Spatially Continuous Near-field Tracking for 6G Wireless Networks

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Abstract

Near-field tracking is a key enabler for providing situational awareness in 6th-generation (6G) wireless networks. However, extreme computational complexity presents significant challenges. This paper proposes precise and time-efficient tracking by utilizing regression neural networks (regression NN). By deriving a spatially continuous solution through regression NN, the proposed method effectively resolves the grid-mismatch problem while reducing computational complexity. Case studies demonstrate that the proposed method provides precise real-time tracking, establishing a viable approach for 6G wireless networks.

I. Introduction

High-precision tracking is a key enabler for emerging 6th-generation (6G) wireless networks [1]. As wireless networks advance toward higher frequencies, signal propagation enters the near-field regime [2] which offers new opportunities for ultra-precise positioning [3]. Current grid search-based near-field tracking methods suffer from high computational complexity, making them ill-suited for real-time applications [4]. Furthermore, grid-based discretization introduces grid-mismatch when the user's true position lies between grid points [5]. To address these challenges, this paper proposes a regression neural network (regression NN)-based framework for spatially continuous near-field tracking. The proposed method eliminates grid-mismatch by directly mapping uplink signals to continuous coordinates while drastically reducing computational costs through parallel processing. Comprehensive case studies compare the proposed method with conventional grid search-based tracking approaches, demonstrating significant improvements in position tracking and computational efficiency, thus establishing its viability for next-generation wireless positioning systems.

II. Near-field Tracking System

A system where a single antenna user is communicating with antenna base station (BS) is considered. Near-field tracking is initiated after the user's position estimation, and the BS tracks the user's position. The received signal at the BS with m-th subcarrier at time k is expressed as

$$\mathbf{z}_{k,m} = \sqrt{\frac{{}_{\mathrm{T}}}{M}}\mathbf{h}_{k,m}x_{k,m}\exp\left(\quad {}_{m}\right) + \boldsymbol{\eta}_{k,m} \in \mathbb{C}^{N\times 1} \tag{1}$$

where ${}_{\mathrm{T}}$ is the transmit power, M is the number of subcarriers, $\mathbf{h}_{k,m} \in \mathbb{C}^{N\times 1}$ is the channel, $x_{k,m}$ is the uplink signal, ${}_{m}$ is the synchronization error, and $\boldsymbol{\eta}_{k,m} \sim \mathcal{CN}\left(\mathbf{0}_{N\times 1}, \sigma_\eta^2 \mathbf{I}_{N\times N}\right)$ is the additive white Gaussian noise.

A non-uniform spherical wave model [2] is considered for the channel $\mathbf{h}_{k,m}$, where the element is expressed as

$$_{k,m,n} = \frac{1}{\sqrt{\alpha_{k,m,n}}}\exp\left(-\frac{2\pi}{\lambda_m}\left\|\mathbf{p}_n' - \mathbf{p}_k\right\|\right) \tag{2}$$

where $\alpha_{k,m,n}$ is the path loss, λ_m is the wavelength of the m-th subcarrier, $\mathbf{p}_n'$ and $\mathbf{p}_k$ are the positions of BS's n-th antenna element and the user in the Cartesian coordinate respectively. The path loss $\alpha_{k,m,n}$ follows:

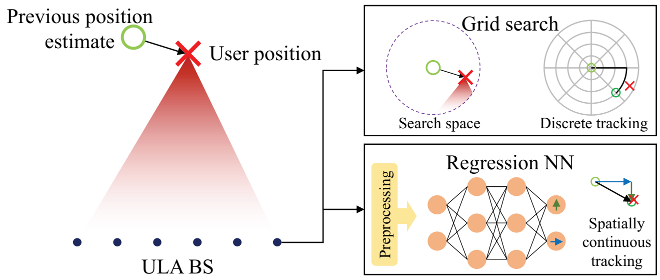


Fig. 1: Illustration of two tracking methods.

$$\alpha_{k,m,n}(\mathrm{dB}) = 20\log_1\left(\frac{4\pi}{\lambda_m}\left\|\mathbf{p}_n' - \mathbf{p}_k\right\|\right). \tag{3}$$

The noise variance for each subcarrier follows

$$\sigma_\eta^2 = k_{\mathrm{B}} T \Delta_{\mathrm{f}} \tag{4}$$

where $k_{\mathrm{B}} = 1.38 \times 10^{-2}$ (J/K) is the Boltzmann constant, T (K) is the Kelvin temperature, Δ_{f} is the subcarrier spacing, and is the noise figure of the BS.

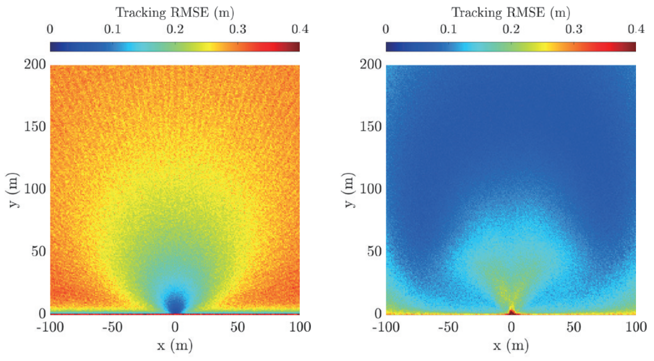
III. Spatially Continuous Near-field Tracking

This section addresses the issues of conventional grid search-based tracking and proposes a regression NN-based framework to resolve these issues. In the grid search, when a fine grid is employed, accurate user tracking can be achieved, but the computational complexity increases and results in increased latency. Conversely, a coarse grid reduces computational costs but introduces grid mismatch, where the actual user position fails to align with the grid.

To resolve these issues, this paper proposes a regression NN-based solution for near-field tracking. The proposed framework employs a regression model to directly track user in a continuous domain which resolves the grid mismatch problem while drastically reducing computational time through parallel processing capabilities as compared in the Fig. 1.

The desired function $f_{\boldsymbol{\omega}^*}(\cdot)$ for tracking is formulated as

$$f_{\boldsymbol{\omega}^*}(\phi(\mathbf{z}_{k,1\ M}, \hat{\mathbf{p}}_{k-1})) = \mathbf{p}_k - \hat{\mathbf{p}}_{k-1} \tag{5}$$



(a) Grid search (# of grids: 500). (b) Regression NN.

Fig. 2: User tracking RMSEs under the considered area.

TABLE I: Simulation parameters

Parameter	Description	Value	Parameter	Description	Value
N	# of antenna elements	64	M	# of subcarriers	4
-	User maximum speed	25 m/s	F	Noise figure	7 dBm
-	Carrier frequency	13 GHz	-	Tracking interval	0.01 s
P_{T}	User transmit power	23 dBm	B	Batch size	32
T	Kelvin temperature	290 K	Δ_{f}	Subcarrier spacing	120 KHz

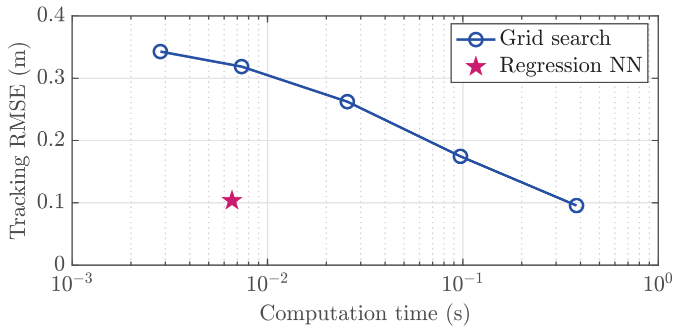


Fig. 3: User tracking RMSEs over the computation time. For the grid search, the tracking RMSE and computational time have a negative correlation.

where $\boldsymbol{\omega}^*$ represents the optimal learnable parameters, and $\phi(\cdot)$ denotes the preprocessing function. The term $-\hat{\mathbf{p}}_{k-1}$ serves a critical role by directing the tracking function to predict displacement from the previous position estimate.

Since the received signal $\mathbf{z}_{k,1\ M}$ and the previous position estimate $\hat{\mathbf{p}}_{k-1}$ are heterogeneous, the preprocessing function $\phi(\cdot)$ is designed to compute the similarity between the received signal and the channel at the previous user position estimate:

$$\phi(\mathbf{z}_{k,1\ M}, \hat{\mathbf{p}}_{k-1}) = \mathbf{z}_{k,1\ M} \odot \check{\mathbf{h}}_{1\ M}(\hat{\mathbf{p}}_{k-1}) \tag{6}$$

The current position is then estimated as:

$$\hat{\mathbf{p}}_k = f_{\boldsymbol{\omega}}(\phi(\mathbf{z}_{k,1\ M}, \hat{\mathbf{p}}_{k-1})) + \hat{\mathbf{p}}_{k-1} \tag{7}$$

The regression tracking network is trained by minimizing the following loss function:

$$\mathcal{L}(\boldsymbol{\omega}) = \frac{1}{\ }\sum_{b=1}^{B} \left\| \left(\mathbf{p}^{(b)} - \hat{\mathbf{p}}^{(b)}\right) - f_{\boldsymbol{\omega}}\left(\phi\left(\mathbf{z}_{1\ M}^{(b)}, \hat{\mathbf{p}}_{-1}^{(b)}\right)\right) \right\|_2^2 \tag{8}$$

where is the mini-batch size, and ( ) denotes the data index in a batch. For simplicity, the time index k is omitted. This formulation enables the network to learn temporal position variations effectively by explicitly modeling position shifts.

IV. Case Studies

This section presents the simulation setup and provides a comprehensive performance analysis of the proposed method. To demonstrate the effectiveness, the proposed method is compared against the grid search. The parameters of the case studies are shown in Table I. The tracking RMSE for the present time, when tracking was valid until the previous time, is shown in Fig. 2. In the case of grid search, a lower number of search grids results in higher grid-mismatch and tracking RMSEs. In contrast, the proposed method completely eliminates grid-mismatch issues, enabling accurate tracking for most of the area as in Fig. 2(b).

A major advantage of the proposed method is not only its accuracy but also its significant time-performance efficiency, as in Fig 3. While the computational time of the grid search increases as the number of grids increases, the regression NN method maintains a tracking RMSE of approximately 0.1m, which is lower than the tracking interval. These results demonstrate that the proposed method provides an effective parallel processing solution that maintains real-time performance while delivering superior tracking accuracy.

V. Conclusions

This paper presents a regression NN-based near-field tracking for 6G wireless networks. The proposed approach eliminates grid-mismatch errors by mapping uplink signals directly to continuous spatial coordinates while significantly reducing computational complexity through parallel processing. Case studies demonstrate that the proposed method achieves superior time-performance efficiency. This advancement enables ultra-precise, real-time position tracking capabilities essential for next-generation wireless networks.

Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. RS-2024-00409492)

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