Improving WiFi Ranging Through Frequency Diversity and Mobility

Sascha Rösler, Nils Eising, Anatolij Zubow, Falko Dressler
School of Electrical Engineering and Computer Science, TU Berlin, Germany
{roesler,eising,zubow,dressler}@tkn.tu-berlin.de

***Abstract*—Indoor positioning with IEEE 802.11 Fine Timing Measurement (FTM) relies on precise estimation of the Round Trip Time (RTT) between a pair of WiFi devices. However, studies have demonstrated that multi-path propagation affect FTM, which tends to overestimate and only rarely underestimates the actual distance. We present `HopFTM` to enhances FTM ranging accuracy by leveraging frequency diversity and space diversity (mobility). Specifically, `HopFTM` performs ranging on multiple radio channels. Additionally, in a mobile scenario, ranging is performed at multiple locations. Our experimental results using low-cost ESP32-S3 hardware reveal that selecting the smallest RTT value from all measured channels significantly improves accuracy, especially in environments with strong multi-path effects or non-line-of-sight conditions. In a static scenario by using the smallest RTT from four channels, we were able to reduce the median ranging error by $4\times$ from 120 cm to 30 cm while the worst-case error was decreased from 15 m to 10 m, compared to a traditional single-channel approach. In a mobile scenario, ranging measurements taken at different locations outside the decorrelation distance can also be fused. Our simulation shows that taking the smallest RTT value over multiple positions can improve FTM ranging error from 1.8 m to 0.76 m.**

***Index Terms*—Ranging, WiFi, fine timing measurement, FTM, frequency diversity, channel hopping**

I. Introduction

Wireless sensing is becoming more relevant for 6G [1] as well as for technologies like 802.11 WiFi [2]. Indoor localization, where GPS is unavailable, drives the development of anchor-based localization technologies [2]. These can rely on ranging, for example on measurement of the Time of Flight (ToF) which can be deducted from the Round Trip Time (RTT) of a signal exchange. With the standardization of Fine Timing Measurement (FTM) as 802.11mc [3] and 802.11az [4] ToF based ranging is introduced for WiFi. FTM defines the exchange of packets on which the RTT can be measured [3]. One of the key advantages is the widespread availability of WiFi, both in terms of deployments and support in end-user devices [2]. WiFi Access Points (APs) can work as anchor points (so called Responders) for FTM and therefore build the FTM infrastructure. By estimating the distances to multiple APs, the position of the station can be determined. This way FTM enables localization services in dense WiFi deployments. Especially, low-cost, commodity microcontroller with a full WiFi stack are now available, enabling the feasibility of ultra-dense deployments with hundreds of devices [5]. Microcontrollers such as the ESP32-S2 also come with FTM capabilities on the chip making ranging easily accessible.

While FTM proposes meter-level accuracy, recent studies using Commercial Off-The-Shelf (COTS) WiFi hardware demonstrated that FTM often fails to meet these expectations, particularly in environments with strong multipath propagation, such as indoors [6], [7]. Authors in [6], [8], [9] show that FTM measurements tend to be noisy and tend to overestimate the true distance and rarely underestimate it. Multipath effects are frequency-dependent and position-dependent and, hence, cannot be averaged out in stationary FTM measurements. The same fact is visible in the data that we present in this paper. Existing countermeasures proposed in the literature come with many limitations, for example they are limited to calibrated or trained environments [7].

In this paper, we take advantage of the fact that FTM is prone to overestimation, which is a novelty in research on FTM. Moreover, we show that the WiFi radio channel used for ranging has a significant impact on accuracy showing the frequency-dependency of FTM. Furthermore, the best-performing channels for different positions vary. Based on these observations, we propose to perform WiFi ranging across multiple radio channels. Selecting the smallest RTT value, we achieve a significant improvement in ranging accuracy without additional training phases. Additionally, we show how mobility can be used to work with position-dependent errors of FTM. Doing multiple measurements in general and measuring on multiple channels in particular comes with the tradeoff of longer measurement times, which we also analyze in this paper. We also study the effect if we decrease the number of channels used for measurements. Since an AP in a WiFi network typically does not frequently switch channels, we developed a system named `HopFTM` system, where the FTM-Responder perform channel hopping to enable ranging on different channels. Additionally, we study the effect of mobility in a simulation.

Our main contributions can be summarized as follows:

- We present `HopFTM`, a system which utilizes spacial diversity and frequency diversity to achieve higher accurate ranging especially indoors,
- A low-cost prototype using ESP32s3 microcontrollers as responder (soft-APs) is presented,
- Comprehensive experimental evaluation in indoor, outdoor and Non-Line-of-sight (NLOS) environments are performed,
- Analysis of trade-offs like ranging delay and accuracy.

II. Related Work

Since its introduction, there has already been extensive research into the capabilities of FTM-based WiFi ranging. Many works show, that FTM measurements come with a low accuracy (2–3 m [10]) especially in indoor environments like hallways [6], [7], [10]–[12] independent of the used hardware [10]. Also persons moving in a room influence the accuracy of FTM [11], [13]. However, using a larger bandwidth reduces the error [10]. Barral Vales et al. [7] show how the distance estimation algorithm of the ESP32 improves the ranging estimation in their indoor scenario while the estimation in the outdoor scenario is worse than the raw FTM measurement. Taking Received Signal Strength Indication (RSSI) as an additional source for ranging and signal quality, the authors train a Machine Learning (ML) model based on their data, which achieves good results in the environment for which the model was trained for. However, there is no improvement visible for an unseen environment. Si et al. [14] proposed an alternative approach, where a Gaussian model was developed to identify whether FTM measurements are done under Line-of-sight (LOS) or NLOS conditions based on the measured RSSI. Using only data from LOS scenarios they significantly improves the overall accuracy of the system to an accuracy of 83.1%. Liu et al. [15] use a SegRNN to filter the sequence of FTM measurements to detect anomalies within the data and discard corrupted measurements. The SegRNN does not require data following a specific distribution. Sun et al. [16] use the available sensors on a smartphone together with WiFi RSSI and FTM fingerprinting to build a localization framework. The data from the sensors and the position out of fingerprinting are combined and smoothened by a particle filter.

In contrast, Horn [9] already studied the nature of the ranging error and stated that the error distribution of FTM is non-Gaussian, highly position-dependent and much larger than the measurement noise. He is already suggesting frequency diversity to limit the position-dependent error by using dedicated non-overlapping channel in the 5 GHz band and proofs with his data that the ranging errors measured on the different channels are independent. Using a weighted average to estimate distances, the author tries to emphasize the fact that FTM tends to overestimate rather than underestimate distances. With FUSIC Jiokeng et al. [17] introduce a framework using the channel state information (CSI) to detect if the FTM measurement was affected by multipath and corrects the ranging measurement based on the time difference of the multipath components estimated by the MUSIC algorithm. With FUSIC the authors decrease the median ranging error from 5.04 m to 1.9 m. Banin et al. [18] improve FTM localization with a Bayesian filter for a moving device based on spacial diversity and constraints given by a map.

So far, only one work was proposing FTM ranging on different channels to increase accuracy. Furthermore, none of the works propose using the smallest RTT value out of multiple measurements.

III. Background

A. Wireless Channel Propagation

A radio signal interacts with its surroundings, such as walls, furniture, and even humans. As a result, the signal is reflected off walls or scatters through obstacles, such that multiple copies of the transmitted signal are created, known as multipath components. These signal components arrive at different times because of the varying path lengths, which results in different phases of the signal, causing constructive or destructive interference. This phase shift of the signal is frequency dependent as $\varphi_n = t_n \cdot f$ where φ_n is the phase of the nth multipath component at the time t_n and f the frequency of the signal. The multipath characteristic of the channel can be observed through the distinct impulses in the Channel Impulse Response (CIR). When assuming a time-invariant channel, so the CIR can be denoted as [19]:

$$h(t) = \sum_{n=0}^{N} a_n e^{-j\varphi_n} \delta(t - t_n) \tag{1}$$

where a_n is the amplitude, N is the total number of multipath components and $\delta(t)$ is the Dirac delta function. The sum of amplitude and phase of these multipath components can result in constructive or destructive interference.

B. FTM Protocol

FTM is a standardized MAC layer protocol in WiFi for ranging between a Station (STA) and a responder (AP) which can be performed without prior association. The APs announce their FTM capabilities in beacon frames or probe response frames. The FTM protocol works in this way: A STA (the initiator) can request a FTM session at the responder. Although the responder does not have to be an AP, some devices, such as the ESP32, only support FTM Responder functionality in AP-mode. Once the responder acknowledges the FTM request, a number of FTM packets are exchanged between the devices, each device measuring the packets' send and arrival times. The responder sends FTM frames including its recorded time measurements of previously sent (t_1) and received packets (t_4) which the initiator acknowledges. The initiator records the points in time when the packets arrive (t_2) and when the Acknowledgement (ACK) was sent (t_3). Hence, the initiator can calculate its distance to the responder based on the RTT and the speed of light c. Mathematically speaking, the distance d is calculated as

$$RTT = (t_4 - t_1) - (t_3 - t_2) \tag{2}$$

$$d = c \cdot \frac{RTT}{2} + k_i \tag{3}$$

where k_i is an offset due to the antenna and chip design [20]. The distance values over the FTM packets in one session are averaged, however, this method cannot average out biases, as multipath fading effects are stationary. FTM relies on a high resolution of the Time of Arrival (ToA) which is higher than the required sample rate by Shannon's theorem (e.g., the sample rate would be 50 ns for a 20 MHz channel).

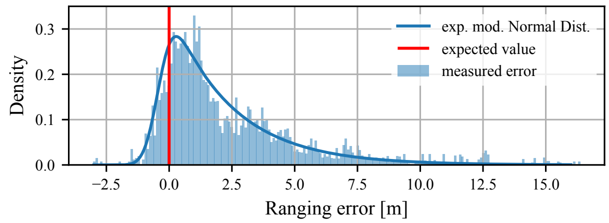

Figure 1. Histogram of ranging errors in studied environments (ESP32 hardware). The data follows a exponentially modified Normal Distribution

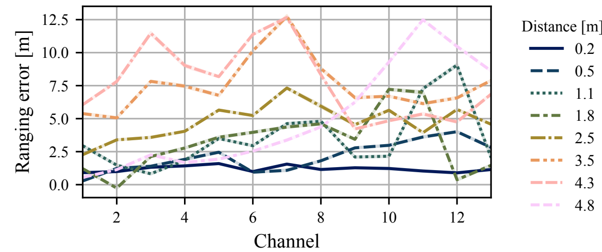

Figure 2. Ranging measurement on multiple channels (indoor, hallway). The error behaves differently depending on the used channel.

Thus, the higher resolution might be achieved by massively oversampling the incoming signal, however, methods relying on the CSI like MUSIC can also be used. However, the concrete implementation of the ToA estimation in COTS hardware is a black box. In case of a multipath environment, the chip might estimate the arrival based on a component which bounced and thereby traveled a longer distance. Indeed, it might always see a mixture of different signal components. Nevertheless, this does not explain underestimations that also occur and might be caused by the ToA estimation algorithm.

IV. System Model & Problem Statement

Indoor ranging based on the FTM protocol is highly affected by multipath propagation, leading to inaccurate distance and, hence, position estimations, as many authors have already discussed [6], [7], [11], [12]. These multipath components arrive so close in time that one sample includes a mixture of multiple components. To overcome multipath effects, two ways are physically possible. One possible way is leveraging spacial diversity, e.g. changing the position as done in [18], [21] or the environment [13]. A change of the position will change the path length of the different multipath components and thereby the phase of each multipath component at the receiver. Another way is changing the frequency of the signal as this will change the phase of the signal without the need of changing the position.

In this paper, we are analyzing the first way for mobile stations and the second way for a static environment and static positions of the STAs and APs. As system model, we assume that an IEEE 802.11 WiFi infrastructure network consisting of some number of APs is deployed in the environment where localization is required. However, this paper elaborates an approach to improve ranging with FTM. Via trilateration ranging can be used or localization. No association of a STA to the APs is required.

The aim of this paper is to improve the ranging accuracy while looking for a standard compliant solution. Our proposed approach does not require any changes to the FTM protocol and is a software-only solution, which could be installed on both user devices (STA) and APs.

V. `HopFTM` Approach

Our proposed approach is based on the following observations. First, with FTM the actual distance is usually overestimated and rarely underestimated. Figure 1 shows the ranging error for each FTM session of different environments we studied like an indoor hallway, a living room and a computer pool with strong multipath as well, as an outdoor scenario (Figure 4) and using COTS WiFi hardware, i.e., ESP32. The ranging error follows a non Gaussian distribution (e.g., an exponentially modified Normal Distribution) where it is more likely to overestimate the true distance rather than underestimating it. The WiFi radio channel used for ranging has a significant impact on the achieved accuracy as shown in Figure 2, where different channels works best for different distances. The figure shows the ranging error depending on the channel for measurements on eight different distances in a computer room with the same hardware.

Therefore, in order to improve the ranging accuracy of WiFi-FTM, we propose the `HopFTM` approach (Figure 3). It performs WiFi ranging on multiple different radio channels where taking the smallest value already results in significant improvement in ranging error. In case of mobility it can also perform ranging measurements at different locations along the trajectory of the STA using spacial diversity. To measure on different channels the responders have to change their operating channels frequently. As the STA is requesting FTM sessions from the AP also the client has to adapt its channel. We like to highlight two different implementation strategies. First, the AP is changing its channel, while the STA has to first do WiFi scanning before executing the ranging with FTM. Another option is to synchronize the STA with the APs using the beacon frames so that the ranging can be performed after each channel switch of the AP.

`HopFTM` comes with three parameters: The number RTT measurements taken into account for preprocessing W, the number of used channels C and the spacing between the chan-

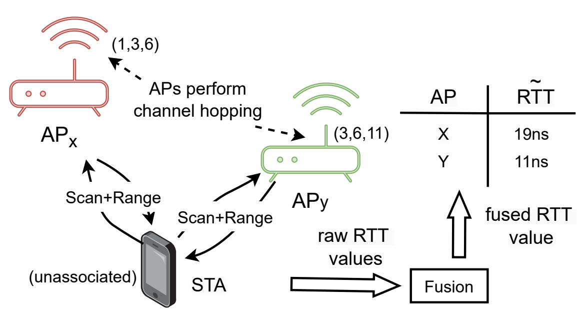

Figure 3. `HopFTM` approach: 1) APs perform channel hopping, 2) STA performs scanning & FTM ranging, 3) obtained per channel RTT results are post-processed to derive final RTT.

(a) Free field (b) Livingroom (c) Hallway

Figure 4. Measurement setup - both STA and AP mounted on tripods (1.5 m above the ground)

nels K. So, the specific hopping sequence $S_i = (c_i^1, \dots, c_i^m)$ of a specific AP i is defined by C and K. As the spectrum is limited, there is a wrap-around in case hopping beyond the highest channel is done. All three parameters have an impact on both, ranging accuracy and overhead. The STA periodically starts FTM sessions, such that there is at least one session on a channel. After performing W different FTM rangings on C different channels towards a specific responder m the STA performs a post-processing on the set of collected RTT data $\mathrm{RTT}^m = \mathrm{RTT}_1^m, \dots, \mathrm{RTT}_W^m$. For a static scenario, we assume that each channel is only measured once ($W = C$). `HopFTM` provides the following two post-processing strategies. First, the `RTT min` strategy takes the smallest RTT value from RTT^m and, hence, the shortest distance. This could be illustrated as only the shortest path (which is the direct path) is measured, however, this would ignore the fact that devices see always a mixture of the different path. Second, in order to deal with outliers the `RTT 3 min` strategy computes the average over the three channels with the lowest RTT values. For comparison, we also apply the strategy of taking the largest RTT measurement (`RTT max`) and the mean value over the measured RTT values (`RTT mean`). As baseline acts the strategy of taking the RTT values without applying any further post-processing (`BL: No window`).

As a proof-of-concept (POC) `HopFTM` was implemented as a prototype with COTS hardware, an ESP32 microcontroller, for both APs and STAs. The AP was realized using ESP32 Soft AP functionality. Channel hopping was performed using the WiFi channels in the 2.4 GHz ISM band and hop through the channels in increasing order. To synchronize to the AP, the STA used WiFi scanning with subsequent ranging. The station does not associate with the AP.

VI. Evaluation

In the following, we first study how `HopFTM` leverages frequency diversity. Therefore, we do experiments using our prototype in a static setup, which we compare against a baseline of using no windowing ($W = 1$) and other different post-processing strategies. We analyze the impact of the number of used measurements and the channel spacing. In a later simulation we analyze the impact of spacial diversity in a mobile scenario. The following six different environments were analyzed:

(a) *Free field* - outdoor environment with little multipath propagation (Figure 4a),
(b) *Livingroom* - indoor environment with short ranges (Figure 4b),
(c) *Hallway* - indoor environment with strong reflections (Figure 4c),
(d) *PC lab* - indoor in university,
(e) *NLOS wall* - environment with LOS blocked by a wall,
(f) *NLOS door* - environment with LOS blocked by a door.

For each environment we collected FTM ranging traces for different distances for which we apply the post-processing strategies. We always collect data from all channels, but for the post-processing we only choose a subset of C channels and process all combinations with respect to limits coming from a given K. So every channel is taken as start channel and the chosen or all possible channel hopping sequences are applied. As performance metric, we computed the ranging error.

A. Impact of Environment

The results for the six different environments and different post-processing strategies are shown in Figure 5 for which we measure a set of $C = 9$ channels. As expected, the ranging error is the smallest in the outdoor environment, and much higher for the five indoor environments. The lowest errors are achieved using `HopFTM` with `RTT min` strategy. It decreases the median ranging error by between 70 cm and more than 1 m for multiple environments under study, e.g., from 45 cm to 1.2 m in the *Hallway* scenario. The worst-case ranging error is decreased by 9 m to 2.5 m in the *Hallway* scenario and to 6.4 m in the *NLOS door* scenario. However, in contrast to the other strategies, this method underestimates the distance slightly for

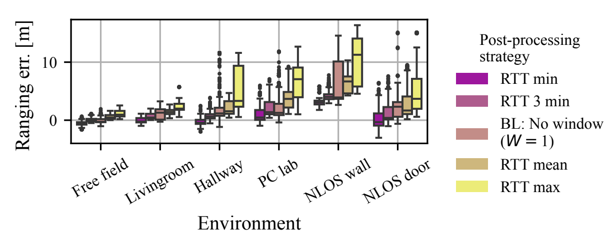

Figure 5. Comparison of post-processing algorithms in different environments

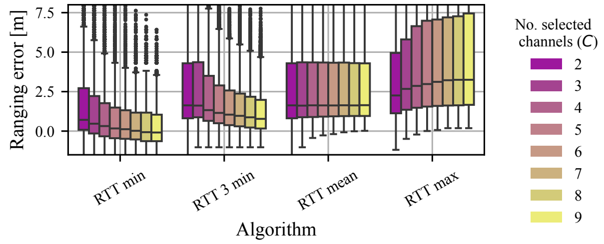

Figure 6. Influence of number of selected channels

Free field (median 36 cm), *Hallway* (median 1 cm) and *NLOS door* (median 66 cm). `RTT mean` and `RTT max` achieve the highest ranging error. The baseline approach of using a single channel only achieves different performances depending on the environment, as the chosen channel sometimes performs well.

B. Impact of Number of Channels

The results of the study on the influence of number of channels C in one hopping sequence are shown in Figure 6. We therefore did measurements in all six environments. We can see that the use of more channels decreases the ranging error and its variation for `RTT min` and `RTT 3 min`. However, as we see larger improvements if the number of channels increases if only a few channels in use, it becomes less effective if more channels are already used. This effect is especially visible for `RTT min` as there is a high probability that the channel with the smallest RTT value or a similar value is already in the data set. Numerically, the median ranging error decreases for `RTT min` to 30 cm if four channels are measured compared to 70 cm for a measurement of two channels and 1.2 m for our baseline. For the worst-case ranging error, we measure an improvement of 5 m when using four instead of two channels, and 8 m if we use 9 channels instead. Compared to it, `RTT 3 min` require more channels to be measured as it takes the lowest three values into account.

C. Impact of Channel Spacing

For a study on the channel spacings K we focus on the algorithm `RTT min`. Note, the channel spacing is measured by taking the difference of the center frequency of the WiFi channel, where a switch to a neighbored channel is $K = 5$ MHz. The start channel is random, indeed, channel hopping beyond channel 12 will cause a wrap starting at channel 1. The results in Figure 7 show a similar behavior for the different channel spacings under study for the different number of channels. We see for two channels an improvement of 15 cm for $K = 15$ MHz) compared to neighboring channels are used ($K = 5$ MHz). But there is a smaller improvement of 10 cm if every

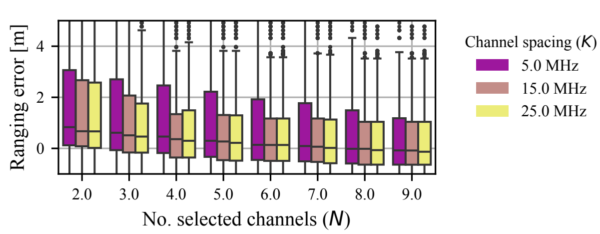

Figure 7. Influence of channel spacing on ranging error

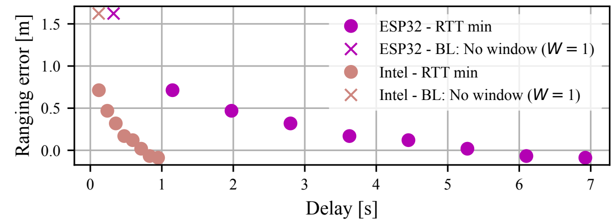

Figure 8. Trade-off between ranging delay and median ranging error

fourth channel is used ($K = 25$ MHz), however, the worst-case ranging error decreases by 4 m. From the results, we see that neighboring channels are similarly affected by multipath effects. If a larger number of channels is taken into account, the effect of the hopping distance is quiet marginal as the real steps between the channel are smaller due to the overflow.

D. Ranging Duration

Even tough the use of more channels for ranging leads to more accurate results, it also introduces additional delay as the ranging is performed on multiple channels. Therefore, for our prototype, we measure the duration of the FTM session which lasts 325 ms for a burst of 16 FTM frames. Additionally, the channel switch on an ESP32s3 takes 500 ms. The overall delay compared to the median ranging error presented in Figure 8 shows an exponential trend which flattens around 4 s (5 channels). The presented theoretical analysis for an Intel chipset-based approach uses our observation of a median FTM measurement duration of 117 ms. Changing a channel takes around 1.3 ms as shown in [22] and therefore around 1% of the measurement duration of a FTM session. Therefore, `HopFTM` can achieve small ranging errors with a measurement duration below 1 s if deployed on Intel hardware.

E. Influence of Mobility

Spatial diversity becomes available in case the WiFi station performing ranging is mobile. Therefore, we stick to our strategy of collecting data into a windows of size W and taking the lowest measured RTT value. In a simulation, we evaluate how taking the minimum RTT value over multiple spatial locations can improve FTM ranging instead of taking the minimum of a measurement over multiple channels. The window now can consist of RTT values measured on the same channel (so $W \geq C$), however, the data is measured at different locations. Our Monte-Carlo simulation uses a random-waypoint mobility model, where a station is moving at constant speed v towards or away from the AP changing its direction at random time. We use the ranging error model for the ESP32 chip from [8] excluding the error caused by the received signal strength. The simulated RTT value ($\widetilde{\mathrm{RTT}}$) follows $\widetilde{\mathrm{RTT}} = \mathrm{RTT} + h + w$. For the position-independent Gaussian error (w) we assume a standard deviation of 75 cm as shown in [8]. The distribution shown in Figure 1 is used for the position-dependent error(h) caused by multipath for which we use the decorrelation distance of one wavelength (12 cm for 2.412 GHz carrier frequency). We assume that the measurements are made immediately at the end of each interval (325 ms).

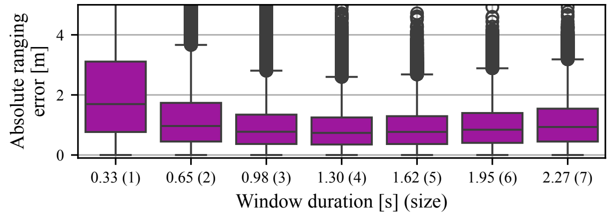

Figure 9. Influence of window duration or window size (W) on the absolute value of ranging error in case a station moves with 1 m/s measuring constantly on one channel.

At first, we study the influence of the window size W on the ranging accuracy for a station moving with $v = 1$ m/s. The results in Figure 9 reveal that the median ranging error decreases from 1.8 m to 0.76 m in case 4 ranging values are taken into account ($W = 4$). Additionally, the deviation of the ranging error decreases, making ranging more reliable. However, increasing W further increases the ranging error as the measurement delay increases, so the best fitting $\hat{W}$ depends on v. Therefore, we run the simulation for $v \in [0.1\,\mathrm{m/s}; 10\,\mathrm{m/s}]$ using two strategies: measuring on a `Single channel` ($C = 1$) or channel hopping over fully uncorrelated channels (`Channel hopping`, $C = 3$). We search $\hat{W}$ that results in the lowest ranging error for a given speed. Figure 10 shows that for $v \leq 5$ m/s there is a benefit if our approach is used, so $\hat{W} > 1$. $\hat{W}$ decreases by speed, so for 1 m/s $\hat{W} = 4$, while for a device moving slowly (0.1 m/s) $\hat{W} = 11$. Using channel hopping, it is possible to decrease $\hat{W}$ for slowly moving stations (e.g. from 11 to 7 for 0.1 m/s). However, this effect vanishes for $v > 0.4$ m/s as measurements on one channel become uncorrelated.

The resulting absolute values of the ranging error for the different speeds v are presented in Figure 11 together with the baseline of normal FTM ranging ($W = 1$). For $v \leq 1$ m/s our approach decreases the ranging error and its spread by around 1 m, while the median error increases above the ranging error of the baseline at higher speeds ($v = 3$ m/s). This shows the limit of our approach. Using channel hopping can improve FTM ranging even further in case of low speeds $v < 1$ m/s. The comparison of our experimental data from the pure channel hopping approach without mobility ($v = 0$) shows in case of $C = 3$ and $C = 5$ a similar median value, however, its spread is wider than the simulated one with mobility. This can be caused by deviations between simulation and a real environment like channels not being uncorrelated and position-dependent errors not being uncorrelated after 12 cm.

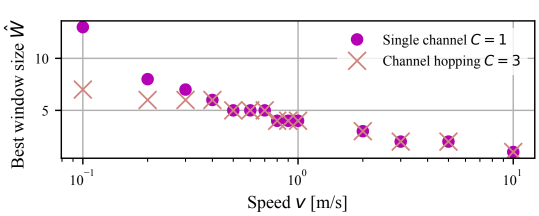

Figure 10. Best window size in depending on the speed of the station without channel hopping (`Single channel`) and with `Channel hopping`

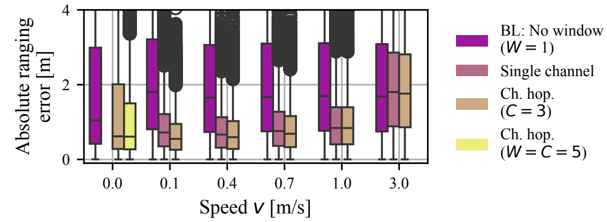

Figure 11. Influence of speed v on the absolute ranging error in scenarios without channel hopping $C = 1$ (`Single channel`) and with channel hopping $C = 3$ (`Channel hopping` ($C = 3$)). `Baseline` without use of windows $W = 1$, experimental data of `HopFTM` for $W = C = 5$

F. Discussion

`HopFTM` can increase the accuracy of wireless ranging and thereby also the accuracy of WiFi based localization. However, it comes with a higher ranging duration in case an ESP32 is used and hence might not be feasible for low-latency or high mobility ranging applications. Nevertheless, our approach is of practical use in case the target STA is moving slowly or has stationary phases. However, our theoretical study shows that the measurement duration can be decreased by using Intel hardware which requires a WiFi AP and higher costs.

Channel hopping of the AP comes with the cost of all associated stations have to switch the channel and airtime is lost by this channel switching procedure. Possible solutions are the usage of dedicated radios or APs for ranging as no normal data traffic needs to be served. Such approaches are also feasible due to the very low costs of COTS hardware, e.g., usage of ESP32. They can be installed just for the purpose of localization without providing data service. Furthermore, `HopFTM` requires multiple measurements either on the same channel or divided over multiple channels resulting in a higher consumption of air time. Frequent channel switching can also cause issues for coexistence mechanisms of other technologies that rely on WiFi staying constantly on one channel.

VII. Conclusion

In this paper, we introduced `HopFTM` and demonstrate that using the smallest RTT value measured under frequency diversity or spacial diversity improves FTM ranging accuracy. Large improvements can be achieved by using just a few uncorrelated channels or positions. Overall, we see a decrease of the median ranging error to $1/4$ and a large decrease of the worst-case. However, it is important to note that the measurement time increases creating a limit due to mobility. As future work we plan to combine FTM ranging measurements from different spectrum bands like sub-GHz, 5, 6 and 60 GHz because the bands have very different channel propagation characteristics.

Acknowledgments

This work was supported by the Federal Ministry of Education and Research (BMBF, Germany) within the 6G Research and Innovation Cluster 6G-RIC under Grant 16KISK020K as well as by the German Research Foundation (DFG) within the projects Resilient Worlds under grant DR 639/30-1 and ZU 235/4-1.

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