. If the hardware loss caused by different APs are similar or the same (this assumption is especially valid when the same model of AP is used for localization purposes), the miscellaneous losses L only depends on the target and reference devices. We now obtain $\overline{R}_{i,j}^t$ and $\overline{R}_{i,j}^r$ using the equations above:

$$\overline{R}_{i,j}^t = 10\log(\frac{P_{AP_i^j}G_{AP_i^j}G_{D_t}\lambda^2}{16\pi^2 d_0^2 L_t}) - 10n\log(\frac{d_{i,j}}{d_0})_{[dB]}$$

$$\overline{R}_{i,j}^r = 10\log(\frac{P_{AP_i^j}G_{AP_i^j}G_{D_r}\lambda^2}{16\pi^2 d_0^2 L_r}) - 10n\log(\frac{d_{i,j}}{d_0})_{[dB]}$$

From the two equations above, we can derive:

$$\overline{R}_{i,j}^t = \overline{R}_{i,j}^r + 10\log(\frac{G_{D_t}L_r}{G_{D_r}L_t}) \quad (3)$$

i.e.,

$$\overline{R}_{i,j}^t = \alpha\overline{R}_{i,j}^r + \beta, \quad (4)$$
$$i \in \{1, \ldots, N\} \text{ and } j \in \{1, \ldots, M_i\}$$

where $\alpha = 1$ and $\beta = 10\log(\frac{G_{D_t}L_r}{G_{D_r}L_t})$. Although (3) shows a simple and nice linear relationship between $\overline{R}_{i,j}^t$ and $\overline{R}_{i,j}^r$, it is important to note the following: *(i)* since $R_{i,j}^t$ and $R_{i,j}^r$ are random variables, the values of $\overline{R}_{i,j}^t$ and $\overline{R}_{i,j}^r$ can only be estimated, *(ii)* it only holds when the reference and target devices are at the exact the same locations, and *(iii)* the above results assume isotropic antennas. In Fig. 1, we show the experimental results obtained in room 170B of the VET building at MTSU. In this experiment, we first measure the RSS values of nearby APs using a laptop computer's internal Wi-Fi module (Intel Dual Band Wireless-AC 7265). We then measure the RSS values of the APs using a USB Wi-Fi dongle (Linksys AE3000). The horizon and vertical axises of Fig. 1 are the RSS values of the APs obtained by the internal and external Wi-Fi modules, respectively. The RSS values are collected via a free program called WiFiInfoView [22], and each value is the average of 100 samples. As shown in Fig. 1, although the data set does not form a strict linear curve (due to the reasons explained above), linear regression is valid to model the relationship between the two RSS values. Specifically, $\alpha = 0.9032$ and $\beta = -8.9962$; this is consistent with other works in the literature [23] [14] where the linear regression coefficients are slightly different.

IV. Calibration Free Localization (CAFLOC)

First of all, we need to point out that the NN approach without calibration does not work well in some scenarios. This can be seen from a simple example. Suppose that there are two locations ($L1$ and $L2$) and three APs. Let us assume that we can obtain the true average of the RSS values of the reference and target devices at the same location, and $\alpha = 1$ and $\beta = -8$. We further assume the fingerprints generated by the reference device at $L1$ and $L2$ are {-30, -40, -50} dBm and {-40, -50, -60} dBm, respectively. Then, the RSS

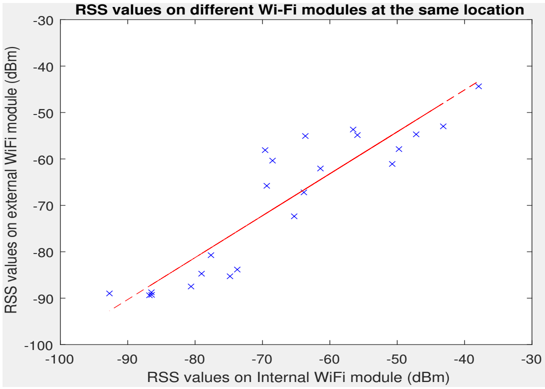

Fig. 1: RSS values of wireless access points obtained by two different Wi-Fi modules at roughly the same location

values of the target device at $L1$ and $L2$ are {-38, -48, -58} dBm and {-48, -58, -68} dBm, respectively. In this case, the location of the target device will always be $L2$ if the NN approach is used.

As we mentioned in Section II, one way of solving this problem is to do calibration. While many existing calibration efforts try to estimate α and β using linear regression, our approach is to *eliminate* α and β in the localization process. What it implies is that our approach will work well regardless of the actual values of α and β. The intuition behind our method is the following: in RSS fingerprinting based approaches, locations are identified by the *variations* of RSS values; therefore, in order to locate a target device, we only need to use the relative (normalized) variation information of the RSS values, not necessarily the absolute RSS values.

Our approach is motivated by the linear relationship shown in (3). Because it is a true CAlibration Free LOCalization method, we call it CAFLOC. We now formally introduce it.

Suppose that the fingerprinting database has been established and the RSS values at the target device have been collected. In order to differentiate the real-world experimental results from the true average values, we use $\widetilde{R}^r_{i,j}$ and $\widetilde{R}^t_{i,j}$ to denote the signal levels collected by the reference and target devices, respectively. Let

$$p_{i\_\min} = \operatorname*{arg\,min}_{j\in\{1,\ldots,M_i\}} \widetilde{R}^r_{i,j} \text{ and } p_{i\_\max} = \operatorname*{arg\,max}_{j\in\{1,\ldots,M_i\}} \widetilde{R}^r_{i,j}$$

$$q_{i\_\min} = \operatorname*{arg\,min}_{j\in\{1,\ldots,M_i\}} \widetilde{R}^t_{i,j} \text{ and } q_{i\_\max} = \operatorname*{arg\,max}_{j\in\{1,\ldots,M_i\}} \widetilde{R}^t_{i,j}$$

The relative or normalized signal levels of RSS values at the reference and the target devices, respectively, are defined as follows:

$$n^r_{ij} = \frac{\widetilde{R}^r_{i,j} - \hat{R}^r_i}{\widetilde{R}^r_{i,p_{i\_\max}} - \widetilde{R}^r_{i,p_{i\_\min}}} \text{ and } n^t_{ij} = \frac{\widetilde{R}^t_{i,j} - \hat{R}^t_i}{\widetilde{R}^t_{i,q_{i\_\max}} - \widetilde{R}^t_{i,q_{i\_\min}}} \quad (5)$$

where $\hat{R}^r_i$ and and $\hat{R}^t_i$ are the convex combinations of $\widetilde{R}^r_{i,j}$ and $\widetilde{R}^t_{i,j}$, respectively, i.e.,

$$\hat{R}^r_i = \sum_{j=1}^{M_i} \lambda_{i,j}\widetilde{R}^r_{i,j}, \ \hat{R}^t_i = \sum_{j=1}^{M_i} \lambda_{i,j}\widetilde{R}^t_{i,j},$$

$$\lambda_{i,j} \geq 0, \ \sum_{j=1}^{M_i} \lambda_{i,j} = 1.$$

When $\lambda_{i,j}$, $j \in \{1,\ldots,M_i\}$ are chosen, n^r_{ij} and n^t_{ij} can be easily calculated using the RSS values collected by the reference and target devices, respectively. Since the denominators in (5) are greater than the numerators, both n^r_{ij} and n^t_{ij} are less than 1. The target's location is determined by:

$$\operatorname*{arg\,min}_{i\in\{1,\ldots,N\}} J_i \quad (6)$$

where

$$J_i = \begin{cases} \frac{1}{M_i}\sum_{j=1}^{M_i}(n^r_{ij} - n^t_{ij})^2, & M_i > 1 \\ 1, & M_i \leq 1 \end{cases} \quad (7)$$

In (6) and (7), we essentially find the location that yields the minimum mean squared error between the normalized reference and target RSS values. Recall that M_i is the number of APs detected by both reference and target devices. If it is not greater than 1 and there are sufficient number of APs covering the indoor space, then it is very likely that the target device is not at location L_i. Therefore, we consider it as a trivial case and assign number 1 (larger than any possible mean squared error) to J_i.

Next, we show why CAFLOC should return the correct location.

Lemma 4.1: Suppose that $M_i > 1$, $\widetilde{R}^r_{i,j} = \overline{R}^r_{i,j}$, and $\widetilde{R}^t_{i,j} = \overline{R}^t_{i,j}$. If L_{i^*} is the optimal location returned by CAFLOC, then $J_{i^*} = 0$.

Proof: Since $\widetilde{R}^r_{i,j} = \overline{R}^r_{i,j}$ and $\widetilde{R}^t_{i,j} = \overline{R}^t_{i,j}$, we can rewrite $n^t_{i^*j}$ and $n^r_{i^*j}$ as follows:

$$n^t_{i^*j} = \frac{\overline{R}^t_{i^*,j} - \sum_{j=1}^{M_{i^*}} \lambda_{i^*,j}\overline{R}^t_{i^*,j}}{\overline{R}^t_{i^*,q_{i^*\_\max}} - \overline{R}^t_{i^*,q_{i^*\_\min}}}$$

and

$$n^r_{i^*j} = \frac{\overline{R}^r_{i^*,j} - \sum_{j=1}^{M_{i^*}} \lambda_{i^*,j}\overline{R}^r_{i^*,j}}{\overline{R}^r_{i^*,q_{i^*\_\max}} - \overline{R}^r_{i^*,q_{i^*\_\min}}}$$

Using (3), we obtain:

$$\begin{aligned} n^t_{i^*j} &= \frac{\alpha\overline{R}^r_{i^*,j} + \beta - \alpha\sum_{j=1}^{M_{i^*}} \lambda_{i^*,j}\overline{R}^r_{i^*,j} - \beta\sum_{j=1}^{M_{i^*}} \lambda_{i^*,j}}{\alpha\overline{R}^r_{i^*,q_{i\_\max}} + \beta - \alpha\overline{R}^r_{i^*,q_{i\_\min}} - \beta} \\ &= \frac{\alpha\overline{R}^r_{i^*,j} + \beta - \alpha\hat{R}^r_{i^*,p_{i^*\_\min}} - \beta}{\overline{R}^r_{i^*,p_{i^*\_\max}} - \overline{R}^r_{i^*,p_{i^*\_\min}}} \\ &= \frac{\overline{R}^r_{i^*,j} - \hat{R}^r_{i^*,p_{i^*\_\min}}}{\overline{R}^r_{i^*,p_{i^*\_\max}} - \overline{R}^r_{i^*,p_{i^*\_\min}}} = n^r_{i^*j} \end{aligned}$$

Therefore,

$$J_{i^*} = \frac{1}{M_i}\sum_{j=1}^{M_i}(n^r_{i^*j} - n^t_{i^*j})^2 = 0 \ \blacksquare$$

The above lemma means that in ideal scenarios, (7) achieves the minimum value 0 for a specific i when L_i is the actual location of the target device. Looking at (7), (6), and (5), the localization process does not rely on the actual values of α and β. Therefore, it is calibration free.

The performance of CAFLOC depends on the selection of $\lambda_{i,j}$ for the convex combination shown in (5). We next show two different methods:

$$CAFLOC1 \;:\; \lambda_{i,j} = \begin{cases} 1, & j = p_{i\_\min} \text{ or } q_{i\_\min} \\ 0, & o.w. \end{cases}$$

$$CAFLOC2 \;:\; \lambda_{i,j} = \frac{1}{M_i}$$

Using CAFLOC1 and CAFLOC2, $\hat{R}_i^r$ and $\hat{R}_i^t$ in (5) become:

$$\hat{R}_i^r = \widetilde{R}_{i,p_{i\_\min}}^r, \; \hat{R}_i^t = \widetilde{R}_{i,q_{i\_\min}}^t,$$

and

$$\hat{R}_i^r = \frac{1}{M_i}\sum_{j=1}^{M_i}\widetilde{R}_{i,j}^r, \; \hat{R}_i^t = \frac{1}{M_i}\sum_{j=1}^{M_i}\widetilde{R}_{i,j}^t,$$

respectively. Essentially, the former is the smallest RSS value, and the latter is the average RSS value.

We need to emphasize again that due to the reasons explained right after (3), it is important to measure the performance of CAFLOC using real-world experiments.

V. Experimental Results

In this section, we present the experimental results in which we compare the CAFLOC algorithm with the NN approach without calibration. In our experiment, we choose four locations in VET170B at MTSU. These locations are marked in Fig. 2. VET170B is roughly a $5m$ by $13.5m$ rectangular LAB space. The distance between $L1$ and $L2$ is $2.7m$, and the distance between $L1$ and $L3$ is $4.7m$. $L3$ is about $5m$ away from $L4$. Three wireless APs are placed on each side of VET170B. All six APs are Linksys E2500 simultaneous dual-band routers. In total, we have twelve wireless signals, six in the $2.4GHz$ band and six in the $5GHz$ band.

Before we run the localization experiments, we first use the laptop's internal Wi-Fi module (Intel Dual Band Wireless-AC 7265) to build the fingerprint database. The fingerprint of each location is obtained by finding the average of 100 RSS samples. During the experiments, we run localization test 100 times at each location; in each test, the RSS data are the average of 20 RSS samples obtained by the external USB Wi-Fi dongle Linksys AE3000. The percentages of successful tests in the above experiments are shown in Table I. The NN algorithm without any calibration works well in general at $L3$ and $L4$. However, its performance is very bad at $L1$ and $L2$ (highlighted in bold face). Both CAFLOC1 and CAFLOC2 outperform NN significantly at these two locations. The same tests are repeated using a different target device: TP-Link Archer T2U dual-band USB dongle, and the results are shown in Table II. NN does a good job at $L1$, $L3$, and $L4$. Its 100% success rate is even better than CAFLOC1 at $L1$. However, NN achieves zero percent success rate at $L2$. The CAFLOC methods, on the contrary, are able to identify $L2$ with over 90% success rate. Note that CAFLOC2 achieves 100% success rate at all four locations. Looking at both tables, CAFLOC1 and CAFLOC2 have over 90% success rate on average, while NN only has around 70% success rate.

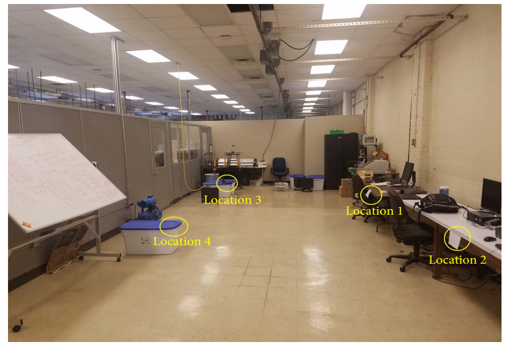

Fig. 2: VET170B: Location of the Experiment

	L1	L2	L3	L4	Average
Nearest Neighbor	**23%**	**48%**	100%	88%	64.75%
CAFLOC1	83%	91%	96%	96%	91.5%
CAFLOC2	93%	91%	100%	100%	96%

TABLE I: Percentages of localization success at each location in VET170B. Six Linksys APs are used. Target Wi-fi module: Linksys AE3000 N900 dual-band USB dongle.

Our experimental results clearly indicate that CAFLOC is better than NN without calibration. Another interesting observation is that CAFLOC2 seems to be better than CAFLOC1. It happens because when CAFLOC1 is used, $n_{ip_{i\_\max}}^r = n_{iq_{i\_\max}}^r = 1$ and $n_{ip_{i\_\min}}^r = n_{iq_{i\_\min}}^r = 0$, which means both $n_{ip_{i\_\max}}^r - n_{iq_{i\_\max}}^r$ and $n_{ip_{i\_\min}}^r - n_{iq_{i\_\min}}^r$ are 0. As a result, only $N_i - 2$ APs' RSS values are involved in localization. CAFLOC2 does not have this problem and uses all N_i APs' data. Therefore, it is not surprising that CAFLOC2 outperforms CAFLOC1.

VI. Conclusions and Future Work

In this paper, we propose CAFLOC, a calibration-free localization algorithm using RSS values and fingerprint databases. To introduce CAFLOC, we first show mathematically that there exists a linear relationship between the mean RSS values of the same AP received by two different wireless modules. The linear relationship is verified by finding the linear fitting of the average RSS values obtained in real-world experiments. The key idea of CAFLOC is to use

	L1	L2	L3	L4	Average
Nearest Neighbor	100%	**0%**	100%	100%	75%
CAFLOC1	73%	93%	100%	100%	91.5%
CAFLOC2	100%	100%	100%	100%	100%

TABLE II: Percentages of localization success at each location in VET170B. Six Linksys APs are used. Target Wi-fi module: TP-Link Archer T2U dual-band USB dongle.

the relative RSS ratios, instead of the absolute values, to calculate the distance between the RSS values received by the target device and the ones in the fingerprint database. We are able to show that under some technical consumptions, CAFLOC will return the correct location. To verify the true performance of CAFLOC, we run experiments in practical indoor environments; our results indicate that CAFLOC outperforms regular NN approach significantly.

Our future work includes using crowdsourcing and probablistic methods to futher improve the accuracy of CAFLOC.

ACKNOWLEDGEMENT

The author would like to thank Joseph Beck, undergraduate student in mechatronics engineering at MTSU, for his contribution to the initial experimental data. The author is thankful for MTSU's undergraduate research center for supporting Joseph Beck's work. The author also would like to thank MTSU's Faculty Research and Creative Activity Committee (FRCAC) for their support.

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