Abstract—Future wireless networks may operate at millimeter-wave (mmW) and sub-terahertz (sub-THz) frequencies to enable high data rate requirements. While large antenna arrays are critical for reliable communications at mmW and sub-THz bands, these antenna arrays would also mandate efficient and scalable initial beam alignment and link maintenance algorithms for mobile devices. Low-power phased-array architectures and phase-less power measurements due to high frequency oscillator phase noise pose additional challenges for practical beam tracking algorithms. Traditional beam tracking protocols require exhaustive sweeps of all possible beam directions and scale poorly with high mobility and large arrays. Compressive sensing and machine learning designs have been proposed to improve measurement scaling with array size but commonly degrade under hardware impairments or require raw samples respectively. In this work, we introduce a novel long short-term memory (LSTM) network assisted beam tracking and prediction algorithm utilizing only phase-less measurements from fixed compressive codebooks. We demonstrate comparable beam alignment accuracy to state-of-the-art phase-less beam alignment algorithms, while reducing the average number of required measurements over time.

Index Terms—Beam tracking, beam prediction, millimeter-wave, machine learning, LSTM

I. INTRODUCTION

Due to large available bandwidth, mmW frequency bands are the key candidates for high data rate cellular and wireless local area networks [1]. Their use, however, comes at the cost of a higher propagation loss than at sub-6 GHz frequencies [2]. The base station (BS) and user equipment (UE) with large antenna arrays need to establish a directional communication link through a beam alignment (BA) procedure to compensate for this loss. Additionally, in highly dynamic mmW environments, where the channel parameters change quickly, the optimal steering beams at the BS and UE need to be tracked between two beam training procedures. In recent years, the beam tracking (BT) problem in mmW networks have attracted significant attention from researchers. Previous work on BT can be roughly divided into two groups, as discussed below.

The first group of work aims to leverage advanced digital signal processing (DSP) techniques and/or array architectures for BT, including different algorithms based on compressive sensing [3], [4] and Kalman filtering [5], [6]. Compressive algorithms exploit the sparsity of mmW channels, reducing the required tracking overhead by taking a small number of signal measurements. On the other hand, Kalman filtering can be leveraged for continuous BT. However, imperfect synchronization and noise can significantly reduce the tracking performance for both the compressive and Kalman filtering methods. DSP algorithms based on phase-less power-based measurements can mitigate this sensitivity problem, as [7] has done for compressive sensing and [8] for Kalman filtering.

In the second group of work, a number of machine learning (ML) algorithms have been proposed for mmW BT and beam prediction (BP). Previous work has considered various recurrent neural network (RNN) architectures to learn and exploit the temporal evolution of the optimal beam steering directions. In [9], the authors proposed an encoder-decoder model with a vanilla RNN network to predict multiple future steering directions based on the previously estimated beams and visual sensing information. [10] proposed a simple LSTM network to estimate the current dominant angles-of-arrival (AoA), while [11] presented an LSTM with autoencoder feature extraction to predict path signal-to-noise ratio (SNR) between multiple mmW BSs. Existing work on ML models for BT and BP primarily focus on sample-based techniques, instead of compressive phase-less measurements.

In this work, we propose a novel RNN algorithm to reduce BT communications overhead for UEs with phased-array antennas. The ML architecture is based on a sequence-to-sequence (Seq2Seq) translation model and LSTM networks, predicting future directional pencil beams for data communications using a buffer of prior compressive BA measurements. To our best knowledge, this is the first work to propose a datadriven BT and BP algorithm using only phase-less received signal strength (RSS) measurements from fixed sensing codebooks, addressing practical hardware constraints. Prior BT and BP algorithms require raw samples or adaptive codebooks.

The remainder of this work is organized as follows: Section II discusses our system model, problem statement, metrics, and existing baseline solutions for phase-less, fixed-codebook BA. Section III details our proposed algorithm design while section IV presents our simulation design and algorithm performance results. Finally, we conclude in Section V.

Notation: Scalars, vectors, and matrices are represented by non-bold lowercase, bold lowercase, and bold uppercase letters respectively. The transpose and Hermitian transpose of A are...
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Therefore, with any w sensing. In this work, we assume that the entire sensing period M arrays, the of from the set \([W] = \{\phi_k^{(t)}\}_{k=1}^{M}, \phi_k^{(t)} \sim \mathcal{CN}(0, \sigma^2 I_{N_e})\) is a complex vector of additive Gaussian noise. After vectorization, the M measurements can be represented as \(y_M^{(t)} = [y_1^{(t)}, \ldots, y_M^{(t)}]^T\).

II. SYSTEM MODEL AND PROBLEM STATEMENT

A. Time-Varying Channel Model

We consider a narrowband mmW line-of-sight (LOS) channel between the BS and UE. Due to the UE’s mobility, the angle and gain of the LOS path may evolve non-linearly over time. We assume that the BS is equipped with a digital uniform linear array (ULA) at the UE, the narrow pencil beams for data communication at the UE side, where the n-th element of the k-th code is \([v_k]_n = \exp(-j2\pi(n-1)\sin(\phi_k^{(t)})/d/\lambda)\). As is common in implementation, \(K > N_e\) for high resolution AoA estimates. In each time step \(t\), the goal of BT is to keep track of the optimal beam \(v_k^{(t)}\) that results in the highest received signal power \(z(k^{(t)}, t) = |v_k^{H} h^{(t)} s_m^{(t)}|^2\). However, in the presence of noise, only an estimate \(\hat{k}(t)\) of the optimal beam index \(k^{(t)}\) is available, and it can be obtained through the exhaustive sweeping of all beams in V. Mathematically, the estimate \(\hat{k}(t)\) is expressed as:

\[
\hat{k}(t) = \arg \max_k |v_k^{H} h^{(t)} s_m^{(t)} + v_k^{H} n_k^{(t)}|.
\]

The ultimate goal of BP based on phase-less measurements is to estimate P beam indices \(k^{(t)} = [\hat{k}(t), \hat{k}(t+1), \ldots, \hat{k}(t+P-1)]^T\) using a set of measurements \(y^{(t-1)} = \{y^{(t-1)} \in \mathbb{C}^{M_L}, y^{(t-2)} \in \mathbb{C}^{M_L}, \ldots, y^{(t-T)} \in \mathbb{C}^{M_L}\}\) made over the last \(T\) time steps, where \(t}\) is the time step when the first prediction is required. Specifically, we aim to estimate \(\bar{k}(t) = \arg \max_k P(\bar{k} = \hat{k}(t)|y^{(t-1)})\). However, since the true probability is difficult to calculate, a BP algorithm \(p(y^{(t-1)})\) is proposed to approximate \(\bar{k}(t)\) as follows:

\[
\bar{k}(t) = \arg \max_k P(\bar{k} = \hat{k}(t)|y^{(t-1)}) \approx p(y^{(t-1)}).
\]

When designing \(p(y^{(t-1)})\), accuracy, gain loss, and number of required measurements serve as performance metrics. Since \(p(y^{(t-1)})\) represents a classification problem, the accuracy of \(p(y^{(t-1)})\) over the \(T\) test time steps is the fraction of time steps with the correct predicted beam direction:

\[
\text{acc} = \frac{1}{\sum_{j=1}^{P} \mathbb{I}[k_j = \arg \max_k P(\bar{k} = \hat{k}(t)|y^{(t-1)})]}.
\]

Accuracy, however, does not capture the impact of incorrect prediction on data communications while tracking. In this work, the alignment quality is measured using gain loss \(g = z(k^{(t)}, t)/z(\hat{k}^{(t)}, t)\) or the difference in gain (in dB) between the optimal pencil beam and the pencil beam selected by the BT and BP algorithm, for a specified percentile of \(P\) estimates. To evaluate the effective reduction in overhead, this work uses the average required number of measurements over a tracking period to meet a maximum gain loss requirement.

The goal of this work is to propose and demonstrate a machine learning based algorithm \(p(y^{(t-1)})\) that uses phase-less measurements from a fixed set of PN beams to reduce the required number of measurements for mmW BT. Two state-of-the-art phase-less BA act as performance baselines, namely a traditional exhaustive search of all pencil beams and the multi-layer perceptron (MLP)-based mmRAPID algorithm [12].

C. Problem Statement

Let \(V = [v_1, \ldots, v_K] \subseteq \mathbb{C}^{N_e \times K}\) be a codebook of narrow pencil beams for data communication at the UE side, where the n-th element of the k-th code is \([v_k]_n = \exp(-j2\pi(n-1)\sin(\pi(k-1)/K-\pi/2)d/\lambda)\). As is common in implementation, \(K > N_e\) for high resolution AoA estimates. In each time step \(t\), the goal of BT is to keep track of the optimal beam \(v_k^{(t)}\) that results in the highest received signal power \(z(k^{(t)}, t) = |v_k^{H} h^{(t)} s_m^{(t)}|^2\). However, in the presence of noise, only an estimate \(\hat{k}(t)\) of the optimal beam index \(k^{(t)}\) is available, and it can be obtained through the exhaustive sweeping of all beams in V. Mathematically, the estimate \(\hat{k}(t)\) is expressed as:

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The goal of this work is to propose and demonstrate a machine learning based algorithm \(p(y^{(t-1)})\) that uses phase-less measurements from a fixed set of PN beams to reduce the required number of measurements for mmW BT. Two state-of-the-art phase-less BA act as performance baselines, namely a traditional exhaustive search of all pencil beams and the multi-layer perceptron (MLP)-based mmRAPID algorithm [12].

III. ALGORITHM DESIGN

While the baseline phase-less BA algorithms focus solely on reductions in the number of compressive measurements required for a single time step, BT algorithms can take advantage of the temporal relationship between UE motion, AoAs, and...
In this work, we propose that the relationship over time between pencil beam indices and measurements can be used to predict future beam angles without additional measurements. This section presents our ML algorithm for BT and BP to predict current and future beam indices from current and past compressive measurements.

Our proposed algorithm utilizes ML instead of traditional compressive sensing or signal processing due to ML’s ability to adapt to hardware impairments and potential for better beam index estimation. Poor synchronization and strong phase noise from mmW oscillators can significantly affect measurement beams, leaving model-based techniques with poor estimation performance due to imperfect knowledge of the sensing dictionary. Also, matching pursuit (MP) compressive sensing methods are known to be sub-optimal, with some ML solutions providing better estimation than RSS-MP [12].

### A. Machine Learning Architecture

To naturally accommodate time series relationships, we selected an LSTM-based Seq2Seq algorithm for BP. LSTM networks are designed to handle feedback of learned features, incorporating the concept of memory and forgetting old information. Likewise, Seq2Seq architectures are commonly used with LSTM networks for machine translation in natural language processing (NLP) [14]. A Seq2Seq algorithm for NLP would use an encoder to learn features sequentially from the words of an input language sentence and use a decoder to predict the following translated word in the output language based on the previous output language word and the learned features from the encoder.

The proposed algorithm borrows from these NLP designs to predict future best pencil beam indices from the previous best beam index estimates and the previous phase-less measurements. This design repeats over non-overlapping frames of \( T + P \) consecutive traditional BA time steps, where \( T \) is the number of steps in the history window where measurements are taken and \( P \) is the number of steps in the prediction window where no measurements are taken. The frames can also be functionally described in three distinct periods conducting BA, BT, and BP as described in Fig. 1. In the initial phase, or the first time step, the UE collects \( M_I \) measurements for the first BA using mmRAPID instance #1. The UE then collects \( M_L \) measurements in the next \( T - 1 \) time steps for the loop phase, using mmRAPID instance #2 for BA as the buffer of measurements required to run the LSTM encoder is filling. The beam index estimate from mmRAPID #1 or #2 at time step \( t \) is denoted as \( \tilde{k}^{(t)} \). Intuitively, we restrict \( M_I \geq M_L \), since the subsequent tracking and prediction likely relies most heavily on the initial beam estimate and more measurements generally leads to higher estimation accuracy. Note that the LSTM encoder uses \( M_I \) measurements at all time steps, including the first step where any additional \( M_I - M_L \) measurements are only used for mmRAPID. Finally, during the prediction phase or the prediction window, no measurements are collected and the LSTM is solely responsible for BP. In total, this algorithm requires \( M_I + M_L (T - 1) \) total measurements to complete BA and BT for the frame, whereas a baseline BA algorithm would require \( M (T + P) \) measurements where \( M \) is the required number of measurements for BA.

Our Seq2Seq architecture is shown in Fig. 2 unrolled over time for clarity. Each block in the Seq2Seq network is labeled with its hidden dimension in parentheses. To improve the training performance, each dense layer has a 10% dropout layer and a batch norm layer at their output and the encoder input features are normalized to have a unit 2-norm. Additionally, the decoder beam index estimates, denoted as \( \tilde{k}^{(t)} \), are used as the predictions for \( P \) time steps \( t, ..., t + P - 1 \) but are discarded for the \( T - 1 \) time steps \( t - T + 1, ..., t - 1 \). The decoder still provides these discarded estimates, since the decoder LSTM may be able to learn from the sequence of prior beam estimates to improve later predictions. During training time, both learning algorithms use the sparse categorical cross entropy loss function, with the RMSprop and Adam as optimizers for the mmRAPIDs and the LSTMs respectively. Both were developed in Tensorflow using the Keras API.

### B. Three-Stage Data-Driven Phase-less Beam Tracking and Prediction

During the lifetime of a UE, the proposed algorithm operates in three major stages for training and operation, based on the two-stage method in [12]. During Stage 1, the algorithm gathers training points for both mmRAPIDs and the LSTM by conducting both an exhaustive search using the directional codebook \( V \) and the compressive measurements with \( M_I \) codewords from \( W \). Once enough distinct AoAs have been collected to train mmRAPID, the UE starts Stage 2 and conducts the exhaustive search and \( M_L \) compressive codewords, solely for training the LSTM. mmRAPID and LSTM training can take place locally on the UE device or remotely in the cloud, with measurement data and labels uploaded for training on a server to save UE power. Finally, during Stage 3, the UE can use the trained mmRAPID and LSTM to predict frames of angles, reducing the overall measurement requirements.

### IV. Algorithm Evaluation

#### A. Simulation Design and Data Preparation

To test our proposed algorithm, we used 60 GHz channel data from the DeepMIMO dataset [15], based on ray-tracing simulations in Wireless Insite [16]. We selected the O1 scenario, an outdoor urban environment, for LOS channels from UEs with \( N_r = 36 \), \( d = \frac{1}{3} \), and 128 pencil beams in \( V \) to a BS at location 1. Since we assume the BS completes BT before the UE with high AoA resolution to maintain consistent...
Fig. 2: Seq2Seq LSTM machine learning architecture unrolled over time. Dropout and batch norm layers are not shown.

Fig. 3: 90th percentile gain loss over varied number of measurements and fixed window lengths $T = 7, P = 2$.

(a) Gain loss of the proposed algorithm

(b) Gain loss of the algorithm with LSTM predictions

Beamforming gain, we emulate the BS array with a single omnidirectional antenna. In practice, the proposed algorithm can reduce the overhead of a joint BS-UE exhaustive scan by repeatedly replacing the UE exhaustive search with each BS sector beam transmission. Also, the UE array’s broadside is always perpendicular to the street and the motion of the UE.

UE trajectories were generated from the DeepMIMO dataset by emulating movement over the 0.2 m grid of available channel measurement locations. For this work, we selected UE locations within the dataset’s longest street (i.e. from UG 1). For each trajectory, our simulations selected a random initial starting position near the right end of the street as well as a random constant velocity, both uniformly distributed over a 26 m by 36 m bounding box and integer velocities between 1 and 10 grid steps (0.2 m) per time step respectively. Simulations then selected positions straight down the street to the left, along the y dimension, on the UE position grid. The measurement frames were generated by collecting all shifted windows within parts of trajectories within a “cell” area near the selected BS, a rectangle 20 m across the street and 40 m along the street. The “cell” area was placed 15 m away from the BS to limit the input angles to around $\pm 53^\circ$, a realistic restriction for antenna arrays. Our dataset’s 30 dB maximum SNR for the beam measurements was constrained by the nearest UE position to the BS. With equivalent BS transmit and noise power, all other UE positions see lower SNR with an average of 15 dB.

In the final dataset, a total of 1000 trajectories were generated. This dataset was randomly split with 10%, 75%, and 15% used for Stage 1 training, Stage 2 training, and testing sets respectively. Note that 10% of the LSTM training data, or 8.5% of the total dataset, was used to validate the LSTM architecture and hyperparameters.

B. Simulation Results

We first compare the 90th percentile gain loss of the proposed algorithm over varied number of initialization measurements $M_I$ and loop measurements $M_L$ with fixed window lengths in Fig. 3. Note that in each of these 3D bar plots, the yellow bars taller than 5 dB have been cutoff for readability and actually exhibit much higher gain loss. The “full algorithm” results in Fig. 3(a) show the combined performance of BA, BT, and BP as described in Section III, while the “LSTM estimates” in Fig. 3(b) show performance of initial BA and the LSTM’s predictions over the rest of the frame. With $T = 7, P = 2$, the results in Fig. 3(a) are dominated by mmRAPID #2’s estimates, demonstrating that the performance is driven by $M_L$. While larger $M_I$ does reduce gain loss after $M_L = 5$, the required number of measurements for mmRAPID as found in separate simulations with the same dataset, the reduction is minimal and does not warrant $M_I > M_L$. Fig. 3(b) supports the Seq2Seq architecture’s prediction capability, as the LSTM prediction gain loss is consistently low for nearly all $M_L$. In fact, the LSTM has lower gain loss at small $M_L$ than the full algorithm, demonstrating that the LSTM is taking advantage of the history window.

Fig. 4 then presents the impact of the prediction and history window lengths on the gain loss. Both plots generally show...
increased gain loss for larger $P$ and smaller $T$, an intuitive result as the former requires the algorithm to extrapolate more predictions from the same data and the latter requires the algorithm to extrapolate the same predictions from less data. The gain loss varies between combinations of $P$ and $T$ due to the stochastic nature of the algorithm training. With large $T$ and small $P$, the LSTM estimates show even lower gain loss than the full algorithm. Fig. 4(b) demonstrates that, for a given number of measurements and enough historical data, the LSTM can provide better estimates than mmRAPID.

When comparing the average required number of measurements over beam tracking frames, we find that the proposed algorithm significantly decreases the beam alignment overhead with 90th percentile gain loss of 3 dB or less. While the exhaustive search and mmRAPID require $M = 128$ and $M = 5$ measurements per time step respectively, the proposed algorithm requires only an average of $1.82$ measurements per time step - a $98.6\%$ or $63.6\%$ reduction in overhead. This was computed from the experiment with $M_I = 5, M_L = 5, T = 4, P = 7$, which used only 20 measurements for 11 time steps and observed only 1.5 dB 90th percentile gain loss.

V. CONCLUSION AND FUTURE WORK

In this paper, we propose a novel phase-less, fixed-codebook UE beam tracking and prediction algorithm. Through LOS ray-tracing simulations, we demonstrate the LSTM Seq2Seq architecture is capable of predicting future beam directions and can save 98.6% of the beam alignment overhead compared to an exhaustive search and 63.6% compared to mmRAPID, a state-of-the-art ML BA algorithm. Several open questions remain with Seq2Seq phase-less BT and BP algorithms. Multipath channels would likely impact prediction performance, as with mmRAPID [17], and would correspond to the algorithm’s ability to generalize to new environments. BP with more complex UE trajectories, alternative sounding codebooks, and joint BS-UE BA have also not yet been explored.

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