Deep Learning Approach for Optimal Localization Using a mm-wave Sensor

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Abstract—Short-range indoor localization is one of the key necessities in automation industries and healthcare setups. With its increasing demand, the need for more precise positioning systems is rapidly increasing. Millimeter-wave (mm-wave) technology is emerging to enable highly precise localization performance. However, due to the limited availability of low-cost mm-wave sensors, it is challenging to accelerate research on real data. Furthermore, noise due to the hardware components of a sensor incurs perturbation in the received signal, which corrupts the estimation of range and the angle of arrival (AoA). Owing to the huge success of data-driven algorithms in solving regression problems, we propose a data-driven approach, which employs two deep learning (DL) based regression models i.e., dense neural network and convolutional neural network, and compare their performance with two machine learning based regression models, linear regression and support vector regression, to reduce errors in the estimate of AoA and range obtained via a mm-wave sensor. Our main goal is to optimize the localization measurements acquired from a low-cost mm-wave sensor for short-range applications. This will accelerate the development of proof of concepts and foster research on cost-effective mm-wave based indoor positioning systems. All experiments were conducted using over-the-air data collected with a mm-wave sensor, and the validity of the experiments was verified in unseen environments. The results obtained from our experimental evaluations, both for in-sample and out-of-sample testing, indicate improvements in the estimation of AoA and range with our proposed DL models. The improvements achieved were greater than 15% for AoA estimation and over 85% for range estimation compared to the baseline methods.

Index Terms—mm-wave, angle of arrival, deep learning, localization, indoor positioning system.

I. INTRODUCTION

INDOOR localization plays an integral role in numerous applications including health care and industries. The market value of indoor positioning systems is expected to increase to 50 billion US Dollars by the year 2027 [1], consequently increasing the need for developing efficient and accurate localization systems. Current indoor localization systems are based on radio frequency (RF) transceivers, which exploit reflections of electromagnetic waves from surroundings to infer the operational environment. These RF sensors are further categorized according to the particular frequency band over which the sensors operate. The performance of the sensor varies with the selected frequency band. Ultra-wideband (UWB) is one of the most commonly used frequency bands for the application of indoor positioning [2]. The high-frequency bandwidth of UWB sensors allows for high positioning accuracy [3]–[5]. Other widely used sensor technologies include Bluetooth [6], wireless fidelity (WiFi) [7], and radio frequency identification (RFID) [8]. On the other hand, mm-wave band allows for increased localization accuracy due to its extremely large bandwidth. However, it suffers from high attenuation during propagation through the channel [9]–[11]. While mm-wave technology may not be appropriate to be used in long-range applications, it is, however, a promising solution for short-range applications including indoor localization [12]–[14]. Short-range indoor localization finds applications in healthcare setups where it is critical to monitor patients’ movements in a room. Moreover, it enables robots to navigate inside an indoor environment. Therefore, it is important to develop an accurate positioning system for short-range applications.

There are various features that help to localize a target such as distance, angle of arrival (AoA), angle of departure (AoD), radar cross section (RCS), and received signal strength (RSS). However, AoA is the most commonly used feature for identifying the location of a particular target [15]–[18]. Some of the most commonly used methods of AoA estimation include multiple signal classification (MUSIC) [15], estimation of signal parameters via rotational invariance technique (ESPRIT) [16], Capon [17], [18], and maximum likelihood estimator (MLE) [19]–[21]. With the advancements in artificial intelligence, data-driven based methods such as machine learning (ML) and deep learning (DL) have also been leveraged to develop efficient AoA estimation algorithms. The task of AoA estimation using ML and DL methods has been implemented using the classification [22]–[24] and the regression method [25]–[27].

II. RELATED WORK

A plethora of research work has been carried out on AoA estimation for positioning applications. Firstly, most of the experiments have been performed on simulations, which cannot accurately represent real-world challenges faced in an over-the-air environment [25], [26], [28], [29]. Mm-wave based indoor positioning has been developed for wireless networks. For instance, in [30], [31], the localization is conducted within a wireless network that involves access points (AP)s and a target client, which is equipped with a transmitter or receiver. In [30], a single AP is used to localize a target client, whereas multiple APs have been employed to achieve better localization in [31]. It is important to note that the experiments in [30], [31] involved localizing a target client that is also equipped with a transmitter/receiver to enable localization. This setup
is fundamentally distinct from our experimental configuration, where radar-based localization is performed using a low-cost single-chip mm-wave device that acts as both transmitter and receiver. Additionally, the target person whose position needs to be localized in our work does not possess any additional sensors leading to device-free detection. In addition, while the study in [31] achieves a position error of 0.37m with the help of multiple APs, our proposed method also achieves a comparable performance in range estimation using only a single-chip mm-wave sensor, and that too with a device-free target.

Other studies developed proof-of-concepts (PoCs) for localization, however, they utilized highly expensive equipment such as software-defined radio, which is barely accessible to most researchers due to its high cost [32], [33]. The inaccessibility of costly transceivers drastically reduces the research development in creating PoCs for the mm-wave based positioning systems. However, there are few low-cost alternatives to expensive transceivers such as mm-wave based positioning sensors from Texas Instruments (TI) [34], [35], which can be quickly deployed to perform experiments. The TI mm-wave sensors have been employed for various applications such as hand gesture classification, people movement detection [36] and tracking [37], [38], and autonomous driving [39].

Most of the research works involved processing the raw in-phase (I) and quadrature-phase (Q) data, generally known as IQ data, which has been obtained using an additional hardware kit i.e., DCA1000EVM by TI. In contrast, the low-cost mm-wave sensor employed in our experiments provides the point-cloud data instead of the raw IQ data. The aim of our work is to optimize the localization performance of a low-cost mm-wave sensor based on point-cloud data only without the need of acquiring additional IQ data. While point-clouds have been used to optimize the localization performance in [38], [40], their experiments have been performed in large spacious rooms with very few objects in the environment. Generally, in most practical scenarios, it is not always the case that the environment is large and sparse to facilitate better localization performance. In contrast, our experiments have been performed in small rooms with the presence of multiple objects in the environment. This approach enables our proposed method to be robust against intense multipath propagation effects. In addition, the study in [40] employed a mm-wave sensor from TI which is different from the sensor we have employed in our experiments. In our work, the employed mm-wave sensor [41] is based on a TI IWR6843 module, however, it comes with an updated firmware designed for the application of people detection, therefore its performance can differ from other TI mm-wave modules. Although our study is based on a specific mm-wave sensor, the idea can still be applied to other low-cost mm-wave sensors to optimize their localization performance.

Not only are there practical limitations and challenges in developing PoCs, but using a low-cost sensor also has its own set of limitations. For instance, thermal noise caused by various hardware components of the device, including analog-to-digital converters, digital-to-analog converters, mixers, filters, and digital down converters, adds perturbations to the amplitude and phase of the received signal [42]–[44]. This phenomenon is known as IQ imbalance [45] and it affects the quality of the received signal, thereby reducing the accuracy of the estimated AoA. Apart from the hardware noise, the propagation channel also incurs attenuation and multipath delays in the received signal due to the non-line-of-sight (NLoS) propagation. Owing to the presence of obstacles in the environment, the multipath delays add errors in the estimates of distance and AoA [5]. In addition, the instantaneous bandwidth of the sensor plays a crucial role in defining the range resolution of the radar. Range resolution does not only define the capability of a radar to distinguish between two objects but it also sets out the limit of the minimum distance required at which the object can be detected correctly. Therefore, low-cost sensors’ performance is inefficient for short-range indoor applications due to limited instantaneous bandwidth. On the other hand, radio transceivers and sensors that support higher instantaneous bandwidths are usually expensive due to which they are hardly employed by most researchers in the community. While the use of low-cost transceivers can help accelerate the research work, their measurements can be unreliable mainly because of the aforementioned issues. Therefore, our research focuses to optimize the short-range localization performance of a cost-effective mm-wave sensor given its limitations.

The outburst of data in the past decade has given rise to the emerging field of artificial intelligence (AI), which exploits the availability of huge datasets to solve complex classification and regression problems in the field of computer vision and natural language processing. More recently, AI has gained attention in various applications of wireless communication networks, such as channel estimation [46], modulation classification [47], and indoor positioning [48], [49]. Therefore, this paper aims to demonstrate a data-driven mechanism that takes noisy measurements of AoA and range from a mm-wave sensor and maps it to an estimate with better accuracy. Unlike our previous work [50], this work extends the study of AoA optimization using convolutional neural network (CNN) and also performs range optimization using data-driven methods. For this purpose, AoA and range measurements have been recorded using the BM201 mm-wave sensor [41]. We propose an end-to-end dense neural network (DNN) and a CNN architecture that learns to associate noisy values of localization parameters with their true values. The DL models are trained using over-the-air datasets, consisting of the point-cloud data, collected from a mm-wave sensor. The DNN and CNN model is chosen for their lesser computational complexity when compared to other complex deep DL models, such as autoencoders and long short-term memory based recurrent neural networks.

ML and DL models have been widely adopted for indoor positioning applications. For instance, previous studies [22], [23], [27], [51] have utilized deep learning models for positioning estimation but not in the context of mm-wave frequency signals. Additionally, most of these studies employed IQ data for preprocessing and training DL models, conducting experiments solely through simulations. In contrast, our study goes beyond simulations by utilizing real over-the-air data.
Furthermore, instead of IQ data, we employed point-cloud data from the mm-wave device to train our ML/DL models. This was necessary because the low-cost mm-wave device we used (BM201) does not provide access to the IQ data, requiring the additional hardware device DCA1000EVM to extract IQ signals for custom signal processing, thus incurring additional costs. While a mm-wave-based work presented in [51] uses a deep learning network (ResNET) to enhance indoor localization, their experimental infrastructure involves localization in a wireless network architecture with multiple APs and a client. In contrast, our work focuses on radar phenomenon, where the target is device-free i.e., it is not equipped with any transmitter or receiver.

In this paper, it has been shown that the DL models require training data, unlike baseline methods that do not need them. However, the use of training data in the DL models leads to improved accuracy in both AoA and range estimation. This finding is consistent with other studies that have proposed data-driven frameworks and compared them with conventional methods [52]–[54]. In summary, while ML/DL models have been applied to indoor positioning applications, we have leveraged their potential to address a problem with distinct objectives and experimental context compared to previous indoor positioning studies. To the best of our knowledge, this is the first attempt to utilize DL for optimizing device-free localization performance using point-cloud data obtained from a low-cost mm-wave device.

The main contributions of this paper are as follows:

1) Unlike most simulated experiments, the experiments in this work have been performed on real-world over-the-air data collected from a mm-wave sensor.

2) Using the proposed DL based approach, the error in the AoA and range estimates are reduced by 15% and 85% from the baselines, respectively.

3) This work implements localization optimization on the point-cloud data obtained from a cost-effective mm-wave sensor. Unlike previous studies, this work does not require obtaining raw IQ samples, thereby reducing the cost of employing additional hardware to acquire and process the IQ samples.

4) The idea of this work paves the way to enhance the performance of low-cost mm-wave transceivers for short-range applications and PoCs development for future research.

The rest of the paper is categorized as follows. A system model is defined in Section III. Section IV describes the methodology of the DL-based methods used to optimize the AoA and range estimation. The experimental setup is described in Section V and results are explained in Section VI. Conclusions along with future directions are discussed in Section VII.

III. System Model

Let us consider a uniform linear array (ULA) of $P$ receiving antennas separated by a distance $d$, as shown in Fig. 1. For $Q$ signals received by the array, the resulting vector $x(t)$ of the signals induced at the inputs of the receiving antennas can be expressed as:

$$ x(t) = As(t) + n(t), $$

where $A$ is the $P \times Q$ array steering matrix, $s(t)$ is the vector of $Q$ incoming signals, and $n(t)$ is the noise vector. The array steering matrix $A$ is defined as:

$$ a(\theta_q) = [a_1(\theta_q), a_2(\theta_q), \cdots, a_P(\theta_q)]^T, q = 1, \cdots, Q, $$

where $a_p(\theta_q)$ is the array steering vector comprising the effect of the $q^{th}$ signal impinging on each of the antenna elements. $a_p(\theta_q)$ is defined as follows:

$$ a_p(\theta_q) = \exp \left( \frac{j2\pi pd \sin \theta_q}{\lambda} \right), p = 1, \cdots, P. $$

According to (3), each column in $A$ represents the output of the antenna array elements for the $q^{th}$ incident signal, whereas each row in $A$ represents the effect of all $Q$ impinging signals on each antenna element. According to (4), steering matrix $A$ can be re-written as:

$$ A = \begin{bmatrix}
\exp \left( \frac{j2\pi \lambda d \sin \theta_1}{\lambda} \right) & \cdots & \exp \left( \frac{j2\pi \lambda d \sin \theta_Q}{\lambda} \right) \\
\cdots & \ddots & \cdots \\
\exp \left( \frac{j2\pi \lambda \sin \theta_1}{\lambda} \right) & \cdots & \exp \left( \frac{j2\pi \lambda \sin \theta_Q}{\lambda} \right)
\end{bmatrix} $$

For ULA, the phase difference caused by the impinging of the $q^{th}$ signal on any two consecutive antenna elements is given by:

$$ \omega = \frac{2\pi}{\lambda} d \sin \theta_q, $$

where the AoA, $\theta_q$, for the $q^{th}$ signal is obtained as:

$$ \theta_q = \sin^{-1} \left( \frac{\omega \lambda}{2\pi d} \right). $$

Since a different phase shift is associated with the receiving signal at each antenna element, therefore, the AoA ($\theta_q$) can be computed by deploying a fast Fourier transform (FFT) over the received signal at the antenna array [55].
IV. METHODOLOGY

This section explains the hardware used for the experiments along with the baselines and proposed DNN and CNN based methods for optimizing AoA and range estimation.

A. Hardware

Fig. 2 shows the Batman-201 (BM201) mm-wave transceiver [41], which consists of Texas Instrument IWR6843 mm-wave chip [34]. The detailed specifications of the mm-wave sensor are listed in Table I. The experiments are conducted for the evaluation of AoA and range estimation. The BM201 mm-wave kit is specifically customized for the application of people and movement detection. It consists of 3 transmitting and 4 receiving antennas. The output of BM201 kit consists of point-cloud data containing the estimates of AoA, range, doppler, and SNR. The estimation of the localization parameters is based on the frequency modulated continuous wave (FMCW) radar technology. Fig. 3 shows the basic data processing pipeline used by IWR6843 for generating the point-clouds. The analogue-to-digital converter (ADC) samples the signals received at the mm-wave front-end of the device. A radar data cube is formed from the sampled data received over multiple pulses and antennas. Fast Fourier transform is applied over the radar data cube to find the estimates for range and AoA [56]. These estimates are used to form point-cloud data that are embedded at the output of the IWR6843 chip [34].

Fig. 4 shows the illustration of some configurations of the experimental setup along with the associated point-cloud data obtained using the mm-wave sensor. A detailed description of the experimental setup and dataset collection is provided in Section V.

B. Baseline Methods

The output of the BM201 kit consists of point-cloud data containing the estimated distance, AoA, and SNR associated with each point. Fig. 4 (e-h) shows some instances of the point-cloud data captured using the BM201 kit with a person standing at different angles and distances from the sensor. It can be seen that the detected point-clouds are scattered across a wide range of angles and distances, which makes it challenging to identify the true value of AoA as well as the range. In other words, the point-cloud must be filtered or clustered to provide an accurate representation of the target’s position. To do so, some of the common methods include averaging the point-cloud or filtering it based on some SNR threshold. We consider two baseline methods for determining the AoA and range from the point-cloud data, namely average-based and maximum SNR based method.

1) Baseline-1: Average-based Estimation: In the first method, the detected point-cloud is averaged, as given in (8), to provide the estimate of the localization parameters \( \psi_i = \{\theta, d\} \), where \( i = 0 \) and 1 associates with the AoA (\( \theta \)) and range (\( d \)), respectively. In (8), \( N \) represents the number of detected points in the point-cloud.

\[
\psi_{avg} = \frac{1}{N} \sum_{i=1}^{N} \psi_i.
\] (8)

To evaluate the error in parameter estimation using the average-based method, we calculate the mean absolute error (MAE) on the test dataset collected using the BM201 kit. Fig. 5 illustrates the method of computing the error of the localization parameters from the point-cloud data using the baseline-1 method. The MAE between the estimated parameter \( \psi_{avg} \) and the true parameter \( \psi_i \) averaged over the entire test dataset is then computed as:

\[
\text{MAE}_{avg}(\psi_i) = \frac{1}{T} \sum_{t=1}^{T} |\psi_{avg} - \psi_i|,
\] (9)

where \( t \) is the index iterating over each example in the test dataset. The results obtained using this method are explained in Section VI.

2) Baseline-2: Maximum SNR-based Estimation: As the name suggests, the estimated parameter is determined from the point-cloud data based on the value of the point exhibiting maximum SNR. Since the mm-wave reflections arising from multipath propagation will have relatively less SNR as compared to the reflection received due to a LoS propagation, therefore the detected point with maximum SNR is most likely to be associated with direct reflection from the target.
Hence, the point having maximum SNR is considered to be the estimated parameter, as given below:

$$\psi_{\text{maxSNR}} = \max(\psi_1(1), \psi_1(2), \ldots, \psi_1(N)).$$  \hfill (10)

The MAE for the maximum-SNR-based method on the test dataset is then calculated as:

$$\text{MAE}_{\text{maxSNR}}(\psi_i) = \frac{1}{T} \sum_{t=1}^{T} |\psi^*_t - \psi_{\text{maxSNR}}|. \hfill (11)$$

Fig. 6 illustrates the method of computing the error of the localization parameters from the point-cloud data using the baseline-2 method. The results obtained using this method are explained in Section VI.

C. Data Preprocessing

Fig. 7 shows the data pre-processing pipeline for the proposed methodology which involves dataset collection and model training. Firstly, the detected points with the range above the maximum operating range of the device [41] have been discarded as noise. For both optimization tasks, since the number of detected points can be different in each data acquisition, only $N = 20$ points for each feature have been collected per acquisition to ensure the constant length of the feature vector $y_i \in \mathbb{R}^N$, where the values 0, 1, and 2 of $i$ represent range, AoA, and SNR, respectively. By using the three feature vectors, an $N \times 3$ feature matrix $Y$ is constructed, as shown below:
Fig. 7. Pipeline for dataset collection and model training. Point-cloud data is acquired for a target person at a certain distance and angle from the mm-wave device. The outlier points are removed based on the range threshold. The filtered points are then passed through a length-check module to ensure the length of the acquired point-clouds in the dataset is same to enable training of the data on ML and DL models. Afterwards, the dataset is split to be used for training and testing of the ML and DL models.

\[
Y = [\mathbf{y}_0, \mathbf{y}_1, \mathbf{y}_2]
\]  \hspace{1cm} (12)

Since the number of detected points in the point-cloud can vary in each measurement, it is important to consolidate a dataset in which each data instance contains a fixed size of the point-cloud data or features. Maintaining a constant size of feature vectors is important as the proposed learning models can only be trained with a fixed size of input nodes, which corresponds to the size of the feature vectors. To ensure a fixed input feature size, zero-padding is applied in the cases where the size of the acquired point-cloud data is less than \( N \). On the other hand, when the size of data points is larger than \( N \), only the first \( N \) points are collected.

**D. Proposed Methodology**

This section describes the proposed DNN and CNN architecture designed to optimize the AoA and range estimates obtained from the mm-wave sensor. Both the DNN and CNN architectures are designed to be used as regression models to predict the values of AoA and range. A basic structure of the proposed methodology is illustrated in Fig. 8.

![Diagram](image)

Fig. 8. Structure of localization optimization from the point-cloud data. For range and AoA optimization, the point-cloud data is given as input to the respective trained models that provide the predicted range and AoA.

The DNN model is based on 6 dense layers, each followed by an activation layer. On the other hand, the CNN model comprises 3 convolutional layers followed by 2 dense layers. The complete architecture of the proposed DNN and CNN model is shown in Fig. 9 and Fig. 10, respectively. The input to both the models is a feature vector \( \mathbf{y} \in \mathbb{R}^{60} \), which is obtained by flattening 3 input feature vectors \( \mathbf{y}_i \in \mathbb{R}^{20} \).

The goal is to find functions \( f_{\omega_y} \) and \( f_{\omega_d} \) for AoA and range optimization, respectively, such that the respective functions map the noisy AoA and range estimates to the closest estimate \( (\hat{\theta}, \hat{d}) \) of the true values \( (\theta^*, d^*) \). Here \( \omega_y \) and \( \omega_d \) represent the trainable weights parameters of the learning models for AoA and range, respectively. For this purpose, the proposed learning methods i.e., DNN and CNN are employed to find the function that lead to minimum estimation error. The estimated parameters, \( \hat{\theta}_\ell \) and \( \hat{d}_\ell \), from the DL model can be expressed as:

\[
\hat{\theta}_\ell = f_{\omega_y}(\mathbf{y}),
\]  \hspace{1cm} (13)

\[
\hat{d}_\ell = f_{\omega_d}(\mathbf{y}),
\]  \hspace{1cm} (14)

where \( \ell = 1, 2, \cdots, L \) represents the training examples. These weights are adjusted during the training phase to minimize the loss between the estimated and true parameter. The mean square error (MSE) has been used to characterize the loss function of the DNN and CNN model as shown below:

\[
\text{MSE}(\hat{\theta}) = \min_{\omega_y} \frac{1}{L} \sum_{\ell=1}^{L} \| \mathbf{a}^{*\ell} - \hat{\theta} \|^2,
\]  \hspace{1cm} (15)

\[
\text{MSE}(\hat{d}) = \min_{\omega_d} \frac{1}{L} \sum_{\ell=1}^{L} \| \mathbf{d}^{*\ell} - \hat{d} \|^2,
\]  \hspace{1cm} (16)

where \( \| \cdot \| \) denotes the \( \ell_2 \)-norm operation.

For the \( g^{th} \) instance of the dataset, the output \( \mathbf{y}_g \) for the \( k^{th} \) dense layer is computed as:

\[
\mathbf{y}_g = W_g y_{g-1} + b_g.
\]  \hspace{1cm} (17)

where \( W_g \) and \( b_g \) represents the weight matrix and bias vector of the \( k^{th} \) dense layer, respectively. To accelerate the training process, batch normalization (BN) is applied to the output of hidden layers. The output of a hidden layer is first normalized as follows:

\[
\hat{y}_g = \frac{y_g - \mu_b}{\sqrt{(\sigma_B)^2 + \epsilon}},
\]  \hspace{1cm} (18)
where $\mu_B$ and $\sigma_B^2$ are the mean and variance of the mini-batch $B$ of the training data and $\epsilon$ is a constant used for numerical stability. The output of the BN layer is obtained by scaling $\hat{y}_g$ with learnable parameters $\gamma$ and $\beta$ as mentioned below:

$$BN(\hat{y}_g) = \gamma \hat{y}_g + \beta. \quad (19)$$

Furthermore, to add non-linearity in the neural network, ReLU and Tanh have been employed as activation functions (AFs). ReLU is defined as:

$$ReLU(\alpha) = [ReLU(\alpha_0), ReLU(\alpha_1), ..., ReLU(\alpha_{-1})], \quad (20)$$

where $\alpha$ is the input vector to the AFs and $\alpha_{-1}$ represents the last element in the vector $\alpha$. Also, Tanh is defined as:

$$tanh(\alpha) = \frac{e^\alpha - e^{-\alpha}}{e^\alpha + e^{-\alpha}}, \quad (21)$$

Unlike other activation functions such as Tanh and Sigmoid which mostly returns non-zero value for each neuron in the hidden layer, ReLU on the other hand returns zero for neurons with negative values. Since ReLU is sensitive to its inputs, as it activates only fewer neurons, this makes ReLU more computationally efficient than other activation functions [57].

Combining all the aforementioned operations on (17), the final output from the $k^{th}$ hidden layer in the proposed DNN model is given by:

$$y^k_{g} = AF(BN(W^k_g y^{k-1}_g + b^k_g)), \quad k = 1, 2, ..., 6 \quad (23)$$

AF represents the selected activation function from ReLU and Tanh. In the case of CNN, for the $g^{th}$ instance of the dataset, the output $y^k_{g}$ for the $k^{th}$ layer can be generalized as:

$$y^k_{g} = \begin{cases} 
AF(BN(W^{k}_g y^{k-1}_g + b^{k}_g)), & k = 1, 2, 3 \\
AF(BN(W^{k}_g y^{k-1}_g + b^{k}_g)), & k = 4, 5, 6 
\end{cases} \quad (24)$$
where $M$ corresponds to the kernel size of the $k^{th}$ convolutional layer and $\Omega$ represents the max-pool operation on the output of the convolutional layer.

Apart from DL models, the performance of machine learning models, such as linear regression (LR) and support vector regression (SVR), has also been analyzed on the recorded dataset. Machine learning-based LR is a supervised learning algorithm used for predicting continuous numeric values based on a linear relationship between input features and target variables [58]. It seeks to find the best-fitting line that minimizes the difference between predicted and actual values. On the other hand, SVR is an extension of the support vector machine model specifically designed for solving the regression problem. It works by finding the hyperplane that passes through the maximum number of data points which are within the margin or support vectors [59]. For features that are not linearly separable, kernels are employed to transform the features into higher dimensions in order to make them linearly separable. Kernels are simply the generalized dot product between two vectors in a higher dimension [60]. Some commonly used kernels include Gaussian RBF and polynomial [59]. The experimental setup is explained in the next section.

V. EXPERIMENTAL SETUP

The experiments are conducted in an indoor environment of dimensions 2.5m x 5.4m. For the experiments on AoA optimization, the target person stands at different angles from the BM201 sensor. The angle between the target and the sensor is calculated by exploiting the trigonometry geometry as shown in Fig. 11. For a fixed distance $b$ and adjusting distance $a$, the desired angle $\theta$ between the sensor and the target can be computed as:

$$\theta = 90^\circ - \Phi$$ (25)

where $\Phi$ is computed as:

$$\Phi = \tan^{-1}\left(\frac{b}{a}\right)$$ (26)

In our experiments, we kept the distance $b$ fixed at 1.5m, while uniformly increasing the distance $a$ with an increment of 0.3m. This resulted in a set of measurements at [-0.9, -0.6, 0.3, 0, 0.3, 0.6, 0.9] meters. By substituting these values of $a$ and $b$ into (26), (25) provides the corresponding target angles of [-31, -22, -11, 0, 11, 22, 31] degrees.

A. Dataset Collection

The dataset used to train the proposed DL and ML models was collected in two different environments, with the same target person (person-1). Room-1 was utilized for collecting all the measurements related to AoA, while Room-2 was used for capturing range measurements. Fig. 12 (a) and (b) illustrates the environment of Room-1 and Room-2, respectively. However, it is important to note that the data collection process involved multiple sessions conducted over several days to introduce temporal variations in the dataset. The number of data instances collected during a single session varied throughout the data collection process, as it spanned multiple days and sessions, aiming to incorporate as much temporal variation as possible. Additionally, while the target person maintained a fixed angle and distance from the sensor, there were slight random motions made by the target person, such as hand, arm, or head movements. These movements resulted in the Doppler effect, causing variations in the captured point-clouds within the same session. The inclusion of these slight random motions in the target person's behavior aimed to reflect real-life scenarios and practical applications, considering that humans are not always completely stationary. This aspect is particularly relevant for people detection and patient monitoring applications.

In our experiments, the dataset for AoA optimization consists of 2000 instances of point-cloud data recorded for each target angle between the target person and the sensor. Given the number of target angles used in the experiment, the total size of the dataset adds up to 14,000 for AoA optimization. Similarly, for range optimization, the dataset contains 10,000 instances of point-cloud data (2000 instances for each target distance) which have been recorded for a target person standing at 1, 2, 3, 4, and 5 meters away from the sensor at a fixed angle of 0°.

The respective datasets for AoA and range measurements have been divided into training and test sets with train and test ratios equal to 80% and 20%, respectively. The dataset was split using Scikit Learn's function for creating the train-test sets. It shuffles the entire dataset randomly before creating the train-test sets to reduce any training bias that could occur due to the measurements taken consecutively within the same session. The training data is further split into training and validation sets. An early stopping mechanism has been employed to train the DNN and CNN over the training datasets. Early stopping keeps track of the validation loss and stops further training when the validation loss does not reduce further, hence avoiding the model from overfitting the training data. The DNN and CNN have been trained with a batch size of 10 using the Adam optimizer.
B. Testing Environments

To assess our model’s performance in unseen environments, we conducted additional experiments in two different environment scenarios, involving two different target persons (person-2 and person-3) who were not part of the experimental data used to train the model. To evaluate the effectiveness of our proposed method, we divided the test data into two scenarios: in-sample testing and out-of-sample testing. In-sample testing involves evaluating the performance of a test dataset that was obtained by splitting the collected dataset from Room-1 and Room-2 into train-test sets. Note that the environment remains the same for both the train and test sets, hence it is referred to as in-sample testing. Nevertheless, the in-sample data also contains variations in it as explained earlier.

On the other hand, out-of-sample testing involves evaluating the performance in two different environments, with the same target person (person-1) used for model training and different target persons (person-2 and person-3) than those used for model training. Table II and Table III display the performance evaluation of the models in terms of MAE and its standard deviation, respectively, for both in-sample and out-of-sample testing. Note that the DL Model listed in Table II and Table III are the models that showed optimal performance for AoA and range optimization. The out-of-sample testing environments are further described below.

1) Sports Hall: Out-of-sample testing took place in a Sports Hall, which is a large basketball court measuring 40m × 34.5m in dimensions. Fig. 13 displays a picture of the testing environment and its corresponding map. To evaluate the performance, experiments were conducted on both target person-1 and person-2 separately. For AoA optimization, 50 point-cloud measurements were collected at each target angle, resulting in a total of 350 instances of point-cloud data. Since the experiments were conducted separately for each target person, a total of 700 test measurements were captured for both targets. Similarly, experiments were carried out for testing the range optimization. A dataset of 500 instances was created, with 250 measurements recorded for each target person (50 measurements at each target range). Separate experiments were conducted for each target person to record this dataset.

2) Studio Room: Another out-of-sample testing experiment was conducted in a Studio Room measuring 3.5m × 6m dimensions. Fig. 14 provides a visual representation of the testing environment and its map. It is important to note that this environment is expected to have a multipath-rich profile due to the presence of multiple objects within it. In this environment, similar to the data collected in the Sports Hall, an equal number of data instances were collected for both target persons (person-1 and person-3) to test the effectiveness of our proposed DL models for AoA and range optimization.

VI. EXPERIMENTAL RESULTS

This section describes the experimental results obtained to validate the proposed methodology for the optimization of AoA and range estimation.

A. AoA Optimization

Fig. 15 shows the in-sample performance analysis in terms of MAE computed at different angles for all models under test. Whereas Fig. 16 compares the MAE computed over the out-of-sample test set collected in the Studio Room. It can be observed from Fig. 15 and Fig. 16 that while the MAE of the baselines increases with the increase in the target’s angle, it is not exactly linear, and hence, the true AoA cannot be predicted accurately by some offset adjustment. Furthermore, it can be noted that while CNN shows a better performance, albeit,
for positive angles only, the DNN, on the other hand, shows the most optimal results considering all the target angles. As shown in Table II, an average MAE of 7.57° is obtained for the in-sample test data, which is about 35.7% less than MAE obtained from the baseline methods.

For the out-of-sample testing in Sports Hall, the performance of the proposed DNN model for AoA optimization is comparable to the baselines, as shown in Table II. This can be attributed to the fact that the proposed DL models were trained using the data collected in a small environment that was rich in multipath effects due to the presence of multiple objects in close proximity to the target person. In contrast, the Sports Hall, being a large open space without nearby objects, exhibits relatively fewer multipath effects. The significant difference in the multipath profiles between these two environments likely contributes to the comparable performance observed between the proposed and the baseline methods. However, it is important to acknowledge that a huge and sparse environment such as a Sports Hall, devoid of objects and obstacles, does not accurately reflect most practical scenarios characterized by intense multipath profiles.

For the Studio Room testing, the proposed DNN model demonstrates a slight improvement over the baseline methods for AoA optimization. Specifically, for the target person-3, a 16.4% reduction in the estimation error is achieved by the proposed DNN model compared to the baselines. However, it can be noted that the performance of the DNN is comparable with the baselines at angles 0° and 11°. This pattern is also exhibited in the in-sample test data as shown in Fig. 15. Nevertheless, the proposed DNN shows better performance over other models for most target angles.

In summary, the out-of-sample testing performance of the proposed DNN method is relatively lower than its in-sample performance due to the completely unfamiliar environment settings. However, the majority of the out-of-sample test cases exhibit better performance than the baselines. This suggests that our proposed DL model is capable of generalizing to new multipath environments. However, in the future, the model
TABLE II
PERFORMANCE ANALYSIS BASED ON MAE FOR THE PROPOSED MODELS AND THE BASELINE METHODS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Environment</th>
<th>Target</th>
<th>Proposed DL Model</th>
<th>LR</th>
<th>SVR-Poly</th>
<th>MAE</th>
<th>SVR-RBF</th>
<th>Baseline-1</th>
<th>Baseline-2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Person-1</td>
<td>7.57° (DNN)</td>
<td>8.6°</td>
<td>8.62°</td>
<td>9.13°</td>
<td>11.78°</td>
<td>16.02°</td>
<td></td>
</tr>
<tr>
<td>AoA</td>
<td>Room-1</td>
<td>Person-1</td>
<td>7.57° (DNN)</td>
<td>8.6°</td>
<td>8.62°</td>
<td>9.13°</td>
<td>11.78°</td>
<td>16.02°</td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>Room-2</td>
<td>Person-1</td>
<td>0.119m (CNN)</td>
<td>0.89m</td>
<td>0.86m</td>
<td>0.81m</td>
<td>2.72m</td>
<td>2.16m</td>
<td></td>
</tr>
</tbody>
</table>

Out-of-Sample Testing

<table>
<thead>
<tr>
<th>AoA</th>
<th>Sports Hall</th>
<th>Person-1</th>
<th>9.6° (DNN)</th>
<th>8.41°</th>
<th>9.28°</th>
<th>8.99°</th>
<th>9.85°</th>
<th>9.95°</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Studio Room</td>
<td>Person-1</td>
<td>10.84° (DNN)</td>
<td>11.66°</td>
<td>11.63°</td>
<td>12.42°</td>
<td>13.68°</td>
<td>14.96°</td>
</tr>
<tr>
<td>Range</td>
<td>Sports Hall</td>
<td>Person-1</td>
<td>0.3m (CNN)</td>
<td>1.83m</td>
<td>2.59m</td>
<td>1.73m</td>
<td>8.33m</td>
<td>0.76m</td>
</tr>
<tr>
<td></td>
<td>Studio Room</td>
<td>Person-1</td>
<td>0.44m (CNN)</td>
<td>1.28m</td>
<td>1.24m</td>
<td>1.16m</td>
<td>3.91m</td>
<td>3.59m</td>
</tr>
<tr>
<td></td>
<td>Person-3</td>
<td>0.38m (CNN)</td>
<td>1.44m</td>
<td>1.40m</td>
<td>1.27m</td>
<td>3.03m</td>
<td>2.78m</td>
<td></td>
</tr>
</tbody>
</table>

TABLE III
PERFORMANCE ANALYSIS BASED ON THE STANDARD DEVIATION OF THE MAE FOR THE PROPOSED MODELS AND THE BASELINE METHODS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Environment</th>
<th>Target</th>
<th>Proposed DL Model</th>
<th>LR</th>
<th>SVR-Poly</th>
<th>St.deviation</th>
<th>SVR-RBF</th>
<th>Baseline-1</th>
<th>Baseline-2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Person-1</td>
<td>6.42° (DNN)</td>
<td>8.11°</td>
<td>7.20°</td>
<td>6.66°</td>
<td>5.19°</td>
<td>18.79°</td>
<td></td>
</tr>
<tr>
<td>AoA</td>
<td>Room-1</td>
<td>Person-1</td>
<td>6.42° (DNN)</td>
<td>8.11°</td>
<td>7.20°</td>
<td>6.66°</td>
<td>5.19°</td>
<td>18.79°</td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>Room-2</td>
<td>Person-1</td>
<td>0.21m (CNN)</td>
<td>0.53m</td>
<td>0.55m</td>
<td>0.56m</td>
<td>0.89m</td>
<td>2.51m</td>
<td></td>
</tr>
</tbody>
</table>

Out-of-Sample Testing

<table>
<thead>
<tr>
<th>AoA</th>
<th>Sports Hall</th>
<th>Person-1</th>
<th>6.70° (DNN)</th>
<th>6.85°</th>
<th>7.99°</th>
<th>5.85°</th>
<th>5.07°</th>
<th>10.60°</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Studio Room</td>
<td>Person-1</td>
<td>6.88° (DNN)</td>
<td>6.23°</td>
<td>6.83°</td>
<td>5.36°</td>
<td>3.93°</td>
<td>11.90°</td>
</tr>
<tr>
<td>Range</td>
<td>Sports Hall</td>
<td>Person-1</td>
<td>0.37m (CNN)</td>
<td>0.75m</td>
<td>1.19m</td>
<td>0.55m</td>
<td>3.88m</td>
<td>2.25m</td>
</tr>
<tr>
<td></td>
<td>Studio Room</td>
<td>Person-1</td>
<td>0.41m (CNN)</td>
<td>0.89m</td>
<td>1.34m</td>
<td>0.64m</td>
<td>4.19m</td>
<td>6.19m</td>
</tr>
</tbody>
</table>

For the task of range optimization, similar ML and DL model architectures have been employed which have been used for AoA optimization. Fig. 17 shows the in-sample performance comparison between baselines and the proposed learning models in terms of the MAE. It is evident from Fig. 17, that CNN outperforms baselines and other learning models. For the in-sample testing, the MAE obtained by CNN is 0.119m whereas the minimum MAE from the baselines is 2.16m. This implies that CNN demonstrates about 94.5% improvement in the range estimation as compared to the baselines.

For the out-of-sample testing, CNN retains its performance, as it continues to outperform other models and baselines, as evident from Fig. 18. For testing in Sports Hall with person-2, the MAE obtained by CNN and baseline-2 is 0.33m and 3.88m, respectively. This shows that CNN has outperformed the baselines by 91.3%. For the out-of-sample testing in Studio Room with person-3, the MAE obtained by CNN and baseline-2 is 0.38m and 27.8m, respectively. This shows that CNN has outperformed the baselines by 86.3%.

In summary, the performance of the proposed CNN model for range optimization remains robust on out-of-sample testing with an average improvement of 88.8% from the baseline that exhibited the minimum MAE.

It is important to note that the performance of the proposed DL model for range optimization significantly outperforms its performance for AoA optimization. This disparity can be attributed to the presence of multiple ghost points in the point-cloud data, which arise due to the multipath effect in mm-wave signal propagation [40], [61]. Upon analyzing the dataset, it was observed that the ghost points appeared at various angles, distinct from the target person’s angle, but remained in proximity to the target person’s range. This phenomenon posed a challenge for the DL model, as it had difficulty learning and associating points dispersed across different angles with the true AoA of the target. Conversely, because the points exhibited relatively less variation across the range, the model successfully learned and mapped them to the correct range, resulting in superior performance in this aspect.

C. Standard Deviation Analysis

Table III displays the mean standard deviations of the MAE obtained for both in-sample and out-of-sample test cases. It is evident that, for most test cases, the standard deviation of AoA generalizability can be enhanced even further by incorporating data from diverse multipath environments to train the model.
for the proposed DL model ranges around 6–7°. This variation can be attributed to the fact that the error is not consistent across all target angles, as it tends to increase as the angle increases, as shown in Fig. 15 and Fig. 16. On the other hand, the mean standard deviation of the range optimization errors is relatively lower for all test cases, ranging between 0.2–0.4m. The low standard deviation indicates better performance of the proposed DL model for all target ranges, as depicted in Fig. 17 and Fig. 18. Nevertheless, it is worth noting that the standard deviations of errors for both AoA and range optimization remain consistent across both in-sample and out-of-sample test cases. This consistency implies the robust and generalized performance of the proposed DL methods even in unseen environments.

### D. Hyperparameter Tuning

The performance of the DL models including the DNN and CNN is further analyzed by tuning the hyperparameters, such as the AF and BN. However, the DO layer has not been removed to induce generalizability and keep the model from overfitting. Table IV shows the performance of DL models for a different setting of hyperparameters. For AoA optimization, it can be seen in Table IV that the DNN with BN and Tanh as the AF outperforms CNN and DNN with different hyperparameter settings. On the other hand, for range optimization, it is the CNN without BN and with ReLU as the AF that tends to exhibit the minimum error.

Table II shows the comparison of the performance of SVR based on the selected kernels. It can be observed that for the task of AoA optimization, the SVR with the Poly kernel slightly outperforms the RBF kernel. This can be explained by the fact that the Poly kernel considers not just the input features, but the combination of the features to find similarities between them. Since a point-cloud contains multiple data points associated with a target person, a combination of these points can help determine the points that are clustered and form a better correlation with the target output values.

However, for the case of range optimization, SVR with RBF kernel tends to show slightly better performance than the Poly kernel.

### E. Complexity Analysis

Although CNN tends to outperform the ML models including LR and SVR for range optimization, however, a comparable performance is achieved among DL and ML models for the AoA optimization. Therefore, apart from the performance, it is also imperative to analyze the complexity of each learning model. Therefore, we analyzed the complexity of the models in terms of the number of trainable parameters used in each model and the training time for each model. Note that for the DL models, the reported time refers to the time it takes to train one epoch. For ML models, including SVR and LR, the reported time refers to the total training time since the optimization is performed on the entire dataset without going through iterations. In addition, experiments have been conducted to calculate the forward pass time or the inference time of each model for a single example. The final results were obtained by averaging the inference time across 100 examples. Table V lists the complexity analysis for each model using the aforementioned metrics. It can be seen that the ML models achieve lesser computational complexity as compared to the DL models.

### Table IV

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Filters</th>
<th>Kernel Size</th>
<th>Strides</th>
<th>AF</th>
<th>DO</th>
<th>BN</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNN</td>
<td>(2, 2), (1, 1)</td>
<td>ReLU 0.3</td>
<td>True</td>
<td>11.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>(2, 2), (1, 1)</td>
<td>Tanh 0.3</td>
<td>False</td>
<td>17.8</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DNN</td>
<td>(2, 2), (1, 1)</td>
<td>ReLU 0.3</td>
<td>True</td>
<td>0.83m</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>(2, 2), (1, 1)</td>
<td>Tanh 0.3</td>
<td>True</td>
<td>0.11m</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table V

<table>
<thead>
<tr>
<th>Model</th>
<th>Trainable Parameters</th>
<th>Epoch/Training Time</th>
<th>Inference Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN</td>
<td>0.7965</td>
<td>2.17s</td>
<td>0.048s</td>
</tr>
<tr>
<td>CNN</td>
<td>1.3073</td>
<td>2.12s</td>
<td>0.057s</td>
</tr>
<tr>
<td>LR</td>
<td>61</td>
<td>1.8s</td>
<td>0.0001s</td>
</tr>
<tr>
<td>SVR (poly)</td>
<td>61</td>
<td>4.7s</td>
<td>0.0014s</td>
</tr>
<tr>
<td>SVR (de)</td>
<td>61</td>
<td>4.7s</td>
<td>0.0012s</td>
</tr>
</tbody>
</table>
VII. CONCLUSION AND FUTURE DISCUSSION

In this paper, we have demonstrated a DL and ML based approach to reduce the error in AoA and range estimates from point-cloud data obtained through a low-cost mm-wave sensor. The experiments have been performed and validated on over-the-air data collected from the BM201 mm-wave sensor. Our results on in-sample test data demonstrate about 35% and 94% decrease in the estimation error of AoA and range, respectively. Whereas, the results on out-of-sample test data demonstrate about 16% and 88% decrease in the estimation error of AoA and range, respectively. However, there are some aspects of this work that can be further improved. For instance, this work can be extended in the following directions:

- The presence of ghost points in the point-cloud data can be filtered to enhance the performance of AoA optimization.
- The performance of ML and DL models can be further improved by devising alternatives to the zero-padding of the input features which was employed to ensure the constant size of the input features. The additional zeros in the input features can act as noise and affect the performance of the models.
- The estimation accuracy can be further improved by investigating other DL networks, such as LSTM recurrent architectures and autoencoders.
- Class weights can be incorporated during the training phase of the model to optimize the accuracy for angles and ranges with higher error.
- Since this work focuses on improving the accuracy of AoA and range for a single target, it can further be extended to distinguish multiple targets.
- The idea of this work can be extended to sensors using any wireless technology for enhancing their measurement accuracy.

This research work is a preliminary step toward making measurements from low-cost sensors more accurate and reliable using the potential of data-driven methods. Moreover, this study demonstrates the point-cloud optimization of a low-cost mm-wave sensor without the need of using additional hardware for acquiring raw IQ data. The use of reliable low-cost transceivers can help accelerate the research in implementing PoCs of novel positioning algorithms.

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