利用機器學習預測ISAC車聯網系統之波束成形

Machine Learning-Based Predictive Beamforming for ISAC V2I Systems

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Introduction

Integrated Sensing and Communication (ISAC) systems has attracted research attention in recent years due to the shared frequency bands of radar sensing and 5G communication. It is expected to provide both robust sensing and wireless connectivity. This research mainly focus on vehicular networks using ISAC signals. This research proposed a system model for vehicle-to-infrastructure (V2I) networks and formulated the communication and sensing problem as an optimization problem. We use a machine learning-based method to predict the optimal beamforming matrix for maximizing the total communication rate under sensing and power constraints.

System Model

Consider a downlink ISAC V2I network, where a roadside unit (RSU) serves K single-antenna vehicles. The RSU is 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. The RSU can receive the signal echoes for sensing while maintaining uninterrupted downlink communications.

Problem Formulation

The objective is to find an optimal beamforming matrix to maximize the total communication rate subject to sensing quality of service (QoS) threshold and power budget. We use the Cramer-Rao lower bound (CRLB) of the azimuth angle of the vehicle as the sensing performance metric.

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

$$s.t.\ \frac{1}{K}\sum_{k=1}^{K} CRLB(\theta_{k,n}, \boldsymbol{w}_{k,n}) \le \gamma_\theta$$

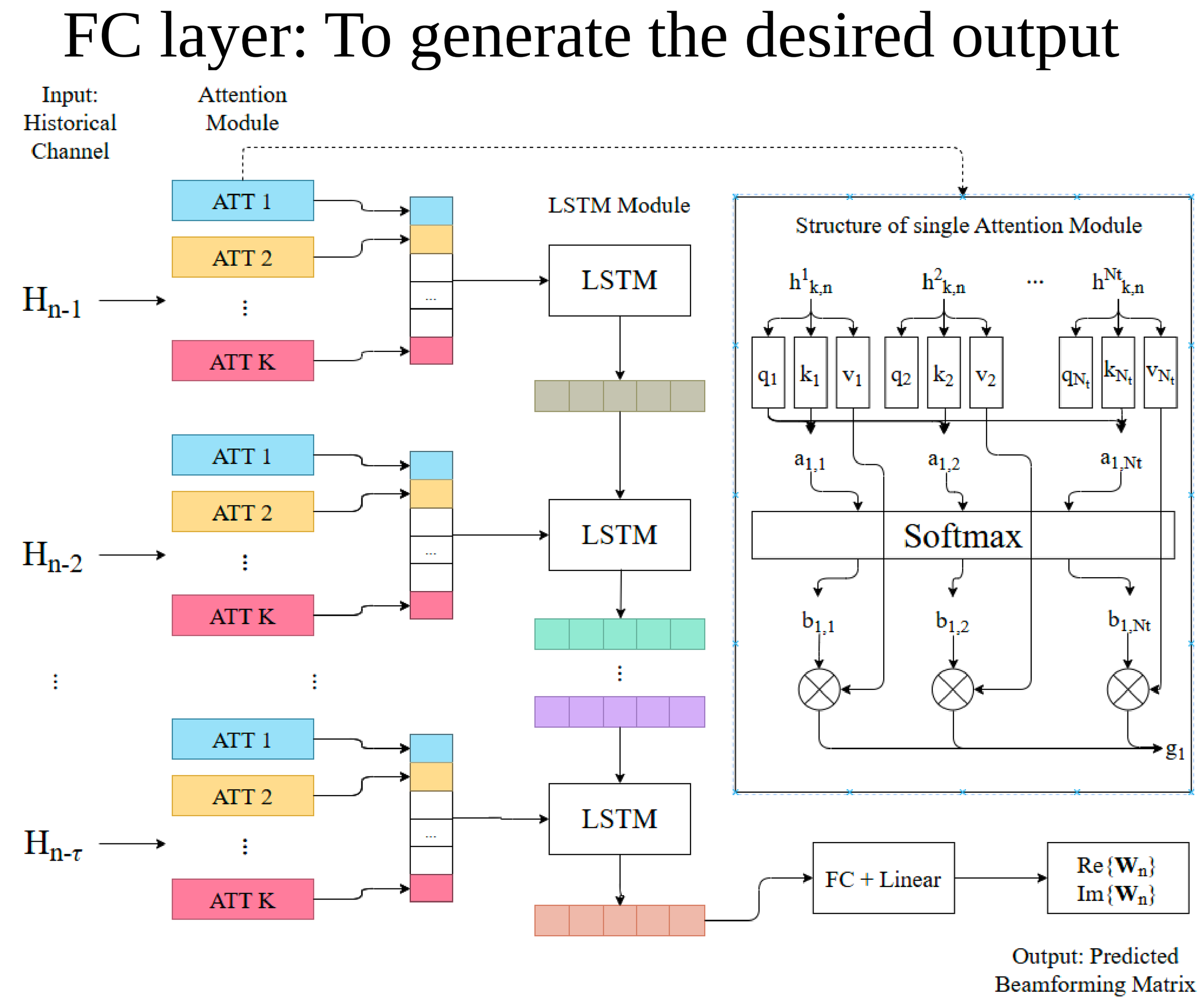
$$\|\boldsymbol{W}_n\|_F^2 \le P.$$

Machine Learning model for predictive beamforming

Input: Channel matrices of previous τ time slots

Output: Predicted beamforming matrix

1. Input layer: Separate the channel data into real and imaginary parts
2. Attention module: Extract spatial features of the channel
3. Concatenate layer: Connect features produced by the attention module
4. LSTM module: Extract temporal features of the channel of past τ time slots
5. FC layer: To generate the desired output



Results

Figure 1: Power vs. Sum rate

The upper bound is the result of the optimization problem without considering CRLB threshold, obtained by SciPy. The ML result is close to the upper bound and shares the same slope with it.

Figure 2: Power vs. CRLB of angle

We set $\gamma_\theta = 0.01$, the square root of CRLB means the standard deviation of the error. The ML result is significantly below the threshold (0.1), which is a successful result.

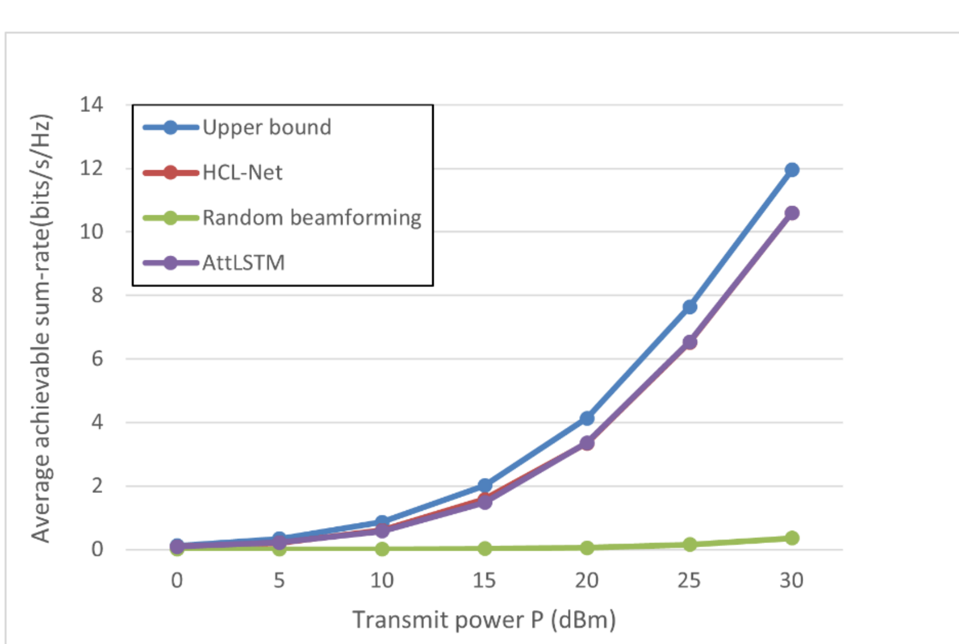


Figure 1

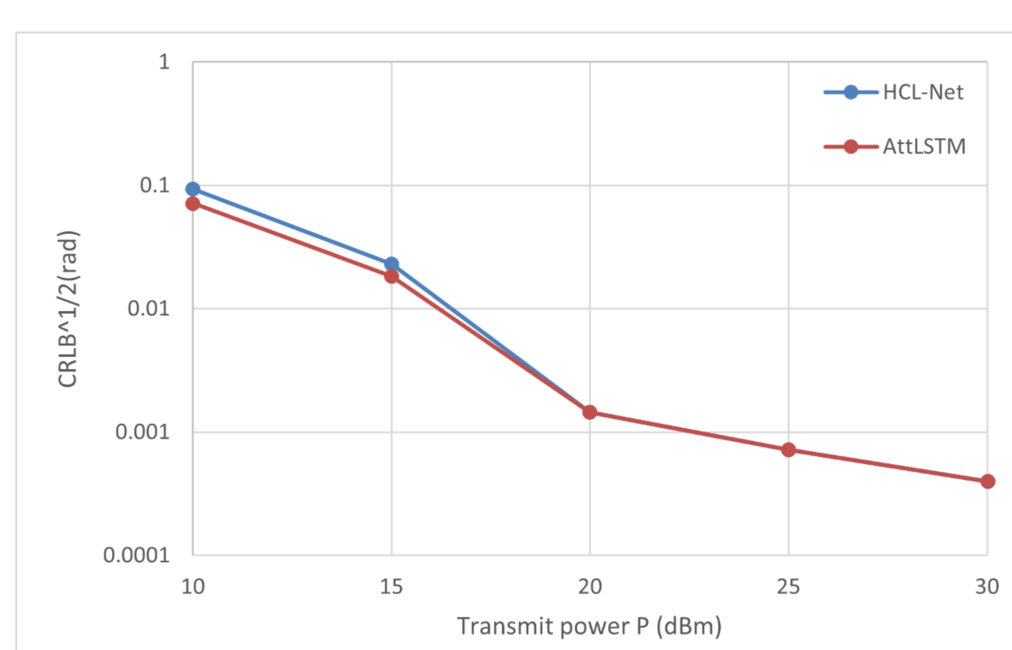


Figure 2

Conclusion

In this research, we used a machine learning-based method to solve the problem for ISAC V2I systems. An attention-LSTM structure is employed to extract the spatial and temporal features of the channel simultaneously. In simulation results, the communication performance of the learning model is near to the performance of the genie-aided value. Moreover, our model exhibits strong sensing capabilities, achieving robust performance even under low power budgets and performs competitively against other machine learning-based models.