Cisco - La Trobe Centre for
Artificial Intelligence and Internet of Things

Satellite-Based Integrated Sensing and Communications: Learning to Design Waveform and Receive Filter

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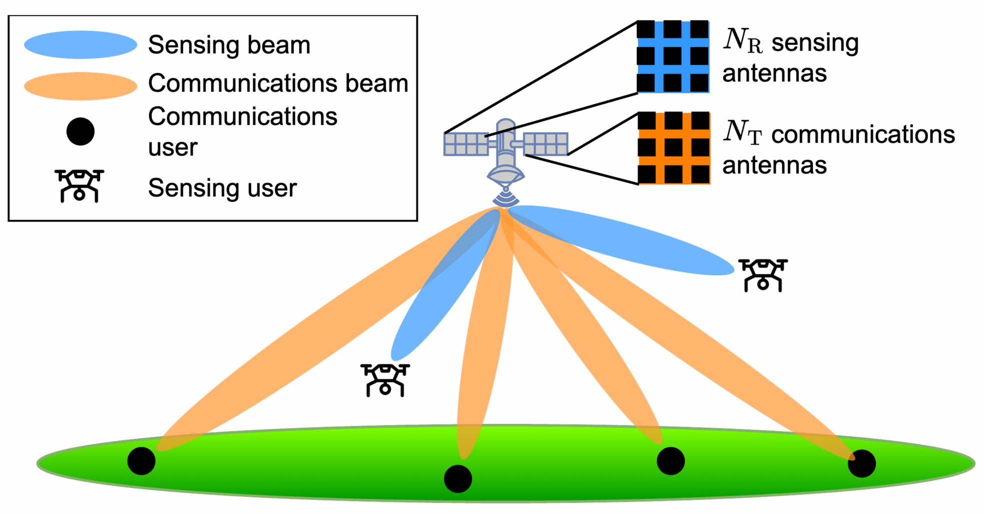
Introduction

In this study, we propose a general framework for a learning-based approach to design waveform and receive filter for integrated sensing and communications (ISAC) over non-terrestrial networks, such as satellites. This approach forms a critical part of our overarching predictive design scheme, which is essential for satellite-based ISAC due to the inherent challenges of propagation delay and significant path loss.

Given the extreme difficulty of the optimisation problem, we propose a data-driven solution, leveraging its ability to adapt and learn from complex, dynamic environments, thus offering more accurate and flexible outcomes than traditional optimisation methods.



An illustration of our system model

Our considered system model consists of K single antenna-equipped ground IoT devices, Q sensing targets, and a satellite with N_T and N_R transmit and sensing receive antennas, respectively.

Practical Challenges

In the joint communications and sensing (JCS) paradigm, **a single waveform must accommodate and be optimised for both tasks**, as the ultimate goal of ISAC is to utilise a common resource block and a single device. However, designing a waveform that satisfies both communications and sensing performance is challenging and requires careful consideration.

Additionally, due to the large distances involved, **the sensing echoes from targets are typically very weak**. Therefore, it is essential to equip the satellite with a receive filter that maximises the sensing mutual information.

Problem Formulation

We formulated our problem as a multi-objective optimisation problem (MOOP) as follows

$$\begin{aligned}&\underset{\mathbf{X}_n,\mathbf{W}_n}{\text{maximise}}\ \mathbb{E}_{\mathbf{H}_n,\mathbf{S}_n,\mathbf{G}_n}\left[U\{U_{\mathrm{C}}(\mathbf{X}_n,\mathbf{H}_n,\mathbf{S}_n),U_{\mathrm{S}}(\mathbf{X}_n,\mathbf{W}_n,\mathbf{G}_n)\}\right],\\&\text{subject to}\quad \|\mathbf{X}_n\|_F^2\le P_{\max},\quad \|\mathbf{W}_n\|_F^2\le 1\end{aligned}$$

Our objective is to maximise the expectation of the network utility function with respect to (w.r.t.) the channel state information (CSI), desired symbols, and target response matrix (TRM). Furthermore, the constraints ensure that the waveform and receive filter adhere to the power budget constraints.

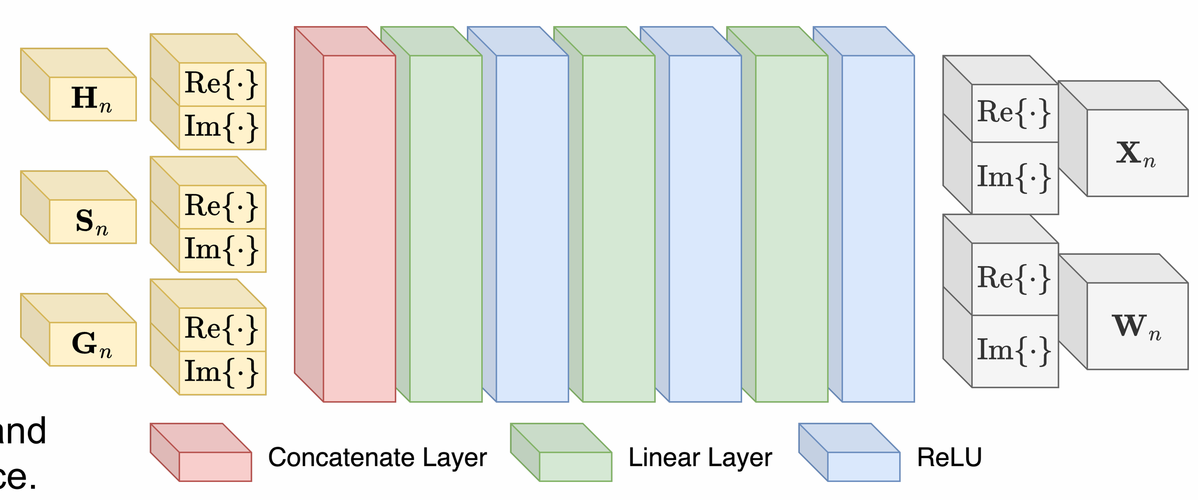
Methods

Our deep neural network (DNN) architecture to design waveform and receive filter is depicted as follows

Pre-processing:
- Complex to scalar

DNN:
- $1\times$ (Concatenate)
- $3\times$ (FC + ReLU)

Post-processing:
- Scalar to complex and normalise to power trace.

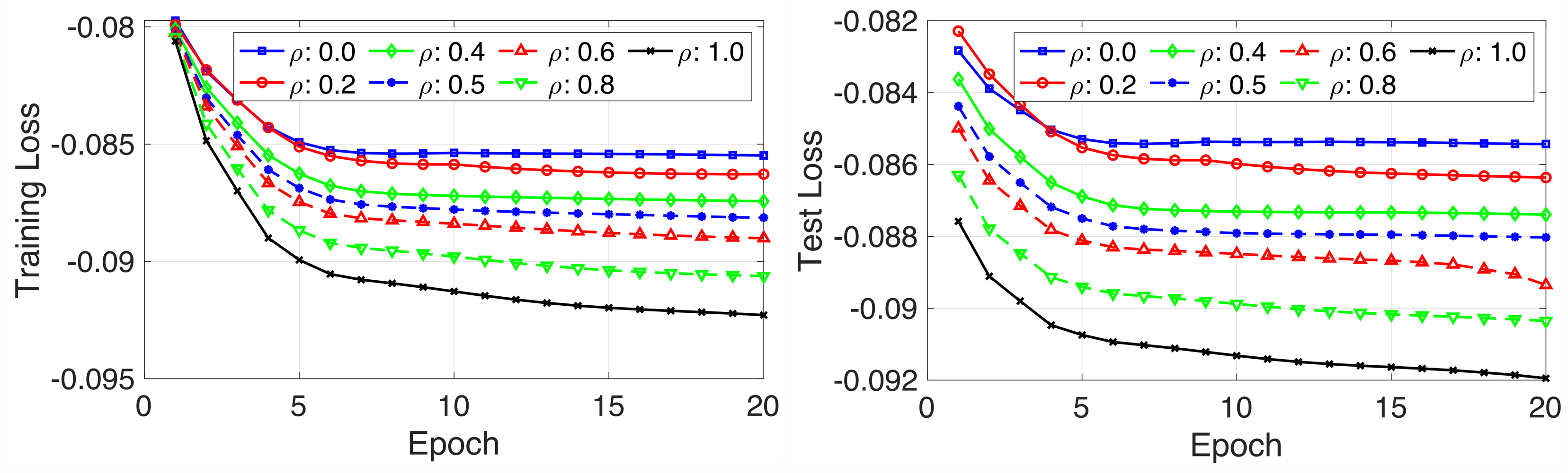


Loss function: $$-\frac{1}{N_s}\sum_{i=1}^{N_s}U(\mathbf{X}_n^{(i)},\mathbf{W}_n^{(i)})+\psi_1\left[\max\left(0,\left\|\mathbf{X}_n^{(i)}\right\|_F^2-P_{\max}\right)\right]^2+\psi_2\left[\max\left(0,\left\|\mathbf{W}_n^{(i)}\right\|_F^2-1\right)\right]^2$$

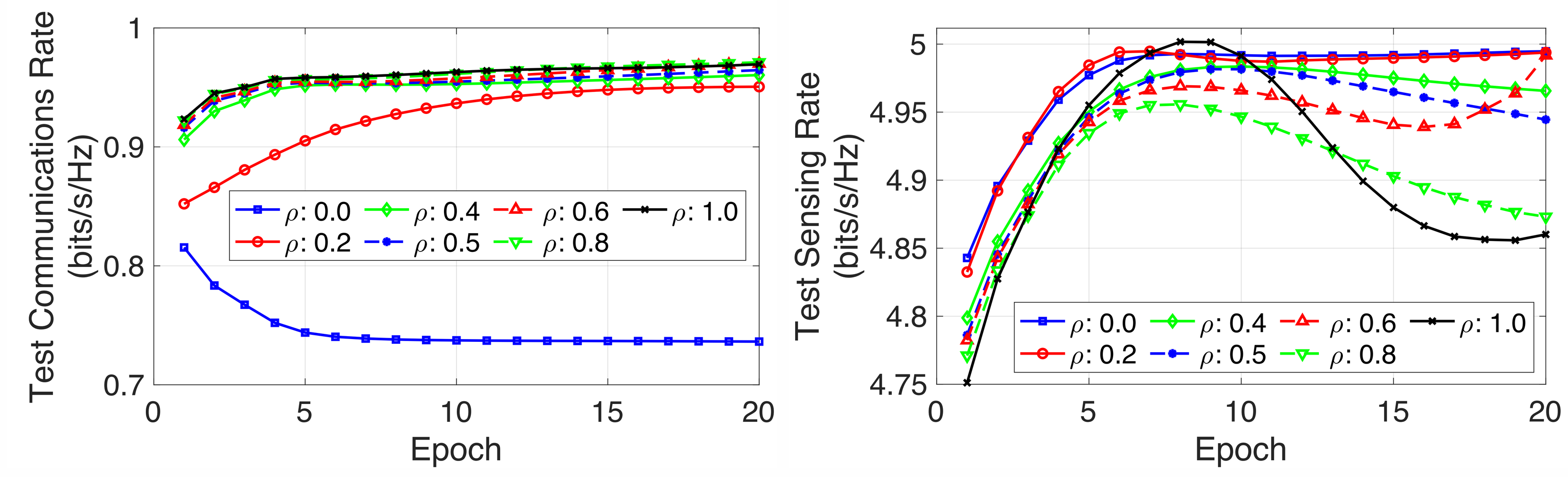
Results

To demonstrate our proposed DNN-based framework, we use normalised rates for the communications and sensing utility functions, and a linear combination with variable ρ to represent their trade-off.

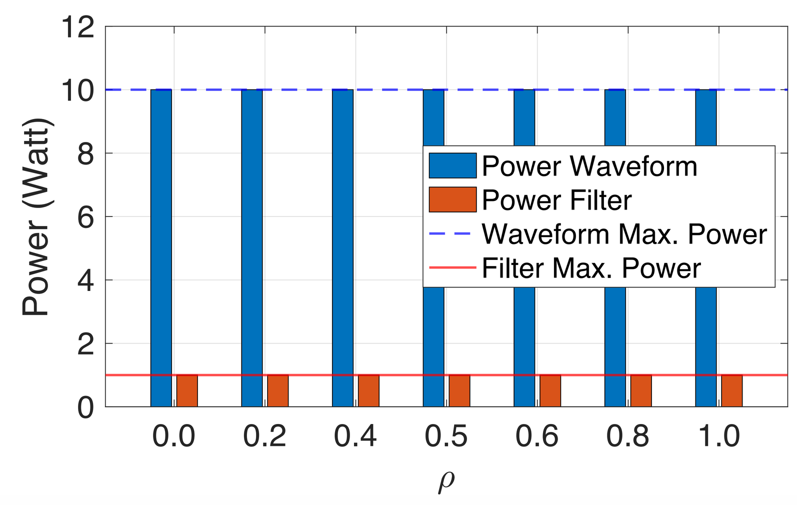
For the main system parameters, we deliberately choose $K=3$ users, $Q=3$ targets, $N_T=16$ transmit antennas, $N_R=16$ sensing receive antennas, and the signal length $L=10$ symbols. The results of the simulation are given as follows.



Training and testing losses for various values of ρ demonstrate convergence to specific minimum points, indicating the effectiveness of our data-driven training phase. We used **8000 samples for training** and **2000 samples for testing**.*

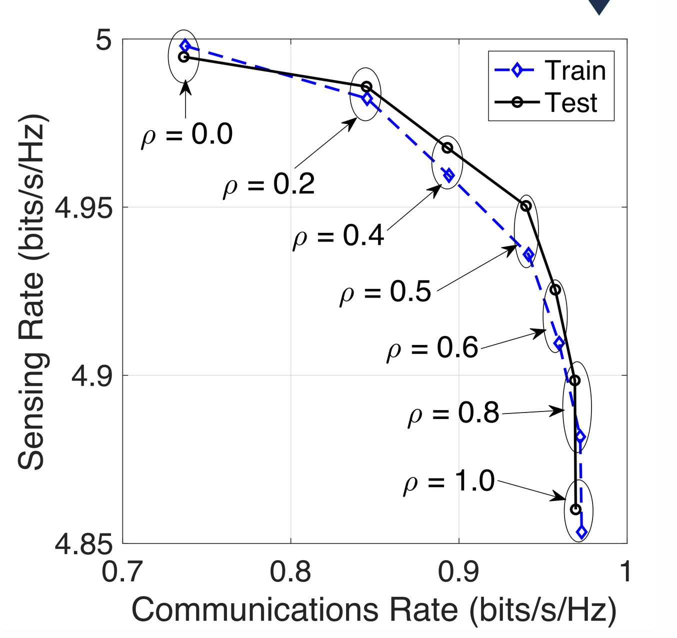


For different values of ρ, the testing values of communications and sensing rates vary. Although the sensing rates exhibit some unusual behaviour, generally, a higher ρ results in a higher communications rate and a lower sensing rate. The following figure illustrates the trade-off between communications and sensing.



Our learning-based solution meets the power budget constraints for waveform and filter due to the penalty method and output normalisation scheme.

Communications and sensing trade-off



** Experiments were conducted using PyTorch on an AMD EPYC 7313 CPU and an NVIDIA GeForce RTX3090 GPU.*

References

[1] W. D. Lukito, *et al.* "Learning to design transceiver for integrated sensing and communications: a non-terrestrial network perspective", *to be submitted to IEEE Trans. Wireless Commun, 2024*

[2] Q. Qi, X. Chen, C. Zhong, C. Yuen, and Z. Zhang, "Deep learning-based design of uplink integrated sensing and communications," *IEEE Trans. Wireless Commun. (Early Access)*, pp. 1–14, 2024, doi: 10.1109/TWC.2024.3373797.

[3] C. Liu, *et al.*, "Learning-based predictive beamforming for integrated sensing and communication in vehicular networks," *IEEE J. Sel. Areas in Commun.*, vol. 40, no. 8, pp. 2317–2334, Aug. 2022, doi: 10.1109/JSAC.2022.3180803.

[4] C. G. Tsinos, A. Arora, S. Chatzinotas, and B. Ottersten, "Joint Transmit Waveform and Receive Filter Design for Dual-Function Radar-Communication Systems," *IEEE J. Sel. Top. Signal Process.*, vol. 15, no. 6, pp. 1378–1392, Nov. 2021, doi: 10.1109/JSTSP.2021.3112295.

[5] T. Jiang, H. V. Cheng, and W. Yu, "Learning to Reflect and to Beamform for Intelligent Reflecting Surface With Implicit Channel Estimation," *IEEE J. Sel. Areas Commun.*, vol. 39, no. 7, pp. 1931–1945, Jul. 2021, doi: 10.1109/JSAC.2021.3078502.

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