Mm-wave Initial Access: A Context Information Overview

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***Abstract*—The attractive features of millimeter-wave (mm-wave) technologies in the forthcoming 5G networks entail a rich set of network access challenges. These technologies are characterized by high-gain array antennas to overcome the huge attenuations, this requires to resort to directional transmissions during every network operation. The initial access phase is one of the most critical, because, if not properly managed, it can introduce a non-negligible access delay caused by multiple transmission attempts along several directions.**

We believe that contextual information about user and network conditions can boost this discovery phase. In this paper, we investigate how differently-rich context information can impact on the duration of the initial cell access. We propose several initial access procedures that can exploit different available information and cope with the presence of obstacles within the service area. Finally, relying on the contextual information on past access attempts, we develop a recommendation system based on machine-learning techniques, which, by processing this information, can derive the best directions to explore to connect incoming users.

I. Introduction

The spectrum crunch problem in conventional sub-6GHz communication bands is a common issue among almost every network operator. Nowadays data-hungry applications like virtual reality or high-definition video streaming are becoming more and more popular, creating a huge pressure on conventional communication bands to accommodate the expected huge traffic growth of the next decade. As the spectral efficiency of these bands has approached the Shannon capacity, efforts to push mobile radio communications to millimeter-wave (mm-wave) bands are generating remarkable momentum [1]: they offer the opportunity to leverage the vast amount of unused bandwidth in mm-wave spectrum to provide a potential venue for radio access communications.

Mm-wave technologies have several remarkable advantages with respect to conventional microwave ones, which led them to be considered a promising solution to 5G systems and beyond. They exhibit: i) a huge available bandwidth (several hundreds of MHz) that provides multi-Gbps rates, ii) miniaturized array antennas with a large number of elements due to the short wavelengths, iii) narrow beams and flexible antenna configurations, which enable spatially dense network layouts by reducing co-channel interference.

Although offering many attractive features, mm-waves are characterized by strong signal attenuations and huge penetration losses, which are the main challenges to be addressed to fully harvest their potential. As a result, mm-wave radio access communication is typically implemented in the form of dense layouts of small cells, usually with a radius of no more than a couple hundred meters. In addition, the mm-wave channel is vulnerable to the blockage of obstacles, as the short wavelength makes it difficult for the signal to penetrate through or get around obstacles. Therefore, an LOS blockage could easily translate into a 30 dB loss [2].

As a consequence of mm-wave propagation impairments, the deployment of a single-layer of base stations (BSs) using mm-wave technology is not practical, as continuous coverage and service cannot be guaranteed [3], especially in urban environments. In order to overcome this issue, the current network operating at lower frequencies has to be maintained. Therefore, the emerging Heterogeneous Network (HetNet) paradigm becomes the ideal candidate for the deployment of such networks. Moreover, the different capabilities of HetNet devices naturally leads towards a functional split between the user (U-) plane and the control (C-) plane, which allows to guarantee an ubiquitous signaling connectivity through large cells operating at lower frequencies with conventional BSs, while mm-wave cells can provide an on-demand multi-Gbps service for data transmissions. As a result, such an architecture is now widespread among several 5G projects[1], papers [4], [5], as well as 5G PPP Architecture White Paper revisions[2].

Although enabling a clear revolution of wireless access experience, the functional split in heterogeneous network architectures introduces additional challenges with respect to conventional cellular networks. Indeed, the functional separation abstracts the resource management, which increases the complexity of resource allocation mechanisms: the best servicing BS must be identified, the perceived user Quality of Experience (QoE) after a BS activation must be estimated, etc.

Even the basic task of establishing a link between user equipment (UE) and BS demands an additional effort in the mm-wave domain: the directional nature of mm-wave communications requires the transmitter and the receiver to be spatially aligned. This is fundamentally different from what assumed in omni-directional transmissions used to broadcast cell discovery information in conventional cellular networks. Therefore, a novel initial access procedure must be carried out. It typically consists in an angular scan at both transmitter and

[1]As an example, please consider5G METIS II (http://metis-ii.5g-ppp.eu/), 5GCROSSHAUL (http://5g-crosshaul.eu/) and 5G-NORMA (https://5g-ppp.eu/5g-norma/)

[2]See https://5g-ppp.eu/white-papers/

receiver side, sweeping through all possible antenna directions until the two sides beam each other. However, advancements in antenna technologies provides a large antenna reconfigurability, with many possible directions and narrow beams to reach longer distances. This translates into long-lasting initial access phases, leading to large delays that harmfully impact on handover procedures and user QoE. In the recent years, this issue has stimulated a fairly high number of works on finding smart solutions to the initial access in mm-wave networks [6]–[8], which have addressed the same problem under different denominations: initial cell access, directional cell discovery, initial beam alignment, etc[3].

A promising solution to this inefficient use of mm-wave resources comes from the availability of contextual information, such as user profiles, user positions, application quality requirements, expected QoE, network status, and traffic prediction. Richer user-context information is essential to properly operate network devices and design initial access procedures that approach the best possible performance. In addition, the broad and reliable coverage of the separated C-plane perfectly matches this need by providing a natural way of conveying contextual information from UEs to the network.

Only few works in literature consider the availability of such information to guide the beam steering towards the directions with highest success probabilities. Nevertheless, a wide range of information richness has been explored. It spans from one extreme [9], which uses only UE location information to drive the weights-vector selection in device equipped with analog beam-forming systems, to the other extreme [10], which assumes the availability of all propagation characteristics in the environment surrounding each mm-wave BS in order to apply a simplified ray-tracing model that identifies the best beam pointing angles.

A type of contextual information which provides a remarkable access speedup is the history of past access attempts. In [11], this information is used to identify the beams that led to the highest number successful accesses in the past, so that they can be reused as first candidates in future discoveries. Work in [12] describes a multi-BS scenario, in which UE location information is used to guide beam steering, whereas past attempts are used to select the best mm-wave BS in charge of providing access to the user. Finally, work in [13] relies on power levels, received after a fast preliminary angular sweep, to estimate beam pointing angles and populate a geo-located database, where deviations with respect to LOS are stored.

A couple of works use ToA/DoA contextual information to help the initial beam alignment relying on the assumption, which may not be always true in outdoor scenarios [14], that a sufficient power level can be received even if no beam-forming is applied. In [15], a UE-BS beaconing system is designed to allow the BS receiver to estimate ToA/AoA and use this information to set the best beam-width and identify UE location for fast beaming. To remove this assumption, the preliminary work in [16] introduces a BS-UE reciprocal sector sweep to estimate devices' relative location and rotation.

[3]In the paper we indifferently refer to these terms as considered equivalent.

A. Our Approach

In this paper, we extend our previous works [17], [18] by investigating a framework for mm-wave initial access relying on contextual information which considers several advanced features. First, we assume smart directional cell discovery algorithms can be applied to both BS and UE devices. Second, different context types and accuracy can be available in real implementations, therefore we show how these information combinations can be exploited and which gains can be achieved when richer and more precise information can be made available. Moreover, we demonstrate that the presence of obstacles in the service area radically changes the initial access behavior, which in turn reflects on the selection of the best cell discovery approach.

Finally, we believe that information on the past access attempts can remarkably boost the performance of initial access procedures. In this perspective, we have designed a Machine Learning approach based on Neural Networks that can process this information to learn the best beam candidates to apply when new users require to access the network. We show how this method can fully exploit the potential of the network experience providing a valuable help when it is indeed necessary.

To the best of our knowledge, this is the first attempt to investigate the impact of differently-rich contextual information on the mm-wave initial access, including the disruptive effect of obstacles and the possibility of running smart discovery algorithms not only at BS side, but also on UE side. Moreover, the development of a recommendation system based on machine learning that processes the knowledge on past connection attempts is an additional novel contribution completing the proposed framework.

The rest of the paper is organized as follows. In Sec. II, we introduce the initial cell access problem in the mm-wave access scenario. We discuss the introduction of user location information in discovery algorithms in Sec. III, where we describe possible approaches and achievable performance. In Sec. IV, we extend the analysis to the case in which information about the location error is available as well, while in Sec. V we describe the recommendation systems based on past connection attempts' information. Finally, Sec. VI concludes the paper.

II. Mm-wave Initial Access with Contextual Information

Mm-wave devices are expected to support dual connectivity: a legacy wireless interface connected to a low-frequency macro-cell layer in charge of providing C-plane and U-plane for conventional data-rate exchanges and a mm-wave interface implementing a U-plane for multi-Gbps services, as shown in Fig. 1.

The initial access to a mm-wave network follows a connection request issued by the user via the C-plane and a UE-BS assignment determined by the network management. Once reciprocally informed, the UE and the candidate BS start to scan different beam directions until they reach a configuration

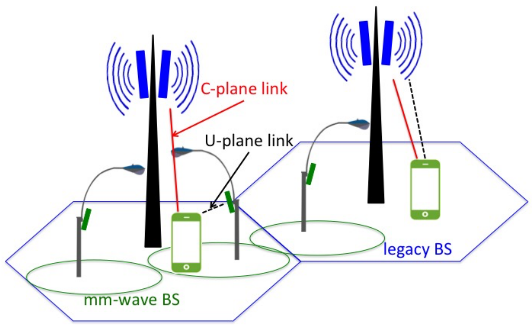


Figure 1: Dual-connectivity scenario in which C-/U-plane connections are shown.

in which they point each other and the link can be established. After this discovery phase, UE and BS can synchronize and perform association procedures.

As advanced antenna technologies allow to have many configuration alternatives [3], thus, the complete exploration of all beam combinations at both BS and UE side is a choice that would require too many attempts before finding a good setup. However, the smart selection of the best beam candidates is characterized by a fundamental trade-off: large beam-widths allow to explore the space surrounding the BS in a smaller number of switches, but only closer UEs can be connected. On the contrary, narrow beams do increase the range but require more beaming attempts on average to find a good alignment.

Information about the context in which the connection request is issued can remarkably speed up the beam alignment process. Ideally, if every aspect would be known (e.g., user position and orientation, antenna capabilities, propagation characteristics of the whole environment, etc.), an algorithm could easily select a pair of beams that allow the link establishment. However, in light of the current technical capabilities, such a result appear to be too ambitious. What contextual information can be reasonably expected to provide is a way to indicate a, preferable small, set of potential beam candidates and a success probability for each of them.

One of the most powerful and widely applied contextual information is location information. Indeed, it allows to easily identify where devices' antennas should point to beam each other and how far each beam has to cover, although its potential benefits can be severely limited by several factors.

Location error can severely harm the potential of location information by deviating beams from the right direction. Note that the intrinsic approximation of the propagation model used to estimate the channel attenuation[4] between UE and BS can be seen as an equivalent UE location error, therefore we do not cover such an approximation in the rest of the paper. An even more critical error is the angular rotation error of the user reference system. While BSs are fixed and their orientation

[4]We assume a fixed transmission power, following current trends in deploying cellular networks. However, our approaches could be easily extended to include power control schemes.

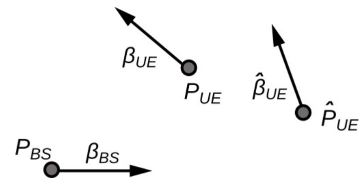


Figure 2: Location information.

can be determined during the deployment, user orientation can only be estimated. On top of location error, a rotation of the UE can lead its antenna array to focus towards wrong directions. Nevertheless, location and orientation accuracy can be estimated and this information can be used by advanced initial access procedures to narrow down the set of possible beam candidates. As we show in Sec. IV, it greatly mitigates the effect of these errors. Fig. 2 shows the overall context view provided to the network by UE's location and orientation information. P_{BS} is the point where the BS is located, while β_{BS} is its orientation angle. The exact UE location and its exact orientation angle are respectively represented by P_{UE} and β_{UE}. Similarly, UE location and orientation declared to the network are represented by $\hat{P}_{UE}$ and $\hat{\beta}_{UE}$, which are unavoidably affected by an error depending on positioning system and mobile sensors accuracy.

A further context aspect to be taken into account is the information on devices' antenna capabilities. It is a key information to estimate which beams can be used to establish the potential link described by the location information. Assuming the BS antenna radiation patterns known, as a consequence of the network deployment phase, each user has ideally to send to the network the precise radiation diagram for each of the available antenna configurations: beam-width and pointing directions. Since it may be not always possible or generate excessive overhead and exact propagation conditions and antenna patterns cannot be determined a priori, we rely on a simplified description in which each UE sends the set of available main-lobe widths (beam-widths) and a constant antenna gain for the whole lobe, thus, the network can only make an ideal representation of the beam pattern and its coverage.

The presence of obstacles is another factor that impacts on the benefits of the location information. Indeed, as described in Sec.I, almost every object is opaque and causes path obstruction. This means that an obstacle blocking the LOS reduces the importance of knowing UE locations, as a deviation is needed to turn around the obstacle. Luckily enough, obstacles can be an opportunity as well. Indeed, mm-wave propagation has a quasi-optical behavior [19] [20]: flat surfaces act like mirrors, making beam reflection a viable alternative. Moreover, NLOS paths are characterized by a non-negligible received power [20].

In order to fully exploit the potential of path reflections, the network needs to learn which reflection is more effective at different locations of the service area. This knowledge can be built on the basis of the past access attempts. Considering the location of successful attempts and their spatial correlation resulting from the complex interaction of environment geometry, antenna patterns, and device capabilities, the most promising beam candidates are identified. To this extent, we have implemented a beam recommendation system based on a Probabilistic Neural Network able to capture this interaction, which, learning from the access history, can provide the most promising beam candidates for a quick link establishment in every point of the service area.

III. Location Information for Initial Access

During the initial access phase, different antenna configurations are iteratively probed by UE and BS until a minimum level of received power allowing a link establishment is found. The sequences of explored antenna configurations followed by UE and BS are fundamental to determine the performance of the mm-wave initial access phase. Several approaches with different complexity can be adopted to design these sequences according to the type of available context information.

We consider as a basic approach the *Sector Level Sweep (SLS)* procedure implemented in the Beam Training phase of IEEE 802.11ad (WiGig) protocol. During SLS procedure, the narrowest beam-width selectable by a device is activated and a circular scan among all possible pointing directions is performed, starting from a random one. This procedure is very simple and does not exploit any contextual information. However, it may lead to extremely long-lasting discovery periods.

Thanks to location information, a first improvement can be introduced to speed up the initial access phase by selecting a suitable beam-width, according to the estimated UE-BS distance. This approach, named *initial Beam-Width Selection* (iBWS), leverages the possibility of a dynamic beam-width configuration provided by current mm-wave antenna technologies. The iBWS procedure processes the UEs location and selects the best combination of beam-widths at both BS and UE side in order to adapt the beam-width according to BS-UE distance, thus minimizing the number of pointing directions to be explored.

Since the overall antenna gain is a combination of the antenna gains at both link sides, different iBWS strategies can be followed:

- Wide BS - Narrow UE (wBS-nUE): selecting the largest beam-width at BS side;
- Narrow BS - Wide UE (nBS-wUE): selecting the largest beam-width at UE side;
- Balanced: selecting the beam-width combination with the minimum difference at BS and UE side.

Each proposed iBWS procedure only provides the initial beam-width at UE and BS, with no other constraint on the design of the beam sequence used to scan the surrounding area. Therefore, once the UE's location is known in terms of both position and orientation, BS and UE can estimate the best reciprocal pointing directions accordingly. Hence, after iBWS procedure, we can further exploit location information.

We propose two different approaches to perform the discovery procedure. The first approach is called *Alternate Direction discovery* (ADd), ADd is a straightforward extension of SLS algorithm: once iBWS selects the proper beam-width ω for UE and BS, a set of beam pointing directions is defined, $\Omega = n\omega$ with $n = 1, ..., \frac{2\pi}{\omega}$, at both devices. Each device evaluates the angular difference between every beam pointing directions and the estimated direction toward the other device. Then, beams are sorted by increasing angular difference to define the beam sequence for the discovery. The area surrounding the devices is scanned according to that sequence. Thanks to the C-/U-plane split, we can assume a loose synchronization among UE and BS. Therefore, the access proceeds as follows: the BS activates a beam according to BS's sequence and keeps it fixed while the UE performs a complete exploration of UE's sequence. At each UE switch, the BS emits a beacon. Then, BS can move to the next beam in the sequence and the UE repeats its sequence. The process stops if a beacon is correctly received at UE, in this case, the discovery process is successful. Or, if all possible BS-UE antenna configurations have been probed and no synchronization has been acquired, the UE is declared unreachable.

The rationale behind ADd algorithm is to focus the discovery around LOS while reducing the cardinality of antenna beams to be probed, as a consequence ADd can strongly speed up the discovery process with respect to SLS-like algorithms. Nevertheless, since ADd and iBWS consider a fixed beam-width that it is not necessarily the narrowest, they may reduce the probability of ending up with a successful discovery in case obstacle blockages and/or inaccurate location information are present.

The second algorithm we consider is named *Alternate Direction discovery with Variable beam-width* (ADdV). ADdV derives from the ADd algorithm previously described by adding the possibility to dynamically select beam-widths during the discovery: considering the beam-width selected by iBWS, ADdV scans all the surrounding area as ADd. If no connection is established, ADdV reduces the beam-width and iteratively scans the area with a larger set of pointing directions. Hence, allowing devices to increase their antenna gain, ADdV can recover from the situations in which the selection made by iBWS procedure cannot guarantee the BS-UE communication.

In the next sections, we analyze the performance of the aforementioned algorithms.

A. Simulation Playground

The performance of the proposed algorithms is assessed by means of numerical simulations carried out by an ad-hoc MATLAB®simulator. We consider the following scenario. One mm-wave BS is placed in the middle of a 450x350m area surrounded by (reflecting) walls, a different number of squared 20x20m size obstacles are randomly placed depending on the scenario, while 2000 UEs are randomly dropped according to a uniform distribution within the area; UEs orientation is randomly chosen.

The user-location uncertainty is modeled by considering the nominal UE position as a symmetric bivariate normal distribution centered in the real UE position with parameter $\rho_x = \rho_y = \rho$. We consider a location error $\epsilon_l = 3\sigma$. As for the orientation uncertainty, we assume that he BS's orientation is perfectly known, while UE orientation error is

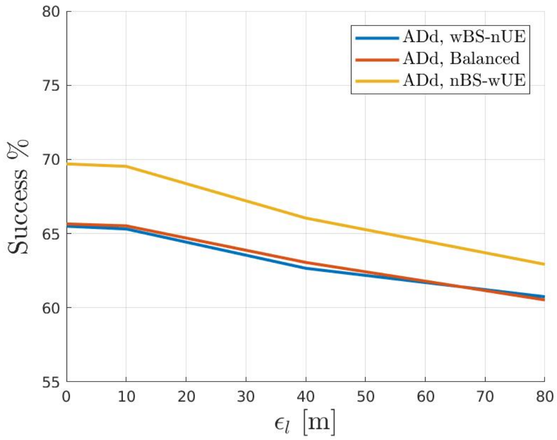
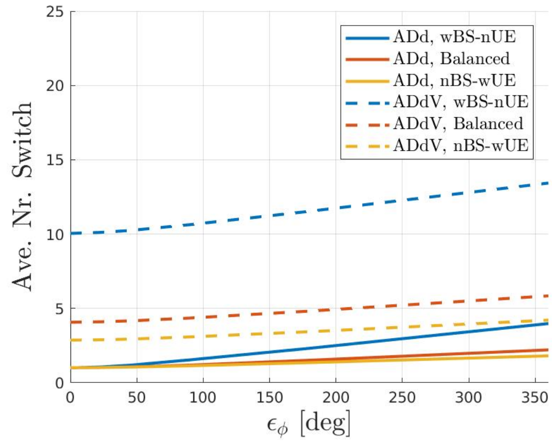
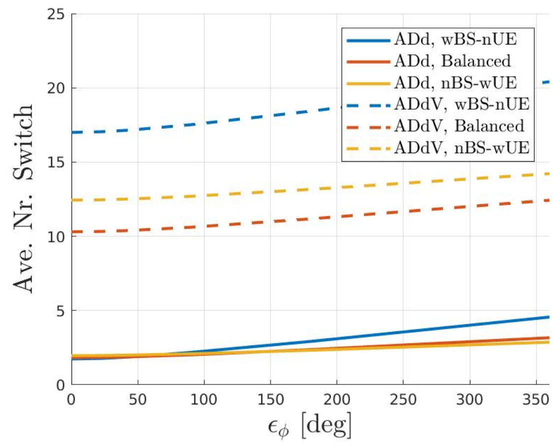


Figure 3: iBWS success rate. No Obstacles.



(a) $\sigma_l = 10m$



(b) $\sigma_l = 80m$

Figure 4: Algorithm performance comparison. No Obstacles.

modeled considering the estimated (nominal) UE orientation as a uniformly distributed random variable with average value corresponding to the real UE orientation and variance equal to $\sigma_\phi^2/3$. We consider an orientation error $\epsilon_\phi = 2\sigma_\phi$.

We adopt Gaussian antenna model, path loss, and reflection model as those described in [21]. In order to reduce the complexity of discovery algorithms, the antenna model considered for their execution is simplified. It is used to identify whether a beam can cover a given point, and thus, can be activated. The algorithms consider a beam radiation pattern with a constant gain within the main beam, which is equal to the average gain of the main lobe of the antenna pattern model in [21]. No side lobes are assumed. We considered only first order reflections in our simulations. The minimum signal level for synchronization acquisition is set to $T_h = 73dBm$, which ensures an SNR greater than $10dB$, [6]. The BS transmitting power is set to $P_t = 30dBm$.

The smallest configurable beam-width at BS side is 3 degrees, which means the availability of 120 equally-spaced beam pointing directions. By proportionally reducing the number of pointing directions to 72, 36, 24, 12, 8, 4, 3, and 1, wider beams are obtained, for a total number of 280 antenna configurations available at BS side. As for MT side, we consider a more limited hardware, thus a reduced set of pointing directions. Namely, 12, 8, 4, 3, and 1 possible equally-spaced beams.

Each outcome is the result over 10 simulation instances, thus 20000 UE access requests.

B. Performance Comparison

We compare now the performance of the described discovery algorithms, with different levels of location information accuracy and different iBWS approaches. As performance metrics, we measure the initial access duration and the achievable coverage. The former is evaluated in terms of antenna configuration switches at UE side (summing over rounds after BS switches), while the latter is evaluated in terms of successfully initial access. We analyze first the performance of different iBWS strategies and discovery algorithms in an obstacle-free scenario, wherein the only aspect affecting cell discovery performance is the context information accuracy.

Fig. 3 shows the iBWS success rate when ADd algorithm is applied. iBWS is considered successful if, given the selected BS and UE beam-widths, UE and BS can successfully set up a connection without changing the beam-width. In other words, if the overall gain provided by the selected antenna configurations can support the link establishment.

Results show that iBWS success rate is maximum when UE is perfectly located, while decreases as the location accuracy ϵ_l decreases. This behavior is due to the quality of the estimated BS-UE distance, which is inversely proportional to ϵ_l. Indeed, if the location declared by the UE is closer to the BS than the real one, the probability of selecting beam-widths that cannot cover the real UE-BS distance increases. Another important aspect to be noticed is that iBWS success rate is limited to 70% because of the simplification introduced in the contextual information on antenna capabilities described in Sec. II. In the following, however, we show that with more advanced discovery algorithms this performance figure can be remarkably improved. Finally, the figure shows that the nBS-wUE approach has a slightly better success rate, about

5%. Also this behavior comes from the simplification of the antenna capabilities' description sent by the user. Indeed, since nBS-wUE maximizes the gain at BS, less directional patterns will be selected at UE. This makes the approximated antenna pattern closer to the real one.

Fig. 4 shows the average initial access duration of ADd and ADdS algorithms with different levels of location error ϵ_l and orientation error ϵ_ϕ. The same discovery algorithm is implemented at both BS and UE side. We can see from the results that in general, discovery duration increases as ϵ_m and ϵ_ϕ, thus, it is proportional to information quality, and that ADd algorithm is in general faster than ADdV, this is due to the difference in the number of beam configurations probed by the two algorithms. However, although the beam-width adaptation mechanism of ADdV increases the search duration, it augments the probability of a successful discovery. Indeed, our simulations have shown a 100% success rate.

Another interesting behavior emerging from these results concerns the effect of iBWS strategies on the algorithms' performance. Fig. 4 shows that pushing the gain to the UE side (wBS-nUE strategy) is detrimental. We can explain this behavior by means of the different sensitivity to location and orientation error experienced by BS and UE. At the BS side, pointing direction is estimated according to BS location, BS orientation, and UE nominal position. So, only UE location error can affect the BS discovery algorithm. Differently, at UE side, the beam is selected according to BS location, UE nominal position and UE orientation, therefore, it is affected by the combined effect of UE location and orientation errors, making the decision at UE side less effective. As for Balanced and nBS-wUE approaches, their different performance depends on location error σ_l. When σ_l is high, in Fig. 4b, the Balanced approach has a better performance, as a reduced directivity at both sides decreases the sensitivity to UE location error. Vice versa, with small UE location errors as in Fig. 4a, the nBS-wUE approach allows to reduce the number of beams the UE needs to scan between each BS switch in order to explore the surrounding environment. This proves to be more effective in determining the initial access duration.

Finally, we measure the algorithms' performance in case of obstacles. Fig. 5 shows the comparison between ADd and ADdV performance in a scenario wherein obstacles are present. We fix the iBWS strategy to nBS-wUE, however, similar observations can be made with the Balanced approach, which we do not show due to space limitations. We can see that the ADd discovery duration is similar to the one experienced in the obstacle-free scenario, while the presence of obstacles strongly affects the ADdV performance. Obstacles have a twofold effect: i) they reduce the achievable coverage ii) some UEs with obstructed LOS are still reachable through reflected paths. This is captured by the results, indeed, the ADd discovery duration is short because the initial access is successful mainly for UEs in good positions, i.e., with free LOS. This is confirmed by the success rate that does not go beyond 56% in simulations. Vice-versa, ADdV duration is much higher than in the obstacle-free scenario, as the

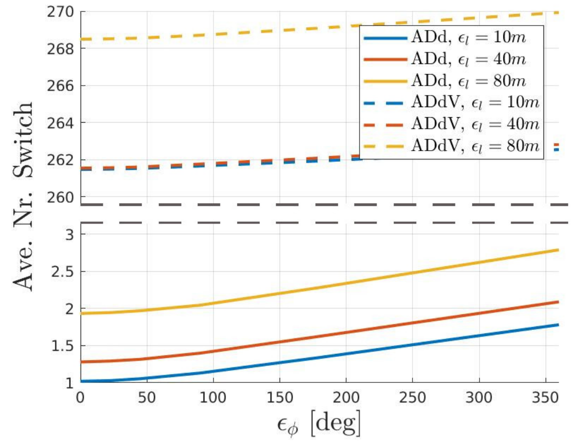


Figure 5: Algorithm performance comparison. 10 Obstacles. nBS-wUE iBWA strategy.

obstacles force the search to explore beams far from LOS that eventually provide connectivity through reflected paths. Indeed, ADdV can reach 88% of the users, which is the maximum achievable within the considered instances. These badly positioned users contribute to remarkably increase the average discovery duration.

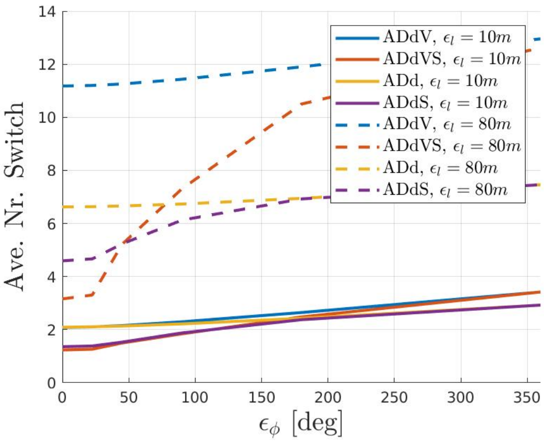
The presence of obstacles exacerbates the trade-off between success rate and performance discussed in the obstacle-free scenario. This leads to make ADd and ADdV hardly applicable with obstacles, therefore more context is needed for the initial access, which can be exploited by the algorithms we present in the following sections.

IV. Information accuracy to enrich the context

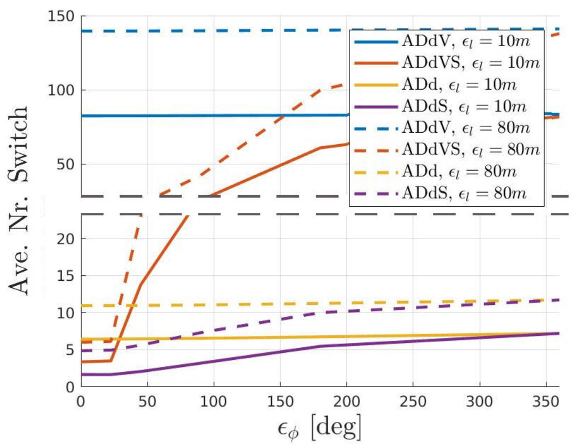
In this section, we assume richer context information available by considering the possibility to collect UE position and orientation together with their accuracy ϵ_l and ϵ_{phi}. Discovery algorithms presented in Sec. III are modified so that to exploit this new information.

BS and UE can take advantage of the information about location and orientation error in different ways. Assuming perfect knowledge of the BS position and orientation, while BS beam selection can be affected only by UE location error, the beam selected at UE side depends on both UE position and UE orientation errors. Between the two, UE orientation error is the one that can have the larger impact on the initial access, as radically changing UE's reference system. This is reflected in the type of algorithms must by designed for the two sides.

At UE side, the orientation angle accuracy allows defining an angular sector S_ϕ wherein the direction towards the BS is most likely to be. Accordingly, the UE can focus the discovery within S_ϕ and avoid the activation of unsuccessful beams. Thus, the UE can reduce the number of beam attempts, thus reducing the discovery duration. This improvement can be applied to both ADd and at ADdV algorithms, which becomes respectively *Alternate Direction discovery within a Sector* (ADdS), and *Alternate Direction discovery Variable beam-width within a Sector* (ADdVS).



(a) No Obstacles.



(b) 10 Obstacles.

Figure 6: Algorithm performance comparison. ADdVS+ at BS side. nBS-wUE iBWA strategy.

At BS side, a more sophisticated approach can be applied, given the negligible impact of UE orientation error and the availability of more powerful computational resources. As an extension of ADdV, we propose a new discovery algorithm named *Alternate Direction discovery within a Sector - Extended* (ADdVS+), which leverages this information as follows. The UE position accuracy allows to define an angular sector wherein UE is expected to be located. This sector points towards the UE position and extends in such a way the circle defining the UE position error is included within the two radii defining the sector. The area surrounding the BS is divided in several of these sectors and each sector is explored according to the ADdVS approach. If the first sector is scanned without a success, all adjacent sectors are alternately (clockwise and counter-clockwise) explored.

A. Performance Comparison

We compare now the performance of the algorithms described above in the same playground as that described in Sec. III-A. Numerical results are shown in Fig. 6 and are obtained by activating ADdVS+ at BS side and several different algorithms at UE side. In absence of obstacles (Fig. 6a), we can note that ADdS and ADdVS algorithms, thanks to the richer context information, are effective in speeding up the initial access duration by the reducing the search space respectively of ADd and ADdV. As the orientation accuracy decreases, the search space increases, hence ADdS and ASdVS performance gets closer to those of ADd and ADdVS. In terms of success rate, this search space reduction comes at the cost of a negligible success rate decreasing: it is always 100% for ADdVS and above 99% for ADdS.

In case of obstacles (Fig. 6b), the performance trend of Fig. 6a is confirmed. However, a small reduction in the success rate appears: for ADdS, the rate ranges from 78% to 80%, while it ranges from 79% to 88% for ADdVS. This is due to the limitation induced by the reduced search space on the possibility of exploiting reflections in case the LOS is blocked. Nevertheless, if we remove the search space reduction at UE side by activating ADdV, is still possible to benefits from the location accuracy availability by activating ADdVS+ at BS side, which is able to remarkably reduce the initial access duration with respect ADdV in case of obstacles (dashed curves in Fig. 5), without scarify the success rate.

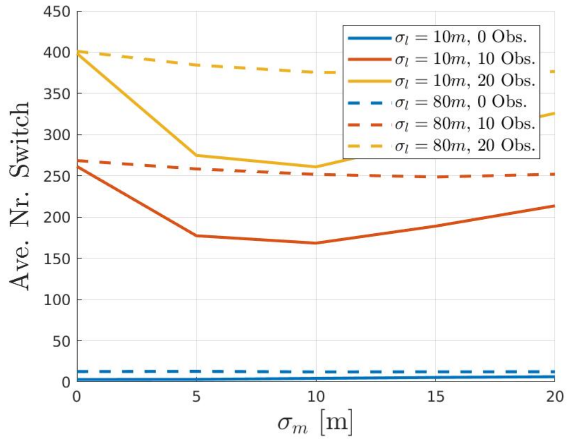
V. Machine learning for past access attempts

The results in the previous sections have clearly shown that there is a remarkable gap in the initial access duration with and without obstacles in the service area. This gap is mainly due to the behavior of the location-based discovery algorithms, which first explore beams around LOS. This becomes no longer the best choice when obstacles force to resort to reflections for establishing a connection.

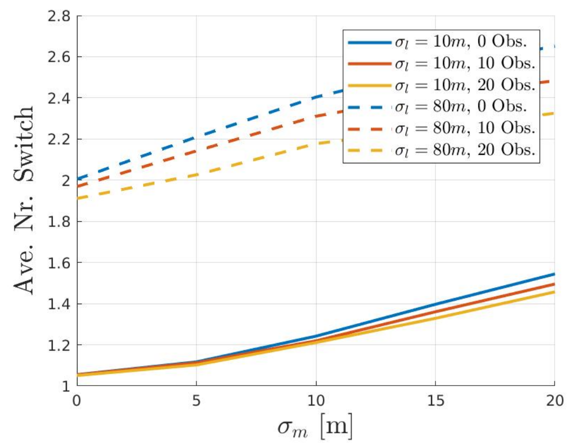
In order to overcome this limitation, we propose a machine learning approach which allows the network to learn online the best way to perform the beam search based on the network experience. In our approach, the network is provided width a geo-located database, which allows, once the UE is connected, to track the successful beam as $\hat{p}_{UE}, w, d$ tuples, where nominal UEs position $\hat{p}_{UE}$ is linked to beam parameters beam-width w and pointing direction d only at BS side. This database is updated in real-time after every access. Based on this database, we can design a smart recommendation system that takes advantage of past attempts to speed up the new access requests, by proposing the most promising discovery beams.

We perform this task by using a Probabilistic Neural Network (PNN) model. PNNs are feed-forward neural networks commonly used in classification and pattern recognition problems. In a PNN the classification function is constructed from the training set of classified data points, which in our case corresponds to the database records. Each data point p belongs to a class, which is identified by parameters w and d, and corresponds to a Pattern Unit (PU), which consists in a radial basis function $f(r)$ with the peak centered on the parameters location $\hat{P_{UE}}$ of p. In our implementation the following radial basis function is applied:

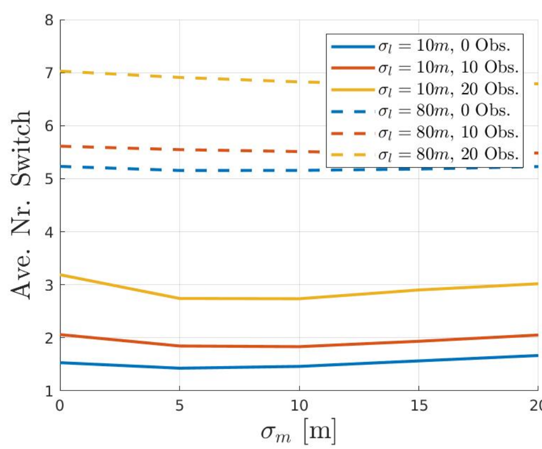
$$f(r) = exp\left(-\frac{r^2}{2\sigma_m^2}\right) \quad (1)$$



(a) ADdV at UE and at BS.



(b) ADd at UE and at BS.



(c) ADdS at UE and ADdVS+ at BS.

Figure 7: PNN performances. $\alpha = 0.2$. $\sigma_\phi = 45[deg]$.

wherein σ_m^2 defines the width of bell-shaped function $f(r)$. PUs of the same class (i.e., corresponding to point with the same w and d) are summed together to create a category unit (CU) of that class. PNN does not require a training phase, therefore new PUs (i.e., data points) can be added at any time to the data-point set. Given an input point, corresponding the new user's coordinates, the value associated to each PU is computed by considering the distance r between the user's coordinates and PU center. The classification process is based on the output of the CUs, which corresponds to a score assigned to each class (i.e. beam configuration). In our implementation, BS selects only beam configurations characterized by a CU score above a given threshold α. These configurations are sorted according to their score in descending order and then sequentially activated in the BS initial access sequence. If the UE is not detected, the BS activates one of the proposed discovery algorithms, without repeating antenna configurations already tested.

Two aspects must be be noted. i) When σ_m is set to 0, the PUs output is 0 as well, hence, the initial access is driven only by the discovery algorithm, while, as σ_m increases, the relevance of the network experience in the initial access increases accordingly. ii) A small value of σ_m leads to a classification mostly driven by the PUs closer to the input point, while, a large value of σ_m leads to a consensus-driven initial access, as the most successful class in the input's neighborhood will likely have the largest score.

A. *Performance comparison.*

We evaluate the performance of the recommendation system by varying PNN parameters σ_m and α in different scenarios with a different number of obstacles, and different values of σ_l and σ_ϕ. Again, the simulation playground is the same as the one described in Sec. III-A.Simulation results are shown in Fig. 7, due to the space limitation, only results with threshold $\alpha = 0.2$ are shown. Different values of α do not significantly change the following comments.

Starting from Fig. 7a, which shows the results obtained by applying ADdV at both BS and UE side and varying the PNN parameter σ_m, we can see that the machine learning mechanism has a remarkable effectiveness when obstacles are present in the area, therefore exploiting the network experience is a good method to manage reflections and reduce the discovery time. However, it is important to note that the advantages of this system depend on the level of UE position accuracy. Indeed, if the database is populated with records associating beam parameters to UE's nominal positions completed uncorrelated with real ones, the recommendation system will process unreliable data, making the PNN decision not reliable as well. This behavior depends on the value of σ_m, which allows to modify the width of the PU function Eq. 1, and whose impact clearly emerges from the curves with small position error. They show a minimum, which is the result of a trade-off between two aspects. Small σ_m values lead to a high score only for the PUs very close to the input UE's position, consequently, a small number of CUs will trigger a beam suggestion, so the network experience is underutilized. Vice-versa, large σ_m values lead to a high score for a large set of PUs, hence a large number of CUs, thus beams, will be activated. However, this introduces in the recommendation even those records that are poorly correlated with the current UE's position, thus resulting in a waste of unsuccessful beam discovery attempts.

Focusing now on the comparison between Fig. 7a and Fig. 7b, wherein ADdV and ADd are respectively applied both at UE and BS, we can note two very different behaviors. On the one hand, when ADdV is implemented, the learning mechanism is able to reduce the cell discovery duration in scenarios with obstacles. On the other hand, when ADd is implemented, the learning mechanism leads to a slightly worse performance. This behavior is caused by the different type of successfully user accesses between ADd and ADdV. When ADd is used, successful user accesses are achieved only for UEs in LOS condition, reflections are very rarely used. This implies that records in the database store the information to reach only LOS users, but it is useless information as LOS users can be directly beamed without the need of an advanced mechanism, like PNN. Even worse, the recommendation system will be used to reach NLOS users as well, but due to the LOS information fed into the PNN, it will typically provide inefficient beam suggestions, thus a worse performance.

On the contrary, when ADdV is used, connections are established even if LOS is not available, thus useful information to overcome obstacles is introduced in the database that, once processed by the PNN, allows the recommendation system to provide successful beam indications. This behavior is confirmed even when more advanced discovery algorithms are implemented. Results shown in Fig. 7c refer to the case in which ADdS and ADdVS+ are implemented at UE and BS, respectively. The benefit of the recommendation system is between the two extremes described for Fig. 7a and Fig. 7b, this is in line with the behavior of the considered discovery algorithms, which intermediate between ADdV and ADd.

VI. Conclusion

We have thoroughly investigated how contextual information can impact on the performance of discovery algorithms during the initial access phase of mm-wave access networks. We believe that such information is essential to provide user connectivity in a number of beam switches that can meet the stringent delay requirements of forthcoming 5G networks.

We have proposed several fast initial access procedures that can exploit information about the context of different type and accuracy. This allowed us to show how this information is crucial to guarantee a fast link establishment. In addition, we have evaluated the impact of obstacles on the discovery procedures. It has a disruptive effect that requires smart solutions relying on richer contextual information. To this extent, we have introduced a recommendation system based on machine learning techniques able to infer the best access strategy from past connection attempts.

References

[1] T. S. Rappaport, R. W. Heath Jr, R. C. Daniels, and J. N. Murdock, *Millimeter wave wireless communications*. Pearson Education, 2014.

[2] S. Collonge, G. Zaharia, and G. E. Zein, "Influence of the human activity on wide-band characteristics of the 60 ghz indoor radio channel," *IEEE Transactions on Wireless Communications*, vol. 3, no. 6, pp. 2396–2406, 2004.

[3] R. J. Weiler, M. Peter, W. Keusgen, E. Calvanese-Strinati, A. De Domenico, I. Filippini, A. Capone, I. Siaud, A.-M. Ulmer-Moll, A. Maltsev *et al.*, "Enabling 5g backhaul and access with millimeter-waves," in *Networks and Communications (EuCNC), 2014 European Conference on*. IEEE, 2014, pp. 1–5.

[4] R. J. Weiler, W. Keusgen, I. Filippini, and A. Capone, "Split control plane functionality in millimeter-wave overlay access," in *5G for Ubiquitous Connectivity (5GU), 2014 1st International Conference on*. IEEE, 2014, pp. 134–139.

[5] T. E. Bogale and L. B. Le, "Massive mimo and mmwave for 5g wireless hetnet: Potential benefits and challenges," *IEEE Vehicular Technology Magazine*, vol. 11, no. 1, pp. 64–75, 2016.

[6] C. N. Barati, S. A. Hosseini, S. Rangan, P. Liu, T. Korakis, S. S. Panwar, and T. S. Rappaport, "Directional cell discovery in millimeter wave cellular networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 12, pp. 6664–6678, 2015.

[7] M. Giordani, M. Mezzavilla, and M. Zorzi, "Initial access in 5g mmwave cellular networks," *IEEE Communications Magazine*, vol. 54, no. 11, pp. 40–47, 2016.

[8] Y. Li, J. G. Andrews, F. Baccelli, T. D. Novlan, and C. J. Zhang, "Design and analysis of initial access in millimeter wave cellular networks," *IEEE Transactions on Wireless Communications*, vol. 16, no. 10, pp. 6409–6425, 2017.

[9] W. B. Abbas and M. Zorzi, "Context information based initial cell search for millimeter wave 5g cellular networks," in *Networks and Communications (EuCNC), 2016 European Conference on*. IEEE, 2016, pp. 111–116.

[10] J. C. Aviles and A. Kouki, "Exploiting site-specific propagation characteristics in directional search at 28 ghz," *IEEE Access*, vol. 4, pp. 3894–3906, 2016.

[11] R. Parada and M. Zorzi, "Cell discovery based on historical user's location in mmwave 5g," in *European Wireless 2017; 23th European Wireless Conference; Proceedings of*. VDE, 2017, pp. 1–6.

[12] R. E. Rezagah, H. Shimodaira, G. K. Tran, K. Sakaguchi, and S. Nanba, "Cell discovery in 5g hetnets using location-based cell selection," in *Standards for Communications and Networking (CSCN), 2015 IEEE Conference on*. IEEE, 2015, pp. 137–142.

[13] J. C. Aviles and A. Kouki, "Position-aided mm-wave beam training under nlos conditions," *IEEE Access*, vol. 4, pp. 8703–8714, 2016.

[14] Q. C. Li, H. Niu, G. Wu, and R. Q. Hu, "Anchor-booster based heterogeneous networks with mmwave capable booster cells," in *Globecom Workshops (GC Wkshps), 2013 IEEE*. IEEE, 2013, pp. 93–98.

[15] E. Park, Y. Choi, and Y. Han, "Location-based initial access and beam adaptation for millimeter wave systems," in *Wireless Communications and Networking Conference (WCNC), 2017 IEEE*. IEEE, 2017, pp. 1–6.

[16] G. E. Garcia, G. Seco-Granados, E. Karipidis, and H. Wymeersch, "Transmitter beam selection in millimeter-wave mimo with in-band position-aiding," *arXiv preprint arXiv:1705.05668*, 2017.

[17] F. Devoti, I. Filippini, and A. Capone, "Facing the millimeter-wave cell discovery challenge in 5g networks with context-awareness," *IEEE Access*, vol. 4, pp. 8019–8034, 2016.

[18] I. Filippini, V. Sciancalepore, F. Devoti, and A. Capone, "Fast cell discovery in mm-wave 5g networks with context information," *IEEE Transactions on Mobile Computing*, vol. PP, no. 99, pp. 1–1, 2017.

[19] M. R. Akdeniz, Y. Liu, M. K. Samimi, S. Sun, S. Rangan, T. S. Rappaport, and E. Erkip, "Millimeter wave channel modeling and cellular capacity evaluation," *IEEE journal on selected areas in communications*, vol. 32, no. 6, pp. 1164–1179, 2014.

[20] R. J. Weiler, W. Keusgen, A. Maltsev, T. Kühne, A. Pudeyev, L. Xian, J. Kim, and M. Peter, "Millimeter-wave outdoor access shadowing mitigation using beamforming arrays," in *Antennas and Propagation (EuCAP), 2016 10th European Conference on*. IEEE, 2016, pp. 1–5.

[21] P. Deliverable, "Fp7-ict-608637 miweba project deliverable d5.1 - channel modeling and characterization, june 2014," *[Online]. Available: http://www.miweba.eu/wp-content/uploads/2014/07/MiWEBA D5.1 v1.01.pdf*, 2014.