Single-Anchor Indoor Localization Using Multi-Frequency RSSI Fingerprinting

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***Abstract*—Indoor localization based on wireless communication networks has attracted a lot of attention in research. It can deliver better accuracy than a traditional Global Navigation Satellite System (GNSS) and operate in environments where satellite signals can not be received. Although more accurate methods have been published, fingerprinting based on Received Signal Strength (RSS) remains interesting. Such a system can be deployed on top of most existing networks without imposing additional requirements or restrictions to the communication. However, existing solutions usually require a larger number of base stations with known locations (anchors) within a mobile node's reception range. This is required to prevent ambiguous fingerprints and deliver accurate results. However, it also increases the network's energy consumption and operating cost. In this paper, we present a new approach that uses multi-frequency fingerprints to eliminate this requirement and operates with only a single anchor node while achieving accuracy that is comparable to existing solutions. In order to efficiently collect RSSI fingerprints across multiple frequencies, we introduce a measurement methodology using Software Defined Radio (SDR).**

***Index Terms*—Indoor Localization, Multi-Frequency, Location Fingerprinting, Software Defined Radio**

I. Introduction

Indoor localization systems based on wireless communication signals are a common research topic because they can often deliver better accuracy compared to a traditional Global Navigation Satellite System (GNSS). Additionally, these systems may be used in situations where other localization is not available such as areas where satellite signals can not be received. Localization that uses a device's Received Signal Strength Indication (RSSI) to determine its position is especially interesting because such a system can easily be deployed on top of an existing wireless network primarily intended for communication. However, most such systems discussed in existing literature either require a larger number of base stations with a known location (anchors) to be within a node's reception range for accurate operation or depend on specialized hardware that is not present in most Commercial Off-the-Shelf (COTS) devices. Because having a large number of base stations is not required in common communication-oriented networks, it creates additional deployment and maintenance effort and increases a deployment's energy consumption. Additionally, measuring the RSSI in parallel to multiple base stations may not easily be possible with all wireless standards. In some cases, this may require an explicit scan of the available base stations during which the device can not perform regular communication. This limits the device's usability and could also result in increased energy consumption which can be challenging for battery-operated devices. In contrast, a solution that does not require additional base stations can be deployed without any changes to the existing hardware and would allow localization without increasing the network's energy consumption.

In this paper, we make the following contributions:

- We propose and evaluate an indoor localization approach that uses multi-frequency RSSI measurements to operate with only a single base station on unmodified COTS hardware.
- We adapt established localization algorithms for a multi-frequency use case.
- We implement a measurement platform using Software Defined Radio (SDR) to efficiently measure across a large number of frequencies within a short amount of time.

We achieve this by leveraging the complex multipath signal propagation that is often encountered in indoor environments and the fact that most effects contributing to these signal propagation patterns are frequency-dependent.

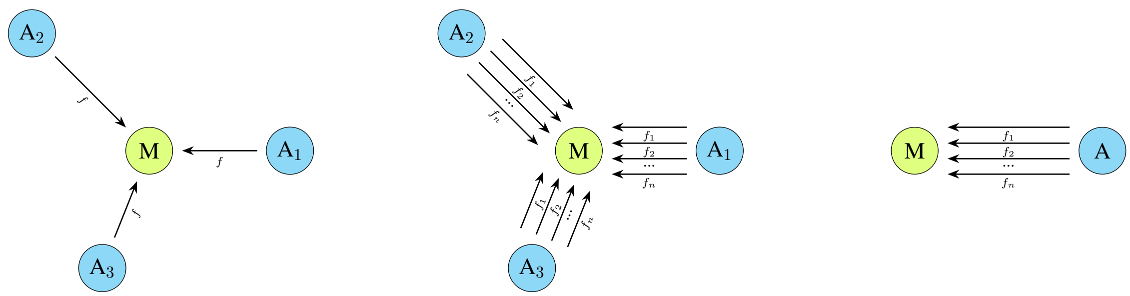
We begin this paper in Section II with a discussion of existing methods for indoor localization and previous work related to RSSI-based systems on which we base our research. Then, we present our measurement methodology for collecting a database of RSSI fingerprints and localization algorithms in Section III and IV. In Section V, we present and discuss an evaluation of our localization system's performance and compare it to results from related publications. Additionally, we discuss potential optimization of our methodology based on these results. Following that, we implement and demonstrate our system on COTS hardware using Bluetooth Low Energy (BLE) in Section VI. Finally, we conclude the paper and discuss future work in Section VII and Section VIII.

II. Related work

Using communication signals to localize nodes in a wireless network has been studied extensively in literature. Table I provides an overview of different types of localization methods for single- and multi-anchor scenarios and briefly describes their method of operation as well as the hardware requirements for implementing each method. This also highlights how our approach implements a localization system with previously unachievable properties as it does not require specific or uncommon hardware capabilities on mobile nodes and base

Single/multi-anchor	Method of operation	Publications	Additional hardware requirements
Multi-anchor	RSSI fingerprinting	[1], [7], [8], [9], [12] [15], [17], [27], [29]	*None*
	RSSI-based ranging	[2], [3], [4], [19], [35]	*None*
	ToF-based ranging	[14], [22]	Precise measurement of signal timing
	Multi-frequency phase difference-based ranging	[20], [28]	Measurement of phase difference
	AoA + RSSI-based ranging	[18]	Rotating directional antenna
Single-anchor	CSI	[30], [31], [32], [33]	IEEE 802.11 hardware with CSI support
	Multi-direction RSSI fingerprinting	[10], [11], [24]	Directional antenna array/ Steerable directional antenna
	Multi-frequency RSSI fingerprinting	*Our approach*	*None*
	AoA/DoA	[10], [21], [34]	Antenna array

TABLE I: Overview of localization methods discussed in related work and hardware requirements for implementing each method



(a) Multi-anchor, single-frequency (b) Multi-anchor, multi-frequency (c) Single-anchor, multi-frequency

Fig. 1: Architecture of RSSI-based localization systems using a mobile node M and different configurations of fixed anchor nodes A_i

stations other than measuring the RSSI across multiple frequencies while also only requiring a single anchor. Fig. 1 illustrates these different configurations.

Many existing approaches use the measured RSSI of a wireless connection to one or multiple anchors in order to determine the location of the mobile node. This can be implemented using *fingerprinting*, where the RSSI measurement is compared to a database of reference values with known positions and the value with the highest similarity is used as the localization result [7], [8], [12], [15], [17], [27], [29]. In addition to simple comparison of fingerprints, approaches based on deep learning have also been shown to produce high-accuracy localization results from fingerprint data [1], [9]. Because RSSI fingerprints with only a single data point are highly ambiguous and can usually match many different locations, these systems require each fingerprint to contain multiple measurements in order to deliver usable results. This is often implemented by measuring the RSSI of connections to multiple anchors but it has also been demonstrated by using directional antennas to measure the RSSI in different directions at each location [10], [11], [24]. Using directional antennas does however limit the usability of such a system as it introduces a requirement for specialized hardware.

An alternative possibility for RSSI-based localization is *ranging*, where nodes use the measured signal strength to calculate their distance to multiple anchors based on a wireless propagation model and determine their location using multilateration [2], [3], [4], [19], [35]. Instead of using RSSI, ranging can also be implemented by measuring the signal's Time of Flight (ToF) [14], [22] or phase differences between signals on different frequencies [20], [28]. However, RSSI may be a preferred choice for general purpose localization systems because typical COTS hardware may not be equipped to measure ToF and phase angles with sufficient precision, if at all.

Additionally, localization based on WiFi Channel State Information (CSI), which includes information about the amplitude and phase angle of individual Orthogonal Frequency Division Multiplexing (OFDM) subcarriers in IEEE 802.11 connections, has also gained popularity. Many publications have demonstrated high localization accuracy based on CSI data, even when only a single anchor/access point is used [30], [31], [32], [33]. However, in addition to not being possible when using most wireless standards other than WiFi, this data may not always be available as measurement and collection of CSI is only supported by a limited selection of WiFi chipsets [16].

Finally, several publications have demonstrated systems that enable localization based on a signal's Angle/Direction of Arrival (AoA/DoA) which require specialized antenna setups such as a rotating directional antenna [18] or an antenna array [10], [21], [34]. Furthermore, [26], [34] and [29] demonstrate that data from on-device sensors such an accelerometer or a compass can be combined with radio-based localization to further improve accuracy if the device being located is equipped with such sensors.

In this paper, we implement RSSI-based fingerprinting using a signal across different frequencies to obtain multiple data points for each fingerprint. We choose this because the ability to measure the signal's RSSI is a commonly found feature on COTS hardware, allowing such a system to be deployed on many different platforms while other methods often limit hardware compatibility through additional requirements.

A large downside of fingerprinting-based approaches is the required fingerprint collection. High-accuracy localization requires a fingerprint database containing a large number of reference points, which can take a large amount of time and effort to collect. To solve this problem, several publications demonstrate algorithms to extrapolate virtual fingerprints from a small number of real measurements using wireless propagation models to greatly reduce the amount of work required [13], [17], [36]. Common approaches include using the *One-slope* and *Multi-wall* models introduced in [6]. The One-slope model only considers the path loss caused by signal propagation in free space using empirical parameters from reference measurements to influence the model's behavior. On the other hand, the Multi-wall model also includes the additional attenuation caused by walls within the signal's path through a parameter that has to be measured for each type of wall in the environment. In this paper, we use the methodology shown in [17] which is based on the One-slope model. While this increases the required effort compared to approaches that use the Multi-wall model because measurements are required to be performed in each room, it reduces the potential error. This error could result from inaccurately measured attenuation caused by a wall or incorrect assumptions about a wall's structure. For example, a wall's attenuation could be affected by varying thickness, materials or internal pipes or conduits which are easy to overlook while conducting a measurement.

The benefit of measuring on multiple frequencies has previously been shown in various existing publications. In [25], the authors analyze multi-frequency fingerprinting and note an overall increase in the uniqueness of fingerprints, which can improve the accuracy of localization systems. [7], [8], [19], [23] and [35] all evaluate multi-frequency measurements for localization using off-the-shelf hardware and protocols such as BLE [8], [19], [23] or IEEE 802.15.4/Zigbee [7], [35] for both ranging- and fingerprinting-based systems using multiple anchors. They find an improvement in localization accuracy when using data collected across multiple frequencies. [12] and [27] use different wireless standards that operate within different frequency bands to achieve a similar result.

III. Fingerprint collection

As mentioned in Section II, localization systems using RSSI fingerprinting require collecting a database of reference fingerprints for each environment in which the system is intended to be used. If the time and effort required for this phase are too large, the system becomes impractical for real-world use. Measuring across multiple frequencies can worsen this problem, as several common wireless technologies such as IEEE 802.11 or IEEE 802.15.4 can only operate on a single channel at a time, requiring separate independent measurements for each frequency at every reference location. To solve this issue, we develop a measurement methodology using SDR for this initial fingerprint collection. Using SDR allows sending and receiving multiple signals at different frequencies simultaneously, limited only by the bandwidth of the SDR hardware and the processing capability of the computer used. This greatly reduces the number of individual measurements required at each location. Furthermore, SDR makes it possible to transmit a signal designed specifically for this measurement, which maximizes the amount of data obtained over a period of time compared to existing protocols which may for example be limited by a fixed packet structure.

In this section, we first present our SDR-based measurement methodology, followed by a brief evaluation to determine the ideal duration for each measurement. Finally, we describe the algorithm we use for predicting RSSI values in order to further reduce the number of required measurements, which we base on a previous publication with adjustments to adapt the algorithm for multi-frequency measurements. The complete measurement process described in this section is laid out in Fig. 2.

A. Measurement methodology

We use an *Ettus Research URSP N210* SDR as a stationary transmitter in combination with a *USRP B205mini* connected to a laptop as a mobile receiver with two identical non-directional antennas with a gain of 7 dBi at 2.4 GHz attached to both SDRs. This setup allows for measuring across all unlicensed frequency bands that are commonly used by off-the-shelf hardware. During our measurements, we concentrate on the 2.4 GHz (2.4-2.48 GHz) and 5 GHz (5.725-5.875 GHz) Short Range Device (SRD) bands with a distance of 1 MHz between individual measurements using the highest transmission power that is permitted by local regulations. Using this configuration results in a total of 230 individual RSSI values at different frequencies per measurement point. The position of the mobile receiver during each measurement is recorded by hand. Because the SDR's bandwidth is not sufficient to measure across an entire frequency band in one step, the center frequency of both SDRs is switched in regular time intervals to move through both bands in steps of 10 MHz. This bandwidth is dictated by the available processing capacity of the computers used to run the signal processing. Switching frequencies is coordinated using the computer's system clocks which are synchronized over the network before starting a measurement. Because the B205mini does not report the measured RSSI in a known absolute unit, we always consider the relative path loss. To calculate this, we capture a reference value by placing both SDRs directly next to each other. We measure for 100 s on each frequency to obtain a reference value by calculating the average over this time.

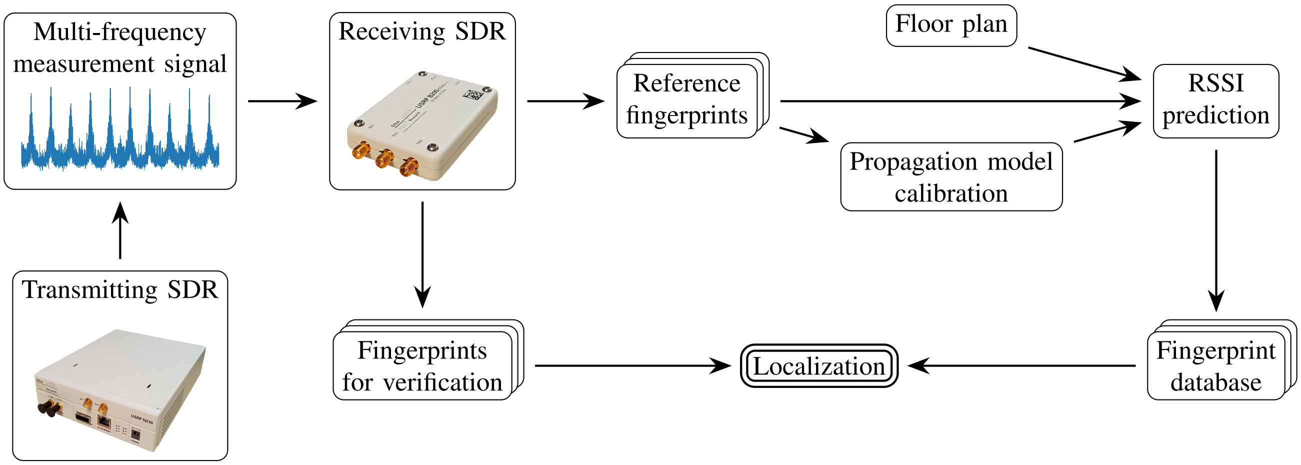


Fig. 2: Measurement and localization process

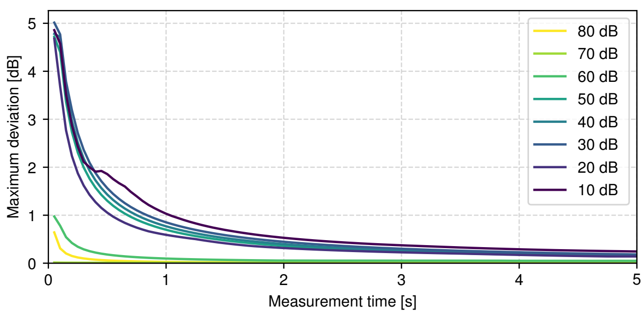


Fig. 3: Maximum observed deviation using different measurement durations at different transmitter gains

Because we are measuring the entire unlicensed frequency band, we expect interference with other wireless transmitters. This requires a method to detect if our measurement signal is being received correctly to avoid falsifying the result by unknowingly recording the signal strength of a different transmission source. To achieve this, we transmit Binary Frequency Shift Keying (BFSK)-modulated data within our signal and only consider a measurement valid if the data was correctly demodulated. This data consists of a repeating randomly generated sequence with a length of about 0.1 s that is transmitted at 1 kb/s. The receiver requires that one full sequence is received without errors, otherwise the affected RSSI samples are discarded. Finally, we calculate the average RSSI for each measurement to correct for fluctuations caused by the SDR hardware.

B. Measurement duration

To find an optimal value for the measurement duration t, we place the transmitting and receiving antenna directly next to each other to minimize propagation effects. We measure the RSSI for a total of 100 s at each end as well as the center of both frequency bands using a single B200mini for transmitting and receiving. Additionally, we vary the transmitter's gain in steps of 10 dB to simulate different amounts of path loss. We then calculate averages for different time windows $t \leq 5\,\mathrm{s}$ and compare those to the average calculated over the entire 100 s. During this step, we consider different possible positions of each time window by moving it in steps of 50 ms to obtain a distribution of possible differences. Fig. 3 shows the maximum observed deviation of the calculated average for different values of t over all frequencies at different transmitter gains. Based on this data, we set the final value of t at 2 s as this lowers the maximum difference compared to a longer measurement duration below 1 dB. We consider this an acceptable trade-off between measurement accuracy and the time requirement of performing a full measurement. Furthermore, we increase the actual measurement duration to 4 s to enable successful measurements even if the reception of the measurement signal is intermittently interrupted by external interference.

C. RSSI prediction

As discussed in Section II, we use the method demonstrated in [17] based on a modified variant of the One-slope model [6] to predict the signal strength from a small number of reference points to reduce the number of measurements needed to create the fingerprint database. Using M reference points with real measurement results, this model predicts the signal strength P with a distance d between the transmitter and the receiver at the predicted location as

$$P = \frac{1}{M} \sum_{m=1}^{M} \left(P_{0_m} + 10\gamma \log \left(\frac{d}{d_{0_m}} \right) \right) \tag{1}$$

with distance d_{0_m} and signal strength P_{0_m} for each reference point m and an empirical propagation coefficient γ. Because this model does not factor in losses caused by obstacles such as walls, we only use reference points that have a direct line of sight to the current position. This information is extracted automatically from a floor plan of the building where we perform our experiments. Following the procedure shown in [17], we measure one reference point for each corner of a room. For rooms that are not rectangular or contain major obstacles, we add additional reference points so that every position within the room has a direct line of sight to at least four. Using this procedure, we are able to collect reference measurements in around 5-10 minutes per room, compared to potentially several hours if no prediction is used, depending on the chosen resolution. As we expect the possibility of failed measurements on some frequencies due to wireless interference, we ignore frequencies that do not have at least four usable reference points in a particular room. Because [17] does not specify a procedure to determine a value for γ, we chose the following algorithm to find an ideal value using the measured reference fingerprints:

1) The algorithm iterates over all pairs of fingerprints i, j that have an unobstructed line of sight between them.
2) The distances d_i, d_j between i, j and the transmitter are calculated.
3) Using the measured power P_i at i, the power P_{pred} that is predicted by the One-slope model for j is calculated.
4) The difference between P_{pred} and the real measured power at j is calculated.
5) The Root Mean Squared Error (RMSE) over all differences is calculated for all pairs i, j.
6) The process is repeated for different values of γ and the value that produces the lowest RMSE is used as the final result.

We begin with an experimentally selected range of values for γ and run an iterative search where each iteration narrows the search range around the previously found best candidate. This procedure is repeated to determine γ for each frequency.

With this methodology, we can calculate a map of fingerprints for any desired resolution. We chose a resolution of one pixel per cm with the intention of setting it as high as possible for the initial evaluation to prevent it from negatively impacting the results while keeping the required memory to process and store each map within a reasonable margin. At this resolution, the uncompressed maps amount to about 9.2 GiB for a map that includes all frequencies.

IV. Localization algorithm

To determine a wireless node's position, we adapt the algorithm described in [17] for multi-frequency data. the algorithm calculates a distance metric between the node's measured RSSI and the fingerprints predicted in sec. III-C for every possible location that has a fingerprint available. Following that, the fingerprint with the overall smallest distance is selected as the node's position. As metric for the distance between a measurement p and fingerprint q, we use the RMSE

$$RMSE(p,q) = \sqrt{\sum_{i=1}^{N} \frac{(p_i - q_i)^2}{N}} \tag{2}$$

which is demonstrated in [8]. The implementations in [8] and [17] use fingerprints containing measurement data from N different anchor nodes. We instead use data measured over N frequencies. Unlike the Euclidean distance used in [17], using a mean allows this metric to work when the number of available measurements N is different between locations. With our fingerprint database, this can be the case when frequencies are excluded due to wireless interference during fingerprint collection as mentioned in sec. III-A.

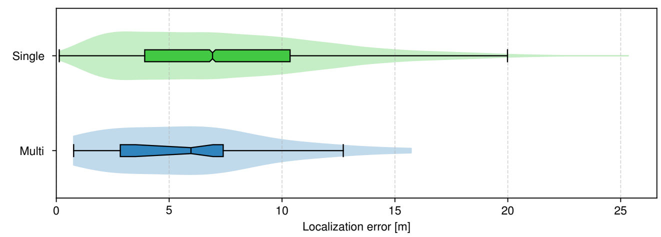


Fig. 4: Error distribution for single- and multi-frequency localization

Our approach uses all available frequencies that have a valid measurement in both the node's current RSSI sample and the fingerprint that it is being compared to. We implement a minimum threshold for the number of frequencies which we set to one tenth of the total number of frequencies that are being used during a measurement. If the number of frequencies with valid data that can be compared during localization drops below this threshold, the associated location is not considered as a possible result. This is implemented because the algorithm could otherwise perform identical to a single-frequency approach in areas with few valid measurements (for example, in case of a weak signal) which could incorrectly bias the localization towards these areas. We consider this equivalent to a realistic deployment where a node does not attempt to determine its position if the signal is detected as being too weak.

V. Evaluation

In this section, we evaluate the achievable localization accuracy using our approach. Following an initial best-case evaluation using all available frequencies, we also investigate the performance impact of using fewer frequencies to potentially reduce computational complexity and memory requirements.

A. Localization performance

To evaluate the performance of our localization approach, we conduct measurements inside our university building with an area of about 23 m x 20 m which is a similar size to the areas that were used for evaluations in several related publications [4], [17], [23], [27]. The area primarily contains offices alongside a single computer lab. We position the transmitter inside one of the offices next to a wall in what we consider to be a realistic possible location for a wireless access point. We chose this because in a real-world deployment, the transmitter's location would be dictated by the already installed hardware. After collecting fingerprints for each room as described in Section III, we collect a total of 32 additional test points at randomly selected locations. When measuring the location of these points, we estimate an error of ± 5 cm.

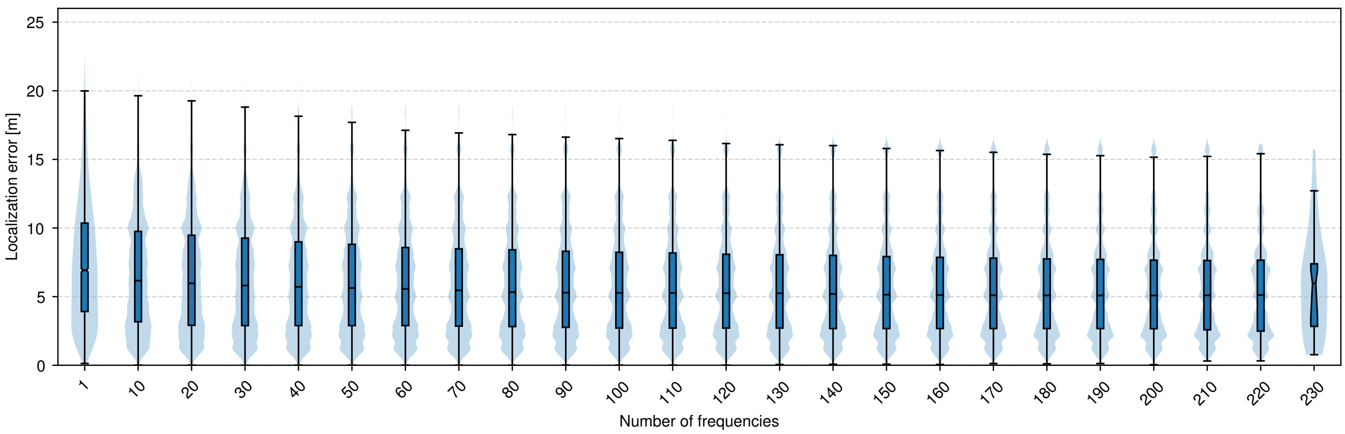


Fig. 5: Error distributions for localization using different numbers of frequencies

Then, we run the localization algorithm shown in Section IV and calculate the Euclidean distance between each point's predicted and real locations as the localization error. Fig. 4 shows the error distribution using our multi-frequency approach and a second distribution using only a single frequency for comparison. For the single-frequency case, a different localization error is calculated for each available frequency. These are shown as a single distribution over all calculated errors within the figure.

As expected, localization using only a single frequency results in large errors due to single-frequency fingerprints being highly ambiguous. The comparison in Fig. 4 shows that using multiple frequencies greatly reduces both the average and maximum error. This shows that the result obtained with our multi-frequency approach is not incidental for this environment and an improvement is made over the naive single-frequency scenario where bad localization performance is expected. With a mean accuracy of about 5.8 m, our result is comparable to the result published in [17] which was measured using six anchors in an environment roughly half the size of our evaluation area. This shows that a multi-frequency approach can produce similar results as existing systems while only requiring a single anchor.

B. Frequency selection

The initial evaluation has demonstrated the achievable accuracy while measuring across two entire frequency bands. Using such a large number of frequencies however results in high computational complexity for the localization process and storage requirements for the fingerprint database. Depending on how easily the node can measure its RSSI across multiple frequencies, it can also increase the time required to acquire a full RSSI sample. To find a potential trade-off between accuracy and complexity, we run the localization using different numbers k out of n total frequencies. Ideally, we would repeat the localization using all $\binom{n}{k}$ possible combinations of frequencies to obtain a full distribution of all possible results. However, this creates an impossibly large number of combinations. Thus, we limit the evaluation to a maximum of 10 000 combinations for each n by randomly selecting frequencies while avoiding duplicate combinations. Fig. 5 shows the resulting error distributions for different numbers of frequencies, with the last distribution to the right of the figure showing the result for localization using all frequencies. These results clearly show: 1) adding additional frequencies never decreases localization accuracy; 2) the performance barely changes after around 70 or more frequencies are being used. Additionally, there is a significant jump between the distributions using 220 and the full 230 frequencies. This can be explained because of the random selection, the distribution for 230 frequencies contains only one data point for each test location for a total of 32 values, while the distribution for 220 frequencies contains $32 \cdot 10^4$. As a result of this difference, these two distributions are not suited for direct comparison. However, this suggests that some frequency combinations may result in better accuracy than others. This lines up with the findings published in [7] which conclude that pre-selecting an ideal set of frequencies achieves the same accuracy as using all available frequencies with much lower complexity.

Following this result, we attempt to find a generic method to make such an ideal frequency selection. First, we investigate the effect of using multiple frequency bands as this adds a potential requirement to the hardware used and may be unavailable if the radio is limited to a single frequency band. Fig. 6 shows the localization error when using all frequencies from each of the two measured frequency bands as well as the full result using both bands that was previously shown in Fig. 4/6 for comparison. Because the 5 GHz band is larger than the 2.4 GHz band, we consider the possibility that the larger number of frequencies might impact the result. To work around this issue, we also perform localization using a subset of consecutive frequencies from the 5 GHz band the same size as the 2.4 GHz band using every possible position of this set within the 5 GHz band. The resulting distribution is labeled "5 GHz (limited)" in Fig. 6. These results show: Localization in the 5 GHz band results in a lower median

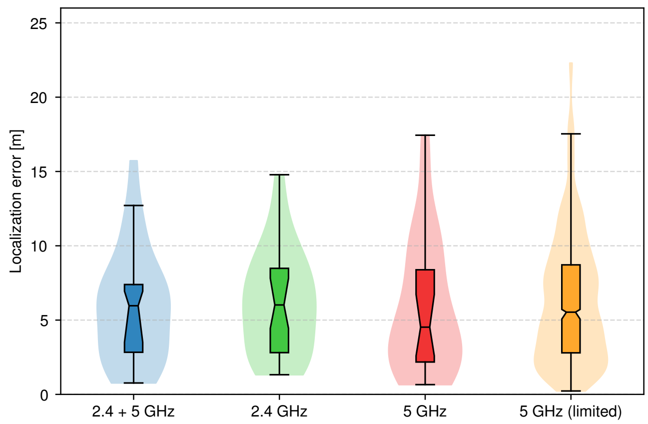


Fig. 6: Error distribution for localization using a single frequency band

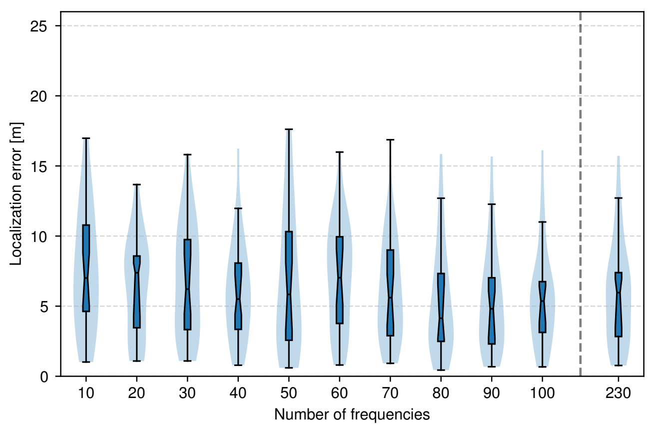


Fig. 7: Error distributions for localization using different numbers of frequencies with equal distance

error compared to the 2.4 GHz band, but we also observe a larger maximum error. The lower median may be caused by the larger number of frequencies because the limited case results in a higher median that is closer to what can be seen for the 2.4 GHz band. Furthermore, none of the two frequency bands appears to be sufficient by itself to obtain the error distribution obtained by using measurements from both bands simultaneously. Given this result, we conclude that if possible, any available frequency band supported by the used hardware should be included in measurements to obtain the best possible localization accuracy.

Considering the significant difference between frequency bands, we formulate the hypothesis that the distance between two frequencies plays an important role in determining the localization accuracy due to a greater difference in propagation characteristics. If this was the case, selecting few frequencies that are spaced far apart could be an ideal choice to reduce localization complexity. To verify this theory, we use different numbers n of frequencies in each frequency band which we lay out so that the distance Δf is equal between all of them

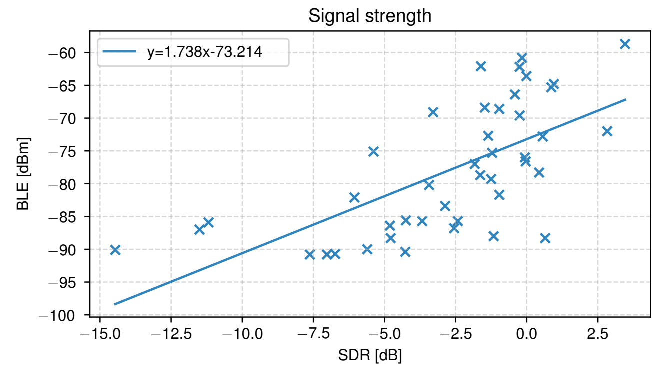


Fig. 8: Example of BLE/SDR calibration ($f = 2.45\,\text{GHz}$)

and the entire frequency band is covered. We test this scenario for up to 100 frequencies because we expect results using more to be highly similar based on the data shown in Fig. 5 and thus not interesting for this evaluation. The results are shown in Fig. 7 alongside the error distribution obtained while using all 230 frequencies for comparison. Most distributions appear similar to what is shown in Fig. 5 at the same number of frequencies. However, there is a visible improvement while using a low number of frequencies ($n \leq 30$). From this, we can conclude that although using a large number of frequencies results in the best accuracy, if the number of usable frequencies is limited, it is ideal to select frequencies that cover as much bandwidth as possible across all available frequency bands.

VI. Off-the-shelf implementation

After demonstrating the possibility of single-anchor localization using SDR, we try to follow the same approach using COTS wireless hardware. We choose a BLE connection for this task because connected BLE nodes use frequency hopping to constantly change their communication channel across the entire 2.4 GHz band [5]. By measuring the RSSI for empty packets that are sent during each BLE connection event while no data is being transmitted, this allows quickly collecting RSSI values for a large number of different frequencies. We implement the following measurements on *Laird Connectivity BL654* development boards running a version of *Zephyr OS* with a small modification that allows us to access the RSSI after every received packet and relay it to an attached computer over the board's serial interface. While measuring RSSI values, we collect 10 samples for each BLE channel. As interference from other wireless transmissions in the area can cause us to not receive enough packets on some channels in reasonable time, we set a time limit of 120 s after which we stop the measurement and save results only for channels where we have received RSSI values for at least 10 packets.

The BLE hardware and the SDR are likely to have different radio characteristics. Thus, we first perform a calibration phase so that we can use RSSI fingerprints collected using SDR to localize a BLE node. For this purpose, we measure RSSI fingerprints using both a BLE node and an SDR at identical

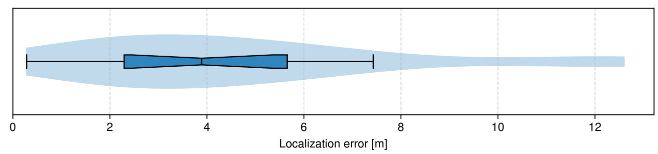


Fig. 9: Error distribution for localization using BLE

locations. By doing so, we can directly compare the results from both devices and derive parameters to convert between them. A database of RSSI fingerprints collected using the SDR is already available after the initial SDR-based evaluation (Section V). We collect the BLE fingerprints in the same locations, allowing us to utilize the already collected SDR fingerprints for this step. While this suggests the option of generating the fingerprint database using the BLE measurements directly, we observed a limited reception range for this hardware, resulting in significantly fewer fingerprints which would make it impossible to create a fingerprint database that covers a large enough portion of our measurement area using the method chosen in Section III-C. Because the BL654 hardware is able to report RSSI in a known absolute unit (dBm), we do not calculate relative values as we do for data captured with the SDR (see Section III-A). We then calculate a linear regression to obtain parameters for each frequency that allow us to calculate the expected BLE RSSI from measurements taken with the SDR. An example of this calibration for a single frequency is shown in Fig. 8.

For the evaluation, we measure RSSI fingerprints in the same locations that we used during the evaluation in Section V. Due to the limited range with BLE, we omitted points in rooms in which the signal was too weak to reliably complete the measurement. This greatly reduces the number of usable data points. Thus, we add additional randomly selected locations for a total of 19 points. The resulting localization error distribution is shown in Fig. 9. Overall, the result is similar to the result of our initial evaluation using SDR. This confirms that our multi-frequency localization approach can be implemented using COTS hardware, achieving an accuracy comparable to what we presented in our initial evaluation. The only limiting factor is the number of frequencies and frequency bands usable by the given hardware and wireless standard.

VII. Conclusion

In this paper, we demonstrate a method for RSSI-based indoor localization that can function with only a single anchor by utilizing multiple frequencies. Our evaluation shows that this method can deliver comparable accuracy to existing RSSI-based methods from literature that require multiple anchors to be within the localized node's reception range in order to function. We introduce a measurement approach using SDR to efficiently collect RSSI fingerprints across several frequencies at the same time. This allows for quickly creating the required fingerprint database for a given environment. Finally, we implement our localization method on off-the-shelf BLE hardware, demonstrating the applicability of our approach on real-world devices as opposed to using SDR exclusively.

While our evaluation shows that our method does not achieve the same accuracy as some other state-of-the-art methods based on measurements such as phase difference or CSI, it does not have any of the additional hardware requirements needed to use those systems. This allows our method to be used across a wide range of unmodified COTS devices, making it especially useful in situations where a localization system is needed while the choice of hardware is limited or dictated by other external factors. We identify the main limitation of our system to be the required memory to store the reference fingerprint database, which may be too large for some memory-constrained embedded devices. This could however be solved by implementing the actual localization on a central server which processes fingerprints received from nodes over the network. Furthermore, like any fingerprinting-based solution, our system requires maintenance as reference fingerprints need to be updated after making significant changes to the environment (such as moving furniture). Because of the implemented fingerprint prediction (see Section III-C), we consider this effort to be minimal enough to not reduce the practicality of our system as updating the reference fingerprints only requires a small number of measurements to be conducted within rooms where the environment was changed while all other fingerprints can be retained.

VIII. Future work

As future work, we are interested in implementing this localization algorithm on other devices using different wireless standards. BLE has the significant advantage of frequency hopping, which allows BLE nodes to quickly collect RSSI for many different frequencies. In contrast, many other wireless standards can not easily switch between different frequencies during operation. One example of this limitation is WiFi, which is of particular interest for future research due to its widespread usage. While it is possible to measure RSSI values for each OFDM subcarrier in a WiFi connection by collecting CSI, this only captures a limited continuous section of the wireless spectrum which may not give ideal performance as shown in Section V-B. A solution for this may be available in WiFi 7. This version of the standard allows devices to use multiple frequency bands simultaneously. Furthermore, we consider using machine learning techniques rather than the simple matching based on similarity of two fingerprints used in this paper. Such approaches have delivered good results in other localization systems (as discussed in Section II). Finally, future work should study the impact of the environment's layout on localization accuracy using this method as the observed difference in signal propagation between different frequencies depends mostly on multipath effects. Consequently, we suspect that environments with lots of possible obstacles might be better suited for the deployment of a localization system using our approach.

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