Machine Learning-based Context Aware Sequential Initial Access in 5G mmWave Systems

Conference Paper · December 2019

2 authors:

Rida Zia-ul-Mustafa
National University of Sciences and Technology

Syed Ali Hassan
National University of Sciences & Technology

Machine Learning-based Context Aware Sequential Initial Access in 5G mmWave Systems

Rida Zia-ul-Mustafa and Syed Ali Hassan
School of Electrical Engineering & Computer Science (SEECS),
National University of Sciences & Technology (NUST), Islamabad, Pakistan
{rmustafa.msee17seecs, ali.hassan}@seecs.edu.pk

***Abstract*—The wide bandwidth available at the millimeter wave (mmWave) frequencies is expected to offer high data rates in the fifth generation (5G) of cellular mobile communication systems. The technology implements directional transmission to overcome increased free-space path loss at high frequencies. The dependence on directionality imposes challenges to establish new control layer protocols because the algorithms implemented in conventional omnidirectional long term evolution (LTE) systems are not suitable for these networks. The mmWave base station (BS) and user equipment (UE) need to be properly aligned for directional communication constituting long-lasting *initial access* (IA) phase. Recently, several research works have been done to devise smart initial access procedures for mmWave systems. Some of these schemes periodically sweep across the cell area to establish the connection while others resort to making use of the available contextual information regarding BS and UE profiles and propagation environment to establish the link. This paper proposes a smart machine learning-based context-aware sequential algorithm for IA in 5G mmWave systems and analyzes its performance in comparison to the conventional exhaustive and iterative search algorithms. The algorithm is shown to provide a comparatively low probability of misdetection and a smaller discovery delay.**

***Index Terms*—5G technologies, mmWave Systems, Initial Access (IA), Context Awareness, Machine Learning**

I. Introduction

The advent of the Internet has uplifted the standard of living, reforming this world as a Global Village. With the passage of time, a soaring increase in the Internet population has been seen due to the emergence of smart devices and the fact that the basic routine and work tasks are, now, strongly dependent and associated with the Internet. The ongoing subscribers growth also imposes crucial limitations on the performance of traditional microwave (μWave) systems in terms of providing low latency for real-time communications as well as to support high throughput for applications including ultra-high definition video streaming or virtual reality. The current sub-6 GHz band for conventional mobile cellular networks is heavily crunched and has also nearly approached the Shannon limit thus, inducing the interest of researchers to push the radio spectrum up to the 30-300 GHz mmWave frequency band for 5G communication systems [1].

The widely available and unutilized bandwidth in the mmWave spectrum is potentially expected to cater for the high data rate requirements of 5G access networks. Additionally, small wavelengths at mmWave frequencies enable to build miniaturized antenna arrays with abundant antenna elements, thereby, offering extra gains through spatial multiplexing and isolation. Moreover, mmWaves provide narrow beamwidths to allow antenna configurations that reduce the co-channel interference to provide spatial efficiency. Alongside several benefits, the mmWave frequency band imposes significant challenges in the way to exploit its potential features. High carrier frequency resulting in short wavelength makes mmWave signal susceptible to get around and penetrate through the blockage of solid obstacles causing severe signal attenuation [2]. Higher mmWave carrier frequencies also offer higher path loss as compared to that of traditional lower frequency communication systems thus compelling to deploy dense spatial layouts of mmWave systems with small cell radius and high gain directional transmissions for compensation.

The demanding propagation impairments in mmWave channel suggest to uphold the existing μWave communication network in order to ensure persistent service and coverage [3], thus paving the way for the heterogeneous network (HetNet) model in which wide connectivity will be provided by the conventional μWave BS and mmWave BS will offer the on-demand service to the UE. Also, the diverse HetNet devices propose a functional split between the control (C-) plane and user (U-) plane to deal with the signaling information and data transmission, respectively.

Furthermore, the mmWave BS and UE must be spatially aligned in order to carry out the directional transmission of signals even during the preliminary task of Initial Access (IA), the process of establishing a physical link between the BS and UE to transfer the data. Thus, the IA process of conventional LTE networks is not suitable for the mmWave systems because in LTE, initially the pilot signal is broadcasted on the omnidirectional channel. Implementing the IA process of LTE in mmWave systems will cause the range mismatch problem, i.e., difference between the range covered by directional data transfer and omnidirectional cell search [4]. The mentioned perspective urges to discover new cell search schemes for IA in mmWave communication systems.

A tremendous amount of work is being carried out to develop efficient mmWave IA strategies, focused on improving the probability of misdetection (PMD) caused due to blockage and deafness, i.e., the beams of UE and the mmWave BS do not direct towards each other in the IA phase, and discovery delay (DD) due to long-lasting directional sweep across the cell area to detect the UE [5]. This research is also dedicated to designing a smart IA algorithm for 5G mmWave communication systems and the imminent sections are organized in a way that Section II provides an insight into the eminent 5G mmWave IA schemes, Section III develops the conceptual and mathematical foundations to our proposed algorithm, Section IV details the simulation environment and performance analysis of the devised algorithm in relation to the conventional mmWave cell search strategies and Section V concludes the study listing future motivation too.

II. Related Work

Researchers are working on devising suitable strategies for the IA phase in 5G mmWave systems. The main focus of research studies is on reducing the discovery delay, imposed due to the long duration of directional cell search, alongside providing the minimum probability of misdetection. In this scenario, the work done so far can be categorized into two major groups, i.e., sequential cell search and context-aware (CA) cell search schemes. The key works related to these categories are detailed in the following subsections.

A. *Sequential Cell Search*

Sequential cell search schemes, as the name suggests, refer to the strategies that sequentially span the 360° cell area through directional beamforming. One of the preliminary sequential cell search procedures is the *exhaustive search* in which both the mmWave BS and UE have predefined beam directions to periodically scan across the cell area [6]. In [7], iterative cell search scheme is analyzed in which mmWave BS firstly spans the large sectors of cell area with wide beamwidth and then sequentially narrow down the beamwidth within the sector most probable to have UE.

Comparative analysis of both schemes reveals that the exhaustive search offers the lower probability of misdetection with narrow beamwidth and high gain to provide connectivity to a larger range of cell area with longer search duration whereas iterative search is capable of providing much lower discovery delay on the expense of high probability of misdetection [8]. Hence, a hybrid search algorithm is proposed in [9] that firstly performs iterative search on broad cell sectors with wide beamwidths to reduce discovery delay as compared to that of exhaustive search, and if the UE is not connected then algorithm starts implementing the exhaustive search within the last sector to provide a lower probability of misdetection than that of iterative search.

B. *CA Cell Search*

CA cell search schemes are expected to exploit the available contextual information regarding the BS and UE location profiles, network quality requirements and the propagation environment, to establish the connection. The concept of designing mmWave IA algorithms utilizing contextual information is quite new in literature but various studies have been conducted that suggest to implement the algorithms that make use of BS and UE position information [10], environmental characteristics [11], past access attempts [12], power levels received after initial scan [13] and time of arrival (ToA)/angle of arrival (AoA) information to propose a pair of best possible beamwidth and search direction to form the connection [13]. Recently, the trending domain of ML is also being deployed alongside CA algorithms to impose significant performance improvements as compared to that of conventional algorithms [14].

In this work, a mmWave IA algorithm is developed which makes use of the strengths of ML and context awareness alongside sequential cell search, providing the lowest discovery delay and the probability of misdetection as compared to that of exhaustive and iterative search schemes. The proposed ML-based CA sequential algorithm firstly obtains contextual information in terms of UE and BS geo-locations, exploits ML using a probabilistic neural network (PNN) to suggest the best possible beamwidth to establish the connection, keeping in view the UE mobility. Finally it sequentially searches the cell area to and forth the given location, to a certain limit to establish the connection.

III. Proposed Algorithm

The proposed ML-based CA sequential algorithm aims to incorporate the strengths of artificial intelligence with the availability of contextual information, which, in our case, is the location information of BS and UE, in devising a suitable beamwidth to establish the connection. Consider an environment with the presence of both stationary and mobile UEs, making requests for connection with the mmWave BS. Also, the system is GPS coordinated in order to extract the respective locations of UE and BSs. The global positioning system (GPS) coordinates initially gathered are referred as the estimated coordinates because UE could potentially has deviated from its original position. Conventional algorithms, i.e., exhaustive and iterative searches, do not concern for the scenarios of mobile UE whereas the proposed algorithm has the ability to deal with such cases by utilizing the ML model. Moreover, we are assuming a software defined networking scenario, i.e., a centralized C-plane is responsible for transferring signaling information and a U-plane is designated to handle the data transmission. Additionally, a HetNet environment is considered such that we have a μWave BS and several associated mmWave BSs.

Holistically the suggested process of IA works as follows. Firstly, the UE initiates a connection request via C-plane and network determines an appropriate mmWave BS for that particular UE keeping minimum distance as a parameter. Afterward, the μWave BS transfers the GPS coordinates of linked mmWave BS to the associated UE and the UE directs its beam towards the linked mmWave BS. Meanwhile, as the linked mmWave BS is aware of the UE coordinates, it determines the optimal beamwidth according to the proposed scheme, described in the sequel, to establish a successful connection. The setup pocess is shown in Fig. 1. For ease of analysis, we are examining the process of IA only on the BS side.

mmWave BS obtains and feeds the estimated GPS coordinates of UE to the input layer of the ML model, which is a probabilistic neural network (PNN), as shown in Fig. 2. PNN is a feed-forward neural network, generally utilized in classification and pattern recognition scenarios. PNN architecture

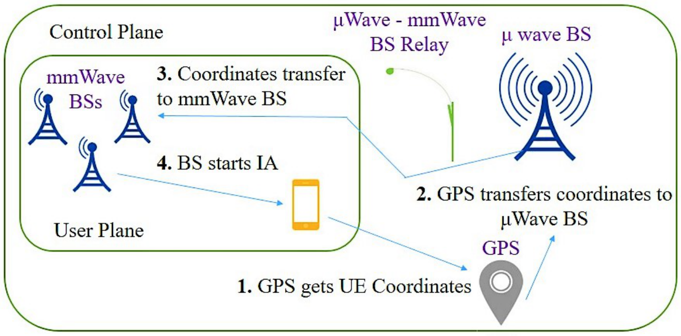

Fig. 1: Fetching UE Coordinates

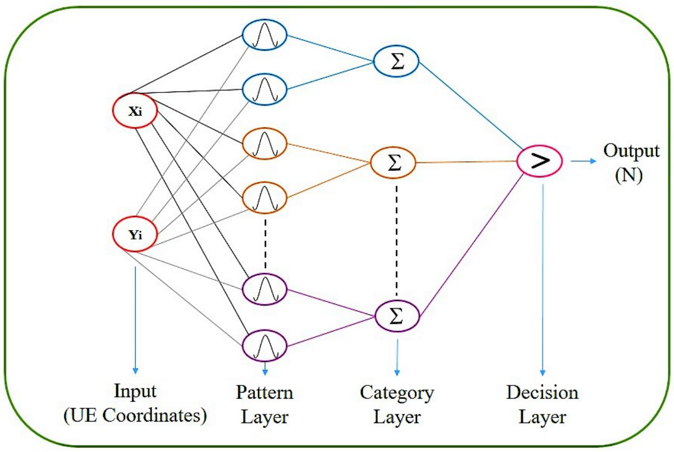

Fig. 2: Probabilstic Neural Network

is comprised of four layers. The first layer, which is stated as the input layer, holds the training set of already classified data points, i.e., x-coordinates and y-coordinates of UEs that established a successful connection with the mmWave BS, in the past. When the input layer gets the estimated x and y coordinates of the new UE, it will form a data point corresponding to a pattern unit in the second layer, just like other trained data points. Pattern unit is basically a Gaussian function with a peak centered on the estimated UE location. For example, if the UE's estimated coordinates are represented as x_o and y_o, then the value associated to each pattern unit can be computed by considering the distance between the UE 's coordinates (x_o, y_o) and the center of pattern unit, associated to trained data points (x, y). Thus, the corresponding Gaussian function is given as

$$f(x,y) = exp - \left\{ \frac{(x-x_o)^2 + (y-y_o)^2}{2\delta^2} \right\}, \quad (1)$$

where δ is the constant that controls the width of the function. Conceptually, δ accounts for the variance of UE's mobility, i.e., if δ has large value, algorithm is suitable to perform for highly mobile UE, else if δ is small, the Gaussian function is narrower in width around its center that is appropriate for stationary or slightly mobile UE. δ can be predefined by keeping in view the environment in which BS is deployed and the precision of the estimated GPS location.

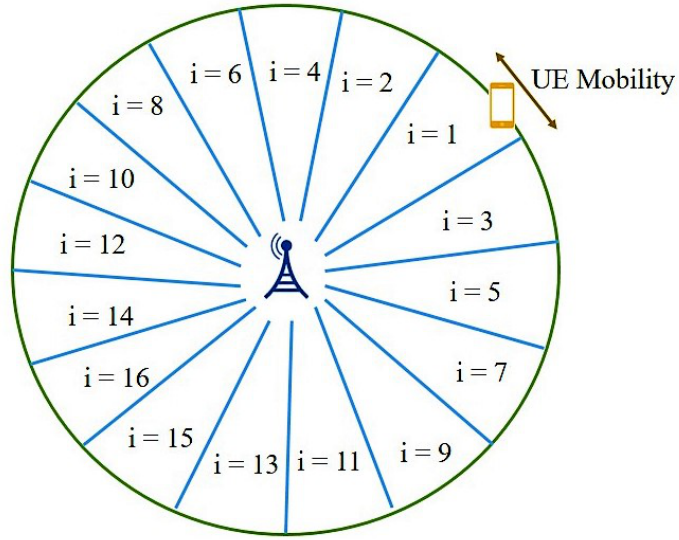

Fig. 3: Cell Search

Moving forward, the pattern units for each category are summed to create a category unit in the third layer of the neural network. In our case, a category unit corresponds to the cardinality (N) of I, where I is a set of natural numbers whose elements, $i \ \epsilon \ I$, represent the number of cell search sectors. Training the network is automatic, i.e., adding new data points to the appropriate category set.

After obtaining the suggested number of cell sectors for search (N), the optimal beamwidth (BW_{opt}^{o}) for the process of IA in a 360° cell area is given as

$$BW_{opt}^{o} = \frac{360^{\circ}}{N}. \quad (2)$$

Once the algorithm acquires the BW_{opt}^{o}, it starts performing the cell search as depicted in Fig. 3. Firstly, it points the beam towards the sector, n, having estimated UE location at θ_n degrees, for T_{sig} seconds to establish the connection. If UE is not discovered at sector n for $i = 1$ (first step), then after a period of T_{per} seconds, the algorithm will steer the beam by increasing a sector in positive direction, i.e., $n+1$ for $i = 2$ followed by $n-1$ for $i = 3$, $n+2$ for $i = 4$, $n-2$ for $i = 5$, and so on. The search region for even values of i is given as

$$\theta_S{}^{\circ} = (i+1) \times BW_{opt}{}^{\circ} \ + \theta_n, \quad (3)$$

$$\theta_E{}^{\circ} \ = i \times BW_{opt}{}^{\circ} \ + \theta_n, \quad (4)$$

whereas the search region corresponding to odd values of i is determined as

$$\theta_S{}^{\circ} = (i-1) \times BW_{opt}{}^{\circ} \ + \theta_n, \quad (5)$$

$$\theta_E{}^{\circ} \ = i \times BW_{opt}{}^{\circ} \ + \theta_n, \quad (6)$$

where θ_S^o identifies the start of the beam and θ_E^o indicates the end of the beam. The algorithm terminates the IA if UE is not found until i reaches N.

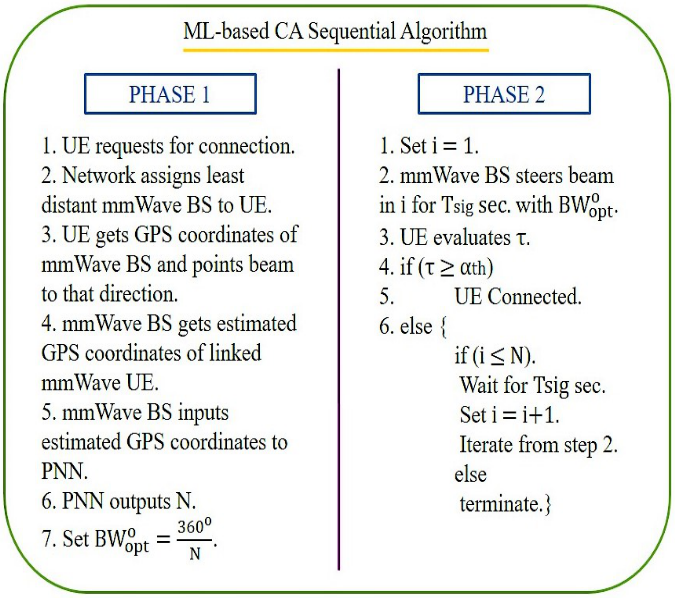

Fig. 4: Proposed Algorithm Flow

Moving forward towards the other parameters for establishing the connection. Consider $G(\theta)$ be the total antenna gain, given as

$$G(\theta) = G_{tx} \times G_{rx} \times BFGain_{tx} \times BFGain_{rx}, \quad (7)$$

where G_{tx} and G_{rx} are the gains at transmitter and receiver antennas, respectively. It should be noted that we are considering sectored approximation, i.e., the search beam provides a constant gain in a sector while ignoring the influence of side lobes. Also, $BFGain_{tx}$ and $BFGain_{rx}$ are transmitter and receiver beamforming gains, respectively. BFGain is given as

$$BFGain = E \times D, \quad (8)$$

where E stands for antenna efficiency and D corresponds to antenna directivity, which is defined as

$$D = \frac{4\pi}{BW_{opt}{}^{o}}. \quad (9)$$

The beam will encounter either a line-of-sight (LoS) or non-line-of-sight (NLoS) channel while searching a sector. In reality, the gain provided by the mmWave link is affected by channel inaccuracies caused by diffraction, fading, scattering, etc., but these factors are ignored for the simplicity of our analysis. Thus, consider the channel path loss to be

$$L(r) = \begin{cases} \rho + 10\alpha_L log(r) + \chi_L & \text{if the link is LoS,} \\ \rho + 10\alpha_N log(r) + \chi_N & \text{otherwise,} \end{cases} \quad (10)$$

where ρ is the fixed path loss factor, α_L and α_N are LoS and NLoS path loss exponents, respectively, r is the mmWave link distance, while χ_L and χ_N correspond to LoS and NLoS zero mean lognormal random variable, respectively that accounts for shadowing.

In our analysis, we have considered the same blockage model as utilized by Bai and Heath [15], given by

$$\Xi = e^{-\beta r}, \quad (11)$$

where β parameter is evaluated by considering the statistics of buildings and r corresponds to the mmWave link distance. Utilizing the analysis for real world environment conducted in [16], we have concluded that if $\Xi(r) \geqslant 0.5$, the link is LoS and if $\Xi(r) < 0.5$, the link will be NLoS. The LoS and NLoS scenarios define whether the envelope follows a Rician or Rayleigh distribution, respectively.

Moving forward, if UE gets a signal from the mmWave BS, then the received power, P_r is calculated as

$$P_r = \frac{P_t G(\theta)\mu}{L(r)}, \quad (12)$$

where P_t denotes the transmit power of the BS and μ is the squared envelope of multipath fading. Interference due to other UEs will be ignored as we are analyzing one mmWave BS and one UE scenario. Hence, the received signal-to-noise ratio (SNR), τ, is defined as

$$\tau = \frac{P_r}{\sigma^2}, \quad (13)$$

where σ^2 accounts for the noise power. The UE is connected with the associated mmWave BS if

$$\tau \geqslant \alpha_{th}, \quad (14)$$

otherwise, the link will not be established where α_{th} represents the SNR threshold. The proposed algorithm flow is illustrated in Fig. 4.

Considering that the UE has been successfully detected, we calculate the discovery delay, DD, i.e., the time spent for discovering the UE. DD for a particular sector $i \ \epsilon \ I$ is given as

$$DD(i) = i \times T_{sig} + (i-1) \times T_{per}. \quad (15)$$

The total discovery delay for a given UE is the sum of discovery delay for each sector searched until the UE is connected.

IV. Performance Evaluation

The performance of exhaustive, iterative and proposed ML-based CA sequential algorithm is evaluated by means of comparative analysis executed by numerical simulations. For simplicity, it is considered that the mmWave BS performs analog beamforming where the effect of atmospheric losses, rain attenuation, and molecular absorption losses is ignored in a cell radius of 100 meters. The simulation parameters are listed in Table 1.

Table 1: Simulation Parameters [16]			
Parameter	**Value**	**Parameter**	**Value**
f_c	73 GHz	Average Requests	20000
P_t	30 dBm	Bandwidth	2 GHz
α_L	2	T_{sig}	10µsec.
α_N	2.45	T_{per}	200 µsec.
Std(χ_L)	5.2 dB	Std(χ_L)	7.2 dB
α_s	20 dB	α_{th}	40 dB
G_{tx}	24.5 dBi	G_{rx}	24.5 dBi
Noise Figure	10 dB	BF	Analog

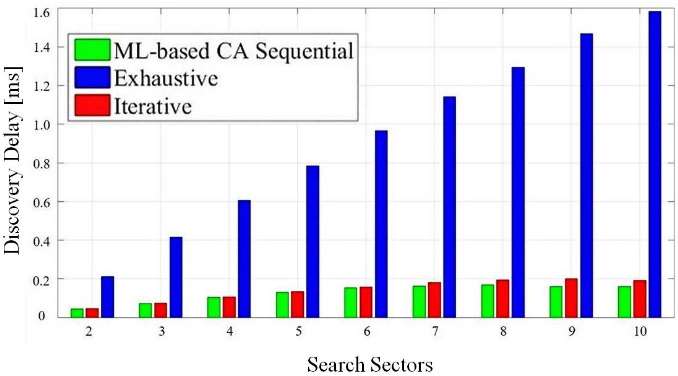

Fig. 5: Stages vs. Discovery Delay

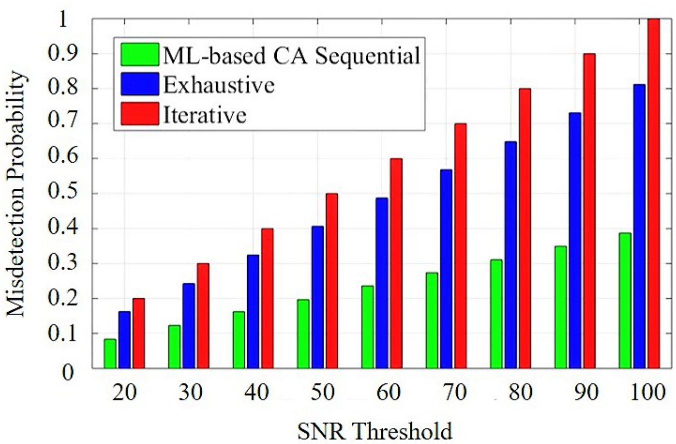

Fig. 6: SNR Threshold (α_{th}) vs. Misdetection Probability

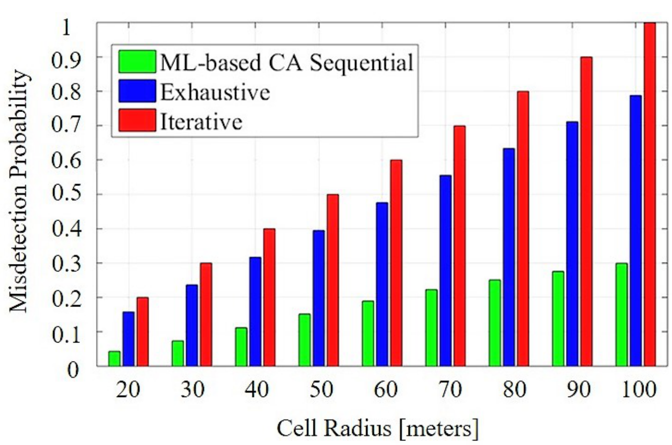

Fig. 7: Cell Radius vs. Misdetection Probability

The comparison of the three algorithms is conducted in terms of two key performance indicators, i.e., discovery delay and the probability of misdetection. Once a UE is connected to the mmWave BS, the discovery delay is measured over the sectors being searched until UE detection. Probability of misdetection depends on several factors but most importantly on cell radius, i.e., UE-BS distance, and received SNR, thus PMD is analyzed with respect to these parameters. Moreover, simulations are approximated over 10^5 Monte Carlo iterations.

A. *Discovery Delay*

Cell Search Sectors: The only system parameter directly related to DD is the number of cell sectors being searched during the IA phase. More the sectors, longer is the time taken by an algorithm to span the area, thus increasing the DD. Bar graphs in Fig. 5 analyze the performance of the algorithms in terms of DD. It is evident that the exhaustive search scheme provides the highest DD, because it searches the 360° cell area with fixed beamwidth of 10° in counterclockwise direction starting from 0° until I reaches its cardinality. On the contrary, iterative search, in the first stage, spans the 360° region with 180° beamwidth, if the UE is connected, the process of searching stops automatically, otherwise based on a loose SNR threshold, which suggests that UE could potentially be located in the particular sector, algorithm further divides the sector and the beamwidth into half and search till maximum of five stages (2 sectors in each stage) stopping at a beamwidth of 11.25°. As iterative search spans the 360° area by smartly reducing the number of sectors as compared to the consecutive sector sweeps of exhaustive search, the DD of iterative search in contrast to that of exhaustive search is significantly lower.

Lastly, the ML-based CA sequential search utilizes the availability of UE's location information to predict the most appropriate beamwidth, responsible for connection, and then directly points the beam towards that location. If the connection does not establish, the algorithm searches the area nearby to UE's given location in a way that if the UE is supposed to be at sector n, and does not connect, it searches the sector $n-1$, then $n+1, n-2, n+2$ and so on till N. As, context aware algorithm, based on UE's location smartly designs the beamwidth and also the sequence of sectors to be searched as opposed to the arbitrary search of exhaustive and iterative methods, the DD of context aware search is lowest of them all.

B. *Probability of Misdetection*

Signal-to-Noise Ratio Threshold: Exhaustive search always spans the 360° area with 10° beamwidth providing a larger range and gain to meet the SNR requirements even to the farthest premises of the cell, resultantly providing lower PMD as depicted by the bar graphs in Fig. 6. Iterative search spans the 360° area in 5 stages, where beamwidth for stage 1 is 180°, for stage 2 is 90°, for stage 3 is 45°, for stage 4 is 22.5° and for stage 5 is 11.25°. In each stage, algorithm spans only two sectors of the cell area. PMD is high for iterative search because firstly it searches the cell with larger sector area and beamwidth, i.e., shorter range thus missing the UEs on distant ends of the cell and also providing lower gains to meet the SNR requirements. Afterward, moving towards narrower bandwidths, although the gain and range are high but the sector area being searched is small.

Finally, the proposed algorithm makes use of available UE location to get the most suitable beamwidth for connection and then directly points it to the given location. If due to certain factors, UE is not detected it searches the adjacent sectors to that location. Well, as ML-based CA sequential search devises the beamwidth and also the search sectors smartly, it offers lower PMD as compared to that of conventional algorithms.

Cell Radius: Small cell radius implies that UEs are in close vicinity of BS, hence small distance will result in high received power, meeting the SNR threshold criteria most of the time and giving low PMD. On the other hand, large cell radius allows UEs to spread on the area far from BS causing a low level of received power to satisfy the SNR requirements to the UEs located on distant premises and thus resulting in higher PMD.

Bar graphs in Fig. 7 analyze the effect of cell radius on exhaustive, iterative and ML-based CA sequential algorithms. As described, a smaller radius means lower PMD while larger radius causes an increase in PMD. Holistically, the proposed algorithm, owing to its smart design, provides a comparatively lower PMD.

V. Conclusion and Future Work

In this research work, we have developed an IA algorithm for 5G mmWave communication systems. The algorithm implements ML alongside CA to smartly search the cell area in order to connect to the UE. Numerical simulations show that the proposed ML-based CA sequential algorithm has managed to offer a lower probability of misdetection alongside lower discovery delay during the IA phase as compared to those of traditional cell search algorithms, i.e., exhaustive and iterative schemes. We are expecting to enhance our work to provide an analysis of the proposed algorithm in terms of energy efficiency.

References

[1] M. Giordani, M. Mezzavilla, and M. Zorzi, "Initial access in 5g mmwave cellular networks," *IEEE Communications Magazine*, vol. 54, pp. 40–47, November 2016.

[2] L. Wei, R. Hu, Y. Qian, and G. Wu, "Key elements to enable millimeter wave communications for 5g wireless systems," *IEEE Wireless Communications*, vol. 21, pp. 136–143, 12 2014.

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

[4] 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, pp. 6664–6678, Dec 2015.

[5] S. Nawaz and S. A. Hassan, "Auxiliary beam pair enabled initial access in mmwave systems: Analysis and design insights," in *2019 IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 1–6, May 2019.

[6] C. Jeong, J. Park, and H. Yu, "Random access in millimeter-wave beamforming cellular networks: issues and approaches," *IEEE Communications Magazine*, vol. 53, pp. 180–185, January 2015.

[7] V. Desai, L. Krzymien, P. Sartori, W. Xiao, A. Soong, and A. Alkhateeb, "Initial beamforming for mmwave communications," in *2014 48th Asilomar Conference on Signals, Systems and Computers*, pp. 1926–1930, Nov 2014.

[8] M. Giordani, M. Mezzavilla, C. N. Barati, S. Rangan, and M. Zorzi, "Comparative analysis of initial access techniques in 5g mmwave cellular networks," in *2016 Annual Conference on Information Science and Systems (CISS)*, pp. 268–273, March 2016.

[9] S. Habib, S. A. Hassan, A. A. Nasir, and H. Mehrpouyan, "Millimeter wave cell search for initial access: Analysis, design, and implementation," in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, pp. 922–927, June 2017.

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

[11] 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.

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

[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] F. Devoti, I. Filippini, and A. Capone, "Mm-wave initial access: A context information overview," pp. 1–9, 06 2018.

[15] T. Bai and R. W. Heath, "Coverage and rate analysis for millimeter-wave cellular networks," *IEEE Transactions on Wireless Communications*, vol. 14, pp. 1100–1114, Feb 2015.

[16] M. S. Omar, S. A. Hassan, H. Pervaiz, Q. Ni, L. Musavian, S. Mumtaz, and O. A. Dobre, "Multiobjective optimization in 5g hybrid networks," *IEEE Internet of Things Journal*, vol. 5, pp. 1588–1597, June 2018.