Deep Reinforcement Learning Based Fast Initial Access For mmWave Based User-centric Systems

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Abstract—User-centric (UC) systems face a complex problem of initial access (IA) beam discovery due to a large number of distributed access points (APs). The use of millimeter-wave (mmWave) frequencies, further exacerbates the IA problem due to its shorter channel coherence time and higher blockage susceptibility compared to the lower frequency bands. In this paper, we provide a novel deep reinforcement learning-based algorithm called RapidIA to efficiently perform IA in mmWave based UC systems. The key advantage of RapidIA is that it can predict the IA beam steering vector using just one reference signal from the user. The policy of the deep reinforcement learning model in RapidIA learns the mapping between received reference signals and the beam codebook. The mmWave channel and the simulation environment are modeled using a ray-tracing approach. Ray-tracing based simulations show that the RapidIA algorithm consistently achieves a beam prediction accuracy level of 100%. With respect to beam discovery delay, RapidIA shows a considerable improvement compared to other beam sweeping based IA systems.

Index Terms—Initial access, 5G and beyond, mmWave, user-centric, MIMO, deep reinforcement learning, beam prediction

I. INTRODUCTION

Future wireless communication systems are expected to provide high-throughput low-latency communications for applications such as virtual reality and autonomous driving. However, cell interference and uncoordinated transmissions of access points (APs) stand as challenges in realizing these objectives. Cell-free (CF) architecture [1] and its extension, user-centric (UC) system [2] have been proposed to alleviate these issues. CF massive MIMO architecture proposes serving a user simultaneously with a very large number of distributed APs. UC is an extension of this CF massive MIMO architecture wherein a user is served by a subset of the available APs, which leads to a lower backhaul overhead and higher rates compared to CF [2].

Densely populated APs in the UC architecture have to perform initial access (IA) for many users simultaneously. Due to the shorter coherence time and blockages associated with millimeter wave (mmWave), the connection may drop frequently, and therefore, IA has to be performed more than in previous generations. Hence, IA in UC MIMO environments is inherently a challenging issue to address. Most conventional IA systems depend on full or partial exhaustive search based beam sweeping mechanisms. IA system presented in release 15 of the third generation partnership project (3GPP) standard [3] adopts a scheme based on an exhaustive search. Here the new radio transmits beams in a fixed predetermined pattern. Then a hierarchical beam refinement strategy is used to narrow down the best beam. An exhaustive beam search requires multiple beam transmissions and user reports which causes considerable inefficiency. This is further worsened with the use of the mmWave frequencies since channel coherence time is shorter compared to the frequency bands used in previous cellular generations. Research work on IA beam discovery could be broadly categorized into two main branches as autonomous search (AS) and context information search (CI). AS systems use signals exchanged between the APs and users for IA while CI exploits external localization methods such as GPS in addition to exchanged signals for IA. Authors in [4] discuss three IA cell search algorithms for 5G mmWave cellular networks. The work in [5] proposes a beam steering vector detection based on compressed sensing for 5G IA. In [6], a fast IA search algorithm that exploits statistics of the signals via online statistics learning for mmWave 5G systems is proposed. Partial or full brute force search based beam sweeping IA algorithms (BSIA) will be obsolete since they are unable to provide quick and efficient IA in the UC mmWave setting. Recently, machine learning (ML) based approaches are explored to alleviate inefficiencies in communication systems [7–9]. Work in [7] presents a wide discussion on the usage of ML in wireless communications from the perspective of 6G and beyond systems. Authors suggest ML will be vital in accommodating the increasing demand for connectivity and other problems in wireless communications. Authors of [10] present an IA algorithm called DeepIA which leverages a deep neural network (DNN) for faster and efficient prediction of beam steering vector for IA. Instead of transmitting all the beams in the codebook, DeepIA proposes to transmit just a subset of beams. User reports on received signal strength (RSS) for these beams are then used in beam steering vector prediction. However, beam sweeping based methods are inherently inefficient due to the multiple beam transmission.

To that end, we propose an IA algorithm called RapidIA which could predict the beam steering vector for mmWave UC systems with just one reference signal transmitted by the user. RapidIA uses a deep reinforcement learning (DRL) based ML model to predict the beam steering vector for IA. Unlike
the ML model used in [10], the online learning nature of DRL architecture enables system deployment without prior training which requires site-specific training data. Obtaining such a dataset of a wireless communication system is cumbersome and could be completely futile due to the wavering nature of the radio propagation environment. By minimizing the number of beam transmissions and user reports used in the IA process, RapidIA can mitigate inefficiencies that plague BSIA systems. A ray-tracing based channel model [11] is adopted to generate realistic environments, propagation phenomena, and channel measurements to train the DRL model. Simulations performed using such realistic models showed that RapidIA constantly achieves 100% prediction accuracy with a significantly lower beam discovery delay.

Contributions of this work are summarized as follows:

- We propose a DRL based IA algorithm called RapidIA which predicts the beam steering vector for IA using only one reference signal from the user.
- DeepIA algorithm proposed in [10] is extended to a DRL setting and presented as DeepIA-DRL.
- RapidIA, DeepIA-DRL, and BSIA algorithms are simulated using realistic environment and channel conditions. BSIA algorithm serves as a reference for RapidIA and DeepIA-DRL.
- We evaluate, analyze, and compare the accuracy and performance of the RapidIA, DeepIA-DRL, and BSIA algorithms.

The rest of this paper is organized as follows. Section II explains the system model used in our work and introduces the problem. Section III provides a quick primer on DRL while Section IV formally presents all the algorithms used in this work. Section V presents the simulation model and results, and this work is concluded in Section VI.

Notations: $(\cdot)^T$ and $(\cdot)^H$ denote transpose and Hermitian transpose, respectively. $\mathbb{R}(x)$ and $\mathbb{I}(x)$ represents the real and imaginary parts of $x$, respectively. $||.||^2$ denotes euclidean norm.

II. SYSTEM MODEL AND PROBLEM FORMULATION

This section introduces the system model used in this work and presents the problem.

A. System Model

Consider an UC architecture wherein a set $K$ of $K$ single-antenna users are served by a set $M$ of $M$-antenna APs. APs are connected to a central entity called the central processing unit (CPU) via backhaul links. An example of an UC system is presented in Fig. 1.

The channel is modeled using a clustered mmWave model with $J$ clusters [12]. Each path cluster is generated with a $L$ sub-paths which are parameterized by path loss, azimuth and elevation angles of arrival, $\theta_{j,l}^a$ and $\Phi_{j,l}^a$, and azimuth and elevation angles of departure, $\theta_{j,l}^s$ and $\Phi_{j,l}^s$, where $j = 1, \ldots, J$ and $l = 1, \ldots, L$ represents cluster and sub-path index, respectively. Channel between an AP-user pair, i.e., $g \in \mathbb{C}^{N \times 1}$, can be presented as

$$g = \frac{1}{\sqrt{L}} \sum_{j=1}^{J} \sum_{l=1}^{L} p_{j,l} h_{j,l} a_k(\theta_{j,l}^a, \Phi_{j,l}^a) a_m(\theta_{j,l}^s, \Phi_{j,l}^s),$$

where $p_{j,l} \in \mathbb{C}$ and $h_{j,l} \in \mathbb{C}$ represents the gain associated with large-scale and small-scale fading in the $j$th sub-path of the $l$th cluster, respectively, and $a_k(\theta_{j,l}^a, \Phi_{j,l}^a) \in \mathbb{C}^{N \times 1}$ and $a_k(\theta_{j,l}^s, \Phi_{j,l}^s) \in \mathbb{C}$ are the array gains for the AP and the user, respectively. The channel matrix $g$ from $k$th user to the $m$th AP is denoted as $g_{k,m}$. Channel reciprocity is assumed since time division duplexing is used in nearly all of the mmWave channels proposed for 5G and beyond systems.

Beams for IA are chosen from a predefined beam codebook $C$ and they are assumed to be implemented with a network of quantized phase shifters. The $b$th entry of $C$, i.e., $f_b$, is given by

$$f_b = \frac{1}{\sqrt{N}} [e^{j\Theta_{b,0}} e^{j\Theta_{b,1}} \ldots e^{j\Theta_{b,N-1}}]^T,$$

where $\Theta_{b,n}$ is the quantized phase shift corresponding to the $n$th antenna in the $b$th entry.

ML model used in the proposed algorithms learns how to map an input which characterizes the channel, to the beam codebook. Characteristics of the physical environment create radio phenomena, i.e., reflections, refractions, and diffractions, which leads to subtle changes in the channel measurements, and these help the ML model to better understand the environment. Hence the channel is generated using a commercial ray-tracing software called Wireless Insite [13] and therefore, realistic behaviors can be expected from the ML models.

B. Problem Formulation

Received signal at the $m$th AP, i.e., $y_m \in \mathbb{C}^{N \times 1}$, is presented as

$$y_m = \sum_{k \in \mathcal{K}} g_{k,m} \Omega_k^H + \omega_m,$$

where $y_m = [y_{m,0} \ y_{m,1} \ldots \ y_{m,N-1}]^T$, and $\omega_m = [\omega_{m,0} \ \omega_{m,1} \ldots \ \omega_{m,N-1}]^T$. Here $\mathcal{K} \subseteq \mathcal{K}$ denotes the set of users requesting IA, $\{y_{m,n}\}$ are the signal samples received
by antennas of the $m$th AP, $\{\omega_{m,n}\}$ are independent and identically distributed circularly-symmetric complex Gaussian noise having a per dimension mean and variance of zero and $\sigma^2$, respectively, and $\Omega_k \in \mathbb{C}$ is the reference signal. For simplicity, reference signals are selected such that they are orthonormal with each other, i.e., $\Omega_k^H \Omega_k = 1$, and $\Omega_k^H \Omega_l = 0$ for $k \neq l$.

Each AP can approximate the channel matrix from the user to the AP, i.e., $\tilde{g}_{k,m} \in \mathbb{C}^{N \times 1}$, by multiplying $y_m$ with the corresponding $\Omega_k$, and it is presented as

$$\tilde{g}_{k,m} = y_m \Omega_k,$$  \hspace{1cm} (4)

$$= g_{k,m} \Omega_k^H \Omega_k + \sum_{l\in K, i \neq k} g_{l,m} \Omega_l^H \Omega_k + \omega_m \Omega_k,$$  \hspace{1cm} (5)

$$= g_{k,m} + \omega_m \Omega_k.$$  \hspace{1cm} (6)

Since channel reciprocity is assumed, $\tilde{g}_{k,m}$ could be considered as the approximated channel matrix from the $m$th AP to the $k$th user. The signal component received at $k$th single-antenna user from $m$th AP, i.e., $y_k \in \mathbb{C}$, is given by

$$y_k = \tilde{g}_{k,m}^H \tilde{f} x_k + \omega_k,$$  \hspace{1cm} (7)

where $\tilde{f}$ is the beam chosen for the transmission, $x_k \in \mathbb{C}$ is the transmitted data symbol and $\omega_k \in \mathbb{C}$ represents the noise at the receiver of the $k$th user. Hence, RSS at the user is given by

$$RSS_{rec} = ||\tilde{g}_{k,m}^H \tilde{f}||^2 \times \alpha P,$$  \hspace{1cm} (8)

where $RSS_{rec}$ is the received RSS at the user, $P$ is the transmit power of $m$th AP, and $\alpha$ is the power allocation coefficient at the AP. These $RSS_{rec}$ values are reported to the AP. For the sake of simplicity, equal power allocation is assumed in this work.

### III. DEEP REINFORCEMENT LEARNING

Reinforcement learning (RL) allows agents to explore their environment and learn the best course of action to accomplish their goals. An agent interacts with its environment by observing the state of the environment, taking actions, and receiving a numerical reward for each action as shown in Fig. 2. Based on a policy, an action is chosen from the set of possible actions, i.e., action-space. A policy could be simply thought of as the mapping between inputs, i.e., state of the environment, and output, i.e., chosen action. However, learning the policy in problems with large sets of states and actions may prove overwhelming. This could be assuaged by using a deep neural network (DNN) to essentially estimating the policy in RL and this approach is called deep reinforcement learning (DRL). Numerical rewards are used for appraising agents’ actions. In this work, a DNN model used for policy approximation and it is implemented using a Keras [14] sequential model with hidden layers. The agent predicts the future reward of each action based on the state of the environment using the approximated policy. Actions are selected by the agent to maximize the cumulative reward. These actions cause the environment to undergo state transitions.

Deciding the compromise between exploitation and exploration is a dilemma in RL policy design. The agent takes random actions to explore the environment during exploration to bolster its knowledge about the environment. However, the agent could follow an exploitation, i.e., greedy, policy, and use its current knowledge to select actions to gain higher rewards. In our work, we adopt a diminishing $\varepsilon$-greedy policy where the agent performs exploration and exploitation with the probabilities of $\varepsilon$ and $1-\varepsilon$, respectively. Initially $\varepsilon$ is set to 1 and it is diminished by a factor of $\varepsilon_{dec}$ at each training episode until it reaches a predefined minimum, i.e., $\varepsilon_{min}$. Defining $\varepsilon_{min}$ is important since it allows the model to evolve with changing environmental conditions even after the learning period.

State of the environment, the action which the agent took based on the state, and the reward received by the agent together considered as an experience. These experiences are stored in memory and at each training iteration, a certain number of experiences are selected randomly and used for training. This is called experience replay and it promotes convergence [15] of the DRL model.

Since the occurrence of IA requests from users is random, it cannot be considered as a part of a sequence, i.e., no state transitions. Such problems can be modeled using contextual bandit models. Each action in the action-space corresponds to choosing a particular entry from the beam codebook. The reward metric for the agent is calculated using $RSS_{rec}$ since it depends on the choice of the beam, i.e. action taken by the agent. However, the effects of the channel and transmit power should be removed from $RSS_{rec}$ via normalization to maintain consistency in the reward metric. Hence, the reward metric for the DRL model, i.e., $R_{k}$, is calculated at the AP as

$$R_{k} = \frac{RSS_{rec}}{||\tilde{g}_{k,m}^H||^2 \times \alpha P}.$$  \hspace{1cm} (9)

### IV. ALGORITHMS

In this section RapidIA, DeepIA-DRL and BSIA algorithms are presented.

#### A. RapidIA Algorithm

RapidIA is a DRL/contextual bandit based fast and efficient IA algorithm for mmWave UC systems. RapidIA predicts the IA beam steering vector using just one known reference signal from the user. Although there are multiple messages and strategies involved in IA in 5G [15] and beyond communication systems, this work is focused mainly on fast and efficient IA beam prediction. RapidIA is formally presented as Algorithm 1.
When a user wants to join the network it transmits a known reference signal via either contention or non-contention based random access in the assigned resource elements. Since UC architecture allows multiple APs to serve a user simultaneously, all APs receiving user request initiates the IA procedure. For the sake of simplicity, we assume that reference signals are orthonormal to avoid collisions. AP receives the reference signal, i.e., \( y_m \), and uses it to estimate \( \hat{g}_{k,m} \) as per (4). The estimated channel matrix \( \hat{g}_{k,m} \in \mathbb{C}^{N \times 1} \) represents the complex channels from the \( k \)th user to \( N \) antennas in the \( m \)th AP.

Real and imaginary parts of \( \hat{g}_{k,m} \) are concatenated into a vector \( \tilde{g}_{k,m} \), and normalized to form the state vector \( \text{STATE} \) as two sets of real numbers. These two sets are concatenated and normalized to form the state vector \( s \in \mathbb{R}^{2N \times 1} \) as shown in step 3 of Algorithm 1 The contextual bandit model used in RapidIA is represented as \( \text{CB}_\text{MODEL} \), and it predicts \( \hat{f} \) using \( s \) as the model input.

After using \( \hat{f} \) for downlink transmission, \( \text{RSS}_{\text{rec}} \) is reported to the AP by the user. Reward \( R_k \) is calculated based on \( \text{RSS}_{\text{rec}} \) using (9). In summary, RapidIA considers \( \tilde{g}_{k,m} \), \( \hat{f} \), and \( R_k \) as the state, action, and reward, respectively, and they are saved in a queue for experience replay. At every iteration, the model is trained with a set of randomly selected experiences. If the user is not satisfied with the actual RSS, it can initiate the IA process again.

**B. DeepIA-DRL Algorithm**

DeepIA presented in [10] is extended to the online machine learning case by implementing DeepIA using a DRL model. It is formally presented as DeepIA-DRL in Algorithm 2.

To initiate IA, APs transmit a subset of beams \( \tilde{C} \subseteq C \) from the codebook. \( \text{RSS}_{\text{rec},f_i} \) is the \( \text{RSS}_{\text{rec}} \) value for the \( i \)th beam \( f_i \in \tilde{C} \) and it is reported to the AP. Unlike RapidIA, DeepIA-DRL uses \( \{\text{RSS}_{\text{rec},f_i}\}_i \) as the state vector, hence, the input layer of \( \text{CB}_\text{MODEL} \) contains \( |\tilde{C}| \) neurons. However, the rest of the DRL model used DeepIA-DRL is identical to RapidIA. The model predicts a beam \( \hat{f} \) for IA as the output. After using \( \hat{f} \) for the downlink transmission, reported \( \text{RSS}_{\text{rec}} \) is used to calculate \( R_k \), analogous to RapidIA. In summary, DeepIA-DRL considers \( \{\text{RSS}_{\text{rec},f_i}\}_i \) as the state, action and reward, respectively, and they are saved for experience replay. Similar to RapidIA, the model is trained at each iteration.

Compared to the \( 2 \times |\tilde{C}| \) message transfers needed in DeepIA-DRL [10], RapidIA requires just one of them for beam prediction. This reduced requirement drastically improves the beam discovery delay.

**C. Beam Sweeping Based IA (BSIA) Algorithm**

A simple brute force search based beam sweeping IA algorithm is considered. AP transmits all the codebook beams. The user measures \( \text{RSS}_{\text{rec}} \) for all the received beams and reports the index corresponding to the highest \( \text{RSS}_{\text{rec}} \) value. AP receiving this report selects the beam corresponding to the reported index for downlink transmission.

### V. PERFORMANCE ANALYSIS

This section introduces the simulation model and the results.

**A. Simulation Model**

Part of an indoor ice-hockey stadium is chosen as the simulation environment as shown in Fig. 3a and Fig. 3b. The 60 m × 30 m skating rink is situated in the middle of the 100 m × 50 m stadium. It is modeled using Wireless Insite [13] ray-tracing simulator. The concrete wall around the stadium extends from the floor to the ceiling. A tempered glass wall of 3 m height is situated around the skating area. The floor of the seating area has a slope such that elevation near the stadium walls is 10 m compared to the skating rink as seen in Fig. 3b. Concrete is used for the floor and the ceiling. ITU 28 GHz compliant models are used for modeling tempered glass and concrete in the simulation so that accurately radio phenomena could be observed. Possible user locations are located 0.25 m apart in a 20 m × 10 m grid on the stadium seating area and they are shown as red color squares in Fig. 3a. APs are located 2 m apart facing downwards in a grid formation on the ceiling which is 15 m above the floor and they are shown as green color cubes in Fig. 3a. Channels from APs to all the possible user locations are generated and saved.

A carrier frequency of 28 GHz with a channel bandwidth of 50 MHz is considered. Each AP is equipped with a 4 × 4 uniform planar antenna array. Antennas are spaced to have half a wavelength of the carrier frequency between them. The beam codebook is consisted of 16 beams, i.e., \(|\tilde{C}| = 16\). Total transmit power at the AP is set to 20 dBm, and the gain and the noise figure at the users are 5 and 3 dB, receptively.

It is assumed that at every simulation episode, 100 users will request for IA from APs. Locations of these 100 users

| Algorithm 1: RapidIA algorithm |
|-------------------------------|
| 1: Receive \( y_m \) |
| 2: Calculate \( \hat{g}_{k,m} \) |
| 3: \( s = \{\text{RSS}_{\text{rec},f_i}\}_i \} / \max(\hat{g}_{k,m}) \) |
| 4: \( \hat{f} = \text{CB}_\text{MODEL}(s) \) |
| 5: Get \( \text{RSS}_{\text{rec}} \) report for \( \hat{f} \) |
| 6: Calculate \( R_k \) |
| 7: Save \( \{\hat{g}_{k,m}, \hat{f}, R_k\} \) |
| 8: Train \( \text{CB}_\text{MODEL} \) |

| Algorithm 2: DeepIA-DRL algorithm |
|-------------------------------|
| 1: for \( f_i \in \tilde{C} \) do |
| 2: Transmit \( f_i \) |
| 3: Receive \( \text{RSS}_{\text{rec},f_i} \) |
| 4: end for |
| 5: \( s = \{\text{RSS}_{\text{rec},f_i}\}_i \) |
| 6: \( \hat{f} = \text{CB}_\text{MODEL}(s) \) |
| 7: Get \( \text{RSS}_{\text{rec}} \) report for \( \hat{f} \) |
| 8: Calculate \( R_k \) |
| 9: Save \( \{\text{RSS}_{k}, \hat{f}, R_k\} \) |
| 10: Train \( \text{CB}_\text{MODEL} \) |
are randomly selected from 3000 possible user locations. It is assumed that every IA related message, i.e., reference signals, user reports, and beam transmissions, transferred between APs and users take 0.01 ms. The processing time required for prediction is negligible compared to message transfer time.

DNN model used in RapidIA and DeepIA-DRL has 4 hidden layers that contain 50 neurons each. Relu activation function and Adam optimizer are used. For DeepIA-DRL, we consider a scenario where a subset of 4 beams is transmitted to gather $RSS_{rec}$ data. Hence the input layer of Deep-DRL contains 4 neurons corresponding to 4 $RSS_{rec}$ user reports. However, the input layer of RapidIA contains 32 neurons to receive the normalized reference signal values from 16 antennas. The output layer has 16 neurons corresponding to the number of actions. All the experiences are saved in a first-in-first-out queue which could hold 50,000 entries. The model is trained every episode using 64 randomly selected experiences from the queue. Values for $\epsilon_{dec}$ and $\epsilon_{min}$ are set to 0.995 and 0.01, respectively. In addition to RapidIA, DeepIA-DRL, and BSIA, a genie-aided algorithm with beam prediction accuracy of 100% is considered as a reference.

Performance measures such as beam prediction accuracy, received signal-to-noise ratio (SNR) at the user, and beam discovery delay are utilized to evaluate the performance of algorithms. Here beam prediction accuracy tracks the percentage of exact matches between the predicted beam and actual best beam. Beam discovery delay tracks the total time taken by the algorithm to predict the correct beam. This includes delays associated with all message transfers. Cumulative reward measure is used for comparing RapidIA and DeepIA-DRL in deep learning terms. Here the reward accumulated by a DRL model over a certain period is measured. These performance measures are defined as follows

**B. Results**

Fig. 4 presents the variations in the average prediction accuracy of RapidIA and DeepIA-DRL during training episodes. Despite using data from just one reference signal for input, RapidIA performs similar to DeepIA-DRL. Both algorithms can consistently perform close to 100% accuracy after the training period. Fig. 5 presents the average SNR achieved at the user using RapidIA, DeepIA-DRL, and genie-aided algorithm. With enough training episodes, both RapidIA and DeepIA-DRL algorithms achieve genie-aided performance in terms of achieved average SNR. Analogous to the case of prediction accuracy, RapidIA performs similar to DeepIA-DRL. However, RapidIA uses just one known reference signal transmission for beam prediction while DeepIA-DRL uses 4 beam transmissions and their $RSS_{rec}$ user reports for beam prediction. Hence using RapidIA is efficient in terms of the number of message transfers needed for the prediction of beams.

Table I presents the cumulative reward achieved by the DRL agents in RapidIA and DeepIA-DRL. Both algorithms scored similar cumulative rewards. However, RapidIA was able to accumulate a slightly larger reward despite using fewer message transfers compare to DeepIA-DRL.

Fig. 6 presents the average total beam discovery delay for RapidIA, DeepIA-DRL, and BSIA algorithms. An additional user transmission that reports the actual $RSS_{rec}$ for the chosen $\hat{f}$ is considered for the DRL based algorithms and this is used for training the ML model. BSIA algorithm has a constant beam discovery delay of 0.17 ms since it requires 17 message transfers, i.e., 16 beam transfers and one user report, for a round of beam predictions. It is assumed that the BSIA algorithm would identify the best beam during its initial round of IA. For a round of beam predictions, DeepIA-DRL needs 10 message transfers, i.e., five beam transfers and five user reports. Hence DeepIA-DRL has an irreducible beam discovery delay of 0.1 ms even at its best case, i.e., 100% beam prediction accuracy. Irreducible beam discovery delay for RapidIA is just 0.03 ms since it only needs three message transfers, i.e., one reference signal transfer for beam...
prediction, one beam transfers, and one user report for training, per prediction round. With training, both DeepIA-DRL and RapidIA algorithms reach their irreducible beam discovery delay.

RapidIA shows a low total beam discovery delay compared to other algorithms and it can accurately predict beams for IA even though it uses just one known reference signal for predictions.

VI. CONCLUSION

In this paper, we have presented an algorithm based on deep reinforcement learning to provide faster and efficient initial access for millimeter wave based user-centric architecture. First, we have studied the use of deep reinforcement learning for the initial access beam prediction problem and propose a solution called RapidIA. The key idea of the RapidIA is to reduce the message transfers between the access points and the users to achieve faster initial access. RapidIA allows the policy in the deep reinforcement learning model to learn the mapping between received reference signals and beam entries in the codebook. Then we extended an existing neural network based algorithm called DeepIA to the reinforcement learning domain. Simulations were performed using geometric ray-tracing based models to evaluate the algorithms in an indoor sports stadium setting. Simulation results have shown that the proposed system can accurately predict the beam steering vector with low beam discovery delay outperforming conventional beam sweeping based initial access systems and DeepIA. Work in this paper can be extended to several research directions such as investigating RapidIA performance using larger antenna arrays, the extension of RapidIA for coordinated beamforming, and fine-tuning machine learning model used in RapidIA algorithm.

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