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Special Topic: Integrated Sensing and Communications Techniques for 6G

Machine learning empowered UAV-based beamforming design in ISAC systems

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Integrated sensing and communication (ISAC) has been proposed as an enabling technology for the realization of the next-generation wireless system, which focuses on performing wireless communication and sensing simultaneously. Among the various potential ISAC-based applications, unmanned aerial vehicle (UAV)-based ISAC plays a significant part in unlocking the potential of future next-generation wireless communication, facilitating low-latency data transmission in high-mobility environments. Inspired by recent advancements, a variety of effective techniques have been investigated to optimize beamforming design in ISAC systems. For instance, the authors in [1] introduced an extended Kalman filtering (EKF)-based method tailored for millimeter wave (mmWave) ISAC systems. Additionally, Ref. [2] proposed an extended interacting multiple model (IMM)-EKF framework designed for vehicular networks with intricate roadway geometries. Despite these advancements, the aforementioned methods typically employ a separate scheme for channel prediction and beam alignment, which introduces additional signaling overhead in real-world scenarios. Therefore, there is a demand for an end-to-end beamforming design approach specifically for UAV-based ISAC systems.

Our contribution. In this article, we propose a machine learning (ML)-based approach for designing a predictive beamforming scheme tailored for UAV-based ISAC systems. Unlike traditional methods that require separate processes for channel modeling and resource allocation, the proposed deep learning-based approach provides an end-to-end solution for beamforming design by leveraging its data-driven capabilities. Specifically, we propose an encoder-decoder network (EDnet) architecture, where the encoder captures spatial and temporal features while the decoder generates the desired beamforming matrix. Finally, simulation results demonstrate that the proposed method enhances sensing performance while achieving satisfactory communication quality.

System model. We consider a dual-function radar communication (DFRC) system equipped with an N_t-antenna uniform linear array (ULA). One UAV hovers in its designated zones to serve K stationary single-antenna users and one moving single-antenna vehicle simultaneously. For ease of exposition, we assume that the UAV remains stationary throughout all time slots within a single ISAC frame. In mmWave systems, the communication channel is usually represented by a line-of-sight (LOS) channel model [3]. The exploration of non-line-of-sight (NLoS) channels is earmarked for our future work. The coordinates of the UAV is set as $\boldsymbol{v}'_n = [x'_n, y'_n]^{\mathrm{T}}$ within one ISAC frame, where x'_n and y'_n are the coordinates on x-axis and y-axis, respectively. Let $\boldsymbol{u}_n^k = [x_n^k, y_n^k]^{\mathrm{T}}$ and $\boldsymbol{v}_n = [x_n, y_n]^{\mathrm{T}}$ denote the locations of kth user and the moving sensing vehicle target at the time slot n, respectively. Consequently, the angle of the UAV relative to the kth user and the target at time n can be expressed as $\theta_{k,n} = \arccos \frac{x'_n - x_n^k}{\|\boldsymbol{v}'_{\boldsymbol{u}} - \boldsymbol{u}_n^k\|^2}$ and $\theta_{0,n} = \arccos \frac{x'_n - x_n}{\|\boldsymbol{v}'_{\boldsymbol{u}} - \boldsymbol{v}_n\|^2}$.

The transmitted signal vector is denoted by $\boldsymbol{s}_n(t) = [s_{0,n}(t), s_{1,n}(t), s_{2,n}(t), \ldots, s_{K,n}(t)]^{\mathrm{T}} \in \mathbb{C}^{(K+1)\times 1}$ where $s_{0,n}(t)$ represents the sensing signal and $s_{k,n}(t)$ is the communication signal for kth, $k \in [1, K]$, user at time instant t within the nth, respectively. The transmitted signal at the UAV is given by $\tilde{\boldsymbol{s}}_n(t) = \boldsymbol{W}_n \boldsymbol{s}_n(t) \in \mathbb{C}^{N_t \times 1}$. Here, $\boldsymbol{W}_n \in \mathbb{C}^{N_t \times (K+1)}$ is the beamforming matrix. The received signal for the kth user is given by $y_{k,n}(t) = G g_{k,n} \mathrm{e}^{\mathrm{j}2\pi\nu_{k,n} t} \boldsymbol{a}^{\mathrm{H}}(\theta_{k,n}) (\sum_{i=0}^{K} \boldsymbol{w}_{i,n} s_{i,n}(t)) + v_{k,n}(t)$, where G is the antenna gain, $g_{k,n}$ is the path loss coefficient, ν_k denotes Doppler shifts. In addition, $v_{k,n}(t) \sim \mathcal{CN}(0, \sigma_u^2)$ represents additive noise at the kth user with σ_u^2 being the noise variance.

The received signal-to-interference-plus-noise ratio

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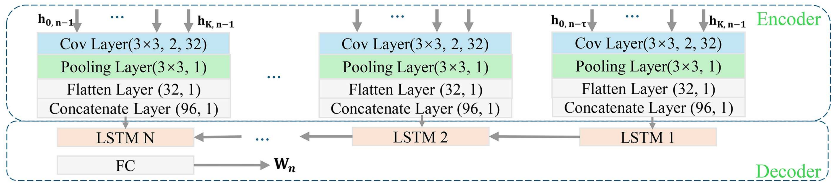

Figure 1 (Color online) Proposed ML-based approach.

(SINR) for the kth user within time slot n can be expressed as $\mathrm{SINR}_{k,n} = \frac{|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_{k,n}|^2}{\sum_{k'\neq k}^{K}|\boldsymbol{h}_{k,n}^{\mathrm{H}}\boldsymbol{w}_{k',n}|^2+|\boldsymbol{h}_{0,n}^{\mathrm{H}}\boldsymbol{w}_{0,n}|^2+\sigma_u^2}$, where $\boldsymbol{h}_{k,n}^{\mathrm{H}} = Gg_{k,n}\boldsymbol{a}^{\mathrm{H}}(\theta_{k,n})$ represents the the equivalent channel vector between the kth user and the UAV at the time slot n. Here, $\boldsymbol{a}(\theta_{k,n})$ denotes the steering vector.

For simplicity, we assume the inter-beam interference from communication users in the uplink echoes is negligible, and the UAV can distinguish the sensing target based on AoAs [4]. Based on the spatial filter process, the round-trip time delay $\check{\mu}_{0,n}$ and Doppler shifts $\check{\nu}_{0,n}$ can be estimated via the conventional match-filtering method, and the received echo at the UAV is given by

$$\begin{aligned}\tilde{r}_{0,n} &\triangleq \int_0^{\Delta T_e} r_{0,n}(t)s_{0,n}^{*}(t-\check{\mu}_{0,n})\mathrm{e}^{-\mathrm{j}2\pi\check{\nu}_{0,n}t}\mathrm{d}t \\ &= \check{G}\check{g}_{0,n}G_m\boldsymbol{a}^{\mathrm{H}}(\theta_{0,n})\boldsymbol{w}_{0,n} + \tilde{v}_{0,n}(t), \qquad (1)\end{aligned}$$

where ΔT_e is the length of the received echo, and G_m is matched-filtering gain. The term $\tilde{v}_{0,n}(t) \sim \mathcal{CN}(0,\sigma_v^2)$ is the noise term with σ_v^2 being the noise variance. The ground truth distance $d_{0,n}$ and estimated $\tilde{\nu}_{0,n}$ obey the observation model as $\tilde{\nu}_{0,n} = \frac{2d_{0,n}}{\mathrm{c}} + \epsilon_{\mathrm{ro},n}$, where c denotes the speed of light. $\epsilon_{\mathrm{ro},n} \sim \mathcal{CN}(0,\sigma_{\mathrm{ro}}^2)$ with σ_{ro}^2 being the estimation errors of $\tilde{\nu}_{0,n}$. Generally, the variance σ_{ro}^2 is depend on the SNR and is give by

$$\sigma_{\mathrm{ro}}^2 = \frac{\rho_{\mathrm{ro}}^2\sum_{i=1}^{K}\check{G}^2|\check{g}_{i,n}|^2|\boldsymbol{a}^{\mathrm{H}}(\theta_{i,n})\boldsymbol{w}_{i,n}+\sigma_v^2}{\check{G}^2|\check{g}_{0,n}|^2|\boldsymbol{a}^{\mathrm{H}}(\theta_{0,n})\boldsymbol{w}_{0,n}|^2}, \qquad (2)$$

where ρ_{ro} is a constant depending on the detailed system deployment and estimation algorithms. Here, the terms of interference from communication users are considered as noise, i.e., $\mathbb{E}\{|s_{k,n}(t)|^2\} = 1$ and $\mathbb{E}\{|\check{v}_{k,n}(t)|^2\} = \sigma_v^2$.

ML-based predictive beamforming method. The objective is to optimize sensing performance while maintaining satisfactory communication quality between the UAV and the ground users. We employ the Cramer-Rao lower bound (CRLB) of the distance as the sensing performance metric and utilize an achievable rate to evaluate communication quality. According to observation model, we can derive the CRLB of $d_{0,n}$ as $\mathrm{CRLB}(d_{k,n},\boldsymbol{w}_{k,n}) = [\frac{1}{\sigma_{\mathrm{ro}}^2}(\frac{2}{\mathrm{c}})^2]^{-1}$. The communication achievable rate $R_{k,n}$ for the kth user with in n time slot can be formulated as $R_{k,n} = \log_2(1+\mathrm{SINR}_{k,n})$. Based on the above, the sensing optimization problem can be written as

$$\begin{aligned}\min_{\boldsymbol{W}_n}\quad & \mathbb{E}\left[\mathrm{CRLB}(d_{0,n},\boldsymbol{W}_n)\right] \\ & + \rho_1\left\{\max\left(0, R_t - \mathbb{E}\left[\sum_k R_k(\boldsymbol{h}_{k,n},\boldsymbol{W}_{k,n})\right]\right)\right\} \\ & + \rho_2\left\{\max\left(0, \|\boldsymbol{W}_n\|_F^2 - P_t\right)\right\}, \qquad (3)\end{aligned}$$

where $\mathbb{E}[\cdot]$ denotes the ergodic average over random channel realizations. The notations R_t and P_t represent the tolerable communication rate threshold and power threshold to guarantee the system performance. The terms $\rho_1 \gg 0$ and $\rho_2 \gg 0$ denote the penalty parameters. By doing so, the original optimization problem can be solved by a data-driven approach.

To better leverage the relationship between estimated historical channels and the optimal beamforming matrix, we utilize an EDnet to extract both spatial and temporal features of the channels, thereby improving beamforming design performance. As illustrated in Figure 1, the proposed ED network comprises $K+1$ convolutional neural modules corresponding to all users and the target, one LSTM module with a time step of τ, and one fully connected (FC) layer. Here, "conv" is an abbreviation for convolutional, and a rectified linear unit (ReLU) is applied after each convolution operation. Additionally, a max-pooling operation is performed in the pooling layer, and a linear activation function is added following the FC layer. The DL-based algorithm is given in Appendix A.

Simulation results. We present simulation results that validate our proposed ML-based approach to beamforming design within an ISAC system. The complete simulation results and detailed experiment analysis are given in Appendix B.

Conclusion and future work. In this study, we proposed an ML-based method for end-to-end beamforming design in a UAV-based ISAC system. Initially, we derive the CRLBs to serve as a metric for assessing sensing performance, while the achievable communication rate is employed to evaluate communication efficiency. Subsequently, an optimization problem is formulated to minimize the sensing metric with constraints on the communication and transmitted power. To solve this optimization challenge, we introduce an efficient EDnet that effectively extracts features from historical channel information to generate the optimized beamforming matrix. Finally, numerical results validate the effectiveness of the proposed EDnet.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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