Towards Grid-Free Positioning for Near-Field Communications

Hyunwoo Park, Andrea Conti*, Moe Z. Win†, and Sunwoo Kim
Department of Electronic Engineering, Hanyang University, Seoul, South Korea
(E-mail: {stark95, remero}@hanyang.ac.kr)
**Department of Engineering and CNIT, University of Ferrara, Via Saragat 1, 44122 Ferrara, Italy*
(E-mail: andrea.conti@unife.it)
†Laboratory for Information and Decision Systems, Massachusetts Institute of Technology, Cambridge, MA 02139 USA
(E-mail: moewin@mit.edu)

***Abstract*—This paper proposes a grid-free positioning algorithm for near-field (NF) communications based on machine learning. Due to the NF effects of large-aperture array antenna, beam training measurements are affected by the angle and the distance of the user, which makes it possible to be used for user positioning. Therefore, unlike conventional beam management, the proposed algorithm is designed to learn the relationship between beam training measurements and the user position, enabling not only the establishment of communication links but also the additional estimation of the user's position. Throughout simulations, we compare the proposed algorithm with the traditional beam training algorithms. The simulation results confirm that the proposed algorithm achieves higher user positioning accuracy compared to beam training.**

***Index Terms*—Beam training, near-field, positioning, machine learning**

I. Introduction

As the carrier frequency increases in next-generation communication systems, ultra-massive MIMO (UM-MIMO) systems have been proposed as a solution to overcome severe path loss [1]. Unlike traditional array antenna communication systems that primarily consider the far-field, UM-MIMO systems can capture the spherical wave characteristics of signals in the near-field (NF) [2]. This capability opens new possibilities for position estimation, which is critical for location-aware services [3]–[5].

Recent studies have focused on maintaining communication links in NF environments by leveraging beam focusing techniques [6], [7]. These works have proposed beam codebooks [6] or discrete grids [7] tailored for NF communication. While rough position estimation can be achieved by identifying the beam with the highest received signal strength, the accuracy is insufficient for practical location-based services. Moreover, the correlation between codebook measurements and user positions is highly complex [8]–[10], necessitating innovative methods to reduce computational complexity.

In this paper, we propose a grid-free positioning algorithm based on machine learning to effectively learn the intricate relationship between codebook measurements and user positions. The proposed algorithm employs a regression model to achieve a closed-form solution for position estimation, significantly reducing computational complexity through the parallel processing capabilities of convolutional neural networks (CNNs [11]). Furthermore, we demonstrate that the algorithm not only maintains communication links using beam codebook measurements but also accurately estimates user positions, making it suitable for location-aware services.

Notations : For a matrix $\mathbf{A}$, its transpose, complex conjugate, and Hermitian transpose are respectively denoted as $\mathbf{A}^{\mathsf{T}}$, $\mathbf{A}^*$, and $\mathbf{A}^{\mathsf{H}}$. The symbol $\imath$ represents the imaginary unit of complex numbers, ($\imath = \sqrt{-1}$). The notation $\mathcal{CN}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ denotes the circularly symmetric complex Gaussian distribution of a random vector with mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$. $\mathbf{I}$ denotes the identity matrix. The notation $\odot$ denotes the Hadamard product. $Re\{\cdot\}$ and $Im\{\cdot\}$ return real and imaginary parts of a complex values, respectively.

II. System Model

We consider an uplink communication system, where a single antenna mobile station (MS) is transmitting pilot signal to a UM-MIMO base station (BS) with a line-of-sight (LoS) path channel. The UM-MIMO BS employs uniform linear array (ULA) antenna with N elements. For each training episode, BS receives the pilot signal with a combiner codebook $\mathbf{W} \in \mathbb{C}^{N \times NS}$ introduced as a polar-domain transform matrix [6] as

$$\mathbf{W} = \left[\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_{NS}\right], \tag{1}$$

where S is the number of distance rings.

The received signal z_k corresponding to the k-th training signal b_k ($|b_k| = 1$ for $k = 1, 2, \ldots, NS$) is expressed as

$$z_k = \mathbf{w}_k^{\mathsf{H}} \mathbf{h} b_k + \mathbf{w}_k^{\mathsf{H}} \boldsymbol{\eta}, \tag{2}$$

where $\mathbf{h} \in \mathbb{C}^{N \times 1}$ is the NF channel vector, and $\boldsymbol{\eta} \sim \mathcal{CN}\left(\mathbf{0}_{N \times 1}, \sigma_\eta^2 \mathbf{I}_{N \times N}\right)$ is the additive white Gaussian noise with standard deviation σ_η. The channel vector $\mathbf{h}$ between the user and the UM-MIMO BS is expressed as

$$\mathbf{h} = \mathbf{a}(\mathbf{p}), \tag{3}$$

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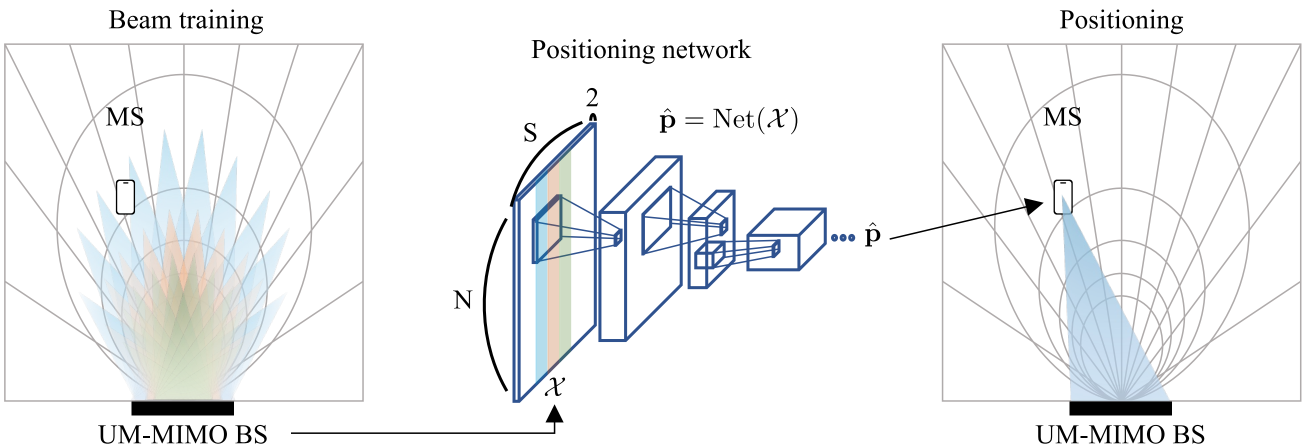

Fig. 1: Procedure of the proposed NF beam training and positioning algorithm.

where $\mathbf{a}(\mathbf{p})$ is the NF array response vector for the MS's position $\mathbf{p}$ in the Cartesian coordinate. The n-th element of the NF array vector is expressed as [12]

$$a_n(\mathbf{p}) = \frac{\lambda}{4\pi\|\mathbf{p}_n' - \mathbf{p}\|} \exp\left(-\imath\frac{2\pi}{\lambda}\|\mathbf{p}_n' - \mathbf{p}\|\right), \quad (4)$$

where λ is a wavelength of a carrier frequency and $\mathbf{p}_n'$ is the position of the n-th element of UM-MIMO array antenna.

III. Grid-Free Positioning Algorithm

At each beam training interval, the BS measures the received signal $z_{1:k}$. Traditional beam training selects the beam for communication with the highest beamforming gain in the codebook, and the position of MS is estimated as the focusing point of the selected beam. However, since the focusing point of combiner codebook is discrete, grid-mismatch exists for position estimation. In particular, as the distance from the BS increases, the grid size widens and the grid-mismatch increases, which is not suitable for location-aware services.

To overcome grid-mismatch of the traditional beam training, we propose an algorithm that leverages machine learning after beam training to accurately estimate the MS's position. The NF beam training and positioning algorithm procedure follows Fig. 1. After beam training, the BS prepossesses the received signal into the real-valued tensor as

$$\mathcal{X} = [Re\{\mathbf{Z} \odot \mathbf{B}^*\}; Im\{\mathbf{Z} \odot \mathbf{B}^*\}] \in \mathbb{R}^{2\times N\times S}, \quad (5)$$

where

$$\mathbf{Z} = \begin{bmatrix} z_1 & z_{N+1} & \cdots & z_{NS-N+1} \\ z_2 & z_{N+2} & \cdots & z_{NS-N+2} \\ \vdots & \vdots & \ddots & \vdots \\ z_N & z_{2N} & \cdots & z_{NS} \end{bmatrix} \in \mathbb{C}^{N\times S}, \quad (6)$$

$$\mathbf{B} = \begin{bmatrix} b_1 & b_{N+1} & \cdots & b_{NS-N+1} \\ b_2 & b_{N+2} & \cdots & b_{NS-N+2} \\ \vdots & \vdots & \ddots & \vdots \\ b_N & b_{2N} & \cdots & b_{NS} \end{bmatrix} \in \mathbb{C}^{N\times S}. \quad (7)$$

TABLE I: Simulation parameters

Parameter	Description	Value
N	Number of UM-MIMO antenna elements	128
-	number of distance rings	4
-	Learning rate	0.001
-	Training interval	4
-	Mini-batch size	32
-	Number of training data	100,000

The real-valued tensor is then feed to the positioning network, and the positioning network outputs the estimated position of the user as

$$\hat{\mathbf{p}} = \mathrm{Net}(\mathcal{X}), \quad (8)$$

where Net is a positioning network. The optimization goal of positioning network is to find the optimal weights and biases of the network, by minimizing the loss function $\mathcal{L}$ which is a mean squared error (MSE) between $\mathbf{p}$ and $\hat{\mathbf{p}}$ as

$$\mathcal{L} = \|\mathbf{p} - \hat{\mathbf{p}}\|_2^2, \quad (9)$$

where $\|\cdot\|_p$ denotes the l_p-norm.

For training, the position of MS is generated within the area following uniform random distribution. The actual position of the MS is labeled as the output corresponding to each input data pair. These data pairs are then used to train the positioning network. After adequate training, the positioning network is capable of estimating the position of the MS based on the input tensor during practical application.

IV. Simulation Results and Discussions

In this section, we first introduce the simulation settings and then compare the performance of the proposed algorithm with the NF beam training only positioning. The positioning root mean squared error (RMSE) is compared for the area inside the focusing points of the codebook.

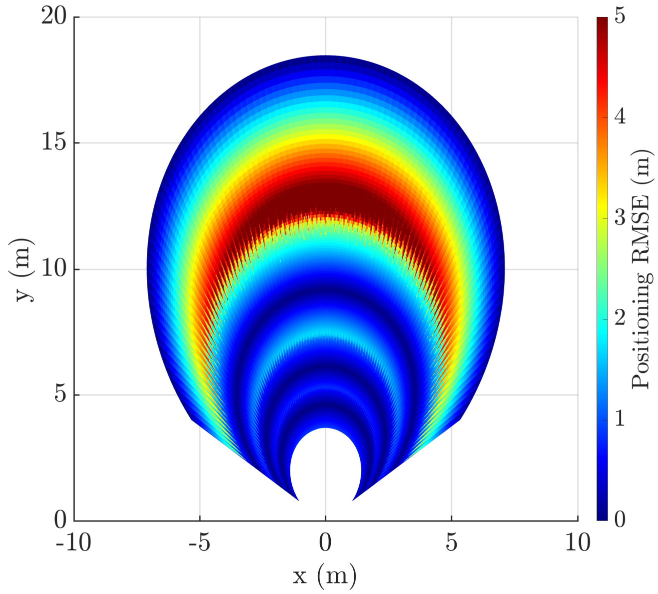

Fig. 2: RMSE of position estimation (Beam training).

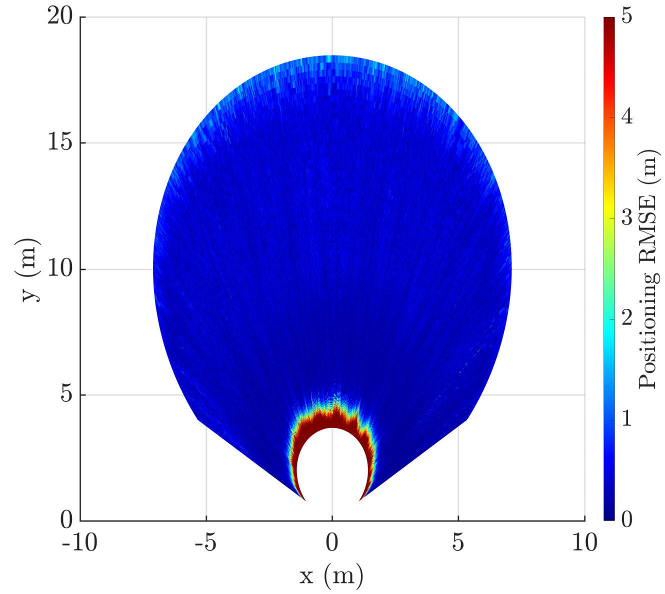

Fig. 3: RMSE of position estimation (Machine learning-based beam training and positioning).

A. Simulation Settings

The center of the UM-MIMO BS is located at the origin, and the position of the MS is within the NF codebook area. The carrier frequency is set as 13 GHz (upper-mid band [13]) and the wavelength is 0.0231 m. The UM-MIMO BS is equipped with uniform linear array (ULA) with $N = 128$ elements. The interval between each antenna element is set to half of the wavelength. The simulation parameters are shown in Table I. To evaluate the performance of the proposed algorithm, the RMSE of position estimation was compared at evenly spaced grid points in the polar domain, within the same range as the region where the training data was generated. For the performance analysis, signal-to-noise ratio (SNR) is set to 10 dB.

The positioning performance of conventional beam training is shown in Fig. 2. Traditional beam training estimates the MS's position as the closest focusing point of the NF codebook. As a result, grid mismatch in the polar domain is unavoidable. Consequently, at longer distances where the spacing between codebook focusing locations is larger, the positioning RMSE significantly increases.

The positioning performance of the proposed algorithm is shown in Fig. 3. The proposed algorithm estimates the MS's position as the output of the positioning network which outputs the position values in the continuous domain. Therefore, it can be observed that grid mismatch does not occur, and low RMSE is maintained across most of the area. There are areas with high RMSE near the BS, which are areas that require further performance improvement. The performance of this area is expected to improve through optional use with existing beam training-based positioning.

V. Conclusion

This paper presents a grid-free positioning algorithm based on machine learning for NF communications. Due to the NF effects of large-aperture array antenna, user positioning became possible by leveraging beam training measurements which are affected by both angle and distance. Proposed algorithm enables accurate user position estimation by learning the relationship between beam training measurements and the user position. Simulation results confirmed the ability to estimate the user position in the continuous domain and high positioning performance compared to beam training only positioning especially when the MS is far from the BS. Future research providing grid-free positioning for a wider range is expected.

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