Localization as a Feature of mmWave Communication

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***Abstract*—mmWave (millimeter-Wave) is a very promising technology for the future wireless communication. To mitigate its high attenuation characteristics, mmWave communication frequently employs directional beamforming for both transmission and reception. Localization commonly takes advantage of directionality in RF frequencies in urban and indoor environments. In this paper, we use lessons learned from classical RF-based localization for discussing a set of feasible localization approaches in the context of mmWave bands. We further map the requirements of each discussed localization approach to design requirements for future mmWave devices and assess the expected accuracy of such approaches for a set of realistic scenarios. Our results show that mmWave-based localization is promising in both its availability and accuracy, even in the presence of a limited number of localization anchor nodes.**

***Keywords*—mmWave, localization, trilateration, triangulation, LoS, NLoS, ToF, AoA, RSS.**

I. Introduction

Providing information about the physical location of a device is a highly desirable feature of future wireless networks [1]. In scenarios where the Global Navigation Satellite System (GNSS) fails to provide acceptable performance, particularly in urban and indoor environments, a variety of alternative localization approaches have been proposed [1]. Use of the available wireless communication infrastructure for localization is especially convenient because it avoids additional deployment costs [2]. Although numerous localization approaches exist for lower industrial, scientific and medical (ISM) frequency bands (2.4 and 5 GHz), this topic has not been equally intensively treated in the context of mmWave bands. mmWave communication is widely considered a promising approach for achieving high data rate and low latency communication in tomorrow's wireless networks, largely because of the availability of a large amount of mmWave spectrum worldwide [3]. Furthermore, mmWave communication using directional radios promises higher spatial density leading to higher overall capacity of wireless networks. After the standardization of IEEE 802.11ad [4] and IEEE 802.15.3c [5] for 60 GHz, mmWave communication is rapidly gaining popularity for applications such as cellular backhaul and wireless High-Definition Multimedia Interface (HDMI) [6]. The expected usage of mmWave in indoor environments triggers an obvious question about the possibility of concurrent communication and localization.

Unfortunately, there is very limited knowledge about leveraging the communication features of mmWave systems for localization purposes. This paper, to the best of our knowledge, is the first attempt to use lessons learned from localization using legacy Radio Frequency (RF)-based communication infrastructure for localization in the mmWave frequencies. Considering expected propagation features and different assumptions about the characteristics of mmWave communication, we discuss a set of feasible approaches for localization in mmWave, specifically 60 GHz. By means of simulation, we derive the assessment of expected accuracies for a number of realistic scenarios. The results demonstrate a strong potential for mmWave as a localization service with decimeter level accuracy and high availability, even in scenarios with a low density of static nodes available for localization purposes.

II. Related Work

The popularity of mmWave for general purpose communication started increasing recently, with new standards (IEEE 802.11ad and IEEE 802.15.3c) and products appearing for these standards [7], [8]. Despite this rise in popularity, the problem of localization, to the best of our knowledge, has only been sparsely addressed in the literature. One early mmWave-based localization approach is the mTrack [9], which uses Received Signal Strength (RSS) and signal's phase as features for localizing and tracking an object. The authors experimentally demonstrate an encouraging 90-percentile error below 8 mm for a fine-grained pen tracking in a small office scenario. The authors in [10] exploit changes in statistics of a sparse beam-space channel matrix in relation to a mobile node's location for localization in mmWave-based MIMO systems not requiring LoS connectivity.

We believe that a great deal of knowledge accumulated in classical RF-based indoor localization, as described e.g. in [11], can be used also in the mmWave context. Signal features used in RF-based localization can roughly be categorized into Angle of Arrival (AoA), Time of Flight (ToF), and RSS [12]. Based on signal features' processing methods, RF-based localization approaches can be classified as proximity, scene analysis (fingerprinting), and geometry-based [11]. Proximity-based approaches estimate proximity of a Mobile Node (MN) to a static Anchor Point (AP). Scene analysis-based approaches estimate the location of a MN by comparing signal features sampled by the MN with the presurveyed set of signal features from different locations in an environment of interest. Finally, geometry-based approaches use geometrical dependencies (distances or angles) between an MNs and APs for location estimation. Proximity-based approaches are envisioned for providing semantic or space-granular localization. Thus, they are frequently used to complement more global, but less precise localization systems. Scene analysis-based approaches assume a high level of stability in an environment with respect to the preobserved signal features. Stability is a hard requirement for directional communication in mmWave, assuming that one of the enabling mechanisms will be dynamic beam-search [3]. We believe that geometry-based approaches are the most promising for supporting mmWave localization, with reasons being discussed in the following section.

III. System Assumptions

Borrowing the classification from [13], in Table I we summarize the raw resolution of different physical layers prominently used for localization. The raw resolution is defined as the speed of light divided by the available bandwidth. For Ultra-Wideband (UWB), where in practice signals are sampled at rates of up to 500 MHz, the achieved raw resolution, or the distance that a signal passes during the 2 ms sampling period is roughly 60 cm. At least 5 GHz of spectrum is unlicensed and available almost everywhere in the world in the mmWave frequencies around 60 GHz. Taking into account the 60 GHz channel bandwidth of 2.16 GHz, as defined in the IEEE 802.11ad, this is substantially larger than the UWB channel bandwidth, yielding the achievable raw resolution of roughly 15 cm, which demonstrates a potential for high accuracy in mmWave-based localization.

TABLE I: Popular physical layers used in localization [13].

Physical layer	Bandwidth	Raw resolution
IEEE 802.11a/g	20 MHz	15 m
IEEE 802.11n	40 MHz	7.5 m
IEEE 802.11ac	<160 MHz	>1.9 m
UWB	>500 MHz	<0.6 m
IEEE 802.11ad	**>2 GHz**	**<15 cm**

Let us assume that certain types of mmWave transceivers will employ directional transmission and reception signaling because directionality is a promising approach in evading high signal attenuation characteristics in mmWave frequencies [14]. Under this assumption, Angle of Departure (AoD) and AoA are signal features that can be extracted from directionally transmitted and received signals. Furthermore, directional communication intrinsically reduces the probability of interference [15]. It has been shown that interference can degrade the performance of localization solutions [16], especially for RSS-based approaches. Therefore, for RSS-based localization, the reduced probability of interference in mmWave can be considered as a benefit for localization. The previous discussion indicates the availability of different signal features in mmWave, i.e. RSS, ToF, and AoA. These signal features are extensively used for localization in lower RF bands. Their availability and promising characteristics suggest good performance for mmWave-based localization.

IV. mmWave-based Localization Service

In our communication system model, we assume an environment with a set of static mmWave-based access points with known locations (referred to as Anchor Points (APs)) and a mmWave Mobile Node (MN) with an unknown location, where both APs and MN adopt directional signal transmission and reception. The MN can communicate with any available and reachable APs using Line-of-Sight (LoS) or Non-Line-of-Sight (NLoS). One such scenario is depicted in Figure 1. In the figure, the MN can establish LoS connectivity with two APs (AP_2, AP_4). Furthermore, the MN can establish NLoS only connectivity to the AP_3 (1^{st} order reflection) because LoS path is obstructed by an obstacle. Finally, the MN can establish both the LoS and NLoS connectivity to the AP_1.

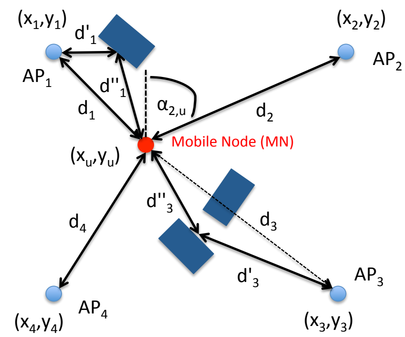

Figure. 1: Assumed communication model

In the case of LoS connectivity, the MN can evaluate the RSS from each of the visible APs, and, from this, can estimate the distance $d_{RSS,n}$ between the MN and the n-th AP. Here we consider only the unobstructed LoS communication links between the MN and an AP. We further assume free space-like attenuation of mmWave signals. We do not account for oxygen absorption in mmWave, because of its minor role in attenuation for the environment sizes of interest, as reported in [17]. The relation between RSS and distance d_{RSS} in the LoS is given by:

$$d_{RSS} = \sqrt{\frac{P_{Tx}}{RSS} \cdot \frac{\lambda^2}{\omega_T \phi_T \omega_R \phi_R}} \tag{1}$$

In the equation, P_{Tx} and λ denote transmit power in *Watts* and signal wavelength in *meters*. Furthermore, (ω_T,ϕ_T) and (ω_R, ϕ_R) denote azimuth and elevation beam-widths at the AP and at the MN, respectively. The relation between ToF and distance d_{ToF} that a signal propagated between an AP and the MN (both in the LoS and in the NLoS) can be estimated by Equation 2, c being the speed of light.

$$d_{ToF} = c \cdot ToF \tag{2}$$

Due to the use of exclusively directional communication, node discovery and consequently beam-searching mechanisms are necessary nontrivial tasks to be performed [3]. We assume the simplest beam-searching mechanism, i.e. the exhaustive search, which is based on finding optimal Signal to Noise Ratio (SNR) between an AP and a MN by probing in all directions of the MN and the AP. The beam-searching procedure can serve for obtaining RSS, ToF and AoA features for various beam directions at both transmitting and receiving side.

A. mmWave-based Localization in LoS Conditions

Given that a MN can establish LoS connectivity to each visible AP and the locations of APs are known to the MN, the MN's location can be estimated. In this case, a feasible localization approach is the standard and well-known trilateration-based method [18]. This approach requires as input the estimates of distances between the MN and each AP. These distances can be estimated using the RSS signal feature, as given in Equation 1. Similarly, if Time of Flight between the MN and each APs is available to the MN, respective distances between the MN and APs can be estimated using Equation 2. If Angle of Arrival signal features from each AP are known to the MN, the MN's unknown location can be estimated using a standard triangulation approach [18].

To estimate a MN's location in a 2D space, all mentioned approaches require at least 3 APs. From the system design perspective, the main benefit of RSS trilateration is that it practically comes with no additional cost because the RSS signal feature is easily obtainable. ToF trilateration requires that a MN is pairwise synchronized with every AP and they all have a common notion of time. AoA-based triangulation requires that a MN is aware of the direction of its transmission, requiring support for extraction of this information. Clearly, locations of APs must be available to the MN for all schema, and therefore a means of reporting locations is required and needs to be incorporated in the design of mmWave devices.

The described localization approaches require LoS connectivity between the MN and each AP. Multiple algorithms exist for distinguishing between LoS and NLoS connectivity conditions, mostly designed in the context of UWB localization [19]. Similar principles can be applied to mmWave-based localization. Determination of LoS connectivity can be based on RSS and ToF, where the distances estimated using RSS and ToF signal features can be compared, and if the absolute difference is below a certain threshold, the nodes are assumed to have LoS connectivity. Since a combination of different measurements is necessary for distinguishing the LoS vs. NLoS connectivity, these measurements can additionally be used for enhancing the localization accuracy. In that sense, it is feasible to combine RSS and ToF either in a Kalman/Particle filter based solution or by averaging the location coordinates obtained by individual processing of each of the different signal features. Furthermore, determination of LoS connectivity can be based on AoA and AoD, where if their absolute difference is equal to 180° (accounting for error), the nodes are assumed to have LoS [20]. In this case, AoD is a necessary metric to be available to the MN, meaning that knowledge of global direction must be included in the design of mmWave devices for supporting such localization approaches.

B. mmWave-based Localization in NLoS Conditions

The previous discussion was based on leveraging LoS connectivity between a MN and APs for localization. However, mmWave links can also be established in NLoS, as depicted in Figure 1. In that case, the location of a MN can still be estimated using at least two NLoS paths, as described in [20]. This approach requires that AoD, AoA and ToF signal features are available to the MN. Furthermore, these signal features must be obtained from signals that have reflected exactly once on their paths between an AP and the MN. The benefit of this approach is that only one AP with its two 1st order reflected signals and respective signal features are required for determining the MN's location. This means that, even in scenarios with NLoS and a relatively small density of APs, the MN's location can be determined. However, this approach requires that AoD be reported to a MN, and therefore knowledge of global directivity is a necessity. Due to the necessity of ToF, pairwise synchronization and knowledge of the global time are also required. Since this approach requires AoD, AoA and ToF, where all of them introduce some level of inaccuracy, and it relies on 1st order reflected paths only, which by itself introduces inaccuracies, a trade-off exist between the reduced number of APs needed for localization and the localization accuracy of this approach.

For estimation of the MN's location, the previously described approach requires that a signal reflects exactly once in its path between an AP and the MN. Algorithms for distinguishing between 1st and higher order reflections are needed for enabling this approach. Such algorithms can be based on the combination of RSS and ToF in a similar way as for the LoS vs. NLoS connectivity, assuming a high attenuation of a reflection in the mmWave frequencies as shown in [3].

C. Combined LoS/NLoS mmWave-based Localization

As a result of performing beam-search, a set of features can be obtained for various paths between a MN and an AP, both in LoS and in NLoS conditions, increasing the number of signal features available for localization. Thus, all obtained signal features (RSS, ToF, AoA in both LoS and NLoS connectivity conditions) can be leveraged for enhancing both accuracy and availability of a mmWave-based localization service. Again, the combination of location estimates obtained using different signal features can be based either on a Kalman/Particle filter based localization solution or by simple averaging of the individual location estimate coordinates. In this scenario, discernment between LoS and NLoS connectivity, as well as between 1st and higher order reflections, is necessary.

A benefit of having all localization computation performed by an MN, which is supported by the previously described approaches, is intrinsic privacy, as the estimated location information is available only to the MN [21]. By contrast, so-called two-way approaches usually enhance the accuracy of localization, trading it off with reduced privacy and increased latency [21]. Namely, RSS, ToF, and AoA observations between a MN and each AP can be made more accurate by measuring them both at the MN and at the AP. The rough protocol would include transmitting a signal from the AP to a MN, which yields a set of RSS, ToF, and/or AoA measurements; transmitting a signal from the MN back to the AP yields another set of measurements; and are then reported back to the MN. Note that in this case so-called two-way ToF can be estimated as follows. First, a signal is transmitted by the MN/AP, and the time to be measured is started. Upon reception of that signal, the AP/MN transmits back a signal containing the estimate of the time passed between the reception of the original signal and transmission of the new signal. Upon the following reception, MN/AP can estimate the two-way ToF by subtracting the time that passed between the reception of the original signal and transmission of a new signal from the total time that passed after the transmission of the original signal. Clearly, in this case, pairwise synchronization between nodes and knowledge of the global time is not a requirement for the mmWave devices.

V. Localization Accuracy Conjecture

In our evaluation, we modeled a square space, where in each of its corners a mmWave AP is positioned. For the NLoS and combined LoS/NLoS evaluation, random obstacles were placed as well. The location of the MN is randomly selected and, using the MN's location and the location of each AP, distances and angles to all APs are calculated. Using the calculated distances, RSS and ToF signal features are obtained using Equations 1 and 2, respectively, while the calculated angles are used as AoA features. Further, variabilities are added to the RSS, ToF, and AoA features, where the variabilities are drawn from Gaussian distributions $\mathcal{N}(0, \sigma_{RSS/ToF/AoA})$. Using the parameters with added variability as inputs, the set of previously discussed localization algorithms is applied in order to estimate the MN's location. In the next step, the localization errors are obtained by calculating the Euclidean distance between the estimated and true locations of the MN. The same procedure is repeated 10000 times, each time for a randomly selected MN location. Modeling variabilities of the used signal features with a Gaussian distribution has been extensively used in the literature. Some examples include [22] for RSS, [23] for ToF, and [24] for AoA signal feature.

The environment size varies in our simulation from 10x10 to 100x100 m^2 and represents a range of likely sizes of many indoor environments. A transmit power of 10 mW has been selected to comply with the worldwide regulations for unlicensed maximum transmit power [25]. The operating frequency is 60 GHz because it is available unlicensed worldwide. For the variabilities of used signal features, we define an "optimistic" and "pessimistic" scenario. For the variability of RSS, we selected σ_{RSS} of 0.3 and 0.8 dBm respectively for the optimistic and pessimistic scenario. Larger RSS variabilities have been reported for omni-directional communication in the lower ISM bands (e.g. [26]). Smaller variabilities are used because we believe that due to directionality, there is less interference, and interference is one of the main causes for RSS variability in the lower ISM bands, as reported e.g. in [27]. However, as it will be demonstrated below, even such optimistic selections of the RSS variabilities yield high localization errors. The variability of ToF feature σ_{ToF} is selected to be 1 and 2 ns for the optimistic and pessimistic scenario, respectively. Due to a large available bandwidth in mmWave, a tight pair-wise synchronization between nodes can be achieved, where the limiting factors are related to the carrier frequency of mmWave devices. For example, in UWB systems the reported synchronization is on the level of hundreds of picoseconds [28], thus even our optimistic scenario is fairly modest. Finally, the AoA variability has been selected based on the results provided in [24]. The setup in [24] consist of an 8-element antenna array, and their reported results include AoA variabilities (σ_{AoA}) of roughly 0.1 and 1.5° for 1 and 4 incident signals, respectively. In our evaluation, we assumed LoS connectivity and two to three 1st order reflections, as will be explained below. AoA variabilities are selected, therefore, to be 0.75 and 1.5° for the optimistic and pessimistic scenarios.

A. Evaluation Results

In the first step of our evaluation, we simulated a set of scenarios in which the MN can establish LoS connectivity to each AP. For such conditions, we derived RSS, ToF and AoA signal features and introduced variabilities to each of them. We used these perturbed features as inputs to a set of localization approaches discussed previously in the context of LoS-based localization in the mmWave. In Figure 2, the achieved localization errors are presented in a regular box-plot fashion for a set of approaches along different variabilities of the used signal features and along different environment sizes.

The figure shows that, for all depicted scenarios, RSS only achieved localization errors comparable or higher than the errors achieved by other approaches. This is despite the relatively small expected variability of RSS features assumed due to the directional communication reducing the probability of interference. The achieved errors for the RSS-based trilateration increase rapidly with the increase in the size of an environment. For example, in our optimistic scenario, the obtained average localization error is roughly 0.3 m for a 10x10 m^2 space, in contrast to more than a 2.5 m error average for a 100x100 m^2 space. The reason for such behavior is the logarithmic dependence between RSS and distance (Equation 1). When the size of an environment increases, the observed RSS values are generally reduced (due to a larger propagation distance that signals propagate), thus even small variabilities in RSS result in large errors in estimated distances, and therefore in high localization errors. If ToF-based trilateration is used, smaller localization errors are generally observed. Due to a linear dependence between ToF and distance, as defined by Equation 2, localization errors for this approach do not scale with the size of an environment, as shown in Figure 2. For all environment sizes, the average localization errors achieved by this approach are roughly 0.3 and 0.6 m for the optimistic and pessimistic scenario, respectively. These errors demonstrate that ToF-based trilateration is scalable in mmWave, in terms of its localization accuracy. However, since it requires a pairwise synchronization between the MN and each AP, which is a task that *per-se* yields a signaling overhead, this approach is expected to be less scalable in terms of the number of APs used for localization purposes. In other words, this approach is expected to have a higher latency of producing location estimates, in comparison of the RSS or AoA-based approaches. Finally, the AoA-based

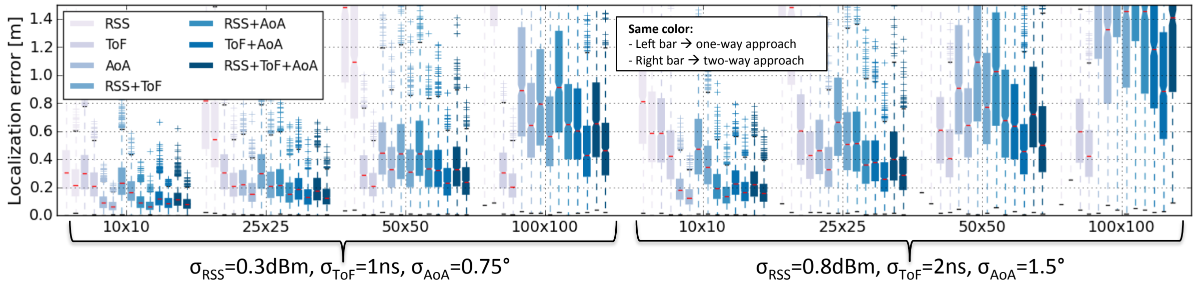

Figure. 2: Expected localization errors for combinations of signal metrics used for LoS-based localization

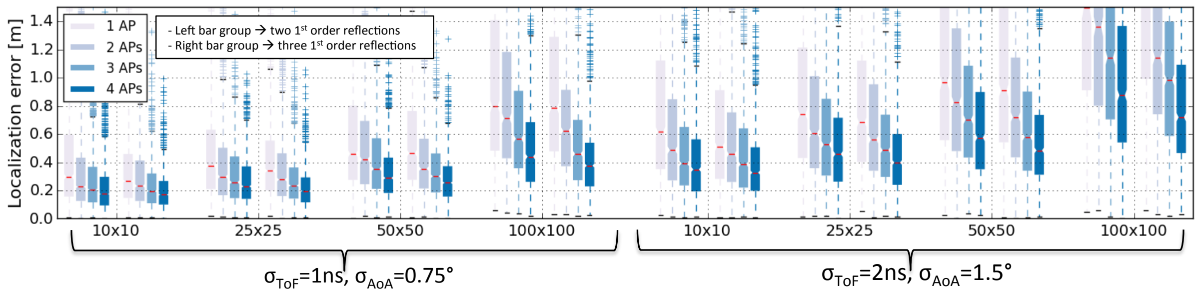

Figure. 3: Expected localization errors for NLoS-based localization

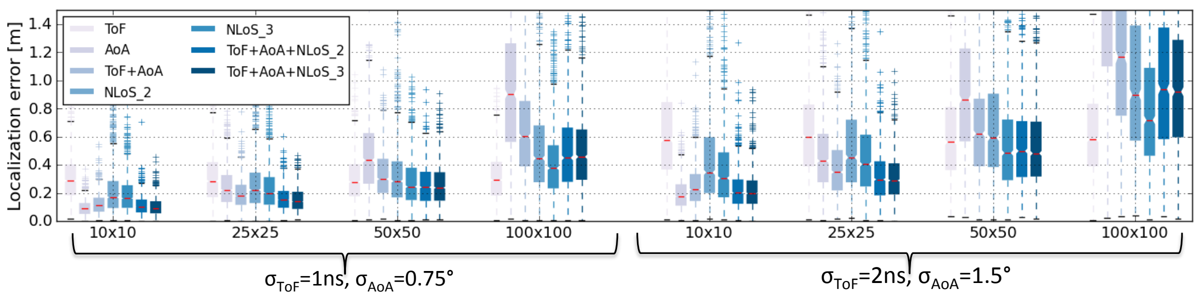

Figure. 4: Expected localization errors for combined LoS and NLoS-based localization

triangulation is shown to be a highly accurate localization approach, especially for smaller environments of interest (e.g. average localization errors of 0.1 and 0.2 m for a 10x10 m^2 space for the optimistic and pessimistic scenario, respectively). In this case, however, errors linearly increase with the increase in size of an environment, as shown in Figure 2. For all three cases, the results show that the two-way approaches are beneficial in enhancing the localization accuracy. The errors of the two-way approaches are the ones depicted on the right hand side of groups of box-plots of the same color.

Assuming that multiple signal features are available, their combination can be leveraged for improving the localization accuracy. In this work, we apply simple averaging of location estimates produced using different signal features, although more complex and presumably more accurate algorithms can be used (e.g. Kalman/Particle filters). In Figure 2, the localization errors for a set of such scenarios are also depicted. As shown in the figure, RSS in combination with any other signal feature does not significantly improve the accuracy of the final location estimation. For the larger size spaces, usage of RSS signal feature actually degrades the localization accuracy substantially because of the logarithmic dependence between RSS and distance. The combination of ToF and AoA signal features results in a more accurate estimation, in comparison to the errors achieved by leveraging each of these features separately. This improvement, however, also depends on an environment size and on the expected variability of the used signal features. Perhaps contrary to what is intuitively expected, for the larger sizes, leveraging only ToF yields optimal localization accuracy because of the scalability of ToF-based trilateration. As previously, two-way approaches are generally beneficial for improving the localization accuracy, roughly resulting in a 30% reduction in average errors, compared to the results achieved by corresponding one-way approaches.

In the second step of the evaluation, we simulated a communication scenario in which only NLoS connectivity exists between the MN and all APs. In this scenario, the MN location can be estimated using the previously discussed approach for NLoS-based localization, assuming that each signal was reflected exactly once between an AP to the MN. The results for this scenario are depicted in Figure 3 for different environment sizes and for a set of ToF and AoA variabilities. We selected two and three as the number of 1^{st} order reflected paths that each signal has in its propagation from an AP to the MN (the achieved localization errors for two and three 1^{st} order reflected paths are depicted on the left and right hand side box-plot groups, respectively, for different environment sizes). The intuition for such selection is taken from the IEEE 802.11ad conference room propagation model [29]. In this model, depending on the location of an AP, generally two or three 1st order reflected signals from that AP are observed. Although the selected numbers are just a rough estimate, these numbers still gives a valuable insight into the expected accuracy of the mmWave NLoS-based localization. Presumably, more than 2–3 such components will exist in most targeted environments, which will generally benefit the localization accuracy. As is visible in Figure 3, location estimates can be obtained even when only two 1st order reflections from one AP are available (or one 1st order reflection from two APs). Even in such cases, the estimates are accurate and improve as the number of 1st order reflections and the number of APs increase. For example, the average localization errors across different environment sizes are improved by roughly 40% when the number of used APs increases from 1 to 4.

Finally, as a result of beam-searching, different signal features from one or multiple APs will be available in practice. For the final step of our evaluation, we assumed both the LoS and NLoS connectivity. As shown in Figure 4, the combination of ToF and AoA signal features obtained in both LoS and NLoS connectivity conditions benefits the accuracy of localization for some environment sizes of interest. For example, in the optimistic scenario of the 25x25 m^2 environment with one LoS connection and three 1st order reflections, the combination of ToF and AoA reduces the average localization errors by 30% and 50% compared to leveraging only LoS-based AoA and ToA, respectively. These improvements, however, again depend on the environment size. For larger sizes, leveraging only LoS-based ToF signal features yield optimal localization accuracy. Finally, the increase in the number of 1st order reflected signals provides a small benefit for the localization accuracy across all evaluation scenarios.

VI. Conclusion

In this work, we discussed a set of potential approaches for localization in mmWave. We demonstrated generally poor performance of a RSS-based only trilateration approach, which is a result of the logarithmic dependence between RSS and distance. Promising localization accuracies have been derived for AoA triangulation and specifically for ToF trilateration, assuming LoS connectivity between the MN and all APs. A combination of ToF and AoA signal features can yield an even better accuracy in certain scenarios. Furthermore, the inclusion of the 1st order reflected signals, more specifically their respective ToF and AoA signal features, greatly improves the availability of a localization service and can also be beneficial for improving the localization accuracy. However, environment size and expected variability of signal features have to be taken into account for achieving the optimal performance. Two-way approaches additionally increase the localization accuracy. For smaller environment sizes of interest, the combination of LoS and 1st order reflections and the usage of ToF and AoA as signal features is a promising approach for localization in mmWave, yielding decimeter level accuracy and high availability of a mmWave localization service. As the size of an environment increases, the LoS-based ToF feature shows good promise for achieving the optimal performance of a mmWave-based localization service, while the combination of ToF and AoA in both LoS and NLoS can be used in cases when the requirement for the number of static nodes is not met, i.e. to increase the availability of a service. Future work will be towards implementing and experimentally evaluating a mmWave-based localization service, taking into account the inferences derived in this work.

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