國立清華大學 電機工程學系
實作專題研究成果摘要

Machine learning-Based Predictive Beamforming for ISAC V2I Systems

利用機器學習預測 ISAC 車聯網系統之波束成形

專題領域：通訊領域

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研究期間：113 年 6 月 1 日至 113 年 11 月 18 日止，共 6 個月

Abstract

The project focuses on applying machine learning to beamforming design in Integrated Sensing and Communication (ISAC) systems for 6G networks, particularly in vehicle-to-infrastructure (V2I) communication scenarios. In ISAC, efficient beamforming is crucial, but precise channel tracking is resource-intensive. The proposed solution uses historical channel state information (CSI) to predict the beamforming matrix that maximizes sum-rate while ensuring sensing performance. The approach combines an attention mechanism and an LSTM network to capture temporal dependencies in CSI data, optimizing the beamforming matrix under power and estimation accuracy constraints (Cramér-Rao lower bound). Simulation results show that the method achieves 80% of the performance of an ideal case with perfect CSI, while reducing computational resources needed for channel tracking. The study demonstrates that machine learning can efficiently design beamforming for ISAC systems, making it a promising approach for future 6G networks.

1. Introduction

Advancements in mmWave technology have led to the integration of radar and communication signals through shared spectrum use, enabling Integrated Sensing and Communication (ISAC) systems. These systems offer dual functionality, utilizing frequency bands traditionally reserved for radar. ISAC provides two key benefits: **integrated gain**, which enhances efficiency by sharing resources like power, bandwidth, and hardware, and **coordination gain**, where mutual assistance between communication and sensing improves system performance. These advantages make ISAC crucial for applications such as IoT, smart cities, and Vehicle-to-Everything (V2X) networks [1].

V2X networks, vital for next-generation wireless systems, require high-speed, reliable communication and advanced environmental sensing, such as detecting pedestrians and obstacles [2]. By leveraging shared spectrum, base stations (BS) communicate with vehicles while simultaneously supporting sensing tasks like tracking vehicle distance and angles. This sensing data helps BS optimize beamforming angles, improving communication sum rates and ensuring quality of service (QoS). However, challenges arise due to inaccuracies in channel and vehicle state estimation, prompting research into optimization techniques to address these issues.

Current ISAC algorithms are sensitive to errors in vehicle state prediction and often rely on simplified movement models that fail to capture real-world dynamics. Traditional beamforming methods struggle with the non-convexity of joint optimization problems. Deep learning (DL), particularly deep neural networks (DNNs), presents a promising alternative due to their ability to model complex nonlinear relationships. DNNs have-proven effective in tasks like beamforming design, signal detection, and channel estimation [3], making them well-suited for optimization challenges with high accuracy and efficiency.

This research focuses on an ISAC Vehicle-to-Infrastructure (V2I) system, using a kinematic model to represent vehicle motion [3]. The communication and sensing problem is framed as a non-convex optimization task, lacking a closed-form solution. To address this, we develop a modified version of the learning framework proposed in [3], called "AttLSTM", to approximate the optimal beamforming matrix. The model processes past echo samples from the previous τ time slots as input and predicts the beamforming matrix for the current time slot. Numerical evaluations show that the proposed model, using estimated channel data, achieves 80% of the performance of the optimal case with perfect channel state information (CSI), while meeting the sensing constraints.

2. Research Methodology

2-1. System Model

In this section, we use the model proposed in [3]. Consider a downlink ISAC V2I network with a roadside unit (RSU) serves K single-antenna vehicles. The RSU is equipped with a dual-function radar communication (DFRC) system with massive

MIMO uniform linear array (ULA), which consists of N_t transmit antennas and N_r receive antennas.

2-1-1. Sensing Model

In this ISAC V2I networks, we use the reflected signals, which carry the information of sensing parameters, as the sensing model. The channel state information and estimated motion parameters can be extracted from the echo signals.

2-1-2. Vehicle Mobility and Observation Model

In the networks, we assume the directions of all vehicles are parallel to the road, then we can characterize the velocity using the model

$$v_{k,n} = v_{k,n-1} + \Delta v_{k,n-1},$$

where $v_{k,n}$ is the average velocity of the k-th at the n-th time slot and $\Delta v_{k,n-1}$ is the velocity increment at the $(n-1)$-th time slot. Assume $v_{k,n} \sim U(v_{min}, v_{max}), \forall k, n.$

The observation model can be obtained by adopting the interference cancellation with the reflected signals. Furthermore, the velocity of each vehicle and the distance between the RSU and the k-th vehicle obey the observation models.

2-1-3. Communication Model

The received downlink signal of vehicle k at time slot n can be expressed as

$$\vartheta_{k,n}(t) = \tilde{G}\sqrt{\alpha_{k,n}}e^{j2\pi\mu_{k,n}t}\boldsymbol{a}^H(\theta_{k,n})\sum_{i=1}^{K}\boldsymbol{w}_{i,n}s_{i,n}(t) + \eta_{k,n}(t),$$

where $\tilde{G} = \sqrt{N_t}$ is the antenna gain. $\alpha_{k,n} = \alpha_0\left(\frac{d_{k,n}}{d_0}\right)^{-\zeta}$ is the path loss coefficient, in which α_0 is the path loss at reference distance d_0 and ζ is the path loss exponent. $\eta_{k,n}(t) \sim CN(0, \sigma_k^2)$ is the noise of the k-th vehicle at time slot n. In this case, the received signal-to-interference-plus-noise ratio (SINR) of the k-th vehicle at time slot n can be expressed as

$$\begin{aligned} SINR_{k,n}(\boldsymbol{h}_{k,n}, \boldsymbol{w}_{k,n}) &= \frac{\left|\tilde{G}\sqrt{\alpha_{k,n}}\boldsymbol{a}^H(\theta_{k,n})\boldsymbol{w}_{k,n}\right|^2}{\sum_{i=1,i\neq k}^{K}\left|\tilde{G}\sqrt{\alpha_{k,n}}\boldsymbol{a}^H(\theta_{k,n})\boldsymbol{w}_{i,n}\right|^2 + \sigma_k^2} \\ &= \frac{\left|\boldsymbol{h}_{k,n}^H\boldsymbol{w}_{k,n}\right|^2}{\sum_{i=1,i\neq k}^{K}\left|\boldsymbol{h}_{k,n}^H\boldsymbol{w}_{i,n}\right|^2 + \sigma_k^2}, \end{aligned}$$

where $\boldsymbol{h}_{k,n}^H = \tilde{G}\sqrt{\alpha_0(\frac{d_{k,n}}{d_0})^{-\zeta}}\boldsymbol{a}^H(\theta_{k,n})$ is the channel vector between vehicle k and the RSU at time slot n.

2-1-4. Transmission Protocol

In this research, we employ a transmission protocol for the system, where the predictive beamforming matrix for the next time slot is determined in advance. In time slot n, the RSU transmits data using the predicted optimal beamforming matrix obtained from time slot $(n-1)$ and receives the signal echoes simultaneously.

2-2. Problem Formulation

Our objective is to maximize the average achievable communication rate by optimizing the beamforming matrix, subject to the power and sensing constraints. The optimization problem can be formulated as follows:

$$\max_{\boldsymbol{W}_n} E\left[\sum_{k=1}^{K} \log_2\left(1 + SINR_{k,n}\left(\boldsymbol{h}_{k,n}, \boldsymbol{w}_{k,n}\right)\right)\right]$$

$$s.t.\ E\left[\frac{1}{K}\sum_{k=1}^{K} CRLB\left(\theta_{k,n}, \boldsymbol{w}_{k,n}\right)\right] \leq \gamma_\theta$$

$$\|\boldsymbol{W}_n\|_F^2 \leq P.$$

In this problem, $\boldsymbol{W}_n$ is the beamforming matrix and $\boldsymbol{h}_{k,n}$ is the channel vector. For sensing performance constraint, we choose the average Cramér-Rao lower bound to characterize the estimation accuracy. $CRLB\left(\theta_{k,n}, \boldsymbol{w}_{k,n}\right)$ denotes the Cramér-Rao lower bound of estimations $\theta_{k,n}$ given $\boldsymbol{w}_{k,n}$, respectively, which can be expressed as [3].

2-3. Machine Learning-Based Predictive Beamforming for ISAC

In this section, we used the ML-based predictive beamforming framework in [3], which formulated the training loss. Then we introduce our proposed model to solve the problem provided in the last section.

2-3-1. ML-Based Predictive Beamforming Framework for ISAC

Since the problem is a constrained optimization problem, however, DL methods cannot handle such problems, so we transform the problem along with the constraints into an unconstrained problem using the penalty method [6]. The problem can be rewritten as follows:

$$\max_{\boldsymbol{W}_n} E[\,f(\boldsymbol{W}_n)] = \max_{\boldsymbol{W}_n} E\left[\sum_{k=1}^{K}\log_2\left(1+SINR_{k,n}\left(\boldsymbol{h}_{k,n},\boldsymbol{w}_{k,n}\right)\right)\right]$$

$$-\lambda_1\left[\max\left(0, E\left[\frac{1}{K}\sum_{k=1}^{K} CRLB\left(\theta_{k,n},\boldsymbol{w}_{k,n}\right)\right]-\gamma_\theta\right)\right]^2$$

$$-\lambda_2[\max(0,\|\boldsymbol{W}_n\|_F^2-P)]^2,$$

However, since the expectation of the sum rate and CRLB cannot be expressed as a closed form, we employ the Monte-Carlo method to approximate the statistical expectation value, which can be expressed as:

$$E[\,f(\boldsymbol{W}_n)] \approx \frac{1}{N_e}\sum_{i=1}^{N_e} f\left(\boldsymbol{W}_n^{(i)}\right) = \frac{1}{N_e}\sum_{i=1}^{N_e} f\left(g_\omega\left(\boldsymbol{\Omega}_n^{\tau\,(i)}\right)\right).$$

The approximation holds when the number of Monte-Carlo experiments N_e is sufficiently large. $g_\omega(\cdot)$ is the DNN-based mapping function between the input historical channel data $\boldsymbol{\Omega}_n^{\tau\,(i)}$ and the output beamforming matrix $\boldsymbol{W}_n^{(i)}$, ω represents the learning parameters of the DNN model and $i = 1, 2, \dots, N_e$ is the index of the Monte-Carlo experiment.

We define the loss function $J(\omega)$ of the machine learning model:

$$J(\omega) = -\frac{1}{N_e}\sum_{i=1}^{N_e} f\left(g_\omega\left(\boldsymbol{\Omega}_n^{\tau\,(i)}\right)\right).$$

Then, we use the machine learning method to obtain the optimal learning parameters ω^* to minimize the training loss, i.e. $\omega^* = \arg\min_{\omega} J(\omega)$. Finally, the optimal beamforming matrix $\boldsymbol{W}_n^*$ for any input channel data $\boldsymbol{\Omega}_n^\tau$ can be expressed as:

$$\boldsymbol{W}_n^* = g_{\omega^*}(\boldsymbol{\Omega}_n^\tau).$$

2-3-2. Machine Learning Model for Predictive beamforming

Since the original problem is nonconvex and hard to analytically solve, we introduced a DNN to optimize the predictive beamforming matrix. We use the channel data of the past τ time slots as the model input. For each time slot, it contains K attention modules and a concatenate layer. The outputs of each time slots are fed into an LSTM module and a fully connected layer.

For the training data, there are N_e training samples for offline training. The training data set can be expressed as $X = \{\left(\widetilde{\boldsymbol{\Omega}}_n^{\tau(1)}, \boldsymbol{H}_n^{(1)}\right), \left(\widetilde{\boldsymbol{\Omega}}_n^{\tau(2)}, \boldsymbol{H}_n^{(2)}\right), \dots, \left(\widetilde{\boldsymbol{\Omega}}_n^{\tau(N_e)}, \boldsymbol{H}_n^{(N_e)}\right)\}$. Each training sample contains the historical channel data $\widetilde{\boldsymbol{\Omega}}_n^{\tau(i)} = [\boldsymbol{H}_{n-1}^{(i)}, \boldsymbol{H}_{n-2}^{(i)}, \dots, \boldsymbol{H}_{n-\tau}^{(i)}]$, where $\boldsymbol{H}_n^{(i)} = [\boldsymbol{h}_{1,n}^{(i)}, \boldsymbol{h}_{2,n}^{(i)}, \dots, \boldsymbol{h}_{K,n}^{(i)}]$ is the channel matrix for the n-th time slot, and the current channel data $\boldsymbol{H}_n^{(i)}$. The loss function of the ML model can be expressed as

$$J(\varsigma) = -\frac{1}{N_e}\sum_{i=1}^{N_e}\sum_{k=1}^{K}\log_2\left(1 + SINR_{k,n}\left(\boldsymbol{h}_{k,n}^{(i)}, \boldsymbol{w}_{k,n}^{(i)}(\varsigma)\right)\right)$$

$$-\lambda_1\left[\max\left(0,\frac{1}{N_eK}\sum_{i=1}^{N_e}\sum_{k=1}^{K}CRLB\left(\theta_{k,n}^{(i)},\boldsymbol{w}_{k,n}^{(i)}(\varsigma)\right)-\gamma_\theta\right)\right]^2$$

$$-\lambda_2\frac{1}{N_e}\sum_{i=1}^{N_e}\left[\max\left(0,\left\|\boldsymbol{W}_n^{(i)}(\varsigma)\right\|_F^2-P\right)\right]^2,$$

where $\boldsymbol{W}_n^{(i)}(\varsigma)$ is the predicted beamforming matrix for the i-th Monte-Carlo experiment and $\boldsymbol{w}_{k,n}^{(i)}(\varsigma)$ is the k-th column of $\boldsymbol{W}_n^{(i)}(\varsigma)$. With the loss function, we can use the back propagation method to update the learning parameters while training the network and minimize the loss.

The training hyperparameters and the block diagram of machine learning model is listed at Table. 1 and Fig. 1.

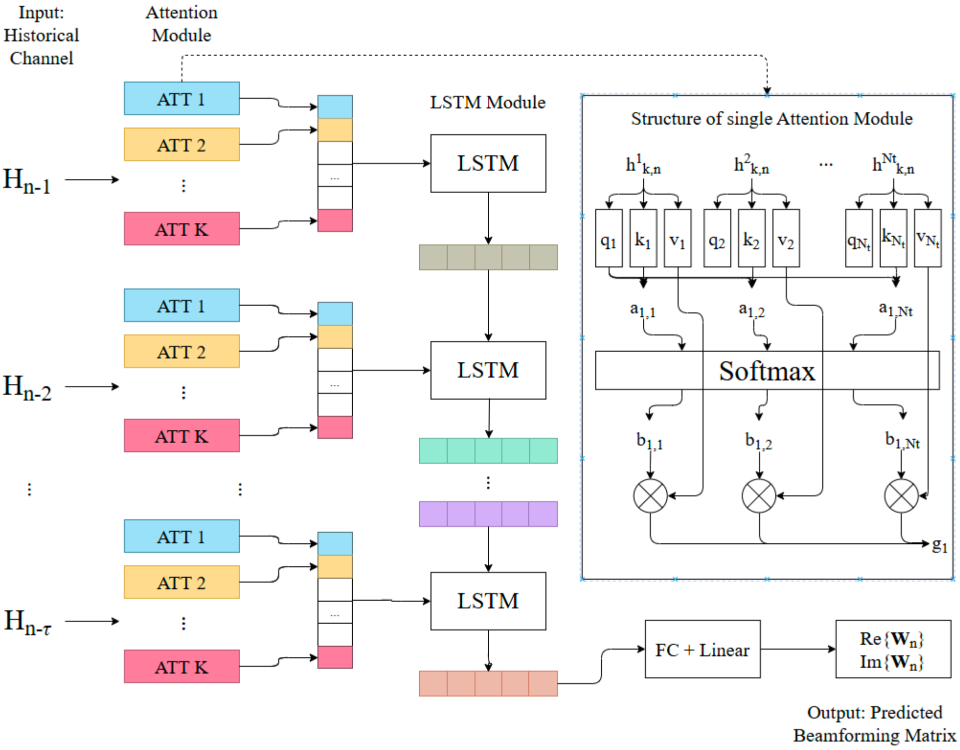

Fig. 1: The proposed ML model[1]

Table. 1: Hyperparameters of the ML model

Input: Historical channel data with size $\tau \times K \times N_t \times 2$		
Layers	Parameters	Values
q_i, k_i	Size	2×1
v_i	Size	Scalar
Attention Module	Output size	32×1
Concatenate layer	Output size	96×1
LSTM module	Output size	64×1
Output: The optimal beamforming matrix $[\mathrm{Re}\{\boldsymbol{W}_n\}, \mathrm{Im}\{\boldsymbol{W}_n\}] \in \mathbb{R}^{N_t \times 2K}$		

3. Numerical Results

In the simulations, we set K = 3, N_t = N_r = 32. Moreover, we employ a 2D system to describe this ISAC based V2I networks. Each of the vehicles is randomly positioned with the mean initial location. We implemented three benchmarks to evaluate the performance of the model. Our proposed model is labeled as "AttLSTM." The following contexts are the details of the other methods:

- Benchmark 1 (Upper bound): A genie-aided value which does not consider multi-user interference and constraint. Perfect CSI is used in this benchmark so that the optimal beamforming matrix can be obtained. This value is viewed as the upper bound of the performance of this problem.
- Benchmark 2 (Random Beamforming): The elements of the beamforming matrix

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[1] To make the diagram simple, we only demonstrate g_1 for the attention module. The evaluation of all output elements is described above.

are randomly set. This method only considers the power constraint.

- Benchmark 3 (HCL-Net): The ML model proposed in [3], which uses a CNN (one convolutional layer, one pooling layer and one flatten layer) and an LSTM block to solve the problem. This method considers both power and sensing constraints.

For our model, the number of training data and test data are set as 8,000 and 2,000, respectively. The number of epochs is 15 and the batch size is 16. Besides, each point in the results is obtained through averaging over 2,000 Monte Carlo realizations.

3-1. Communication Performance

The achievable sum rate of these methods and the ML model is shown in Fig. 2.

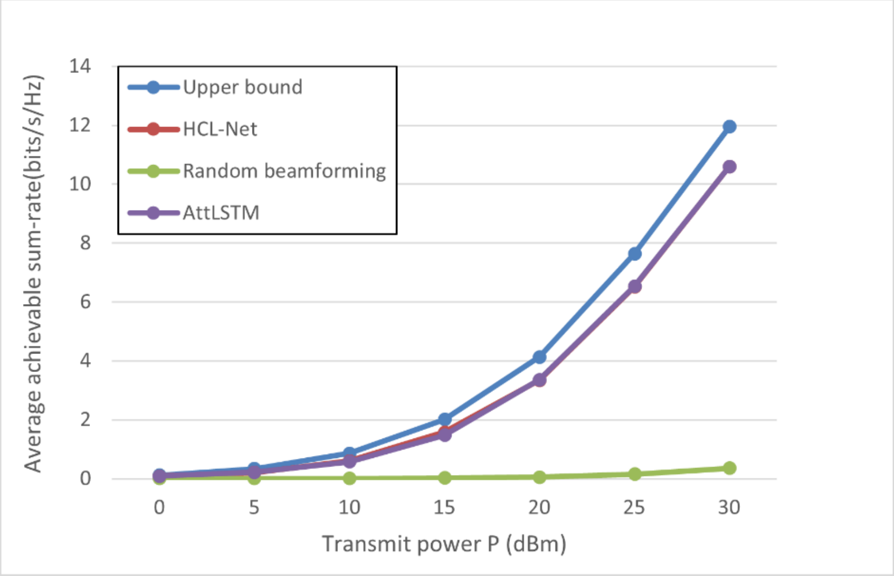

Fig. 2: The average achievable sum-rate under different power constraints

The results show that the average achievable sum rate increases with transmit power, as higher power enhances signal strength and SINR, improving communication performance. The AttLSTM model outperforms random beamforming, which neglects vehicle positions and movement, and achieves performance similar to HCL-Net, indicating that the attention mechanism effectively captures spatial channel features. Furthermore, the attention module requires fewer parameters, reducing offline training complexity compared to CNN-based models. Notably, AttLSTM achieves 80% of the upper bound performance, demonstrating its ability to accurately predict the beamforming matrix by extracting spatial and temporal features from historical channel data with lower complexity.

3-2. Sensing performance

In this part, we investigate the sensing performance of our proposed model and other ML models. The CRLB of the estimated angle of different models under different power budgets are shown in Fig. 3:

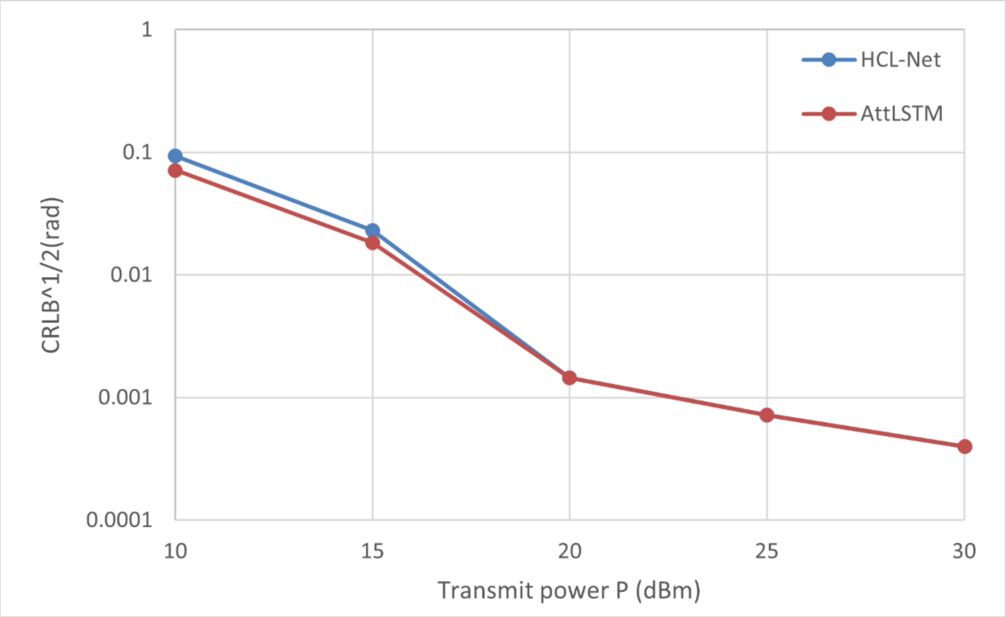

Fig. 3: The square root of CRLB of angle under different power constraints

The square root of the CRLB for angle estimation, representing the standard deviation of the error (which must be below 0.1 rad), is satisfied in all cases. Sensing performance improves with higher transmit power due to better SINR, enhancing accuracy. The AttLSTM model slightly outperforms HCL-Net in sensing, demonstrating the attention mechanism's ability to effectively capture spatial features of the channel.

4. Conclusion

In this research, we formulated the communication problem as an optimization task and applied a machine learning-based solution. An attention-LSTM architecture was used to capture both spatial and temporal channel features. Simulation results show that the communication performance of our proposed model is comparable to the genie-aided benchmark. Additionally, our model demonstrates strong sensing capabilities, maintaining robust performance even with low power budgets. These findings highlight that our model effectively balances communication and sensing objectives, performing competitively with other machine learning-based models.

5. Review and Reflections

在這次研究中，我們除了認識在現代通訊領域裡面的研究主題以及知識之外，也了解了在學術領域中做研究的過程。前期，我們在每周的會議中逐漸掌握閱讀論文以及摘要的方法，也在論文中吸收到了有關於通訊領域的知識以及研究趨勢。而在後期的實作過程中，我們寫了不同的學習模型和算法，充分瞭解到了通訊系統的最佳化以及機器學習的運作機制。在這幾個月的研究過程中，我們除了各司其職，也在每次的會議中互相討論與協助彼此的工作進度，透過分工合作的方式，讓研究變得更有效率。許多收穫之餘，也體會到自己在各方面仍有許多不足，像是目前所掌握的專業知識，仍舊還有許多進步的空間。對於會繼續研讀相關領域的我們而言，透過這次的專題，除了幫助我們審視自己的能力和成長，也更確立彼此努力的目標和方向。最後也謝謝教授與助教們的細心指導，才能讓我們順利的做出研究。

6. Reference

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