Low-Complexity MMSE Receivers for ISAC: Fixed and Adaptive Weight Approaches

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***Abstract*— Designing receivers for integrated sensing and communications (ISAC) systems is challenging due to mutual interference between communication and sensing. To address this, we first propose a basic MMSE receiver for joint processing and then introduce two enhanced and low-complexity designs, a fixed-weight MMSE receiver and an adaptive-weight MMSE receiver. The fixed-weight MMSE receiver provides controlled performance trade-offs through weight factors, while the adaptive-weight MMSE receiver dynamically optimizes weights based on instantaneous channel conditions, enhancing system flexibility. We develop comprehensive theoretical analyses for both designs, establishing performance bounds for the fixed-weight approach and convergence properties for the adaptive mechanism. Simulation results demonstrate that the proposed MMSE-based receivers achieve superior robustness against sensing power variations and significantly reduce complexity compared to conventional methods, while maintaining balanced performance between communication and sensing functionalities.**

***Index Terms*— ISAC, MMSE, joint receiver, low-complexity.**

I. Introduction

INTEGRATED sensing and communication (ISAC) is expected to play a key role in next generation wireless systems [1], which uses the same time-frequency resources to perform both communication and sensing tasks [2]. By integrating communication and radar into one system by sharing hardware and signal processing modules achieves immediate benefits of reduced cost, size, and weight compared to independent communication and radar systems. Moreover, ISAC significantly increases spectral efficiency by making spectral resources accessible to communication while maintaining their use for sensing, addressing spectral congestion issues and leveraging the mutual benefits of communication and sensing [1].

Considerable work has been done on ISAC [3], with comprehensive surveys highlighting the fundamental limits and performance bounds of various ISAC systems [4], as well as signal processing approaches [5] for ISAC. However, most of the existing signal processing approaches focus on the transmitter-side design and only few studies have considered addressing receiver-side processing. For instance, [6] proposed channel-matched beamformers and zero-forcing receivers for clutter mitigation in massive multiple-input multiple-output (MIMO). In [7], authors explored sensing-integrated discrete Fourier transform (DFT)-spread orthogonal frequency division multiplexing waveform and deep learning-based receivers for Terahertz joint sensing and communication, and [8] introduced an integrated method using pilot and data signals, optimized via a model-driven ISAC network. To address mutual interference in uplink ISAC systems, [9] explored projection-based approach, though it faces challenges with rank deficiency and computational complexity. Additionally, [10] proposed a joint signal detection and target estimation method using successive interference cancellation and a tailored minimum mean squared error (MMSE) estimator. While their approach achieves optimal sensing performance by leveraging the structural information of the communication signal, it relies on interference cancellation (IC) that can lead to residual errors and suboptimal performance in dynamic environments. Additionally, it has significantly higher complexity.

In this letter, we address these limitations by proposing novel MMSE-based low-complexity receiver algorithms. In particular, we introduce two MMSE-based receivers including a fixed-weight MMSE receiver that effectively controls performance trade-off between communication and sensing via weight factors, and an adaptive-weight MMSE receiver that dynamically adjusts weights based on channel conditions. The adaptive-weight ensures stability and enhances system flexibility by automatically adjusting to varying channel conditions without manual intervention. In addition, we provide rigorous theoretical analyses for the proposed algorithms, including discussion on performance bounds for the fixed-weight scheme and an analysis of convergence guarantees for the adaptive strategy. Simulation results demonstrate that the proposed MMSE-based receivers achieve superior performance compared to conventional methods.

Notation: Scalars are denoted by lowercase letters (e.g., $s(n)$, $\alpha(n)$), vectors by lowercase boldface letters (e.g., $\mathbf{h}_c(n)$, $\mathbf{g}$), and matrices by uppercase boldface letters (e.g., $\mathbf{W}$, $\mathbf{H}$). The operators $(\cdot)^T$, $(\cdot)^H$, and $(\cdot)^{-1}$ denote transpose, Hermitian transpose, and inverse, respectively. $\mathbb{E}\{\cdot\}$ represents the expectation operator, $\text{tr}(\cdot)$ denotes the trace operation, and $\|\cdot\|$ is the Euclidean norm, while $\mathbf{I}_N$ denotes an $N \times N$ identity matrix. Key system parameters include N_t and N_r for transmit and receive antennas, β and γ for communication and sensing signal powers, σ^2 for noise variance, and $w_c(n)$ and $w_s(n)$ for adaptive weights. Channel-related variables include $\mathbf{h}_c(n)$ for the communication channel, $\alpha(n)$ for the reflection coefficient, and $\xi(n)$ for the channel quality factor.

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II. System Model and Problem Formulation

We consider a MIMO ISAC system where a base station (BS) equipped with a uniform linear array (ULA) of N_t transmit and N_r receive antennas processes uplink communication signals from a single-antenna user while simultaneously detecting a target. The user transmits a complex baseband signal $s(t)$, sampled at the BS as $s(n) \in \mathbb{C}$ for the n-th sample

$$s(n) = \sum_{k=0}^{K-1} d_k p(nT_s - kT), \tag{1}$$

where K represents the total number of transmitted symbols in the block, d_k is the transmitted symbol, T_s and T are the sampling period and symbol duration, respectively, and $p(t)$ is the pulse shaping filter. Received communication signal at the BS is

$$\mathbf{y}_c(n) = \mathbf{h}_c(n) \odot s(n) + \mathbf{z}_1(n), \tag{2}$$

where $\mathbf{z}_1(n)$ is additive white Gaussian noise (AWGN) and $\mathbf{h}_c(n) \in \mathbb{C}^{N_r \times 1}$ is time-varying single-input multiple-output (SIMO) uplink channel following Rayleigh fading

$$\mathbf{h}_c(n) = \sqrt{\beta}\sqrt{\frac{1}{2}}(\mathbf{x}(n) + j\mathbf{y}(n)), \quad \mathbf{x}(n), \mathbf{y}(n) \sim \mathcal{N}(0, \mathbf{I}), \tag{3}$$

where β is the path loss coefficient.

For sensing, the BS transmits radar signals $x(n)$ with beamforming vector $\mathbf{f} \in \mathbb{C}^{N_t \times 1}$. The transmit and receive steering vectors for the ULA are [5]

$$\mathbf{a}(\theta) = \frac{1}{\sqrt{N_t}}[1, e^{j2\pi d \sin(\theta)}, \ldots, e^{j2\pi (N_t-1) d \sin(\theta)}]^T, \tag{4}$$

$$\mathbf{b}(\theta) = \frac{1}{\sqrt{N_r}}[1, e^{j2\pi d \sin(\theta)}, \ldots, e^{j2\pi (N_r-1) d \sin(\theta)}]^T, \tag{5}$$

where $d = \lambda/2$ is the antenna spacing. The reflected echo signal is

$$\mathbf{y}_s(n) = \alpha(n) \odot (\mathbf{b}(\theta)\mathbf{a}^H(\theta)\mathbf{f}x(n)) + \mathbf{z}_2(n), \tag{6}$$

where $\alpha(n)$ is the complex reflection coefficient

$$\alpha(n) = \sqrt{\frac{1}{2}}(v_1(n) + jv_2(n)), \quad v_1(n), v_2(n) \sim \mathcal{N}(0, 1). \tag{7}$$

We can express the combined received signal at the BS as

$$\mathbf{y}(n) = \beta(\mathbf{h}_c(n) \odot s(n)) + \sqrt{\gamma}(\alpha(n) \odot \mathbf{g}x(n)) + \mathbf{z}(n), \tag{8}$$

where β and γ denote communication and sensing signal power, $\mathbf{g} = \mathbf{b}(\theta)\mathbf{a}^H(\theta)\mathbf{f}$, and $\mathbf{z}(n)$ is combined AWGN with variance σ^2. The received signal model highlights the interaction between communication and sensing signals. The communication signal $\beta\mathbf{h}_c s(n)$ affects target parameter estimation accuracy, while the sensing signal $\sqrt{\gamma}\alpha(n)\mathbf{g}x(n)$ impacts communication symbol detection, potentially increasing bit errors. To evaluate performance, we use bit error rate (BER) for communication

$$\text{BER} = \frac{1}{L\log_2 M}\sum_{n=1}^{L}\sum_{k=1}^{\log_2 M} |b_k(\hat{s}(n)) - b_k(s(n))|, \tag{9}$$

and mean square error (MSE) for sensing performance

$$\text{MSE} = \frac{1}{L}\sum_{n=1}^{L} |\hat{\alpha}(n) - \alpha(n)|^2. \tag{10}$$

Due to interference between sensing and communication signals, conventional separate processing of sensing and communication signals fails, thus a joint processing approach is necessary. The joint estimation problem is formulated as

$$\begin{aligned} \min_{\mathbf{W}} \quad & \mathbb{E}\{(\mathbf{W}\mathbf{y}(n) - \mathbf{x}(n))^H(\mathbf{W}\mathbf{y}(n) - \mathbf{x}(n))\} \\ \text{s.t.} \quad & \text{BER} \le \text{BER}_{\text{th}}, \quad \text{MSE} \le \text{MSE}_{\text{th}} \\ & \mathbf{W} \in \mathbb{C}^{2 \times N_r} \end{aligned} \tag{11}$$

where $\mathbf{W}$ is the MMSE receiver matrix and $\mathbf{x}(n) = [s(n), \alpha(n)]^T$. The QoS constraints ensure that both communication and sensing maintain satisfactory performance levels, with BER_{th} and MSE_{th} representing the maximum acceptable BER and MSE, respectively. These constraints are satisfied through the proposed adaptive weight mechanism that dynamically adjusts the receiver parameters based on real-time performance monitoring. We design two MMSE-based receivers to solve this optimization problem.

III. Proposed ISAC Receivers

We develop new ISAC receivers in this section. We start discussion from fundamental MMSE principles and fixed-weight MMSE receiver that lead to an advanced adaptive solution. The development of MMSE-based ISAC receiver relies on specific statistical properties that characterize the system model. The received signal in matrix form is

$$\mathbf{y}(n) = \mathbf{H}\mathbf{x}(n) + \mathbf{z}(n) \tag{12}$$

where $\mathbf{H} = [\sqrt{\beta}\mathbf{h}_c, \sqrt{\gamma}\mathbf{g}]$, $\mathbf{x}(n) = [s(n), \alpha(n)]^T$, and $\mathbf{g} = \mathbf{b}(\theta)\mathbf{a}^H(\theta)\mathbf{f}x_T(n)$. The communication channel follows Rayleigh fading with correlation property $\mathbb{E}\{\mathbf{h}_c\mathbf{h}_c^H\} = \beta\mathbf{I}_{N_r}$, where β is the communication signal power. Another key property related to additive noise in the system is characterized by $\mathbb{E}\{\mathbf{z}(n)\mathbf{z}^H(n)\} = \sigma^2\mathbf{I}_{N_r}$, representing spatially and temporally white Gaussian noise. This property defines the noise covariance matrix $\mathbf{R}_n$ in the MMSE solution, influencing weight selection and directly impacting the performance bounds of communication and sensing. Normalized communication and sensing signals, $\mathbb{E}\{|s(n)|^2\} = 1$ and $\mathbb{E}\{|\alpha(n)|^2\} = 1$, ensure consistent analysis and performance comparison. These properties enable tractable analysis, efficient weight selection, and justify linear processing techniques, forming the foundation for the fixed-weight MMSE receiver in ISAC systems.

A. Proposed Fixed-Weight MMSE-Based ISAC Receiver

Let the error vector be

$$\mathbf{e}(n) = \mathbf{W}\mathbf{y}(n) - \mathbf{x}(n) \tag{13}$$

where $\mathbf{x}(n) = [s(n), \alpha(n)]^T$ contains the communication symbol and reflection coefficient. The optimization objective is

$$J(\mathbf{W}) = \mathbb{E}\{(\mathbf{W}\mathbf{y}(n) - \mathbf{x}(n))^H(\mathbf{W}\mathbf{y}(n) - \mathbf{x}(n))\} \tag{14}$$

Using the correlation properties, we define

$$\mathbf{R}_{yy} = \mathbf{H}\mathbf{H}^H + \sigma^2\mathbf{I}_{N_r}, \mathbf{R}_{xy} = \mathbf{H}^H, \mathbf{R}_{xx} = \mathbf{I}_2. \quad (15)$$

Here, $\mathbf{R}_{yy}$ represents the received signal autocorrelation, $\mathbf{R}_{xy}$ describes the cross-correlation between desired parameters and the received signal, and $\mathbf{R}_{xx}$ is the autocorrelation of the desired parameters. The basic MMSE solution is

$$\mathbf{W}_{\text{MMSE}} = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H + \mathbf{R}_n)^{-1}. \quad (16)$$

This solution treats communication and sensing equally without considering their individual QoS requirements, which may not be desirable in practical ISAC systems. To address this, we design a fixed-weight MMSE receiver by introducing a weight factor w_c in the noise covariance term, resulting in a weighted cost function that addresses both communication and sensing objectives. The modified cost function is

$$J(\mathbf{W}, w_c) = \text{tr}\{\mathbf{W}(\mathbf{H}\mathbf{H}^H + w_c\mathbf{R}_n)\mathbf{W}^H - 2\Re\{\mathbf{W}\mathbf{H}^H\} + \mathbf{I}_2\}. \quad (17)$$

The weight w_c balances noise suppression and performance tradeoffs. A larger w_c favors communication while a smaller w_c enhances sensing. By taking gradient of cost function with respect to $\mathbf{W}^H$, i.e., $\frac{\partial J(\mathbf{W}, w_c)}{\partial \mathbf{W}^H} = \mathbf{W}(\mathbf{H}\mathbf{H}^H + w_c\mathbf{R}_n) - \mathbf{H}^H$ and setting it to zero, we obtain fixed-weight MMSE receiver

$$\mathbf{W}_{\text{MMSE}} = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H + w_c\mathbf{R}_n)^{-1}. \quad (18)$$

This solution combines matched filtering $\mathbf{H}^H$ and whitening $(\mathbf{H}\mathbf{H}^H + w_c\mathbf{R}_n)^{-1}$ to suppress interference and noise.

Performance Analysis: To analyze the effectiveness of joint processing and the impact of fixed weights, we examine the theoretical performance bounds of the fixed-weight MMSE receiver. The error covariance matrix representing joint estimation performance is

$$\mathbf{R}_e = \mathbb{E}\{(\hat{\mathbf{x}}(n) - \mathbf{x}(n))(\hat{\mathbf{x}}(n) - \mathbf{x}(n))^H\} \quad (19)$$

where $\hat{\mathbf{x}}(n) = [\hat{s}(n), \hat{\alpha}(n)]^T$. Substituting the fixed-weight MMSE solution (18), the error covariance becomes

$$\mathbf{R}_e = (\mathbf{H}^H\mathbf{H} + w_c\mathbf{R}_n)^{-1}. \quad (20)$$

The diagonal elements of $\mathbf{R}_e$ represent individual estimation errors for communication and sensing

$$\begin{aligned} \text{MSE}_s &= [\mathbf{R}_e]_{22} = w_s\text{tr}(\mathbf{W}_s\mathbf{R}_n\mathbf{W}_s^H), \\ \text{MSE}_c &= [\mathbf{R}_e]_{11} = w_c\text{tr}(\mathbf{W}_c\mathbf{R}_n\mathbf{W}_c^H), \end{aligned} \quad (21)$$

where $\mathbf{W}_s$ and $\mathbf{W}_c$ correspond to sensing and communication rows of $\mathbf{W}_{\text{MMSE}}$. The weight w_c controls the trade-off: larger w_c favors communication by reducing MSE_c, while smaller w_c enhances sensing by reducing MSE_s.

The total system error is

$$\text{MSE}_{\text{total}} = \text{tr}(\mathbf{R}_e) = \text{MSE}_c + \text{MSE}_s. \quad (22)$$

The minimum achievable estimation error is bounded by

$$\text{MSE}_{\text{min}} = \text{tr}(\mathbf{R}_e) \geq \text{tr}((\mathbf{H}^H\mathbf{H} + w_c\mathbf{R}_n)^{-1}). \quad (23)$$

This reveals the fundamental limits of the system, requiring $\beta\|\mathbf{h}_c\|^2 \gg w_c\sigma^2$ and $\gamma\|\mathbf{g}\|^2 \gg w_c\sigma^2$ for reliable operation. Decomposing the bound into communication and sensing components

$$\begin{aligned} \text{MSE}_{c,\text{min}} &\geq [\text{tr}((\mathbf{H}^H\mathbf{H} + w_c\mathbf{R}_n)^{-1})]_{11}, \\ \text{MSE}_{s,\text{min}} &\geq [\text{tr}((\mathbf{H}^H\mathbf{H} + w_c\mathbf{R}_n)^{-1})]_{22}, \end{aligned} \quad (24)$$

highlights inherent trade-offs between both functionalities.

The sensitivity of total MSE to weight selection is

$$\frac{\partial \text{MSE}_{\text{total}}}{\partial w_c} = \text{tr}(\mathbf{W}_{\text{MMSE}}\mathbf{R}_n\mathbf{W}_{\text{MMSE}}^H). \quad (25)$$

This reveals three regions: (1) high sensitivity ($\partial\text{MSE}/\partial w_c \gg 0$), requiring precise weight selection and typically occurs when $\text{cond}(\mathbf{H}^H\mathbf{H}) = \frac{\lambda_{\text{max}}}{\lambda_{\text{min}}} \gg 1$; (2) moderate sensitivity, offering robust operation; and (3) low sensitivity ($\partial\text{MSE}/\partial w_c \approx 0$), where weight selection has minimal impact. These insights guide weight selection and highlight stable operating regions for the fixed-weight ISAC receiver. The fixed-weight approach is simple to implement but lacks adaptability to channel variations, requiring manual tuning of w_c. This motivates the development of an adaptive weight mechanism for dynamic optimization of communication and sensing trade-offs.

IV. Adaptive-Weight MMSE Receiver Design

The adaptive-weight receiver extends the fixed-weight approach by introducing a time-varying weight factor $w_c(n)$. The proposed adaptive receiver design incorporates a channel-aware adaptation mechanism to optimize performance while maintaining the fundamental MMSE structure. The adaptive MMSE receiver can be expressed as

$$\mathbf{W}_{\text{MMSE}}(n) = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H + w_c(n)\mathbf{R}_n)^{-1}. \quad (26)$$

where $w_c(n)$ dynamically adjusts to optimize performance under varying channel conditions. The weight adaptation employs a hybrid mechanism combining channel-aware adaptation and QoS feedback. To assess instantaneous channel conditions, we define a channel quality factor

$$\xi(n) = \frac{\|\sqrt{\beta}\mathbf{h}_c(n)s(n)\|^2}{\|\sqrt{\gamma}\mathbf{g}x_T(n)\|^2 + \sigma^2}, \quad (27)$$

which quantifies the relative strength of communication and sensing components. Based on this, we design a logarithmic weight adaptation law

$$w_c(n) = \text{clip}_{[w_{min}, w_{max}]}\{w_c^0(1 + \delta\log(1 + \xi(n)))\} \quad (28)$$

where δ controls adaptation speed, and w_c^0 is the initial weight. The logarithmic adaptation provides stable weight updates while the clipping operation prevents extreme values, ensuring robust operation across varying channel conditions. In addition, the QoS-based adjustments are applied as follows

$$\begin{aligned} &\text{If } \text{BER}_w > \text{BER}_{th}: \ w_c(n) \leftarrow \min(0.9, w_c(n)(1 + \delta_c)), \\ &\text{If } \text{MSE}_w > \text{MSE}_{th}: \ w_s(n) \leftarrow \min(0.9, (1 - w_c(n))(1 + \delta_s)) \end{aligned} \quad (29)$$

where QoS adjustments are applied when performance over a sliding window violates thresholds BER_{th} and MSE_{th}, with monitoring activated after collecting a sufficient window size of samples. The sensing weight is maintained as $w_s(n) = 1 - w_c(n)$. The weight adaptation mechanism eliminates manual tuning and provides automatic adaptation to both channel dynamics and QoS requirements, making it suitable for practical ISAC with dynamic operating conditions. The weight adaptation mechanism is summarized in Algorithm 1.

Algorithm 1 QoS-Aware Adaptive Weight Mechanism

Initialize $w_c^0 = 0.7$, $\delta = 0.1$, bounds $[0.3, 0.9]$, QoS parameters
for each sample $n = 1$ to L **do**
  Compute $\xi(n)$ and update $w_c(n) = \text{clip}_{[0.3,0.9]}\{w_c^0(1 + \delta \log(1 + \xi(n)))\}$
  if $n > W$ **then**
    Compute recent BER and MSE over window $[n - W + 1, n]$
    if BER $>$ BER$_{\text{th}}$ **then**
      $w_c(n) = \min(0.9, w_c(n)(1 + \delta_c))$
    end if
    if MSE $>$ MSE$_{\text{th}}$ **then**
      $w_s(n) = \min(0.9, (1 - w_c(n))(1 + \delta_s))$, $w_c(n) = 1 - w_s(n)$
    end if
  end if
  Apply MMSE: $\mathbf{W}(n) = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H + w_c(n)\mathbf{R}_n)^{-1}$
end for

Performance Analysis of Adaptive-Weight Design: The Performance analysis of the proposed adaptive-weight receiver requires examination of both the dynamic behaviour and the steady-state aspects, accounting for time-varying weights. The total adaptation range is defined as

$$\Delta w_c = w_c^0 \delta \log(1 + \xi_{\max}), \tag{30}$$

where $\xi_{\max}$ is the maximum channel quality factor. The instantaneous weight variation is

$$\Delta w_c(n) = w_c^0 \delta[\log(1 + \xi(n+1)) - \log(1 + \xi(n))], \tag{31}$$

ensuring gradual changes and preventing rapid fluctuations.

The convergence behaviour of adaptive weights exhibits transient and steady-state properties. Under stable conditions, the weights converge as

$$\lim_{n \to \infty} \mathbb{E}\{w_c(n+1) - w_c(n)\} = 0. \tag{32}$$

This fundamental property ensures that weight adoption stabilize over time. The steady-state behaviour is

$$\mathbb{E}\{\xi(n)\} = \quad \xi_{\text{ss}}, \mathbb{E}\{w_c(n)\} \to w_c^0(1 + \delta \log(1 + \xi_{\text{ss}})). \tag{33}$$

The convergence rate depends on channel dynamics and adaptation factor δ. To analyze convergence quantitatively, we define the weight error vector

$$e(n) = w_c(n) - w_c^{\text{opt}}, \tag{34}$$

where w_c^{opt} is the theoretical optimal weight. The mean square convergence of this error is

$$\mathbb{E}\{|e(n)|^2\} \leq \rho^n \mathbb{E}\{|e(0)|^2\}, \tag{35}$$

where $\rho = 1 - 2\delta \min_n \xi(n)$ is the convergence factor, determining the rate of error decay.

The time-varying MSE for communication and sensing is

$$\text{MSE}_c(n) = w_c(n)\sigma^2 \text{tr}((\mathbf{H}^H\mathbf{H} + w_c(n)\mathbf{R}_n)^{-1})_{11}, \tag{36}$$

$$\text{MSE}_s(n) = w_s(n)\sigma^2 \text{tr}((\mathbf{H}^H\mathbf{H} + w_c(n)\mathbf{R}_n)^{-1})_{22}. \tag{37}$$

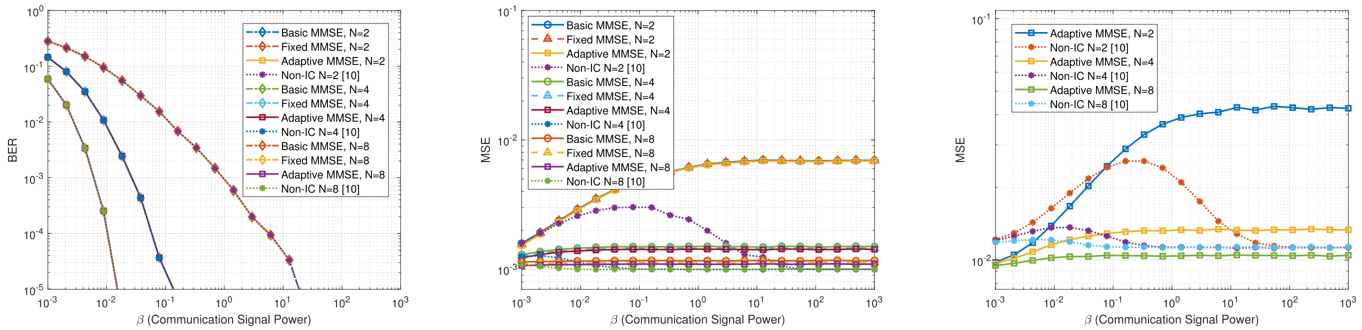
These expressions show how time-varying weights affect performance through modified noise covariance and scaling by $w_c(n)$ and $w_s(n)$.

V. Computational Complexity Analysis

The conventional IC method, a two-stage approach that first decodes communication symbols and then subtracts the decoded signal to estimate sensing parameters from the residual signal [10], exhibits a complexity of $\mathcal{O}(L(MN_r + N_r^3))$ for processing L symbols, where M is the modulation order. The non-IC method, a joint processing approach that simultaneously estimates sensing parameters while accounting for the structural information of communication symbols without IC [10], shows a higher complexity of $\mathcal{O}(LMN_r^3)$ due to exponential calculations for each constellation point. The proposed fixed-weight MMSE receiver computes $\mathbf{W}_{\text{MMSE}} = \mathbf{H}^H(\mathbf{H}\mathbf{H}^H + w_c\mathbf{R}_n)^{-1}$ with $\mathcal{O}(N_r^3)$ complexity for initialization (matrix inversion) and $\mathcal{O}(N_r^2 + M)$ per-symbol processing (filtering and detection), resulting in total complexity $\mathcal{O}(N_r^3 + L(N_r^2 + M))$. The adaptive-weight MMSE receiver dynamically updates $\mathbf{W}_{\text{MMSE}}(n)$ at each step, adding $\mathcal{O}(N_r)$ for channel quality computation and $\mathcal{O}(1)$ for weight adaptation. The per-symbol complexity increases to $\mathcal{O}(N_r^3 + N_r + M)$ due to repeated matrix inversions, yielding total complexity $\mathcal{O}(N_r^3 + L(N_r^3 + N_r + M))$. While the fixed-weight design is efficient for static channels, the adaptive-weight approach, despite slightly higher complexity, optimizes performance in dynamic environments with minimal overhead. However, both methods offer significant computational advantages over existing IC and non-IC methods. which makes both MMSE designs particularly attractive for practical implementations, especially in systems with high modulation orders or large antenna arrays, where the computational efficiency becomes crucial for real-time processing.

VI. Numerical Results

We evaluate the performance of different ISAC receivers through extensive Monte Carlo simulations. The system is configured with $N_t = 4$ transmit antennas and varying number of receive antennas $N_r = \{2, 4, 8\}$ employing 8-PSK modulation that is commonly used in modern wireless systems to make a practical balance between spectral efficiency and implementation complexity. The target is positioned at $\theta = 30^\circ$ with half-wavelength ($d = \lambda/2$) antenna spacing, which are standard configurations for uniform linear arrays in radar and communication systems, ensuring sufficient spatial resolution while avoiding grating lobes. The noise variance is set to -30 dB (corresponds to typical SNR conditions in cellular environments) unless otherwise specified. For the adaptive MMSE, we set the initial weight $w_c^0 = 0.7$ with an adaptation factor $\delta = 0.1$.



(a) BER vs β (MMSE). (b) MSE vs β (MMSE). (c) MSE vs β (MMSE and non-IC).

Fig. 1. Performance comparison of various ISAC receivers: (a) BER versus communication signal power β; (b) MSE versus communication signal power β for sensing parameter estimation; (c) MSE versus communication signal power β with increased sensing power $\gamma = 1.1$.

Figure 1(a) shows the BER performance versus communication signal power β for different numbers of receive antennas. It can be observed that all receivers achieve nearly identical performance. However, compared to non-IC method, the proposed MMSE-based designs attain this with significantly lower complexity, demonstrating their efficiency. Figure 1(b) shows the MSE performance of sensing parameter estimation versus β with $\gamma = 1$. The non-IC method initially shows higher MSE at lower β values and eventually flattens out at higher values, especially for smaller antenna configurations. The proposed MMSE-based designs maintain competitive and consistently low MSE across the entire range of β, except for the case when $N = 2$. Although non-IC yields marginally better MSE, it comes at the cost of higher complexity compared to the proposed MMSE variants that offer a more efficient trade-off between performance and computational complexity. Figure 1(c) demonstrates the sensing performance with increased sensing power $\gamma = 1.1$ and -20 dB noise variance. This slight increase in γ reveals an important distinction between the non-IC method and the proposed adaptive MMSE approach, particularly in their robustness to sensing power variations. The non-IC method exhibits notable sensitivity to this change in sensing power, which becomes more pronounced with $N_r = 4$ and $N_r = 8$. The proposed adaptive MMSE maintains consistent performance across all antenna configurations despite the increased sensing power and outperforms the non-IC method, especially for $N = 8$, demonstrating the inherent robustness of the adaptive MMSE approach to variations in sensing power. This comparison reveals that the adaptive MMSE design can maintain reliable sensing performance even with variations in system parameters. Thus, sensitivity analysis underscores the practical superiority of the adaptive MMSE approach in realistic scenarios where perfect power control may not be achievable. This robustness, combined with its lower computational complexity, makes the adaptive MMSE particularly suitable for practical ISAC implementations.

VII. Conclusion

We have investigated the joint receiver design for ISAC systems, addressing the challenges of mutual interference between communication and sensing. We have proposed a basic MMSE receiver and introduced two enhanced designs, fixed-weight and adaptive-weight MMSE receivers, along with comprehensive theoretical analysis. Both designs significantly reduce computational complexity, making them suitable for practical implementation. Simulation results demonstrate superior robustness against sensing power variations while maintaining balanced performance between communication and sensing functionalities. This work can be extended to multi-user scenarios, investigating robustness under imperfect channel knowledge, and exploring machine learning-enhanced adaptation mechanisms for next-generation ISAC systems.

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