DEEP ACTIVE LEARNING APPROACH TO ADAPTIVE BEAMFORMING FOR MMWAVE INITIAL ALIGNMENT

Foad Sohrabi, Zhilin Chen, and Wei Yu

Department of Electrical and Computer Engineering
University of Toronto, Toronto, ON, Canada, M5S 3G4
Emails: {fsohrabi, zchen, weiyu}@ece.utoronto.ca

ABSTRACT

This paper proposes a deep learning approach to the adaptive and sequential beamforming design problem for the initial access phase in a mmWave environment with a single-path channel model. In particular, for a single-user scenario where the problem is equivalent to designing the sequence of sensing beamformers to learn the angle of arrival (AoA) of the dominant path, we propose a novel deep neural network (DNN) that designs a sequence of adaptive sensing vectors based on the available information so far at the base station (BS). By recognizing that the posterior distribution of the AoA provides sufficient statistic for solving the initial access problem, we consider the AoA posterior distribution as the main component of the input to the proposed DNN for designing the adaptive beamforming strategy. However, computing the AoA posterior distribution can be computationally challenging when the fading coefficient is unknown. To address this issue, this paper proposes to use the minimum mean squared error (MMSE) estimate of the fading coefficient to compute an approximation of the posterior distribution. Numerical results demonstrate that as compared to the existing adaptive beamforming schemes utilizing predesigned hierarchical codebooks, the proposed deep learning-based adaptive beamforming achieves a higher AoA detection performance.

1. INTRODUCTION

Millimeter-wave (mmWave) communication is a promising technology that can address the ever-increasing demand for higher data rates in future wireless communication systems [1, 2]. Although the pathloss and absorption are more severe in mmWave bands than the conventional frequency spectrums, the small wavelength in mmWave frequencies can be exploited to deploy large-scale antenna arrays in relatively small areas. This leads to the advent of the massive multiple-input multiple-output (MIMO) concept for mmWave communications, in which the transceivers with large-scale antenna arrays form highly directional beamformers in order to combat the poor propagation characteristics of mmWave channels [3, 4]. However, constructing such directional beamformers requires an accurate estimate of the channel state information (CSI) that must be obtained in the initial access phase. In this paper, we focus on the massive MIMO system in which a BS with a single RF chain communicates with a single antenna user in a mmWave environment with a single dominant path channel model. For such a system, the initial alignment problem is equivalent to actively learning the angle of arrival (AoA). The main point of this paper is that the deep learning framework can be used to learn the AoA by adaptively designing the sensing vectors in the initial access phase.

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The problem of designing the optimal adaptive sensing strategy for AoA acquisition, in general, is quite challenging. To make such an AoA acquisition problem more tractable, [5] develops a hierarchical codebook which, in the noiseless setting, allows for an adaptive bisection search over the angular space. By utilizing the same hierarchical beamforming codebook in [5], the authors in [6] propose an alternative adaptive beamforming strategy, called *hierarchical posterior matching* (hiePM), which accounts for the measurement noise statistics and selects the beamforming vectors from the hierarchical codebook based on the AoA posterior distribution. It is shown that the hiePM algorithm in [6], which is mainly devised from the algorithms for sequential noisy search strategies [7] and Bayesian active learning from imperfect labelers [8, 9], can achieve better performance as compared to the bisection algorithm in [5]. While the original hiePM algorithm is restricted to the scenario that the fading coefficient of the single-path channel is known at the BS, the recently proposed variants of hiePM extend the results to the more realistic case in which the fading coefficient is unknown, either by using Kalman filter tracking of the fading coefficient in [10] or by using the variational Bayesian inference framework in [11].

Nevertheless, the hiePM algorithms in [6, 10, 11] still employ the hierarchical codebook, and as a result, their overall performances are governed by the quality of this codebook. In this paper, we show that it is possible to design a better adaptive beamforming strategy by employing a codebook-free deep learning approach. In particular, we propose a deep neural network (DNN) that adaptively designs the sensing vectors based on the currently available information at the BS in order to optimize the final AoA detection performance. Motivated by the posterior matching methods [6, 10, 11], which show that the AoA posterior distribution is a sufficient statistic for adaptive sensing, we use the AoA posterior distribution as the main input feature to the DNN. However, as shown in [10], the exact computation of the AoA posterior distribution involves computing several computationally-demanding integrals, rendering the use of exact posterior distribution computationally infeasible. To address this issue, this paper first uses the minimum mean squared error (MMSE) estimate of the fading coefficient in order to compute an approximation of the AoA posteriors, then considers the approximated AoA posterior distribution as the input to the proposed DNN. Numerical results show the proposed deep learning-based adaptive beamforming approach outperforms the existing adaptive beamforming strategies that employ the hierarchical codebook.

2. SYSTEM MODEL AND PROBLEM FORMULATION

We consider a mmWave communications setup in which a BS with M antennas and a single RF chain serves a single-antenna user. To establish a reliable link between the BS and the user, we consider an uplink pilot channel training procedure consisting of τ time frames, where the user transmits uplink pilots $\{x_t\}_{t=1}^{\tau}$, satisfying the power constraint $|x_t|^2 \leq P$. Due to the single RF chain constraint, the BS observes the baseband received pilot signals after combining analog signals at the antenna elements by employing analog beamforming (or sensing) vectors $\{\mathbf{w}_t\}_{t=1}^{\tau}$, i.e.,

$$y_t = \mathbf{w}_t^H \mathbf{h} x_t + \mathbf{w}_t^H \mathbf{z}_t, \quad \forall t \in \{1, \ldots, \tau\}, \tag{1}$$

where $\mathbf{h} \in \mathbb{C}^N$ is the channel vector between the BS and the user, $\mathbf{z}_t \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$ is the additive white Gaussian noise, and without loss of generality we assume $\|\mathbf{w}_t\|^2 = 1$ and $x_t = \sqrt{P}, \forall t$.[1] We further assume that the mmWave channel between the BS and the user can be modeled by a single dominant path [5], i.e.,

$$\mathbf{h} = \alpha \mathbf{a}(\phi), \tag{2}$$

where $\alpha \sim \mathcal{CN}(0, 1)$ is the complex fading coefficient of the channel, ϕ is the corresponding AoA, and $\mathbf{a}(\cdot)$ is the array response vector. For a uniform linear array with half-wavelength antenna spacing, we have $\mathbf{a}(\phi) = \left[1, e^{j\pi \sin\phi}, ..., e^{j(M-1)\pi \sin\phi}\right]^T$.

The estimation of the AoA (i.e., ϕ) from the baseband received signals (i.e., $\{y_t\}_{t=1}^{\tau}$) is an important problem in many applications, including localization [12] and the downlink beamforming design for time-division duplex massive MIMO systems [13]. This procedure is also known as *initial beam alignment*. Note that since y_t is observed through a sensing vector $\mathbf{w}_t$, the BS can potentially optimize the quality of its AoA estimation by designing the best $\mathbf{w}_t$ at each time frame, possibly sequentially in an adaptive manner. This means that the sensing vector in time frame $t+1$ can be considered as a mapping from the past observations, i.e., the measurements and the beamforming vectors prior to time frame $t+1$, as:

$$\mathbf{w}_{t+1} = \mathcal{G}_t\left(y_{1:t}, \mathbf{w}_{1:t}\right), \quad \forall t \in \{0, \ldots, \tau-1\}, \tag{3}$$

where $\mathcal{G}_t : \mathbb{C}^t \times \mathbb{C}^{tM} \to \mathbb{C}^M$ is the adaptive beamforming (or sensing) strategy. Furthermore, the final AoA estimate, $\hat{\phi}$, is obtained as a function of the sensing vectors and the baseband received signals in τ time frames as:

$$\hat{\phi} = \mathcal{F}\left(y_{1:\tau}, \mathbf{w}_{1:\tau}\right), \tag{4}$$

where $\mathcal{F} : \mathbb{C}^\tau \times \mathbb{C}^{\tau M} \to \mathbb{R}$ is the AoA estimation scheme.

In this paper, we consider a simplifying assumption that the AoA for each coherence block is taken from a uniform grid of N points, i.e., $\phi \in \{\phi_1, \phi_2, \ldots, \phi_N\}$ where $\phi_i = \phi_{\min} + \frac{i-1}{N-1}(\phi_{\max} - \phi_{\min})$. In this setup, the task of the BS is to declare one of those candidates in the grid set as $\hat{\phi}$ and the quality of the established link can be determined in terms of the accuracy of the final estimate of ϕ; see [6]. One way to pursue this program is to formulate it as a detection (classification) problem as follows:

$$\min_{\{\mathcal{G}_t(\cdot)\}_{t=0}^{\tau-1}, \mathcal{F}(\cdot)} \quad \mathbb{P}\left(\hat{\phi} \neq \phi\right) \tag{5a}$$

$$\text{s.t.} \qquad \mathbf{w}_{t+1} = \mathcal{G}_t\left(y_{1:t}, \mathbf{w}_{1:t}\right), \ \forall t \in \{0, \ldots, \tau-1\}, \tag{5b}$$

$$\hat{\phi} = \mathcal{F}\left(y_{1:\tau}, \mathbf{w}_{1:\tau}\right), \tag{5c}$$

[1] Note that the analog beamformer $\mathbf{w}_t$ in RF chain limited systems is typically implemented via a network of phase shifters, and accordingly, $\mathbf{w}_t$ satisfies the constant modulus constraint. However, in order to fairly compare the proposed design with the existing active AoA learning methods such as [6] that only consider the total beamforming power constraint, this paper focuses on the total power constraint, i.e., $\|\mathbf{w}_t\|^2 = 1$.

in which both ϕ and $\hat{\phi}$ belong to a grid.

The joint design of the adaptive beamforming strategy and the AoA estimation scheme by directly solving the problem (5) can be quite challenging. To make such an AoA estimation problem more tractable, the exiting adaptive beamforming schemes in the literature typically design the sensing vectors by selecting that from a predesigned set of beamformers, called beamforming codebook. The hierarchical beamforming codebook, initially developed in [5], is an example of such codebooks that has been widely used for the initial alignment problem, e.g., [5, 6, 10, 11]. In this paper, we aim to show that it is possible to design a better adaptive beamforming strategy if we do not restrict ourselves to use such predesigned codebooks. In particular, we propose a DNN architecture in which the available information at the BS in time frame t is directly mapped to the beamforming vector for obtaining the next measurement, i.e., $\mathbf{w}_{t+1}$. In this way, the proposed deep learning-based adaptive beamforming strategy is not restricted to any particular codebook, and can achieve better performance as compared to the existing algorithms, e.g., [5, 6, 10, 11], that utilize the hierarchical codebook.

3. CODEBOOK-FREE ADAPTIVE BEAMFORMING FOR INITIAL ALIGNMENT USING DEEP LEARNING

In this section, we present how to use the deep learning framework to obtain the codebook-free adaptive beamforming strategy for the initial beam alignment problem in (5). As the first step and to fix ideas, we make the simplifying (and unrealistic) assumption that the fading coefficient α is perfectly known at the BS (similar to [6]). This assumption is removed in Section 3.2, where we consider a more practical setup in which only the statistical information of α is available.

3.1. Known Fading Coefficient Scenario

In this part, we aim to tackle the AoA detection problem in (5) for the case that the complex fading coefficient α is assumed to be fully known at the BS. As discussed earlier, the sensing vector in each time frame can be designed as a function of all past measurements and sensing vectors, see (5b). However, in this paper, we follow the same strategy as in [6], where instead of directly using past observations, we design $\mathbf{w}_{t+1}$ based on the posterior of the AoA at time t, which is a sufficient statistic. Mathematically speaking, if we denote the AoA posterior distribution at time frame t by an N-dimensional vector $\boldsymbol{\pi}_t$, with the i-th element being:

$$\pi_i^{(t)} = \mathbb{P}\left(\phi = \phi_i \mid y_{1:t}, \mathbf{w}_{1:t}\right), \quad \forall i \in \{1, \ldots, N\}, \tag{6}$$

then the sensing vector for the next measurement can be written as:

$$\mathbf{w}_{t+1} = \widetilde{\mathcal{G}}_t\left(\boldsymbol{\pi}_t\right), \quad \forall t \in \{0, \ldots, \tau-1\}, \tag{7}$$

where the function $\widetilde{\mathcal{G}}_t : [0, 1]^N \to \mathbb{C}^M$ determines the adaptive beamforming strategy in time frame $t+1$.

By applying the Bayes's rule to the measurement model in (1) under the assumption that the fading coefficient α is known, the posterior distribution in time frame $t+1$ can be computed as:

$$\pi_i^{(t+1)} = \frac{\pi_i^{(t)} f\left(y_{t+1} \middle| \phi = \phi_i, \mathbf{w}_{t+1} = \widetilde{\mathcal{G}}_t\left(\boldsymbol{\pi}_t\right)\right)}{\sum_{j=1}^N \pi_j^{(t)} f\left(y_{t+1} \middle| \phi = \phi_j, \mathbf{w}_{t+1} = \widetilde{\mathcal{G}}_t\left(\boldsymbol{\pi}_t\right)\right)}, \tag{8}$$

where

$$f\left(y_{t+1} \middle| \phi = \phi_i, \mathbf{w}_{t+1} = \widetilde{\mathcal{G}}_t(\boldsymbol{\pi}_t)\right) = \frac{1}{\pi} e^{-\|y_{t+1} - \sqrt{P}\alpha \mathbf{w}_{t+1}^H \mathbf{a}(\phi_i)\|^2}$$

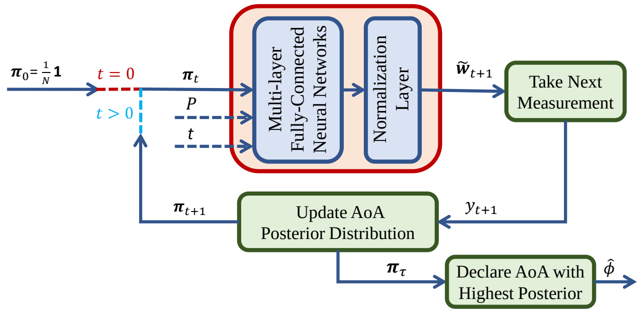

Fig. 1. The block diagram of the proposed adaptive beamforming strategy for AoA detection in the initial access phase of a mmWave communications system.

is the conditional distribution of the measurement y_{t+1} given the AoA and the current sensing vector. Once the pilot training phase is completed at the end of the time frame τ, we declare the angle in the grid set with the maximum posterior probability as the final estimate of ϕ, i.e.,

$$\hat{\phi} = \phi_{i^\star}, \quad \text{where } i^\star = \underset{i}{\operatorname{argmax}}\ \pi_i^{(\tau)}. \tag{9}$$

In the active AoA learning procedure explained above, the only remaining part to design is the function $\widetilde{\mathcal{G}}_t(\cdot)$, which maps the AoA posterior distribution to the next sensing vector. Unlike the existing methods which seek to address this challenging design problem by searching over a fixed codebook, e.g., hierarchical codebook [5,6,10,11], in this paper, we propose an alternative data-driven framework to undertake this design. In particular, we propose an L-layer fully-connected DNN that takes the current posterior distribution together with the other available system parameters as the input, i.e., $\mathbf{v}_t = \left[\boldsymbol{\pi}_t^T, P, t\right]^T$, and outputs the sensing vector for the next measurement as:

$$\widetilde{\mathbf{w}}_{t+1} = \sigma_L\left(\mathbf{A}_L \mathcal{R}\left(\cdots \mathcal{R}\left(\mathbf{A}_1 \mathbf{v}_t + \mathbf{b}_1\right)\cdots\right) + \mathbf{b}_L\right), \tag{10}$$

where $\{\mathbf{A}_\ell, \mathbf{b}_\ell\}_{\ell=1}^L$ is the set of the trainable weights and biases of the DNN, $\mathcal{R}(\cdot) = \max(\cdot, 0)$ is the ReLU activation function, $\sigma_L(\cdot) = \frac{\cdot}{\|\cdot\|}$ is the normalization activation function at the last layer ensuring the power constraint is satisfied, and $\widetilde{\mathbf{w}}_{t+1}$ is the real representation[2] of the beamforming vector in time frame $t+1$, i.e.,

$$\widetilde{\mathbf{w}}_{t+1} = \left[\Re\left(\mathbf{w}_{t+1}^T\right), \Im\left(\mathbf{w}_{t+1}^T\right)\right]. \tag{11}$$

Note that, in the proposed DNN architecture, it would be possible to employ different weights and biases for different time frames. However, in this paper, we propose using a common set of DNN weights and biases for all the time frames, and instead, we consider the time frame index as the input to the DNN. The primary motivation for this consideration is that such a common DNN structure can potentially lead to a more scalable and faster training procedure by reducing the dimensions of the trainable parameters.

The block diagram of the overall proposed AoA detection strategy is illustrated in Fig. 1. As it can be seen from Fig. 1, the adaptive beamforming module implemented by the DNN as in (10) and the posterior distribution update computed by (8) interact with each other to obtain an accurate estimate for the AoA at the end of the time frame τ. Since we assume no prior information is available about the AoA distribution, we start the algorithm with a uniform posterior distribution at $t=0$, i.e., $\boldsymbol{\pi}_0 = \frac{1}{N}\mathbf{1}$, where $\mathbf{1}$ denotes the all-one vector.

By unrolling the loop in the proposed adaptive detection algorithm in Fig. 1, we can think of the proposed end-to-end architecture as a very deep neural network. The ultimate goal of this DNN is to successfully recover the AoA value. This detection task can be treated as a classification problem for which the categorical cross-entropy is the typical choice of the loss function. Accordingly, we can train the proposed DNN architecture by employing the stochastic gradient descent algorithm to minimize the average cross-entropy between the final posterior distribution at time frame τ and the one-hot representation of the actual AoA, i.e., $\mathbf{e}_\phi = [e_1^{(\phi)}, \ldots, e_N^{(\phi)}]$ where $e_i^{(\phi)}$ is 1 if the actual AoA is ϕ_i and 0 otherwise, i.e.,

$$\mathcal{L} = -\mathbb{E}_{\mathbf{u}}\left[\sum_{i=1}^N e_i^{(\phi)} \log \pi_i^{(\tau)}\right], \tag{12}$$

where the expectation is over all the stochastic parameters of the system, i.e., $\mathbf{u} \triangleq [\alpha, \phi, \mathbf{z}]$ with $\mathbf{z} = [z_1, \ldots, z_\tau]$.

3.2. Unknown Fading Coefficient Scenario

We now deal with the more practical scenario where the fading coefficient α is unknown. Toward this end, we need to modify the expression for updating the posterior distribution in (8), which has been derived for a given α in Section 3.1. As shown in [10], when α is unknown, the expression of the conditional distribution involves computing computationally-demanding integrals. Therefore, the exact computation of $\boldsymbol{\pi}_t$ for unknown α may be computationally infeasible. To address this issue, in this paper, we propose an alternative approach in which the fading coefficient is first estimated in each time frame using an MMSE estimator. Subsequently, the MMSE estimate of the fading coefficient is used to compute an approximate of the AoA posteriors.

In particular, assuming that the actual AoA is ϕ_i, we first seek to estimate the fading coefficient at time frame t from the available measurements, i.e.,

$$\mathbf{y}_t = \mathbf{c}_{i,t}\alpha + \mathbf{n}_t, \tag{13}$$

where $\mathbf{y}_t = [y_1, \ldots, y_t]^T$, $\mathbf{c}_{i,t} = \sqrt{P}[\mathbf{w}_1 \ \ldots \ \mathbf{w}_t]^H \mathbf{a}(\phi_i)$, and $\mathbf{n}_t \sim \mathcal{CN}(\mathbf{0}, \mathbf{I})$. Given that the fading coefficient has the standard complex Gaussian distribution, i.e., $\alpha \sim \mathcal{CN}(0,1)$, the MMSE estimate of the fading coefficient at time frame t can be computed as:

$$\hat{\alpha}_i^{(t)} = \left(\mathbf{c}_{i,t}^H \mathbf{c}_{i,t} + 1\right)^{-1} \mathbf{c}_{i,t}^H \mathbf{y}_t. \tag{14}$$

The MMSE estimate of the fading coefficient in (14) can then be used to approximate the AoA posterior distribution. In particular, we propose to approximate the AoA posterior distribution by regarding the MMSE estimate for α in (14) as the actual value of the fading coefficient. With this approximation in place, we can show that the i-th element of the AoA posterior distribution at time frame t can be computed as:

$$\pi_i^{(t)} = \frac{\prod_{\tilde{t}=1}^t e^{-\|y_{\tilde{t}} - \sqrt{P}\hat{\alpha}_i^{(t)} \mathbf{w}_{\tilde{t}}^H \mathbf{a}(\phi_i)\|^2}}{\sum\limits_{j=1}^N \prod_{\tilde{t}=1}^t e^{-\|y_{\tilde{t}} - \sqrt{P}\hat{\alpha}_j^{(t)} \mathbf{w}_{\tilde{t}}^H \mathbf{a}(\phi_j)\|^2}}. \tag{15}$$

Note that as the number of available measurements is increased, the MMSE estimate becomes more accurate. Accordingly, in (15),

[2] To use the existing deep learning libraries that only support real-value operations, we consider the beamforming vector's real representation as the output of the DNN.

we compute the posteriors in time frame t based on the most updated estimate of the fading coefficient, i.e., $\hat{\alpha}_i^{(t)}$. Once the approximated posteriors are obtained using (15), analogous to the known fading scenario in Section 3.1, we employ a DNN that directly maps the approximated posterior distribution and the additional system parameters to the next sensing vector. In this way, the overall proposed AoA detection strategy for the unknown fading coefficient scenario can also be illustrated as in Fig. 1, but in this case the step of updating the posteriors further involves estimating the fading coefficients.

4. NUMERICAL RESULTS

In this section, we illustrate the performance of the proposed deep learning-based adaptive beamforming method for initial beam alignment in a mmWave environment. We compare the performance of the proposed method against several exiting schemes in the literature. Before presenting the numerical results, we first provide a brief explanation for each of the considered AoA detection baselines.

1) Compressive sensing (CS) with fixed beamforming: In this approach, we randomly generate the sensing vectors for all τ frames. Denoting the collection of all sensing vectors by $\mathbf{W} = [\mathbf{w}_1 \dots \mathbf{w}_\tau]$ and the collection of response vectors for all N possible AoAs by $\mathbf{A}_{\text{BS}} = [\boldsymbol{\alpha}(\phi_1) \dots \boldsymbol{\alpha}(\phi_N)]$, the received signal at the BS in τ time frames can be written as $\mathbf{y}_\tau = \mathbf{W}^H \mathbf{A}_{\text{BS}} \mathbf{x} + \mathbf{n}_\tau$, where $\mathbf{x}$ is an unknown 1-sparse vector. The AoA detection problem can now be cast as finding the support of $\mathbf{x}$. This sparse recovery problem can be tackled by employing CS techniques. Here, we adopt a widely-used CS algorithm called orthogonal matching pursuit (OMP) [14].

2) Hierarchical codebook with bisection search (hieBS) [5]: This adaptive beamforming scheme employs a hierarchical codebook with $S = \log_2(N)$ levels of beam patterns such that each level s consists of a set of 2^s beamforming vectors which partition the AoA search space, i.e., $[\phi_{\text{min}}, \phi_{\text{max}}]$, into 2^s sectors. The beamforming vector in each sector is designed such that the beamforming gain is almost constant for AoAs within that sector, and nearly zero otherwise. Further, the sensing vector in each time frame is selected from such a hierarchical codebook using the binary search algorithm, which requires $\tau = 2S = 2\log_2(N)$ time frames for AoA detection from an N point grid set.

3) Hierarchical codebook with posterior matching (hiePM) [6]: This design also adopts the hierarchical codebook in [5]. However, unlike [5], the proposed method in [6] selects the beamforming vectors from the hierarchical beamforming codebook based on the AoA posterior distribution. It should be mentioned that, in this approach, the value of the fading coefficient is assumed to be known at the BS such that the AoA posterior distribution can be accurately computed.

In our numerical experiments, we consider that the BS is equipped with $M = 64$ antennas and the AoA is uniformly drawn from an $N = 128$ grid point set with $\phi_{\text{min}} = -60^\circ$ and $\phi_{\text{max}} = 60^\circ$. To fairly compare our proposed methods with other baselines, we set the number of uplink pilot transmission as $\tau = 2\log_2(N) = 14$. Further, we implement the proposed network on TensorFlow [15] by employing Adam optimizer [16] with a learning rate progressively decreasing from 10^{-3} to 10^{-5}. We consider 4-layer neural networks with dense layers of widths $[1024, 1024, 1024, 2M]$, respectively. For faster convergence, each dense layer is preceded by a batch normalization layer. We consider 10 batches per epoch, each of which contains 2^{12} samples. To investigate the ultimate performance of the proposed approach, we assume that we can generate as many data samples as needed for training the DNN. We monitor the performance of the DNN during training by computing the loss function for a validation data set of 10^5 samples and keep the model

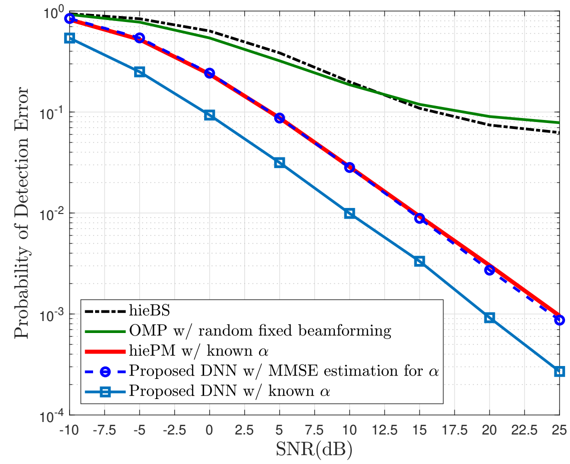

Fig. 2. Average detection error probability versus SNR for different methods in a system with $M = 64$ and $\tau = 14$.

parameters that have achieved the best performance so far. The training procedure is terminated when the detection performance for the validation set has not improved over 300 epochs.

In Fig. 2, we plot the error probability in AoA detection for different methods against signal-to-noise-ratio, i.e., $\text{SNR} \triangleq \log_{10}(P)$. It can be seen that the OMP algorithm using random fixed beamforming and the hieBS algorithm both suffer from an error floor in the high SNR regime. However, the detection performance of the proposed deep learning approach and the hiePM algorithm, both of which design the sensing vectors based on the AoA posterior distribution, continuously improves as the SNR increases. This observation matches with the conclusion in [6] that exploiting the measurement noise statistics via posterior matching can indeed improve the AoA detection performance. Furthermore, Fig. 2 shows that the proposed approach for the known fading coefficient scenario can significantly outperform the hiePM algorithm in [6], which is developed based on the assumption that the fading component is given. This indicates that the proposed DNN can indeed design a better adaptive beamforming strategy as compared to the hiePM that employs the hierarchical codebook. Finally, we can see that the MMSE estimation strategy proposed in Section 3.2 to deal with the unknown fading coefficient scenario is indeed effective, i.e., the proposed DNN without knowing α performs almost the same as hiePM that is assumed to have access to the actual value of α.

5. CONCLUSION

This paper develops a deep learning framework for active learning of the angle-of-arrival of the channel's dominant path by adaptively designing the sequence of sensing vectors in the initial access phase of a mmWave communication. In particular, this paper proposes a DNN that directly maps the current AoA posterior distribution to the sensing vector of the next measurement. Further, to alleviate the computational burden of computing the AoA posterior distribution, this paper proposes to use the MMSE estimate of the fading coefficient to obtain an approximation of the AoA posteriors. Numerical results indicate the proposed codebook-free deep learning-based approach significantly outperforms the existing adaptive beam alignment techniques that utilize predesigned codebooks.

6. REFERENCES

[1] T. S. Rappaport, S. Sun, R. Mayzus, H. Zhao, Y. Azar, K. Wang, G. N. Wong, J. K. Schulz, M. Samimi, and F. Gutierrez, "Millimeter wave mobile communications for 5G cellular: It will work!" *IEEE Access*, vol. 1, pp. 335–349, May 2013.

[2] C. Wang, F. Haider, X. Gao, X. You, Y. Yang, D. Yuan, H. M. Aggoune, H. Haas, S. Fletcher, and E. Hepsaydir, "Cellular architecture and key technologies for 5G wireless communication networks," *IEEE Commun. Mag.*, vol. 52, pp. 122–130, Feb. 2014.

[3] A. F. Molisch, V. V. Ratnam, S. Han, Z. Li, S. L. H. Nguyen, L. Li, and K. Haneda, "Hybrid beamforming for massive MIMO: A survey," *IEEE Commun. Mag.*, vol. 55, no. 9, pp. 134–141, Sept. 2017.

[4] F. Sohrabi and W. Yu, "Hybrid digital and analog beamforming design for large-scale antenna arrays," *IEEE J. Sel. Topics Signal Process.*, vol. 10, no. 3, pp. 501–513, Apr. 2016.

[5] A. Alkhateeb, O. El Ayach, G. Leus, and R. W. Heath, "Channel estimation and hybrid precoding for millimeter wave cellular systems," *IEEE J. Sel. Topics Signal Process.*, vol. 8, no. 5, pp. 831–846, Oct. 2014.

[6] S. Chiu, N. Ronquillo, and T. Javidi, "Active learning and CSI acquisition for mmWave initial alignment," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 11, pp. 2474–2489, Nov. 2019.

[7] Sung-En Chiu and T. Javidi, "Sequential measurement-dependent noisy search," in *IEEE Inf. Theory Workshop (ITW)*, Cambridge, UK, Sept. 2016, pp. 221–225.

[8] M. Naghshvar, T. Javidi, and K. Chaudhuri, "Bayesian active learning with non-persistent noise," *IEEE Trans. Inf. Theory*, vol. 61, no. 7, pp. 4080–4098, July 2015.

[9] S. Yan, K. Chaudhuri, and T. Javidi, "Active learning from imperfect labelers," in *Adv. Neural Inf. Process. Syst. (NIPS)*, Barcelona, Spain, Dec. 2016, pp. 2128–2136.

[10] N. Ronquillo, S.-E. Chiu, and T. Javidi, "Sequential learning of CSI for mmWave initial alignment," Dec. 2019. [Online]. Available: https://arxiv.org/abs/1912.12738

[11] N. Akdim, C. N. Manchón, M. Benjillali, and P. Duhamel, "Variational hierarchical posterior matching for mmWave wireless channels online learning," in *Proc. IEEE Workshop Signal Process. Adv. Wireless Commun. (SPAWC)*, Atlanta, GA, USA, May 2020, pp. 1–5.

[12] M. Li and Y. Lu, "Angle-of-arrival estimation for localization and communication in wireless networks," in *Eur. Signal Process. Conf. (EUSIPCO)*, Lausanne, Switzerland, Aug. 2008, pp. 1–5.

[13] L. Zhao, D. W. K. Ng, and J. Yuan, "Multi-user precoding and channel estimation for hybrid millimeter wave systems," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 7, pp. 1576–1590, July 2017.

[14] J. A. Tropp and A. C. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," *IEEE Trans. Inf. Theory*, vol. 53, no. 12, pp. 4655–4666, Dec. 2007.

[15] M. Abadi et al., "TensorFlow: Large-scale machine learning on heterogeneous distributed systems," Mar. 2016. [Online]. Available: https://arxiv.org/abs/1603.04467

[16] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," Dec. 2014. [Online]. Available: https://arxiv.org/abs/1412.6980