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Special Topic: Integrated Sensing and Communications Techniques for 6G

Measuring discrete sensing capability for ISAC via task mutual information

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Thanks to its ubiquity, using radio frequency (RF) signals for sensing has found widespread applications. In traditional integrated sensing and communication systems, such as joint radar-communication systems, common sensing tasks include target localization and tracking. Recently, increasingly intelligent systems, such as smart agriculture, low-altitude economy, and smart healthcare, have demanded more comprehensive and continuous information sensing capabilities to support higher-level decision-making. RF sensing has the potential to offer both spatial and temporal continuity, meeting the multi-dimensional sensing needs of these intelligent systems. Consequently, numerous advanced systems have been proposed, expanding the application scope of RF sensing to be more pervasive, including discrete state ubiquitous sensing tasks (such as material identification [1]), and continuous state ubiquitous sensing tasks (such as health monitoring [2]). With the advent of the 6G era, it is anticipated that the sensing potential of RF systems will be further unleashed.

However, despite the vigorous development of existing perception applications, the current evaluation schemes mainly rely on posterior experimental evaluations. Moreover, different tasks have differences. For example, the positioning task often uses positioning error as an indicator, while material recognition uses accuracy as an indicator. Although experimental evaluation is a crucial evaluation method, due to the severe impact of environmental interference on experimental results (for example, the research by Chen et al. [3] demonstrated that simply opening a window, a minor environmental change can cause the accuracy of indoor localization algorithms to drop by 80%) and the high cost of conducting comprehensive experimental evaluations, increasingly intelligent systems often involve multiple types of perception tasks. If an abstract model can be used to represent the utility of heterogeneous perception tasks, it will help optimize the resources (such as spectrum and computing power) of intelligent integrated sensing and communication (ISAC) systems through collaborative optimization.

Traditionally, the system sensing capability usually be evaluated by analyzing how the received signals reflect the channel status, such as sensing mutual information $I(\boldsymbol{H};\boldsymbol{Y})$, where $\boldsymbol{Y}$ is the received signal and $\boldsymbol{H}$ is the channel status [4]. However, it is difficult to obtain complete information about the signal itself. We can only identify the sensory objects by analyzing several received signal features, such as the time-of-arrival (ToA), angle-of-arrival (AoA), and received signal strength (RSS). The relationship between the sensing capability of such features and the signal itself is ambiguous. For example, when containing the same level of noise, the orientation difference of antennas may lead to an AoA estimation error exceeding tenfold [5]. In addition, many sensing tasks are discrete (for example, in personnel presence detection, there are only two states: present and absent), so some common indicators for estimating the performance of continuous parameters (such as the Cramér-rao lower bound) cannot be directly adapted.

In this study, we propose a general sensing channel encoder model to help determine the sensing capability of a discrete ubiquitous sensing system—the upper bound and lower bound of error in restoring the sensed object from given wireless signal features. We consider a system performing discrete sensing tasks.

Definition and bounds. A typical sensing process often comprises several components: the target status (W) to be sensed, the feature (X^n) designed to sense the status, the sensing channel embedding (Y^n) obtained through the sensing system, and the outcome ($\hat{W}$) derived after processing the signal. We analyze the sensing system as shown in Figure 1. The status W has m possible values, which together form the set $\mathcal{W} = \{w_1, \ldots, w_m\}$. The probability that the target is in the i-th status is $\Pr(W = w_i) = p(w_i)$. To facilitate the sensing of statuses, we construct n-dimensional independent features X^n to represent the status W. Given

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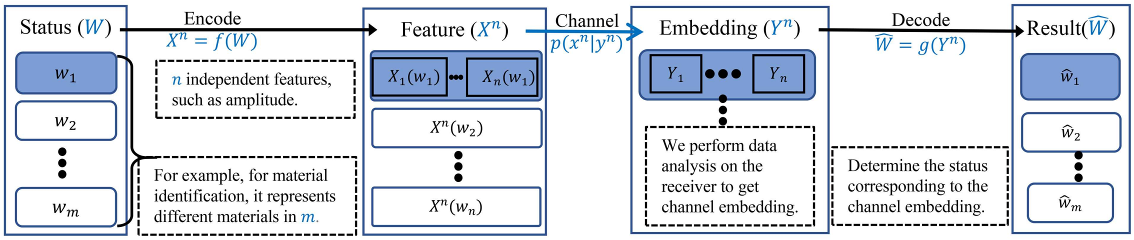

Figure 1 (Color online) Sensing channel encoder.

the status as w_i, the feature $X^n(w_i)$ is given by $X^n(w_i) = [X_1(w_i), \ldots, X_n(w_i)]$. Upon transmission and subsequent data processing, the receiver is likely to receive this feature with a probability denoted as $p(y^n|x^n)$, which we represent as Y^n. Subsequently, the receiver assesses the condition of the sensed target utilizing the acquired features Y^n and decoding rules g. The result is given by $\hat{W} = g(Y^n)$. For instance, in a task of material identification using RF signals, the targets possess varying materials (W). We exploit the characteristic that different materials affect RF signals differently to design feature X^n, which are related to the amplitude of RF signals. Then, using a receiver that captures electromagnetic waves in the space and processes them according to a sensing algorithm, we acquire the sensing channel embedding denoted as Y^n. Finally, based on certain decision rules, we correlate Y^n with the corresponding X^n to ascertain the result $\hat{W}$.

Definition 1. The discrete task mutual information (DTMI) is defined as the mutual information between the feature X^n and the channel embedding Y^n, i.e., $I(X^n; Y^n)$.

Definition 2. The conditional error probability ξ_i when the target status is w_i is defined as

$$\xi_i = \Pr(\hat{W} \neq w_i | W = w_i). \tag{1}$$

Definition 3. The expected value of the error, defined as P_E^n, is articulated as follows:

$$P_E^n = \sum_{i=1}^{m} p(w_i)\xi_i. \tag{2}$$

Theorem 1. For a sensing task W with m statuses, we use n independent features to describe the status of the target. The expected value of the error P_E^n satisfies the following lower bound:

$$P_E^n \geqslant \frac{H(W) - I(X^n; Y^n) - H(P_E^n)}{\log m},$$

where $H(P_E^n) = -P_E^n \log P_E^n - (1 - P_E^n)\log(1 - P_E^n)$.

Theorem 2. For a sensing task with m statuses, we use n independent features to describe the status of the target. For sufficiently large n, the expected value of the error P_E^n satisfies the following upper bound:

$$P_E^n \leqslant \varepsilon + \sum_{k=1}^{m} p(w_k) \sum_{j \neq k}^{m} 2^{3n\varepsilon - \sum_{i=1}^{n} I(X_i(w_j); Y_i(w_k))}.$$

Theorem 3. For a sensing task with $m = 2^{nR}$ statuses, we use n independent features to describe the status of the target. For a sufficiently large n, if R satisfies the following equation:

$$R < \min_{k \neq j} I(\bar{X}^n(w_k); \bar{Y}^n(w_j)) - 3\varepsilon, \tag{3}$$

where $\bar{X}(w_j)$ and $\bar{Y}(w_j)$ are the mean $X^n(w_j)$ and $Y^n(w_j)$, we have $\xi_j \to 0$.

The proof of the theorem is in Appendix A. It can provide theoretical explanations for existing sensing phenomena, as described in Appendix B.

Results. We validate the effectiveness of the proposed sensing system model in several real-world cases, including binary classification tasks such as Wi-Fi-based human identification and radio-frequency identification (RFID)-based displacement detection, and multi-classification tasks such as direction sensing based on electromagnetic signals and device identification based on traffic features. The results of the case study are presented in Appendix C.

Conclusion. In this study, we establish a channel model suitable for ubiquitous sensing, where we associate the sensing task with the received channel embedding through discrete task mutual information. For discrete task sensing channels, we provide upper and lower bounds for the expected error of sensing based on discrete task mutual information, and give a sufficient condition for achieving lossless sensing. The abstract model we constructed can consistently represent the utility of heterogeneous perception tasks, which will help optimize the resources of intelligent ISAC systems through collaborative optimization. We conduct case studies on four common sensing applications based on experimental data and simulation data. The results show that discrete task mutual information has a strong similarity with sensing accuracy. This provides a theoretical evaluation method for the performance of integrated sensing and communication systems beyond experimental evaluation.

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Supporting information Appendixes A–C. 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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