EM Information Analysis for Joint Communication and Environmental Sensing in Scattering-Intensive Wireless Systems

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***Abstract*—This work overcomes a key limitation in Shannon theory by quantifying electromagnetic (EM) information parameters in complex scattering environments for integrated sensing and communication (ISAC). Moving beyond classical additive white Gaussian noise (AWGN) models, we establish that dynamic scatterer-induced uncertainty (not receiver noise) constrains EM information transfer. Our framework models non-stationary scattering with randomized scatterer positions, eliminating reliance on ideal channel coherence and also on the channel state tracking. We derive mutual information metrics through non-parametric conditional probability distributions and jointly quantify source-to-receiver communication performance and environment sensing capability (via scatterer density). The framework models dynamic scattering environments as ensembles of randomly distributed spherical dielectric scatterers positioned between static dipoles. Using Monte Carlo electromagnetic simulations, we rigorously compute scatterer contributions to received fields via Foldy-Lax multiple scattering theory, capturing environment-induced uncertainty beyond conventional AWGN and static-channel assumptions. Source symbols are encoded using M-level amplitude shift keying (M-ASK), and conditional probabilities are estimated non-parametrically from simulated electric field data using kernel density estimation (KDE). The joint mutual information framework demonstrates robust performance in dynamic scattering regimes, establishing a foundation for real-time environment-aware communication systems.**

***Index Terms*—Electromagnetic (EM) information, non-Gaussian, scatterers, SISO, communication, environment sensing, multiple scattering, Foldy-Lax.**

I. Introduction

In classical Shannon information theory, the mutual information characterization between transmitter and receiver in wireless systems primarily models two factors: (1) the scattering environment and (2) additive noise at the receiver [1]. This framework assumes Gaussian-distributed noise at the receiver to derive likelihood probabilities for mutual information, even in scenarios where no scattering environment exists. When scattering is considered, it is typically modeled as a statistical channel impulse response (e.g., Rayleigh or Rician fading), which accounts for line-of-sight (LOS) and non-line-of-sight (NLOS) propagation paths. Critically, these models impose Gaussian assumptions on the real and imaginary components of the complex channel response, treating them as independent and identically distributed (iid) processes. Mutual information is then calculated under the idealized assumption that the channel remains static during a coherence period, requiring periodic channel estimation (e.g., via pilot symbols) to update the deterministic channel response.

The classical Shannon framework has following limitations that are likely to impact its general applicability. First, its reliance on additive white Gaussian noise (AWGN) as a foundational assumption restricts its use; mutual information may not be meaningfully defined if noise deviates from Gaussian statistics. For instance, impulsive electromagnetic interference—a common non-Gaussian noise source in practical systems—cannot be accommodated. Second, the stationarity assumption for scattering environments is often invalid because the rapidly varying scatterer configurations render periodic channel estimation (via pilots or similar methods) ineffective, as the estimated channel becomes obsolete before coherence times expire. Third, the Gaussian (iid) channel model might not always represent the true statistical behavior of scattering environments, where non-Gaussian field distributions are prevalent due to dynamic scatterer variations.

This work introduces a scattering-centric framework to characterize mutual information, explicitly addressing the limitations of classical Shannon theory. We abandon the Gaussian noise, assuming that noise is not the dominant factor in information transfer for scattering-rich environments. Instead, we model the continuous spatial variations of scatterers and their corresponding scattered fields at the receiver as the primary drivers of mutual information. The joint EM scattering and information analysis quantifies wave-scatterer interactions (reflections, diffractions, etc.) and bridges the gap between idealized approximations of channel behavior and the true potential of information transfer capabilities in cluttered environments. By employing the Foldy-Lax multiple scattering theory, an effective approach for multiple scattering analysis, we achieve high-fidelity approximations of scattered fields [3] [4]. The likelihood or conditional probabilities are derived from the fields using kernel density estimation (KDE) [2], a non-parametric method that is useful when the distribution of continuous scattered fields does not meet Gaussian criteria. Crucially, our framework unifies communications and environment sensing, as the source symbols and scatterer density are inferred from the same received fields. This approach provides a robust, physics-driven alternative to classical methods, particularly in dynamic environments where scatterer configurations are continuously evolving.

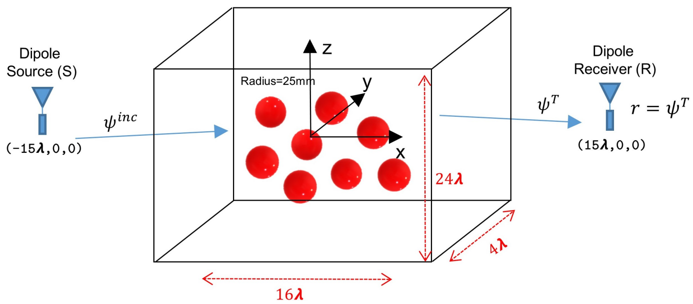

Fig. 1. System configuration with Tx/Rx dipoles and spherical scatterers

II. EM Information Analysis for Joint Communication and Sensing

The proposed single-input single-output (SISO) system comprises a transmitting dipole antenna and a co-polarized receiving dipole positioned in the far-field regime, separated by 30 wavelengths ($\lambda = 12.5$ cm, at frequency 2.4 GHz) as illustrated in Fig. 1. The scattering environment between the antennas contains multiple spherical scatterers (radius $r = 25$ mm), each with the same relative permittivity $\varepsilon_r = 5.0$. The density of scatterers is chosen from the Total scatterers density (TSD) set $\{10, 30, 50, 90, 110, 150, 170, 190\}$. The scatterers are retained at a fixed number across N realizations, while their positions are randomized within a cuboid volume of dimensions $16\lambda \times 4\lambda \times 24\lambda$ along the x, y, and z axes, respectively. Each configuration realization generates complex total electric fields at the receiver, computed via Foldy-Lax multiple scattering theory (MST) without additive noise [3] [4]. The total electric field $\psi^T = \psi^{\text{inc}} + \sum_{i=1}^{d} \psi_i^s$ at the receiver, combines the incident field ψ^{inc} from the transmitting dipole and scattered fields ψ_i^s from d scatterers, computed through Foldy-Lax multiple scattering theory (MST) [3] [4]. Each scattered field $\psi_i^s = G_o T_i \psi_i^E$ arises from the interaction of the i-th scatterer's exciting field (ψ_i^E) with the Green's function (G_o) and a transition operator (T_i) that captures both near-field and far-field scattering effects. These interdependent field relationships form a coupled system resolved through iterative MST calculations, as described in [3], [4]. Achieving reasonable saturation results at N = 10000 realizations.

For digital communication, the source in this work employs M-ary amplitude shift keying (M-ASK) with $M \in \{2, 4, 8\}$ [5]. The discrete symbol set $S = \{s_1, ..., s_M\}$ corresponds to dipole moments $I_l \in [1, M] \times 10^{-3}$ A·m. Environmental sensing utilizes either a subset or the complete Total Scatterers Density (TSD), where the selected scatterer densities $D = \{d_1, ..., d_{N_D}\}$ are drawn from the TSD. Both S and D follow equiprobable distributions with entropies: $H(S) = \log_2 M$, $H(D) = \log_2 N_D$, where N_D denotes the number of distinct scatterer densities in D.

The receiver observes complex-valued fields $R \in \mathbb{C}^{N \times 1}$, which comprise the incident and scattered wave components from N independent realizations. Statistical analysis via Anderson-Darling and Jarque-Bera tests applied to these realizations rejected the null hypothesis of normality at $\alpha = 0.05 (p < 0.05)$, where p quantifies the probability of observing the test statistics under Gaussianity [7]. This confirmed the non-Gaussian nature of both the real $\Re(R)$ and imaginary $\Im(R)$, necessitating non-parametric density estimation.

To model the joint distribution of $\Re(R)$ and $\Im(R)$, we employ a multivariate kernel density estimator (KDE) with Gaussian kernels. The estimated conditional probability density function is given by:

$$\hat{f}(x) = \frac{1}{N h_1 h_2} \sum_{i=1}^{N} \prod_{j=1}^{2} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{x_j - x_{ij}}{h_j} \right)^2 \right) \quad (1)$$

The 2D vector $x = (x_1, x_2)$ corresponds to $\Re(R)$ and $\Im(R)$, where x_{ij} is the j-th (Re/Im) component of the i-th realization. Optimized Bandwidths h_1, h_2 are cross-validated over 100 grid points per dimension.

Mutual information metrics [6] quantify both communication capacity and environmental sensing capability, while known statistical independence between S and D:

$$I(S, R) = \sum_{k=1}^{M} \frac{1}{M} \iint_{\mathbb{C}} P(r|s_k) \log_2 \frac{P(r|s_k)}{P(r)} \, dr_{\text{re}} dr_{\text{im}} \quad (2)$$

$$I(D, R) = \sum_{k=1}^{N_D} \frac{1}{N_D} \iint_{\mathbb{C}} P(r|d_k) \log_2 \frac{P(r|d_k)}{P(r)} \, dr_{\text{re}} dr_{\text{im}} \quad (3)$$

where marginal probability $P(r) = \sum_{k=1}^{M} P(S = s_k) P(r|s_k)$ for $I(S, R)$, and $P(r) = \sum_{l=1}^{N_D} P(D = d_l) P(r|d_l)$ for $I(D, R)$. This joint analysis demonstrates simultaneous information extraction from a single receiver output stream.

III. Simulation Results

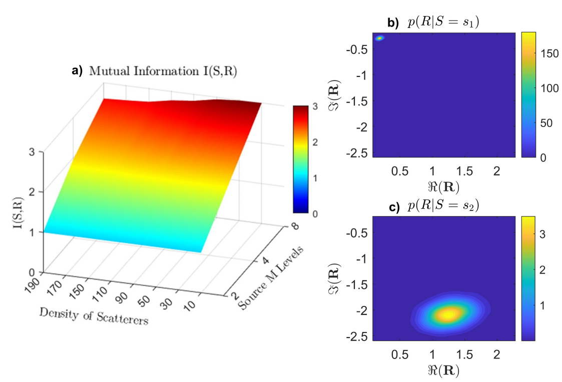

Fig. 2. a)Mutual information : a) $I(S, R)$ vs varying M-levels and individual scattering densities. $P(R|S)$ distributions for $M = 2$ source symbols and 190 scatterers b) $S = s_1$ ($Il_1 = 1 \times 10^{-3}$ A.m), c) $S = s_2$ ($Il_1 = 2 \times 10^{-3}$ A.m).

Figure 2a demonstrates that mutual information $I(S, R)$ generally remains robust or closer to the theoretical upper bounds $H(S)$ across individual scattering densities, retaining the higher system's communication capability. This aligns with the KDE-derived conditional probabilities $P(R|S)$ (see Fig. 2b,c) where distinct clusters emerge for s_1 and s_2 source symbols for $M = 2$, despite scattering effects at $d = 190$.

However, the increase in the individual scatterers density causing moderate information reduction at higher M-levels. For example, $I(S,R)$ is 2.60 bits for $M = 8$, at maximum density ($d = 190$) due to partial overlap in the complex field distributions. The mutual information $I(S,R)$, previously

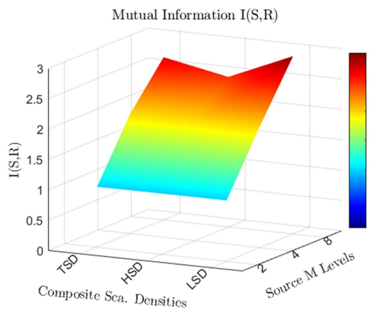

Fig. 3. Mutual Information $I(S,R)$ influenced by varying M -levels and the composite scatterer density sets, like LSD, HSD and TSD.

analyzed for individual scatterer densities, follows a similar trend in Fig. 3 when evaluated for composite scatterer density sets (groupings of multiple densities from the TSD set). The $I(S,R)$ decreases as the composite set transitions from lower to higher scatterer densities. Specifically, $I(S,R)$ = 2.93 bits for the low-scatterer-density composite set (LSD: 10–90 scatterers) and 2.47 bits for the high-scatterer-density set (HSD: 110–190 scatterers). Notably, the complete TSD composite set (10–190 scatterers) exhibits a slight increase to 2.68 bits, outperforming the HSD subset. This suggests that diverse scattering configurations—spanning both low and high densities—enhance symbol distinguishability by leveraging environmental multipath diversity.

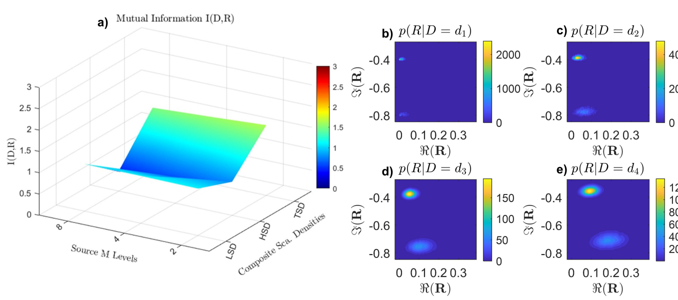

Fig. 4. a) Mutual Information $I(D,R)$ for three composite scatterer density sets and varying M - levels. $P(R|D)$ sample distributions for scatterer densities b) d_1 = 10, c) d_2 = 30, d) d_3 = 50, e) d_4 = 90.

Findings for the mutual information $I(D,R)$ demonstrate the potential to estimate environmental parameters (e.g., scatterer density) directly from received fields without signal processing overhead at the receiver (see Fig. 4a). The scattering characteristics (defined by the TSD set) moderately influence the received signal, achieving a maximum of 1.64 bits for the complete TSD set. However, $I(D,R)$ can be further enhanced using machine learning techniques, etc, to refine the distinguishability of conditional probability distributions $P(R|D)$. For-example, adjacent densities in the Low-Scatterer-Density (LSD: 10–90) subset in Fig. 4b-e exhibit significant overlap in $P(R|D)$, making it challenging to resolve small density differences.

IV. Conclusion

This study demonstrates a novel scattering-centric framework in which electromagnetic (EM) information metrics are characterized without relying on deterministic channel assumptions, even in continuously varying scattering environments. The proposed integrated EM scattering and information analysis quantified wave-scatterer interactions and established practical upper bounds for information transfer in communication and environment sensing within dense scattering environments. The derived mutual information parameters $I(S,R)$ for source-receiver communication and $I(D,R)$ for density-receiver environmental sensing—quantify dual-aspect information extraction from non-Gaussian received fields.

The results demonstrated significant potential for decoding source symbols and estimating scatterers density solely through observed received fields in rapidly varying environments. The mutual information $I(S,R)$ asymptotically approaches theoretical upper bounds (e.g., entropy $H(S)$) in sparse scattering regimes (e.g., low scatterer density, LSD: 10–90), indicating robust communication performance. Meanwhile, $I(D,R)$ exhibits moderate sensitivity to coarse density variations, reflecting its utility for environmental sensing despite dynamic channel conditions. To resolve finer density variations, machine learning architectures could augment feature extraction from non-Gaussian field distributions. Future work could jointly optimize M-ASK constellations and scattering configurations, while adopting multi-antenna (MIMO) transceivers to exploit spatial diversity for enhanced dual-functional capabilities.

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