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Loss Function Design for Enhanced Joint Beamforming in RIS-Aided ISAC Systems

Yifan Fang[1*†], Shen Ye[2†], Youzhou Liao[3†], Tianyu Li[4†]

[1]*School of Engineering, The University of Edinburgh, Edinburgh, United Kingdom*
[2]*Beijing University of Posts and Telecommunications, Beijing, China*
[3]*Beijing Jiaotong University, Beijing, China*
[4]*Soochow University, Soochow, China*
**Corresponding Author. Email: S2631624@ed.ac.uk*
[†]*These authors contributed equally to this work and should be considered co-first author.*

Abstract. Reconfigurable Intelligent Surface (RIS)-aided Integrated Sensing and Communication (ISAC) systems are important for next generation wireless networks (e.g., 6G), because it combines RIS's capability to intelligently map wireless propagation environments and ISAC'S capability to realize radar sensing and data transmission at the same frequency band for higher spectrum use and lower hardware cost. The joint beamforming design for these systems is challenging: traditional optimization-based approaches are very time-consuming and cannot be used in real-time applications, while current learning-based methods typically involve large amounts of labeled data, which are expensive and hard to obtain in practice. We present a better unsupervised learning framework, whose primary focus is on designing a new loss function with 3 tunable coefficients {{γ}}, α, β. In particular, coefficient {{γ}} scales the overall loss gain to keep the optimization running, β focuses on the sensing gain term to guide the model to prioritize the echo power for sensing performance, and β weights the communication gain term in order to explicitly guarantee user-side link quality. In this way, the proposed design can adaptively balance the sensing signal-to-noise ratio (SNRs) and communication SNRc during training, rather than sacrificing one for the other. Through extensive simulations, we show that compared with the original unsupervised learning scheme, the modified loss function not only achieves a better trade-off between sensing and communication, but also significantly improves SNRs and ensures SNRc meets practical thresholds, while maintaining low computational overhead.

Keywords: ISAC system, RIS, Beamforming

1. Introduction

Sensor and communication integration is an essential goal of next generation wireless networks (e.g., 6G), to improve spectrum use, cost, and new applications [1]. The combined approach, called Integrated Sensing and Communication (ISAC), allows a single system to perform radar-like sensing and data transmission over the same frequency band, while Reconfigurable Intelligent

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Surfaces (RIS) are an emerging technology which is capable of effectively reshaping the wireless propagation environment by controlling the phase changes software-controlled, leading to increased channel quality and coverage [2,3].

The combination of RIS and ISAC can simultaneously improve sensing accuracy and communication reliability, but joint design of beamforming at BS (base station) and RIS is non-convex optimization problem. Iterative methods are costly and impractical for real-time applications [4,5] and learning-based methods often require lots of labeled data, which is hard to obtain [6]. To overcome this issue, [6] proposed a light neural network, IBF-Net, and an unsupervised learning framework that removes the need for labeled data.

Based on these works, we also proposed an innovation in this framework. Tunable correction coefficients---"γ", α and β---enrich the effective participation of the communication channel in the optimization process and dynamic balance between sensing SNR (SNR) and communication SNR(SNRc). With the proposed loss function, "γ" scales the overall loss term, which guides the model to focus on echo power, and "β" weighs the communication gain, which explicitly constrains the quality of the user-side link. Through simulations, we prove that the proposed loss is more powerful to balance sensing and communication performance.

The rest of this paper is organized as follows: Section II describes the system model and problem formulation. Section III contains the modified loss function and experiments. Section IV presents simulation results. We conclude with the conclusion of the paper and a future work.

2. RIS based communication system

2.1. System model

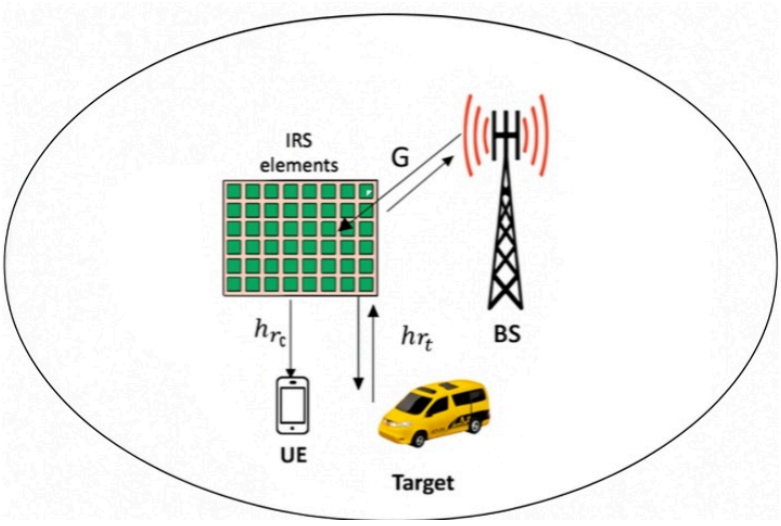

Figure 1. The overall design

As Figure 1 presented, on the right is the BS, with the RIS panels arranged on the left side. At the bottom, the car represents the target, and the smartphone represents the user equipment. The base station is equipped with M antennas, the RIS consists of N reflecting elements, each capable of independently adjusting its phase.

$$\Theta = \text{diag}\left(e^{j\theta_1}, e^{j\theta_2}, \ldots, e^{j\theta_N}\right) \tag{1}$$

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In the formula, you can see Θ, which is a diagonal matrix used to control the phase shift of each element. Specifically, the BS transmits signal ws, where s is the unit-power baseband signal, and w $\in C^{M\times1}$ represents the transmit beamforming vector. The signal travels through the channel G $\in C^{N\times M}$ from the BS to the RIS surface. After phase adjustments at the RIS, the signal is directed toward the user via the channel $h_{rc}^{H} \in C^{1\times N}$, while simultaneously illuminating the target through the channel $h_{rt}^{H} \in C^{1\times N}$. With the target illuminated, the reflected echo is captured by the RIS and then received back at the BS.

The signal received by user is given as

$$y_c=h_{rc}^{H}\Theta^{H}Gws+n_c \tag{2}$$

The target echo received by the BS is given as

$$y_r=G^{H}\Theta h_{rt}h_{rt}^{H}\Theta^{H}Gws+n_r \tag{3}$$

And two SNR in both channels are given as follow:

$$\gamma_c = \frac{\left|\boldsymbol{h}_c^H\boldsymbol{w}\right|^2}{\sigma_c^2} \tag{4}$$

$$\gamma_r = \frac{||\boldsymbol{H}_t\boldsymbol{w}||^2}{\sigma_t^2} \tag{5}$$

Where $\boldsymbol{H}_t = \boldsymbol{h}_t\boldsymbol{h}_t^H$ and $\boldsymbol{h}_t^H = \boldsymbol{h}_{rt}^H\boldsymbol{\Theta}^H\boldsymbol{G}$.

2.2. Learning objective

Overall, our purpose is to improve γ_r, however, improving the γ_r still requires satisfying several boundary conditions.

$$\max_{w,\Theta} \ \gamma_r \tag{6a}$$

$$s.t.\gamma_c \geq \tau_c \tag{6b}$$

$$||\boldsymbol{w}||^2 \leq P_t \tag{6c}$$

$$|\boldsymbol{\Theta}_{n,n}| = 1, \forall n = 1, \ldots, N \tag{6d}$$

Let us first examine the physical meanings of the four constraints:

Condition (6a): Maximizing γ_t, which is our core objective.

Condition (6b): Ensuring the communication rate, where γ_c must not fall below the threshold τ_c (10 dB).

Condition (6c): Limiting the total transmit power so that it does not exceed P_t.

Condition (6d): Representing hardware constraints, where each RIS element's phase must have a unit modulus. Only the phase is adjusted without altering the amplitude, which is consistent with the characteristics of passive devices.

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When φ is fixed, the constrains turn into following 7a and 7b, the objective function remains the maximization of $\|H_t w\|^2$

$$\max_{\mathbf{w}} \ ||\mathbf{H_t}\ \mathbf{w}\ ||^2 \tag{7a}$$

$$s.t. |h_c^H w|^2 \geq \tau_c \sigma_c^2, ||w||^2 \leq P_t \tag{7b}$$

Therefore, through mathematical modeling, we apply an unsupervised learning algorithm to this system.

Our experiments employ the ISAC Beamforming Network (IBF-Net) proposed in [7]. The input channel matrices (□, h_{rc} , h_{rt})are split into real and imaginary parts and stacked into four feature maps, which carry both amplitude and phase information. These are normalized and passed through a lightweight convolutional backbone combining standard, depthwise, and pointwise convolutions. The feature dimension gradually increases (32→64→128), while the spatial resolution decreases, and the final outputs are mapped to the RIS phase vector $\theta = [\theta_1,\ldots,\theta_n]$.

It should be emphasized that in our work, we did not alter the network architecture itself but adopted the IBF-Net as presented in the original paper [1]. Instead, our contribution focuses on the loss function design, which directly shapes the trade-off between communication and sensing objectives. Based on ensuring that the communication-side SNR meets the requirement specified in the original paper, our objective is to further maximize the sensing-side SNR, thereby enhancing the overall performance of joint beamforming.

3. Loss function design

In the initial design, the loss function was treated as a combination of two rather practical considerations: the correlation between the two channels and the sensing channel gain. During experiments it became clear that maximizing the correlation term effectively let the sensing and communication paths share part of the spatial resources, which in turn pushed the beamforming stage to behave more efficiently.

$$l_1 = -\frac{1}{S} \sum_{s=1}^{S} \left(\left|\left| H_t^S h_c^S \right|\right|_2 + \alpha \left|\left| H_t^S \right|\right|_F \right) \tag{8}$$

However, the double fading effect inherent in the sensing channel cannot be ignored, therefore only optimizing for correlation often led to excessively strong communication performance while in the meantime degrading sensing capability.

In order to solve this problem, a sensing channel gain term was incorporated into the loss function to compensate for the radar channel's inherent setback. While to some extent this adjustment helped balance communication and sensing, its efficacy heavily depended on the choice of a balancing coefficient. The improved loss function enhances the original formulation by introducing an additional term for communication channel gain, thereby enabling more inclusive system optimization.

$$l_2 = -\frac{1}{S} \sum_{s=1}^{S} \left(\gamma \left|\left| H_t^S h_c^S \right|\right|_2 + \alpha \left|\left| H_t^S \right|\right|_F + \beta \left|\left| h_c^S \right|\right|_F \right) \tag{9}$$

Specifically, the correlation term encourages cooperation between sensing and communication, while the sensing gain term improves radar channel efficiency. Meanwhile, the newly added

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communication gain term ensures that user-end communication quality is maintained, helping the SNR requirements to be consistently met.

Unlike earlier approaches that relied on a single balancing coefficient to trade off sensing and communication, our method incorporates multiple performance parameters, letting the network gradually find a natural equilibrium during training. Simulation results show that this new loss function not only boosts sensing SNR but also keeps communication reliable, leading to overall performance noticeably better than the original scheme.

4. Algorithm explanation

By using mathematical model, we apply an unsupervised learning algorithm to this system.

Algorithm 1 Unsupervised Learning for RIS-ISAC Beamforming

Input: $\mathbf{G} \in \mathbb{C}^{N\times M}$, $\boldsymbol{h_{rc}} \in \mathbb{C}^{N\times 1}$, $\boldsymbol{h_{rt}} \in \mathbb{C}^{N\times 1}$, τ_c, P_t

Output: γ_c , γ_r

1: Generate normalized channel samples $\{\mathbf{G}, \boldsymbol{h_{rc}}, \boldsymbol{h_{rt}}\}$

2: for epoch = 1 to 30 do

3: for each mini-batch do

4: Predict RIS phases: $\hat{\theta}$ = IBF-Net($\mathbf{G}$, $\boldsymbol{h_{rc}}$, $\boldsymbol{h_{rt}}$)

5: Enforce unit-modulus: $\bar{\theta}_n = \cos\hat{\theta}_n + j\sin\hat{\theta}_n$

6: Construct Θ = diag($e^{j\bar{\theta}_1}$, ..., $e^{j\bar{\theta}_N}$)

7: Compute end-to-end channels:

8: $\boldsymbol{h_c^H} = \boldsymbol{h_{r,c}^H}\boldsymbol{\Theta^H}$ G

9: $\boldsymbol{H_t} = \boldsymbol{h_{rt}}\boldsymbol{h_{rt}^H}$ where $\boldsymbol{h_t^H} = \boldsymbol{h_{rt}^H}\boldsymbol{\Theta^H}$ G

10: Compute orthonormal basis:

11: $\mathbf{u}_1 \leftarrow \mathbf{h}c / \|\mathbf{h}c\|$

12: $\mathbf{u}_2 \leftarrow \frac{h_t-(u_1^H h_t)u_1}{||h_t-(u_1^H h_t)u_1||}$

13: if $P_t \,|\, \boldsymbol{h_c^H}\boldsymbol{h_t} \,|^2 \geq \tau_c\sigma_c^2 \,\|\mathbf{h}t\|^2$ then

14: $\mathbf{w} \leftarrow \sqrt{P_t}\frac{h_t}{||h_t||}$

15: else

16: Compute coefficients:

17: $x_1 \leftarrow \sqrt{\frac{\tau_c\sigma_c^2}{||h_c||^2}}\frac{u_1^H h_t}{|u_1^H h_t|}$

18: $x_2 \leftarrow \sqrt{P_t - \frac{\tau_c\sigma_c^2}{||h_c||^2}}\frac{u_2^H h_t}{|u_2^H h_t|}$

19: $\mathbf{w} \leftarrow x_1u_1 + x_2u_2$

20: end if

21: Verify constraints:

22: $\|\mathbf{w}\|^2 \leq P$

23: $\|\boldsymbol{h_c^H}\,\mathbf{w}\|^2 \geq \tau_c\sigma_c^2$

24: return $\mathbf{w}$

25: Evaluate unsupervised loss:

26: $l = -\frac{1}{S}\sum_{s=1}^{S}\left(\gamma\left|\left|H_t^{(s)}h_c^{(s)}\right|\right|_2 + \alpha\left|\left|H_t^{(s)}\right|\right|_F + \beta\left|\left|h_c^{(s)}\right|\right|_F\right)$

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27: Enhance channel correlation by adjusting Θ
28: end for
29: Compute validation metrics:
30: $\gamma_c = \frac{|h_c^H w|^2}{\sigma_c^2}$
31: $\gamma_r = \frac{||H_t w||^2}{\sigma_r^2}$
32: Check $\gamma_c \geq \sigma_c$ constraint satisfaction
33: end for
34: Return optimal γ_r

The inputs are three key channels: the channel from the base station to the RIS, denoted as G; the channel from the RIS to the user, denoted as h_{rc} ; and the channel from the RIS to the target, denoted as h_{rt} . The outputs are the desired parameters, γ_c and γ_t .

We aim to determine the transmit vector w to maximize the SNR. Our observations show two distinct situations. In trials with strong channel correlation (step 13), the communication and sensing directions naturally aligned, which allowed us to concentrate most transmission power on the sensing channel. During cases of weak correlation (step 15), we found that allocating power along an orthogonal vector was necessary to maintain satisfactory performance for both channels.

When correlation is high, the same power resources can effectively serve both systems, boosting spectrum efficiency and improving SNR.

Therefore, we introduce the loss function(step 26), and through 30 epochs of iterative learning, the correlation is maximized. The RIS adjusts the direction of the channel subspace via phase tuning. By optimizing the phase matrix, we ultimately realize high-SNR performance.

5. Results analysis and discussion

As introduction mentioned, the two types of SNR and the loss of the system can reflect the performance. In this case, we train the model with different loss functions by changing the parameters and get the best loss function by comparing the SNR and loss value. Some of the model parameters have been preset in advance, τc = 10 dB, P = 8 dB, and $\sigma_r^2 = \sigma_c^2$ =20. The number of base station antennas are 8, the number of RIS elements are 32 and the number of user antennas is set to 1. The learning rate is set to 0.001 and the training mbs is 200. The whole training dataset has 100,000 samples, and 100 samples for testing. All the sample are generated by the channel $G \in \mathbb{C}^{N \times M}$ from the BS to the RIS surface, channel $\boldsymbol{h_{rc}} \in \mathbb{C}^{1 \times N}$ and $\boldsymbol{h_{rt}} \in \mathbb{C}^{1 \times N}$.

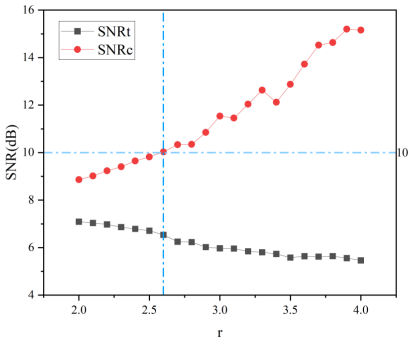

Figure 2. Dependence of the SNR value on r for different types of SNR

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Figure 2 illustrates the relationship between SNRc and SNRt and r. It can be observed that when r increases, SNRc has an apparent increasing trend, while SNRt shows a completely opposite trend of change. As mentioned earlier, we must fulfill particular condition to get the best performance. The SNRc value is below 10 initially, it doesn't meet the condition requirement. When $\gamma > 2.6$, SNRc exceeds 10 and increases, which means the value of r must be larger than 2.6.

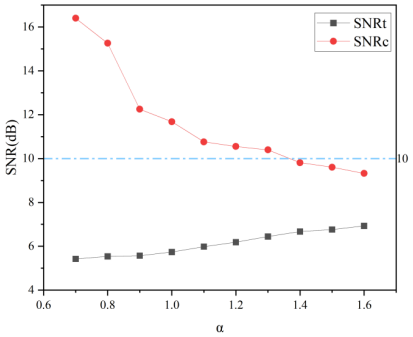

Figure 3. Dependence of the SNR value on α for different types of SNR

Figure 3 shows the relationship between SNRc, SNRt with α. It can be observed that when α increases, SNRc has an apparently decreasing trend, while SNRt shows a completely opposite trend of change but much more gradual. When $\alpha < 1.4$, SNRc exceeds 10 and decreases, which means the value of γ must be smaller than 1.4.

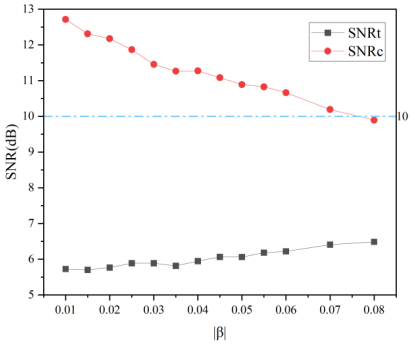

Figure 4. Dependence of the SNR value on β for different types of SNR

In order to have a more clarity observation, we take the absolute value of β. Figure 4 shows the relationship between SNRc, SNRt with |β|. It can be observed that when β increases, SNRc has an apparent decreasing trend, while SNRt shows a completely opposite trend of change but much more gradual. Which is similar to the situation as α changed When $|\beta| < 0.08$, SNR_c exceeds 10 and decreases, which means the value of r must be smaller than 0.08.

From these analyses, it is clear that the three key parameters in the loss function, γ, α and |β|, play significant roles in balancing the performance of sensing and communication channels in the system. In order to determine the optimal range of these parameters, we further adjusted the parameters value to ascertain the best performance.

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Table 1. The SNR and loss values for different parameter combinations

(γ , α, β)	Loss value	SNRt	SNRc
(2.6, 1.1, -0.04)	-0.1617	6.5349	10.0289
(3.0, 1.3, -0.04)	-0.1910	6.4432	10.3981
(3.0, 1.1, -0.07)	-0.1638	6.4078	10.1916
Original (1.0, 1.1, 0.0)	-0.1299	5.0178	3.7840

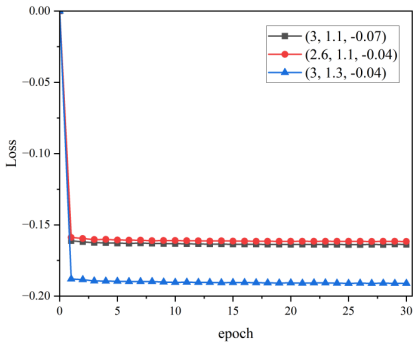

Figure 5. Dependence of the loss value on the epoch for different parameters

Table 1 shows the data for different parameter combinations, all the combinations with parameter β can achieve the requirement condition and the value of SNRt are similar, without obvious difference. Compare with the original data, the three combinations indicated that, the loss function with new parameter β has a positive impact on the training of the model. The SNRc of the original data can't satisfy the requirement of the set condition, and the loss value is much higher than the others. When γ = 3, α = 2.3, β = -0.04, the loss value is the smallest, while the SNRt is very close to the largest combination. As shown in figure 5, the convergence effects of the loss for all three sets of parameters are particularly rapid and excellent. And (3, 1.3, -0.04) has the lowest value of the loss, which means it has a better performance.

6. Conclusions

We have achieved innovation and improvement of the loss function based on an unsupervised learning method for beamforming design in the RIS-assisted ISAC system. Specifically, to achieve a simple and effective beamforming design, a lightweight IBF-Net model is developed using customized image-shaped channel samples. On this basis, we modify a loss function to balance the correlation between the sensing and communication channels and the sensing channel gain, making it have a stronger promoting effect on SNRt and SNRc. Subsequently, the transmit beamformer is obtained through a closed-form expression. Simulation results show that the proposed unsupervised learning-based beamforming method has better performance than the original method, greatly reduces the computational complexity, and enhances the channel strength.

7. Further suggestions

First, reduce the possibility of gradient vanishing and make the model applicable in more cases. Then, this model has the potential for further optimization, allowing for a trade - off between its

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space complexity and time complexity in specific scenarios. One needs to select appropriate parameters (such as the number of channels and the size of convolution kernels) and optimization methods (such as fast convolution and model pruning) according to the application scenarios (such as hardware resources and real - time requirements) to achieve a balance among "time - space - accuracy". For example, in embedded devices, priority should be given to reducing space complexity (e.g., using a small number of channels and quantizing the model), while in server scenarios, priority should be given to reducing time complexity (e.g., using FFT convolution and large - batch training).

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