Enhancing ISAC Performance through Predictive Beamforming in E-MIMO Systems

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ABSTRACT

In this paper, we explore the enhancement of Integrated Sensing and Communication (ISAC) performance through predictive beamforming within Extreme Multi-Input Multi-Output (E-MIMO) systems. We present a framework that anticipates user movements, enabling the ISAC system to preemptively align its beams, thereby ensuring robust communication links and precise sensing. Our approach addresses the challenge of beam misalignment in dynamic environments, significantly reducing the latency and overhead associated with conventional beam training and tracking methods. The results demonstrate a marked improvement in ISAC efficacy, with lower overhead, making it a viable solution for high-mobility scenarios.

I. INTRODUCTION

With the fifth generation (5G) mobile communication networks being deployed worldwide, attention is shifting towards 6G wireless systems to support advanced applications like immersive reality, the metaverse, and autonomous vehicles. Key technologies under consideration for 6G include integrated sensing and communication (ISAC) and extreme MIMO (E-MIMO), which significantly increases number of antennae from several hundreds to thousands to enhance spectral efficiency and spatial resolution [1]. ISAC systems, which use combined infrastructure for both data transmission and environmental sensing, are set to become a core technology in the upcoming 6G era. These systems are particularly valued for their ability to boost communication performance by incorporating sensing data into network operations [2].

However, user mobility in dynamic environments disrupts communication links due to beam misalignment from outdated channel information. Conventional beam training methods add latency and overhead [3-6]. This paper presents a study on using predictive beamforming for E-MIMO ISAC systems. By anticipating user movements, the system preemptively adjusts beams, maintaining robust communication and precise sensing.

II. SYSTEM MODEL

We consider a near field ISAC system with E-MIMO, which consists of a dual functional radar and communication (DFRC)-enabled base station (BS) with $M \gg 1$ antennae, respectively, and a single antenna UE. The BS transmits a radar signal to UE on downlink and receives echo signal reflected from the UE to estimate the state of the UE including AOA/AOD, distance and velocity.

A. *Near-Field Sensing Model*

DFRS-enabled BS transmits the $x_n(t)$ signal at the n_{th} epoch and time t can be expressed as

$$\mathbf{s}_n(t) = \mathbf{w}_n x_n(t) \in \mathbb{C}^{M\times 1} \tag{1}$$

$\mathbf{w}_n \in \mathbb{C}^{M\times 1}$ is the transmit beamforming vector. The reflected echo signal received at the BS is given by

$$\mathbf{r}_n(t) = \zeta\, \mathbf{a}(r_n,\theta_n)\mathbf{a}^{H}(r_n,\theta_n)\mathbf{s}_n(t-\tau_n) + \mathbf{z}(t) \tag{2}$$

where ζ is a complex reflection coefficient that includes the impact of radar cross section (RCS) of the target. $\mathbf{z}(t) \in \mathbb{C}^{M\times 1}$ is the additive white Gaussian noise (AWGN) with zero mean and variance of σ_m^2. $\mathbf{a}(r_n,\theta_n) = \frac{\sqrt{\alpha_0}}{r_n}\bar{\mathbf{a}}(r_n,\theta_n)$ denoted the near-field array response vector with α_0 is the pathloss at the reference distance $1m$ and the m_{th} element, $\forall m \in \{-M,\dots,M\}$ of $\bar{\mathbf{a}}(r_n,\theta_n)$ is given by

$$[\bar{\mathbf{a}}(r_n,\theta_n)]_m = e^{-j\frac{2\pi}{\lambda}r_m(r_n,\theta_n)} \tag{3}$$

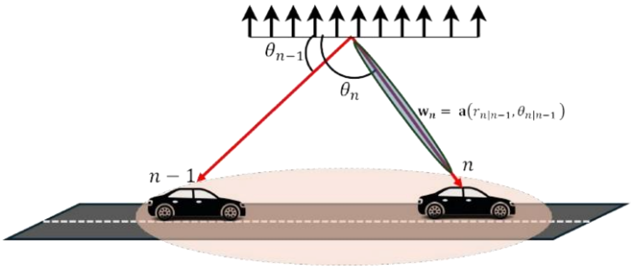

Figure 1: Near-field predictive beamforming

where $r_m(r_n,\theta_n) = \sqrt{r_n^2 + m^2l^2 - 2r_n ml\cos\theta_n}$, is the distance of m_{th} element from UE, r_n is showing the distance of central element of ULA located at [0,0] from the UE located at $[r_n\cos\theta_n,\ r_n\sin\theta_n]$ and l is the spacing of the array element in ULA.

B. *Communication signal Model*

The UE receives the signal from the BS at the n_{th} epoch and time t is given by

$$c_n(t) = \bar{\zeta}\ \mathbf{a}^{H}(r_n,\theta_n)\mathbf{w}_n x_n(t) + n(t) \tag{4}$$

The beamforming vector $\mathbf{w}_n$ is designed based on the prediction of the angle and distance.

$$\mathbf{w}_n = \mathbf{a}\left(r_{n|n-1},\theta_{n|n-1}\right) \tag{5}$$

The achievable rate of UE is given as

$$R_n = \log_2\left(1 + \frac{p_n\left|\mathbf{a}^{H}(r_n,\theta_n)\mathbf{a}\left(r_{n|n-1},\theta_{n|n-1}\right)\right|^2}{\sigma^2}\right) \tag{6}$$

III. LSTM-BASED PREDICTIVE BEAMFORMING

Equation (6) illustrates that maximizing the communication throughput depends on the accurate prediction of the beamformer based on historical information of UE. We propose a historical information based long short-term memory (LSTM) network for predictive beamforming in ISAC-based E-MIMO system. We discuss the LSTM-based network for the angle and distance prediction based on historical information represented as $\mathbf{H}_n^{\tau} = [\mathbf{h}_{n-1},\mathbf{h}_{n-2},\dots,\mathbf{h}_{n-\tau}]$ and $\mathbf{h}_n = \mathbf{a}(\hat{r}_n,\hat{\theta}_n)$ with $\hat{r}_n$ and $\hat{\theta}_n$ being the estimated angles and distances in the previous $n-1$ to $n-\tau$ time slots. The detailed architecture of the proposed LSTM is shown in Fig. 2, which consists of two LSTM layers, and one fully connected (FC) layer. The LSTM layers are adopted to exploit the temporal dependency of the historical information which is given for the past τ time slots. Generally, in one LSTM layer, same LSTM structure is adopted for each time step. In LSTM layer 1, after each n_{th} time step, LSTM keeps a copy of the output $p_n^{L_1}$ and passes to LSTM layer 2 for further processing. Considering LSTM layer 1 & 2 as the LSTM block, the output of the LSTM block is given by

$$p_n^{L_2} = f(\mathbf{H}_n^\tau)$$

Next, the output is given to FC layer with a linear activation function to fully exploit the extracted features from LSTM block and finally we get the predicted output $\mathbf{a}(r_{n|n-1}, \theta_{n|n-1})$.

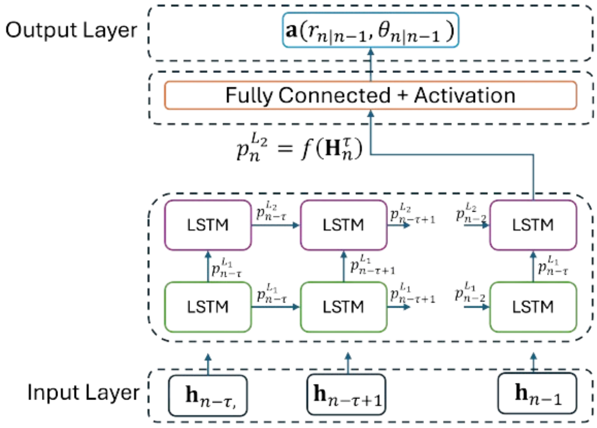

Figure 2: LSTM-based proposed architecture

IV. SIMULATION RESULTS

In this section, we provide the numerical results to validate the performance of proposed beamforming scheme in E-MIMO ISAC systems. The BS is equipped with M antennae having $d = \frac{\lambda}{2}$, spacing. We set the noise density power as -174 dBm/Hz. The carrier frequency is set to 28 GHz. We set antenna gain and radar cross section as 1 and -23dB, respectively. We use 1000 previous time instants for training the LSTM-based predictive beamforming architecture.

Figure 3 shows the training loss across successive epochs for different numbers of BS antennas. It is observed that a higher number of antennas results in greater training loss. This occurs because increasing the number of transmit antennas enhances the network's complexity. Training such a network requires a larger set of data and a more sophisticated LSTM architecture. However, using the same architecture in this instance leads to varying training losses.

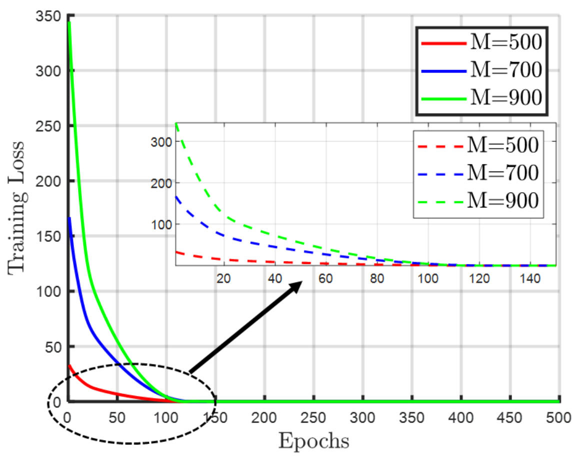

Figure 3: Training Loss with successive epochs.

Figure 4 illustrates the achievable rate of the proposed predictive beamforming approach compared to the optimal beamforming. It is observed that the proposed method achieves near-optimal performance within just a few epochs.

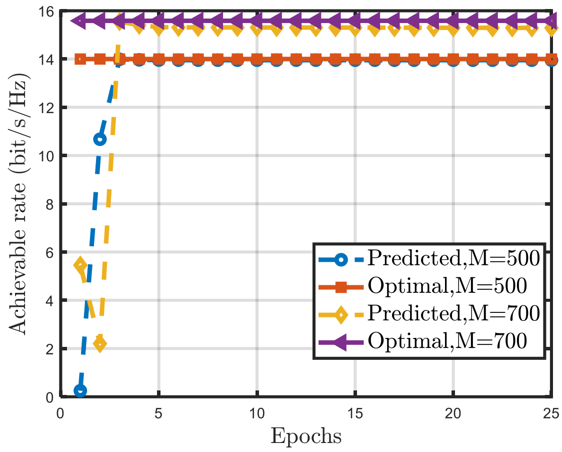

Figure 4: Achievable Rate on successive epochs.

CONCLUSION

This paper proposes a deep learning-based predictive beamforming technique for E-MIMO ISAC systems. This method anticipates user movement to preemptively adjust beams, maintaining robust communication and precise sensing in dynamic environments. By eliminating the need for continuous beam training, the proposed approach reduces overhead and improves system performance, making it particularly suitable for high-mobility scenarios encountered in 6G applications like autonomous vehicles.

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