Abstract—While initial beam alignment (BA) in millimeter-wave networks has been thoroughly investigated, most research assumes a simplified terminal model based on uniform linear/planar arrays with isotropic antennas. Devices with non-isotropic antenna elements need multiple panels to provide good spherical coverage, and exhaustive search over all beams of all the panels leads to unacceptable overhead. This paper proposes a location- and orientation-aware solution that manages the initial BA for multi-panel devices. We present three different neural network structures that provide efficient BA with a wide range of training dataset sizes, complexity, and feedback message sizes. Our proposed methods outperform the generalized inverse fingerprinting and hierarchical panel-beam selection methods for two considered edge and edge-face antenna placement designs.

Index Terms—millimeter wave, beam alignment, location-aware, orientation-aware, multi-panel

I. INTRODUCTION

Directional beamforming by employing antenna arrays with a large number of elements is the most common way to compensate for the higher propagation and penetration loss at the millimeter-wave (mmWave) and sub-terahertz bands. Codebook-based analog or hybrid analog-digital beamforming are popular solutions for arrays with a number of radio-frequency (RF) chains significantly smaller than the number of antenna elements [1]. In order to overcome the pathloss, access point (AP) and user terminal (UT) should then select beams from their respective codebooks which are aligned with the directions of departure/arrival of a strong multipath component of the channel. Finding the optimal beam pair at the AP and UT using an exhaustive search yields unacceptable latency due to the large beam space. On the other hand, hierarchical beam search (HBS) suffers from low signal-to-noise ratio (SNR) at the first search stages [2]. Data driven methods like inverse fingerprinting (IFP) and machine learning (ML) approaches use context information (CI) in addition to prior knowledge of the environment to reduce the search space by proposing a beam candidate list [3], [4]. Besides user location and orientation information, light detection and ranging (LIDAR) and visual images are helpful CI for beam selection and blockage prediction [5]. However, most of these methods have been proposed and assessed assuming isotropic antenna elements at the transceivers.

In practice, antenna arrays at mmWave transceivers are implemented using non-isotropic antenna elements, such as patch antennas, leading to directional coverage. To provide full spherical coverage, multi-panel antenna designs are often used in UT designs [6]. Such multi-panel designs should be taken into account in both the definition of codebooks and the design of beam alignment (BA) algorithms. As hand blockage can impact the coverage of a UT, data-driven approaches are proposed in [7], [8] to generate a non-directional beamforming codebook considering the effects of hand blockage on the antenna radiation pattern. The grip-aware analog beam codebook adaptation presented in [9] provides better spherical coverage over the grip-agnostic scheme by finding a codebook for each hand-gripping mode. Authors in [10] proposed a beam switching approach to detect hand blockage by utilizing power detectors at all the panels, and in case of blockage, use beams on other panels. However, they focus on beam adjustment after successful initial access. UT panels can be connected to a single or multiple RF chains, possibly with constraints such as each RF chain only being connected to a panel in partially connected hybrid beamforming architectures [11]. Incorporating the limitations and features of multi-panel antenna design in the initial BA process allows for higher spectral efficiency and lower power consumption by efficiently turning off some RF chains [12].

This paper proposes location- and orientation-aware methods to reduce the overhead of initial BA for multi-panel devices by recommending a short beam/panel candidate list. We present two multi-network (MN) designs that are tailor-made for multi-panel devices. In addition, we generalize the single-network (SN) structure in [4]. MN designs containing fewer trainable parameters can outperform SN design, especially when trained with datasets of limited size. We consider two baselines for evaluations: generalized IFP (GIFP) as a benchmark using context information and hierarchical panel-beam selection (HP-BS) as a context-free approach. We use 3-dimensional (3D) ray tracing modeling of the channel responses using an IEEE standard indoor environment. This study considers static and mobile blockers like humans in the environment, while the impact of hand blockage on the initial BA process is left for future work. In our simulations, we use patch antenna elements with radiation pattern following a 3GPP model. The results demonstrate the performance improvement in latency and achievable rate using the proposed...
deep learning (DL)-based methods over the baselines.

II. SYSTEM AND CHANNEL MODEL

A single-panel fixed AP and a multi-panel mobile UT are located in an indoor 3D scenario. The AP panel is made of a standard uniform planar array (UPA) with size of \( N_{AP} \) and \( N_{AP} \) elements. The UT has \( N_U \) panels where each panel is made of a standard uniform linear array (ULA) or UPA in each module. The \( n \)th panel of the UT consists of a \( \{N_{UT_n}^{(p)}, N_{UT_n}^{(p)}, N_{UT_n}^{(p)}\} \) antenna array with \( N_{UT_n}^{(p)} = N_{UT_n}^{(p)} N_{UT_n}^{(p)} N_{UT_n}^{(p)} \) elements. The total number of UT antenna elements is thus \( N_{UT} = \sum_{n=1}^{N_U} N_{UT_n}^{(p)} \). The UT contains 3 ULA panels, while the edge-face design includes additional UPA modules on the device’s face and back.

The position and orientation of the AP and UT are defined in a global coordinate system (GCS) [13]. Both the AP and UT have their own local coordinate systems (LCS) such that the AP’s UPA and the UT’s screen are oriented parallel to the \( yz \) and \( xy \) plane of their respective LCSs. The AP is placed at \( p_{AP} = (x_{AP}, y_{AP}, z_{AP}) \in \mathbb{R}^3 \) with their LCSs rotated by angles \( \psi_{AP} = (\phi_{AP}, \beta_{AP}, \gamma_{AP}) \) around \( z \), \( y \), and \( x \) axes of the GCS. The UT takes a random position in the environment at position \( p_{UT} = (x_{UT}, y_{UT}, z_{UT}) \in \mathbb{R}^3 \) with rotation vector \( \psi_{UT} = (\alpha_{UT}, \beta_{UT}, \gamma_{UT}) \) defined analogously to \( \psi_{AP} \) [14].

Two modes of device orientation are considered in this study: portrait and landscape. In portrait mode, \( \beta_{UT} = 0 \) and \( \alpha_{UT}, \gamma_{UT} \) are uniformly random in the range \( \alpha_{UT} \in [-\pi, \pi) \) and \( \gamma_{UT} \in [0, \pi/2] \). In the landscape mode, \( \gamma_{UT} = 0 \) and \( \alpha_{UT}, \beta_{UT} \) are drawn uniformly in the range \( \alpha_{UT} \in [-\pi, \pi) \) and \( \beta_{UT} \in [-\pi/2, 0] \).

A. Channel and Signal Model

We use Altair WinProp™ as ray-tracing software [15] to generate channel responses between AP and UT panels for each considered UT location and orientation. The channel to each UT panel is built using the outputs of the tool such as angle of departure (AoD), angle of arrival (AoA), and gains of all paths between the AP and the panel. The channel matrix \( H^{(p)} \in \mathbb{C}^{N_{UT}^{(p)} \times N_{AP}} \) between the AP and the \( p \)th UT panel is modeled as

\[
H^{(p)} = \sum_{l=0}^{L^{(p)}} \sqrt{\rho_l^{(p)}} e^{j\phi_l^{(p)}} a_{UT}^{(p)}(\psi_l^{(p)}, \omega_l^{(p)}) a_{AP}^{H}(\psi_l^{(p)}, \omega_l^{(p)})
\]

where \( L^{(p)}, \rho_l^{(p)}, \phi_l^{(p)} \) and \( \omega_l^{(p)} \) denote the number of multipath components reaching the \( p \)th panel, the received power, and the phase of the \( l \)th path, respectively. \( a_{UT}^{(p)} \) and \( a_{AP}^{(p)} \) show the antenna array response of the \( p \)th UT panel and the AP. Also, \( \phi_l^{(p)} \) and \( \omega_l^{(p)} \) are the azimuth and elevation AoAs of the \( l \)th path in the UT LCS, respectively. Likewise, \( \psi_l^{(p)} \) and \( \omega_l^{(p)} \) denote the azimuth and elevation AoDs of all paths between the AP and the panel. The channel matrix of beams as the number of elements in the panel. We consider the set \( \mathcal{U} = \{u_1, \ldots, u_{N_{AP}}\} \) including all the accessible beamforming vectors at the AP. For the \( p \)th UT panel, we define \( \mathcal{V}^{(p)} = \{v_1^{(p)}, \ldots, v_{N_{UT}^{(p)}}^{(p)}\} \) as the panel codebook. The set

\[
y^{(p)} = \sqrt{P_{AP}} v^{(p)} H^{(p)} u_s + v^{(p)} H n^{(p)}
\]

where \( P_{AP} \), \( s \), and \( u \) respectively denote the transmission power, the unit-power transmitted symbol, and the beamforming vector used at the AP. \( v^{(p)} \), \( n^{(p)} \) are, respectively, the combiner and a zero-mean complex Gaussian noise vector with variance \( \sigma^2_n \) at the \( p \)th panel of the UT.

B. Analog and Hybrid Beamforming

This study considers analog phased antenna arrays with one RF chain at the AP. The UT has \( N_{RF} \) RF chains, where \( 1 < N_{RF} < N_U \) and a panel is either turned off or connected to one RF chain. In case of \( N_{RF} = 1 \), only one panel at a time is sensing the environment. When \( N_{RF} > 1 \), simultaneous sensing with different panels can be performed. For simplicity, however, we do not consider multi-panel beamforming in this study. In addition, discrete Fourier transform (DFT)-based codebooks using analog phase shifters are used. For the codebook of each AP or UT panel, we consider the same number of beams as the number of elements in the panel. We consider the set \( \mathcal{U} = \{u_1, \ldots, u_{N_{AP}}\} \) including all the accessible beamforming vectors at the AP. For the \( p \)th UT panel, we define \( \mathcal{V}^{(p)} = \{v_1^{(p)}, \ldots, v_{N_{UT}^{(p)}}^{(p)}\} \) as the panel codebook. The set
where $S$ includes all combiners at the UT, as the union of all panel codebooks. The received signal strength (RSS) using the beamforming vector $u_i$ and combiner $v_j$ at the AP and UT can be written as

$$R_{i,j} = |\sqrt{P_{AP}}v_j^H H^{(p_j)} u_i s + v_j^H n|^2 \quad (7)$$

where $p_j$ denotes the panel corresponding to combiner $v_j$.

**III. DEEP LEARNING BASED BEAM SELECTION**

The UT location and orientation can be obtained using different sensors and positioning systems on the device at the expense of additional implementation cost and overhead to the system [16]. In beyond 5G systems, joint communication, sensing, and localization will further facilitate location- and orientation-aware BA [17]. As the environment geometry affects the potential LOS and strong NLOS paths from static objects, the UT location and orientation can be used to reduce the beam search space.

**A. Beam Selection Procedure**

Let the set $B$ include the indices of all possible combinations of beamforming vectors and combiners in the AP and UT. Beam ranking, as a beam selection approach for a UT with a known position and orientation, is a way to reduce the search space by recommending a subset $S$ from $B$. We call the set $S$ the beam-pair candidate list. This approach can be seen as an optimization problem in finding the subset $S$ from $B$ which minimizes the misalignment probability, i.e.,

$$\min_S P\left[\max_{(i,w)\in S} R_{i,w} < \max_{(i,j)\in B} R_{i,j}\right], \quad (8)$$

where $C$ is a pre-defined constant specifying the number of beam pairs in the candidate list. The optimal AP/UT beam pair for transmission is

$$i^*, j^* = \arg \max_{(i,j)\in B} R_{i,j} \quad (9)$$

In addition, we define $p^*$ as the panel corresponding to the optimal AP beam $j^*$. $P_{i,j} = P[(i,j) = (i^*, j^*)]$ denotes the probability of beam pair $(i, j)$ being optimal, i.e., being the beam pair in the codebook yielding the highest RSS. The AP and UT sense the environment with the beam pairs included in $S$, and the UT reports the beam pair $(i, j)$ with highest RSS as a result of the beam selection procedure. For known UT location and orientation, the optimal $S$ includes beam pairs with the highest probabilities of optimality [3].

We present next our proposed deep learning methods, which estimate optimality probabilities of all beam pairs. We consider three different approaches to propose a candidate list for a UT with known location and orientation. The first approach, which is an extension of the solution we proposed in [4], uses one network to predict, for all beam pairs, their probability of being optimal. In addition, we propose two novel designs, each using two networks to adapt beam selection for multi-panel devices. In this approach, the first network estimates probabilities of being optimal for all beams at AP. The corresponding list of panels or combiners at the UT for each AP beam are subsequently found by using the second network multiple times.

**B. Single-Network Design**

In this structure, the UT location and orientation are fed to a network with $N_h$ hidden layers with $n_h$ neurons each. There are $N_{UT}N_{AP}$ neurons at the output layer, each neuron yielding an estimate of $P_{i,j}$ for the $(i,j)$th beam pair. The network includes $7n_h + (N_h - 1)(n_h + 1)n_h + (n_h + 1)N_{UT}N_{AP}$ trainable parameters [14]. After sorting the network’s outputs, a beam candidate list $S$ including the first $N_b$ indices of beam pairs is made. The AP communicates the combiners selected in $S$, and then the transceivers sense the environment using $N_b$ time slots during the BA phase [4]. Originally, this method was developed assuming a UT with a single array and RF chain. In this paper, we generalize this method to propose a beam candidate list accounting for hybrid beamforming at UT. The generalization is achieved by re-sorting the beam candidate list to allow for sensing multiple beam pairs with different panels in each time slot. A UT with $N_{RF}$ RF chains can sense $N_{RF}N_b$ beam pairs in $N_b$ time slots, thus set $S$ has $N_{RF}N_b$ members. Here, $S$ includes the beam pairs with the highest probabilities of optimality but considering two extra constraints. First, the beam pairs sensed in each time slot should have the same AP beam. Second, the UT beams sensed in each time slot should correspond to different panels.

**C. Multi-Network Panel Selection Design**

The multi-network panel selection (MN-PS) design uses two networks to propose pairs of AP beams and UT panels. Fig. 3 shows the networks $NET_1^P$ and $NET_II^P$ of this method. The role of $NET_1^P$ is to sort AP beams based on the UT location. As the rotation of the device does not change the AP beamforming, $NET_1^P$ does not require orientation information of the UT. The outputs of $NET_1^P$ are therefore estimates of $P_i = P[i = i^*]$. $NET_1^P$ has $4n_h + (N_h - 1)(n_h + 1)n_h + (n_h + 1)N_{AP}$ trainable parameters.
Thus, in this case, with all the panels, and there is no need for panel selection.

per panel), then each AP beam can be sensed simultaneously likely to change. If the UT has change the optimal UT beam, but the optimal panel is less orientation information, as slight changes in orientation may be done using only UT location.

As antenna panels are placed on different sides of the device, rotations of the device may change the optimal reception panel. Thus, both the UT location and orientation information are fed to \( NET^P_1 \). \( NET^P_1 \) also has \( N_h \) hidden layers, but the first hidden layer has \( n_h/2 \) neurons, where the first layer outputs are concatenated with \( n_h/2 \) neurons from the embedding layer. The embedding layer maps the AP beam index to a point in \( \mathbb{R}^{n_h/2} \), and the mapping is also a part of the learning process in training. \( NET^P_1 \) includes \( (7+N_{AP})n_h/2+ (N_h-1)(n_h+1)n_h+(n_h+1)N_P \) trainable parameters. We run \( NET^P_1 \) multiple times with different indices of AP beams to get estimates of the optimality probabilities of each panel for the chosen AP beam, \( P_{p|i} = P[p = p^*|i = i^*] \). The estimates of joint probabilities of AP beam \( i \) and UT panel \( p \) as the optimal choice can be obtained as

\[
P_{i,p} = P_{p|i}P_i. \tag{10}
\]

A beam-panel candidate list can be made by selecting the combinations providing the highest probabilities. In this method, all the beams at the selected panels should be sensed by the UT. In case of using multiple RF chains at UT, in a time slot with a fixed beamforming vector \( i^* \) at AP, we can sense the environment simultaneously with the \( N_{RF}-1 \) other panels that provide higher \( P_{i^*,p} \). MN-PS is robust to inaccuracy in orientation information, as slight changes in orientation may change the optimal UT beam, but the optimal panel is less likely to change. If the UT has \( N_P \) RF chains (one RF chain per panel), then each AP beam can be sensed simultaneously with all the panels, and there is no need for panel selection. Thus, in this case, \( NET^P_1 \) is not needed, and the BA can be done using only UT location.

**D. Multi-Network Beam Selection Design**

The multi-network beam selection (MN-BS) design follows a structure similar to the MN-PS one, with the second network providing optimality probabilities directly for the UT beams, instead of for the UT panels. The design of \( NET_B^P \) is exactly like \( NET^P_1 \) in the UT panel selection method. The structure of \( NET_B^P \) is the same as \( NET^P_1 \) except with \( N_{UT} \) neurons at the output instead of \( N_P \). \( NET_B^P \) provides estimates of conditional probabilities of UT beam \( j \) as the optimal beam for a given AP beam, i.e.,

\[
P_{j|i} = P[j = j^*|i = i^*]. \tag{11}
\]

The joint probabilities of transceivers beam pair \((i, j)\) as the optimal beam pair can be written as:

\[
P_{i,j} = P_{j|i}P_i. \tag{12}
\]

The candidate beam list \( S \) is made of beam-pairs with the highest estimated probabilities \( P_{i,j} \) of being optimal. In case of having multiple RF chain at UT, we use the approach described in Section III-B to sense with \( N_{RF} \) panels simultaneously.

**IV. Simulation Results**

In this study, we consider the living room proposed in the IEEE 802.11ad task group as an indoor environment with \( 7 \times 7 \times 3 \) meters dimension. The user grid is a rectangle of \( 4 \times 7 \) meters at 1.5m height above the floor. The scenario and its propagation properties are described in detail in [18]. As shown in Fig. 4, the AP is fixed and located in the center of one of the side walls. The AP is made of a UPA panel with \{1, 8, 8\} antenna elements. In this evaluation, we consider both designs for antenna placement shown in Fig. 1. Panels P1 to P3 have ULAs with 4 antenna elements and UPAs with the configuration of \{2, 2, 1\} antenna elements are used for P4 and P5. We use the antenna radiation pattern described in [19] to simulate the antenna gain of a patch antenna. We use \( tanh \) and \( softmax \), respectively, as the activation function of the hidden layers and output layer for all the proposed NN structures. In addition, \( P_t = 24 \) dBm, and \( \sigma^2 = -84 \) dBm are used. For all the networks, we consider \( N_h = 5 \) and \( n_h = 128 \) and follow the training procedure explained in [4]. Thus, for the edge-face design, the SN, MN-PS, and MN-BS include \( 232K, 146K, \) and \( 148K \) trainable parameters, respectively. To replicate the numerical results, the datasets and code are publicly available at https://github.com/SajadRezaie/MultiPanelBeamSelection.

Fig. 5 shows the spherical coverage with all the panels for the edge design with 12 beams and the edge-face design.
with 20 beams. The edge design provides lower antenna gain in the directions perpendicular to the device face and back, and suffers from the lack of panel at the bottom. To evaluate the performance of DL-based BA methods, we consider two baselines: GIFP and HP-BS methods. The GIFP is a look-up table method and is described in detail in [3], [14]. In the HP-BS, the UT senses the environment with a wide beam for each panel while the AP transmits with a wide beam. Then, all beams of the selected panel are used to find the UT beam that provides the highest RSS. Later, the AP finds the best AP beam using a HBS algorithm [14].

The UT position is uniformly drawn from the user grid, and the UT orientation is 50% in portrait mode and 50% in landscape mode, as defined in Section II. The line-of-sight (LOS) path is available in half of the realizations, while the other half is generated in non-LOS conditions to emulate blockage situations. The training and test datasets for the proposed DL models are constructed as follows. The AP and UT sense the environment with all possible combinations of beamforming vectors and combiners. We collect the RSS measurements in a dataset, besides each sample’s UT location and orientation. To evaluate the performance of CI-based methods with different training dataset sizes, training datasets $D_T^5$ and $D_T^7$, respectively include 56,000 and 560 training samples. We use a test dataset with 14,000 samples for evaluation. To account for the overhead introduced by the beam alignment procedure, we evaluate the achievable spectral efficiency of the different methods. We assume that the beam pairs chosen during the beam selection procedure are used in a frame of duration $T_{fr}$, smaller than the channel’s coherence time. The effective spectral efficiency (ESE) of a BA procedure using $N_b$ time slots is modeled as $\text{SE}_{\text{eff}} = \frac{T_f r - N_b T_s}{T_{fr}} \log_2(1 + \text{SNR}_{i,j})$, where $i$ and $j$ are the indices of the AP and UT beams chosen after the beam scanning procedure. Also, $\text{SNR}_{i,j}$ and $T_s$ denote the SNR of $(i, j)$th beam pair and the beam scanning time slot duration, respectively. $T_{fr} = 20$ms and $T_s = 0.1$ms are used in this study [20].

### A. Numerical Evaluation

The performance of the described BA methods using $D_T^5$ with 56,000 training samples is shown in Fig. 6. The MN-BS method has the highest accuracy, which shows the power of the multi-network design using the embedding layer. Also, we see almost no performance degradation in DL-based methods using only 1 RF-chain instead of all 5 RF-chains at the device. As a result of a large training dataset, the MN-BS is trained to reach high accuracy. Thus, at each time slot with a selected AP beam, the MN-BS predicts the proper UT beam from the right panel, and there is nothing to gain by simultaneously sensing with other panels. Thus, the UT can save power during the BA procedure by turning off all the panels except one of them. The MN-PS method senses all the beams at each panel, which leads to inefficiency compared to MN-BS. However, MN-PS with 5 RF chains can perform well using only the UT location as a unique solution.

The MN-BS method using 3 beam scanning time slots provides 5% more ESE and 50% less latency than the GIFP method, which uses 6 beam sensing time slots. Although the HP-BS using 22 sensing time slots does not require any CI and has negligible computational complexity [21], it provides 30% less ESE and around 7 times more latency than the MS-BS method with sensing in 3 time slots. Also, note that the computations of the DL-based methods are done on the AP

![Fig. 5. Antenna array factor for (a) Edge design (b) Edge-face design.](image)

![Fig. 6. Misalignment probability and effective spectral efficiency for the edge-face design with 56,000 training samples in $D_T^5$.](image)
side. In conclusion, the CI-based BA methods using a large training dataset outperform the HP-BS method significantly.

Since the acquisition of training data is costly, it is of interest to examine the performance of DL-based methods when trained with small datasets. Fig. 7(a) shows the performance of the different BA methods using $D_{2}^{5}$ with 560 training samples. Having fewer trainable parameters, the MN designs offer a significant gain compared to the SN structure. In spite of the small dataset size, the MN-BS method significantly outperforms the GIFP as an alternative data-driven approach. Moreover, due to the fact that our proposed methods are DL-based, the transfer learning technique proposed in [22] can be used with the proposed DL-based method to reduce further the performance gap with large training datasets. The edge design has advantages over the edge-face design in hardware complexity and cost with only a slight performance degradation, as shown in Fig. 7(b).

V. CONCLUSIONS

This work shows the usefulness of UT location and orientation in the initial BA of multi-panel devices in mmWave communications. Our results show that the deep learning-based methods offer excellent performance in proposing proper beam/panels which leads to power saving by turning off panels for a given UT coordinate and orientation. The numerical evaluations show that the multi-network designs provide the best performance in limited training dataset sizes due to having fewer trainable parameters than the single-network structure. The edge design can offer comparable performance to the edge-face design while reducing the cost and power at UT. Future research will focus on DL based methods with low computational complexity.

REFERENCES

[1] M. Giordani, M. Polese, M. Mezzavilla, S. Rangan, and M. Zorzi, “Toward 6G Networks: Use Cases and Technologies,” IEEE Commun. Mag., vol. 58, no. 3, pp. 55–61, Mar. 2020.

[2] M. Giordani, M. Mezzavilla, and M. Zorzi, “Initial Access in 5G mmWave Cellular Networks,” IEEE Commun. Mag., vol. 54, no. 11, pp. 40–47, Nov. 2016.

[3] V. Va, J. Choi, T. Shimizu, G. Bansal, and R. W. Heath, “Inverse Multipath Fingerprinting for Millimeter Wave V2I Beam Alignment,” IEEE Trans. Veh. Technol., vol. 67, no. 5, pp. 4042–4058, May 2018.

[4] S. Rezaie, C. N. Manchón, and E. de Carvalho, “Location- and Orientation-Aided Millimeter Wave Beam Selection Using Deep Learning,” in Proc. IEEE Int. Conf. Commun., Jun. 2020, pp. 1–6.

[5] W. Xu, F. Gao, S. Jin, and A. Alkhateeb, “3D Scene-Based Beam Selection for mmWave Communications,” IEEE Wireless Commun. Lett., vol. 9, no. 11, pp. 1850–1854, Nov. 2020.

[6] V. Raghavan, M.-L. Chi, M. A. Tassoudji, O. H. Koymen, and J. Li, “Antenna Placement and Performance Tradeoffs With Hand Blockage in Millimeter Wave Systems,” IEEE Transactions on Communications, vol. 67, no. 4, pp. 3082–3096, Apr. 2019.

[7] V. Raghavan, R. A. Motos, M. A. Tassoudji, Y.-C. Ou, O. H. Koymen, and J. Li, “Mitigating Hand Blockage with Non-Directional Beamforming Codebooks,” arXiv:2104.06472 [cs, math]. Apr. 2021. [Online]. Available: http://arxiv.org/abs/2104.06472

[8] J. Mo et al., “Beam Codebook Design for 5G mmWave Terminals,” IEEE Access, vol. 7, pp. 98387–98404, 2019.

[9] A. Almamouri, J. Mo, B. L. Ng, C. C. Zhang, and J. G. Andrews, “Hand Grip Impact on 5G mmWave Mobile Devices,” IEEE Access, vol. 7, pp. 60532–60544, 2019.

[10] W.-T. Shih, C.-K. Wen, S.-H. Tsai, and S. Jin, “Fast Antenna and Beam Switching Method for mmWave Handsets with Hand Blockage,” IEEE Trans. Wireless Commun., pp. 1–1, 2021.

[11] X. Song, T. Kuhne, and G. Caire, “Fully-Partially-Connected Hybrid Beamforming Architectures for mmwave MU-MIMO,” IEEE Trans. Wireless Commun., vol. 19, no. 3, pp. 1754–1769, Mar. 2020.

[12] Y. Heng et al., “Six Key Challenges for Beam Management in 5.5G and 6G Systems,” IEEE Commun. Mag., vol. 59, no. 7, pp. 74–79, Jul. 2021.

[13] A. Ali, J. Mo, B. L. Ng, V. Va, and J. C. Zhang, “Orientation-Assisted Beam Management for Beyond 5G Systems,” IEEE Access, vol. 9, pp. 51832–51846, 2021.

[14] S. Rezaie, E. de Carvalho, and C. N. Manchón, “A Deep Learning Approach to Location-Aided Orientation-aided 3D Beam Selection for mmWave Communications,” arXiv:2110.06859 [eess], Oct. 2021, arXiv: 2110.06859. [Online]. Available: http://arxiv.org/abs/2110.06859

[15] “Altaf Feko WinProp,” [online] Available: https://www.altair.com/feko.

[16] M. Kok, J. D. Hol, and T. B. Schön, “Using Inertial Sensors for Position and Orientation Estimation,” Found. Trends Signal Process., vol. 11, no. 1-2, pp. 1–153, 2017.

[17] C. De Lima et al., “Convergent Communication, Sensing and Localization in 6G Systems: An Overview of Technologies, Opportunities and Challenges,” IEEE Access, vol. 9, pp. 26902–26925, 2021.

[18] A. Maltsev, “Channel models for 60GHz WLAN systems,” IEEE802. 11 09/0334r8, 2010.

[19] 3GPP, “Study on channel model for frequencies from 0.5 to 100 GHz,” TR 38.901 V16.1.0, 2020. [Online]. Available: http://www.3gpp.org/DynaReport/38901.htm

[20] M. Hussain and N. Michelusi, “Second-Best Beam-Alignment via Bayesian Multi-Armed Bandits,” in Proc. IEEE GLOBECOM, Dec. 2019, pp. 1–6.

[21] V. Raghavan, J. Cezanne, S. Subramanian, A. Sampath, and O. Koymen, “Beamforming Tradeoffs for Initial UE Discovery in Millimeter-Wave MIMO Systems,” IEEE J. Sel. Top. Signal Process., vol. 10, no. 3, pp. 543–559, Apr. 2016.

[22] S. Rezaie, A. Amirí, E. de Carvalho, and C. N. Manchón, “Deep Transfer Learning for Location-Aware Millimeter Wave Beam Selection,” IEEE Commun. Lett., vol. 25, no. 9, pp. 2963–2967, Sep. 2021.