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# Strong Converse for Bi-Static ISAC with Two Detection-Error Exponents

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**Abstract**—The paper considers an information-theoretic bi-static integrated sensing and communication (ISAC) model and provides new results on the fundamental limits of this model. Specifically, we show a strong converse result for memoryless ISAC where the channel transition law depends on an underlying binary hypothesis, which the radar receiver wishes to determine with largest exponential decay rates of the probabilities of detection error under the two hypotheses. In this sense, the channel is a compound channel, and we establish a strong converse under maximum probability of error criteria. We further prove that the fundamental limits of our ISAC system remain unchanged under average probability of error criteria as long as the admissible channel decoding errors are bounded by  $1/2$ .

**Index Terms**—Integrated sensing and communication, bi-static radar, detection error exponent.

## I. INTRODUCTION

Huge technological efforts are being made to integrate radar systems with communication systems, in particular in view of the future 6G mobile communication standard [1], [2] and its deployment for autonomous navigation or smart manufacturing sites. In *integrated sensing and communication systems (ISAC)*, the idea is to use a common waveform for both tasks: the emitted signals are modulated so as to achieve reliable data communication while the backscatters of these signals are used to sense the environment, detect hazardous events, or infer properties of other terminals (e.g., velocities or directions of other cars).

ISAC has already inspired a plethora of works in the signal processing and communications communities, see for example [3]–[10] and references therein, as well as (to a lesser extent) in the information-theoretic community [11]–[21]. The results in [17]–[20] and the present manuscript all focus on the system model in Figure 1 consisting of a transmitter (Tx) sending a message to a receiver (Rx) over a state-dependent discrete memoryless channel (SDMC). A bi-static radar receiver close to the Tx receives the backscattered signal, and due to the proximity to the Tx, this radar receiver also knows the Tx’s channel inputs and compares them to the backscatterers.

We follow the model in [17]–[20], where the channel is memoryless and stationary with a transition law that depends on a binary hypothesis. The goal of the radar receiver is to detect the underlying hypothesis. In a real-world application, the hypothesis can correspond to the presence or absence of an obstacle, which the radar receiver wishes to determine. As in [18], we measure sensing performance in terms of the

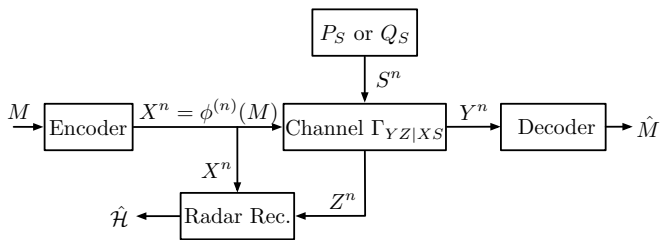


Fig. 1: Bi-static Radar ISAC Model

two exponential decay-rates of the detection error probabilities under the two hypotheses. The difference between [18] and the present work is that we allow for positive probabilities of decoding error in the communication and determine the fundamental limits of ISAC under this assumption. In particular, we prove a strong converse by showing that even when one allows for positive decoding error probabilities neither the achievable rate nor the achievable sensing performance can be improved. Our results are based on maximum error-probability criteria. In fact, since the communication channel is a compound channel (on a set of two channels) it is known that a general strong converse fails under average-probability of error criteria even for only the channel coding part [22], [23].

The converse proof in this paper is an extension of the channel coding strong converse proof in [24] to incorporate also the sensing bounds, see also [20] for a strong converse for bi-static ISAC when sensing performance is measured in terms of Stein’s exponent or distortion. Strong converse proofs based on change-of-measure arguments go back to Gu and Effros [25], [26] and can be also found in various other works, e.g., [27]. The proof method was formalized and first applied to channel coding by Tyagi and Watanabe [28].

**Notation:** Upper-case letters are used for random quantities and lower-case letters for deterministic realizations. Calligraphic font is used for sets. All random variables are assumed finite and discrete. We abbreviate the  $n$ -tuples  $(X_1, \dots, X_n)$  and  $(x_1, \dots, x_n)$  as  $X^n$  and  $x^n$ . We further abbreviate *independent and identically distributed* as *i.i.d.* and *probability mass function* as *pmf*. Pmf’s of i.i.d. random tuples are denoted by  $P^\otimes$ .

Entropy, conditional entropy, and mutual information functionals are written as  $H(\cdot)$ ,  $H(\cdot|\cdot)$ , and  $I(\cdot;\cdot)$ , potentially with pmf’s in the subscripts. The Kullback-Leibler divergence is

denoted by  $D(\|\cdot\|)$ . We denote by  $\pi_{x^n}$  the type of a sequence  $x^n$ . We also use Landau notation, where  $o(1)$  denotes a function that tends to 0 as  $n \rightarrow \infty$ .

## II. SETUP AND MAIN RESULTS

Consider the bi-static radar receiver model over a memoryless channel in Fig. 1. A transmitter (Tx) that wishes to communicate a random message  $M$  to a receiver (Rx) over a state-dependent channel. The message  $M$  is uniformly distributed over the set  $\mathcal{M} = \{1, \dots, 2^{nR}\}$  with  $R > 0$  and  $n > 0$  denoting the rate and blocklength of communication, respectively. The channel from the Tx to the Rx depends on a state-sequence  $S^n = (S_1, \dots, S_n)$  which depends on a binary hypothesis  $\mathcal{H} \in \{0, 1\}$ . Under the null hypothesis  $\mathcal{H} = 0$  it is i.i.d. according to the pmf  $P_S$  and under the alternative hypothesis  $\mathcal{H} = 1$  it is i.i.d. according to the pmf  $Q_S$ . For a given blocklength  $n$ , the Tx thus produces the  $n$ -length sequence of channel inputs

$$X^n = \phi^{(n)}(M) \quad (1)$$

for some choice of the encoding function  $\phi^{(n)}: \{1, \dots, 2^{nR}\} \rightarrow \mathcal{X}^n$ .

Based on  $X^n$  and  $S^n$  the channel produces the sequences  $Y^n$  observed at the Rx and the backscattered signal  $Z^n$ . The channel is assumed memoryless and described by the stationary transition law  $\Gamma_{YZ|SX}$  implying that the pair  $(Y_t, Z_t)$  is produced according to the channel law  $\Gamma_{YZ|SX}$  based on the time- $t$  symbols  $(X_t, S_t)$ .

The Rx attempts to guess message  $M$  based on the sequence of channel outputs  $Y^n$ :

$$\hat{M} = g^{(n)}(Y^n) \quad (2)$$

using a decoding function of the form  $g^{(n)}: \mathcal{Y}^n \rightarrow \{1, \dots, 2^{nR}\}$ .

Performance of communication is measured in terms of maximum error probability

$$p^{(n)}(\text{error}) := \max_{\mathcal{H} \in \{0, 1\}} \max_{m \in \{1, \dots, 2^{nR}\}} \Pr \left[ \hat{M} \neq M | \mathcal{H} = \mathcal{H}, M = m \right]. \quad (3)$$

We assume a radar receiver close to the Tx, that wishes to guess the underlying hypothesis based on the inputs and backscattered signals. I.e., it produces a guess of the form

$$\hat{\mathcal{H}} = h^{(n)}(X^n, Z^n) \in \{0, 1\}. \quad (4)$$

Radar sensing performance is measured in terms of error-exponent pairs. That means, it is required that the type-I and type-II error probabilities

$$\alpha_n := \max_{m \in \mathcal{M}} \Pr \left[ \hat{\mathcal{H}} = 1 \mid \mathcal{H} = 0, M = m \right] \quad (5)$$

and

$$\beta_n := \max_{m \in \mathcal{M}} \Pr \left[ \hat{\mathcal{H}} = 0 \mid \mathcal{H} = 1, M = m \right] \quad (6)$$

decay exponentially fast to 0 with largest possible exponents.

*Definition 1:* A rate-exponent pair  $(R, \theta)$  is  $(\epsilon, r)$ -achievable over the state-dependent DMC  $(\mathcal{X}, \mathcal{Y}, \Gamma_{YZ|XS})$  with state-distributions  $P_S$  and  $Q_S$ , if there exists a sequence of encoding, decoding, and estimation functions  $\{(\phi^{(n)}, g^{(n)}, h^{(n)})\}$  such that for each blocklength  $n$  the maximum probability of error (over the two hypotheses) satisfies

$$\overline{\lim}_{n \rightarrow \infty} p^{(n)}(\text{error}) \leq \epsilon, \quad (7)$$

while the detection error probabilities satisfy:

$$-\underline{\lim}_{n \rightarrow \infty} \frac{1}{n} \log \alpha_n \geq r, \quad (8)$$

$$-\underline{\lim}_{n \rightarrow \infty} \frac{1}{n} \log \beta_n \geq \theta. \quad (9)$$

We use the abbreviations:

$$P_{YZ|X}(y, z|x) := \sum_{s \in \mathcal{S}} P_S(s) \Gamma_{YZ|SX}(y, z|s, x) \quad (10)$$

$$Q_{YZ|X}(y, z|x) := \sum_{s \in \mathcal{S}} Q_S(s) \Gamma_{YZ|SX}(y, z|s, x). \quad (11)$$

Let also  $P_{Y|X}$ ,  $P_{Z|X}$  and  $Q_{Z|X}$ ,  $Q_{Y|X}$  denote the respective conditional marginals.

*Theorem 1:* For any  $\epsilon \in [0, 1)$  and  $r > 0$ , a rate-exponent triple  $(R, \theta, r)$  is  $(\epsilon, r)$ -achievable, if and only if, there exists a pmf  $P_X$  satisfying

$$R \leq \min\{I_{P_X P_{Y|X}}(X; Y), I_{P_X Q_{Y|X}}(X; Y)\}, \quad (12)$$

and

$$\theta \leq \min_{\substack{P_{Z|X}: \\ \mathbb{E}_{P_X}[D(P_{Z|X} \| P_{Z|X})] \leq r}} \mathbb{E}_{P_X} [D(\bar{P}_{Z|X} \| Q_{Z|X})]. \quad (13)$$

*Proof:* Achievability follows by standard random coding arguments for a compound channel, where the transmitter uniformly picks the codewords over the set of  $n$ -length sequences of a fixed type  $P_X$  and the decoder uses a universal decoding rule such as a maximum mutual information (MMI) decoder. The radar receiver checks the conditional type of the received sequence  $z^n$  given the transmitted codeword  $x^n$  and decides on  $\hat{\mathcal{H}} = 0$  if the conditional type  $\pi_{z^n|x^n}$  satisfies

$$\mathbb{E}_{P_X} [D(\pi_{z^n|x^n} \| P_{Z|X})] \leq r. \quad (14)$$

The converse, which is the main contribution of this paper, is proved in Section III. ■

*Remark 1:* Above Theorem 1 applies to a setup with maximum probabilities of error, see (3), (5), and (6). The theorem however applies unchanged also when the definitions (3), (5), and (6) are replaced by the following average probabilities of error:

$$p^{(n)}(\text{error}) := \max_{\mathcal{H} \in \{0, 1\}} \Pr \left[ \hat{M} \neq M | \mathcal{H} = \mathcal{H} \right]. \quad (15a)$$

$$\alpha_n := \Pr \left[ \hat{\mathcal{H}} = 1 \mid \mathcal{H} = 0 \right] \quad (15b)$$

$$\beta_n := \Pr \left[ \hat{\mathcal{H}} = 0 \mid \mathcal{H} = 1 \right] \quad (15c)$$

under the condition that  $\epsilon \in [0, 1/2)$ . The converse proof under these average probability of error criteria is obtained by first applying expurgation arguments and then following similar steps as in Section III.

### III. STRONG CONVERSE PROOF

Fix a sequence of encoding, decoding, and estimation functions  $\{(\phi^{(n)}, g^{(n)}, h^{(n)})\}_{n=1}^{\infty}$ . Assume that (7) and (8) are satisfied. For readability, we will also write  $x^n(\cdot)$  for the function  $\phi^{(n)}(\cdot)$ . Choose a sequence of small positive numbers  $\{\mu_n\}_{n=1}^{\infty}$  satisfying

$$\lim_{n \rightarrow \infty} \mu_n = 0 \quad (16)$$

$$\lim_{n \rightarrow \infty} n \cdot \mu_n^2 = \infty. \quad (17)$$

Let  $T$  be uniform over  $\{1, \dots, n\}$  independent of all other quantities and consider an increasing subsequence of blocklengths  $\{n_i\}$  so that the expected type  $\mathbb{E}_M[\pi_{x^n(M)}(x)]$  converges and denote the convergence point by  $P_X(x)$ :

$$P_X(x) := \lim_{i \rightarrow \infty} \mathbb{E}_M[\pi_{x^{n_i}(M)}(x)], \quad x \in \mathcal{X}. \quad (18)$$

In the remainder of this proof, we restrict attention to this subsequence of blocklengths  $\{n_i\}_{i=1}^{\infty}$ .

**Proof of Channel Coding Bound:** We first prove the converse bound for channel coding. We start by considering the case  $\mathcal{H} = 0$  and channel transition law  $P_{Y|X}$ .

Fix a blocklength  $n \in \{n_i\}$ . Based on the two conditions

$$g^{(n)}(y^n) = m \quad (19a)$$

$$|\pi_{x^n(m)y^n}(a, b) - \pi_{x^n(m)}(a)P_{Y|X}(b|a)| \leq \mu_n, \quad (19b)$$

define for each message  $m \in \mathcal{M}$  the set

$$\mathcal{D}_{\mathcal{C}, m} := \{y^n: \quad (19a) \text{ and } (19b)\}. \quad (20)$$

Introduce the new random tuple  $Y_{\mathcal{C}}^n$  with the following conditional pmf given the message  $M$ :

$$P_{Y_{\mathcal{C}}^n|M}(y^n|m) = \frac{P_{Y|X}^{\otimes n}(y^n|x^n(m))}{\Delta_{\mathcal{C}, m}} \cdot \mathbb{1}\{y^n \in \mathcal{D}_{\mathcal{C}, m}\}, \quad (21)$$

for

$$\Delta_{\mathcal{C}, m} := \sum_{y^n} P_{Y|X}^{\otimes n}(y^n|x^n(m)) \cdot \mathbb{1}\{y^n \in \mathcal{D}_{\mathcal{C}, m}\}. \quad (22)$$

By the union bound, by (7), and by [29, Remark to Lemma 2.12], we have:

$$\Delta_{\mathcal{C}, m} \geq 1 - \epsilon - \frac{|\mathcal{X}||\mathcal{Y}|}{4\mu_n^2 n}, \quad \forall m \in \mathcal{M}. \quad (23)$$

Continue to notice that:

$$R \stackrel{(a)}{=} \frac{1}{n} I(M; Y_{\mathcal{C}}^n) \quad (24)$$

$$\leq \frac{1}{n} \sum_{i=1}^n H(Y_{\mathcal{C}, i}) - \frac{1}{n} H(Y_{\mathcal{C}}^n|M) \quad (25)$$

$$= H(Y_{\mathcal{C}, T}|T) - \frac{1}{n} H(Y_{\mathcal{C}}^n|M) \quad (26)$$

$$\leq H(Y_{\mathcal{C}, T}) - \frac{1}{n} H(Y_{\mathcal{C}}^n|M), \quad (27)$$

where we defined the random variable  $T$  to be uniform over  $\{1, \dots, n\}$  independent of the other random variables. Here, (a) holds because  $M = g(Y_{\mathcal{C}}^n)$  by Condition (19a).

Define next  $X_T = x_T(M)$  (the  $T$ -th symbol of codeword  $x^n(M)$ ), and notice that

$$P_{X_T Y_{\mathcal{C}, T}}(x, y) = \frac{1}{n} \sum_{t=1}^n P_{X_t Y_{\mathcal{C}, t}}(x, y) \quad (28)$$

$$= \frac{1}{n} \sum_{t=1}^n \mathbb{E}[\mathbb{1}\{(X_t, Y_{\mathcal{C}, t}) = (x, y)\}] \quad (29)$$

$$= \mathbb{E}[\pi_{x^n(M)Y_{\mathcal{C}}^n}(x, y)] \quad (30)$$

$$= \mathbb{E}_M[\pi_{x^n(M)}(x)] \cdot P_{Y|X}(y|x) + o(1), \quad (31)$$

where the last equality holds by Condition (19b). By continuity of the entropy functional and the definition in (18):

$$\lim_{n_i \rightarrow \infty} H(Y_{\mathcal{C}, T}) = H_{P_X P_{Y|X}}(Y). \quad (32)$$

Next, by definition and by (21):

$$\begin{aligned} & \frac{1}{n} H(Y_{\mathcal{C}}^n|M = m) \\ &= -\frac{1}{n} \sum_{y^n \in \mathcal{D}_{\mathcal{C}, m}} P_{Y_{\mathcal{C}}^n|M=m}(y^n) \log P_{Y_{\mathcal{C}}^n|M=m}(y^n) \end{aligned} \quad (33)$$

$$\geq -\frac{1}{n} \sum_{y^n \in \mathcal{D}_{\mathcal{C}, m}} P_{Y_{\mathcal{C}}^n|M=m}(y^n) \log \frac{P_{Y|X}^{\otimes n}(y^n|x^n(m))}{\Delta_{\mathcal{C}, m}} \quad (34)$$

$$\begin{aligned} &= -\frac{1}{n} \sum_{t=1}^n \sum_{y_t \in \mathcal{Y}} P_{Y_{\mathcal{C}, t}|M=m}(y_t) \log P_{Y|X}(y_t|x_t(m)) \\ & \quad + \frac{1}{n} \log \Delta_{\mathcal{C}, m}, \end{aligned} \quad (35)$$

$$\begin{aligned} &= -\frac{1}{n} \sum_{t=1}^n \sum_{y \in \mathcal{Y}} \mathbb{E}[\mathbb{1}\{Y_{\mathcal{C}, t} = y\} | M = m] \log P_{Y|X}(y|x_t(m)) \\ & \quad + \frac{1}{n} \log \Delta_{\mathcal{C}, m}, \end{aligned} \quad (36)$$

$$\begin{aligned} &= -\frac{1}{n} \sum_{t=1}^n \sum_{y \in \mathcal{Y}} \mathbb{E}\left[\sum_{x \in \mathcal{X}} \mathbb{1}\{x_t(m) = x, Y_{\mathcal{C}, t} = y\} | M = m\right] \\ & \quad \cdot \log P_{Y|X}(y|x) \\ & \quad + \frac{1}{n} \log \Delta_{\mathcal{C}, m}, \end{aligned} \quad (37)$$

$$\begin{aligned} &= -\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} \mathbb{E}\left[\pi_{x^n(m)Y_{\mathcal{C}}^n}(x, y) | M = m\right] \cdot \log P_{Y|X}(y|x) \\ & \quad + \frac{1}{n} \log \Delta_{\mathcal{C}, m} \end{aligned} \quad (38)$$

$$= -\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} \pi_{x^n(m)}(x) P_{Y|X}(y|x) \cdot \log P_{Y|X}(y|x) + o(1), \quad (39)$$

where the last equality holds by Condition (19b) and because the two Inequalities (23) and  $\epsilon \in [0, 1)$  imply that  $\frac{1}{n} \log \Delta_{\mathcal{C}, m}$

vanishes as  $n \rightarrow \infty$ . Taking the average over all messages yields:

$$\frac{1}{n} H(Y_C^n | M) \geq - \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} \mathbb{E} [\pi_{x^n(M)}(x)] \log P_{Y|X}(y|x) + o(1). \quad (40)$$

Using the definition of  $P_X$ , we obtain:

$$\begin{aligned} \lim_{i \rightarrow \infty} \frac{1}{n_i} H(Y_C^{n_i} | M) &= - \sum_{x \in \mathcal{X}} P_X(x) \sum_{y \in \mathcal{Y}} P_{Y|X}(y|x) \log P_{Y|X}(y|x) \\ &= H_{P_X P_{Y|X}}(Y|X). \end{aligned} \quad (41)$$

Combining (27) with (32) and (41), we can conclude that

$$R \leq H_{P_X P_{Y|X}}(Y) - H_{P_X P_{Y|X}}(Y|X) \quad (42)$$

$$= I_{P_X P_{Y|X}}(X; Y), \quad (43)$$

for  $P_X$  as defined in (18).

Following the same steps (19)–(43) but with the channel law  $Q_{Y|X}$  instead of  $P_{Y|X}$ , one can show that

$$R \leq \min \{ I_{P_X P_{Y|X}}(X; Y), I_{P_X Q_{Y|X}}(X; Y) \}. \quad (44)$$

**Proof of the Error Exponents:** Fix a small value of  $\delta > 0$  and consider any conditional type  $\bar{P}_{Z|X}$  so that

$$\mathbb{E}_{P_X} [D(\bar{P}_{Z|X} \| P_{Z|X})] < r - \delta. \quad (45)$$

Fix a sufficiently large blocklength  $n \in \{n_i\}$  and a message  $m$ , for which the following two inequalities hold:

$$\begin{aligned} \mathbb{E}_{\pi_{x^n(m)}} [D(\bar{P}_{Z|X} \| P_{Z|X})] &\leq \mathbb{E}_M [\mathbb{E}_{\pi_{x^n(M)}} [D(\bar{P}_{Z|X} \| P_{Z|X})]] \\ &< r - \delta/2. \end{aligned} \quad (46)$$

$$(47)$$

Then, based on the conditions

$$h^{(n)}(x^n(m), z^n) = 0 \quad (48a)$$

$$|\pi_{x^n(m)z^n}(a, b) - \pi_{x^n(m)}(a) P_{Z|X}(b|a)| \leq \mu_n, \quad (48b)$$

define the set

$$\mathcal{D}_{S,m} \triangleq \{z^n : (48a) \text{ and } (48b)\}. \quad (49)$$

Define also the new random variable  $Z_S^n$  of conditional law

$$P_{Z_S^n}(z^n) = \frac{P_{Z|X}^{\otimes n}(z^n | x^n(m))}{\Delta_{S,m}} \cdot \mathbb{1}\{z^n \in \mathcal{D}_{S,m}\}, \quad (50)$$

for

$$\Delta_{S,m} := \sum_{z^n} P_{Z|X}^{\otimes n}(z^n | x^n(m)) \cdot \mathbb{1}\{z^n \in \mathcal{D}_{S,m}\}. \quad (51)$$

Defining  $D_b(a||b) := a \log_2 \frac{a}{b} + (1-a) \log_2 \frac{1-a}{1-b}$ , we notice the sequence of (in)equalities:

$$\begin{aligned} &-\frac{1}{n} \log \Pr [\hat{\mathcal{H}} = 0 | \mathcal{H} = 1, M = m] \\ &\leq -\frac{1}{n} \log \sum_{z^n \in \mathcal{D}_{S,m}} Q_{Z|X}^{\otimes n}(z^n | x^n(m)) \end{aligned} \quad (52)$$

$$= \frac{1}{n} D_b \left( \sum_{z^n \in \mathcal{D}_{S,m}} P_{Z_S^n}(z^n) \parallel \sum_{z^n \in \mathcal{D}_{S,m}} Q_{Z|X}^{\otimes n}(z^n | x^n(m)) \right) \quad (53)$$

$$\leq \frac{1}{n} D \left( P_{Z_S^n} \parallel Q_{Z|X}^{\otimes n}(\cdot | x^n(m)) \right) \quad (54)$$

$$\begin{aligned} &\leq \frac{1}{n} \sum_{z^n \in \mathcal{Z}^n} P_{Z_S^n}(z^n) \log \frac{P_{Z|X}^{\otimes n}(z^n | x^n(m))}{Q_{Z|X}^{\otimes n}(z^n | x^n)} \\ &\quad - \frac{1}{n} \log \Delta_{S,m} \end{aligned} \quad (55)$$

$$\begin{aligned} &= \frac{1}{n} \sum_{x \in \mathcal{X}} \sum_{t \in \{1, \dots, n\}: x_t(m)=x} \sum_z P_{\tilde{Z}_{S,t}}(z) \log \frac{P_{Z|X}(z|x)}{Q_{Z|X}(z|x)} \\ &\quad - \frac{1}{n} \log \Delta_{S,m}, \end{aligned} \quad (56)$$

where Inequality (53) holds because  $\sum_{z^n \in \mathcal{D}_{S,m}} P_{Z_S^n}(z^n) = 1$ .

To bound the term  $\Delta_{Z,m}$ , let  $\mathcal{T}_{x^n(m)}(\bar{P}_{Z|X})$  be the set of  $z^n$  sequences satisfying (48a) (and thus  $\mathcal{D}_{Z,m} \subseteq \mathcal{T}_{x^n(m)}(\bar{P}_{Z|X})$ ) and notice that

$$\alpha_n \geq \Pr [\hat{\mathcal{H}} = 1 | \mathcal{H} = 0, M = m] \quad (57)$$

$$\geq \sum_{z^n \in \mathcal{T}_{x^n(m)}(\bar{P}_{Z|X}) \setminus \mathcal{D}_{S,m}} P_{Z|X}^{\otimes n}(z^n | x^n(m)) \quad (58)$$

$$= \sum_{z^n \in \mathcal{T}_{x^n(m)}(\bar{P}_{Z|X})} P_{Z|X}^{\otimes n}(z^n | x^n(m)) - \Delta_{S,m} \quad (59)$$

$$= 2^{-n} \left( \mathbb{E}_{\pi_{x^n(m)}(x)} [D(\bar{P}_{Z|X} \| P_{Z|X})] + o(1) \right) - \Delta_{S,m}, \quad (60)$$

where the last equality holds by a conditional version of Sanov's theorem. Therefore,

$$\Delta_{S,m} \geq 2^{-n} \left( \mathbb{E}_{\pi_{x^n(m)}(x)} [D(\bar{P}_{Z|X} \| P_{Z|X})] + o(1) \right) - \alpha_n, \quad (61)$$

and by the condition on the type-I error probability (8) and our assumption (46)–(47):

$$-\frac{1}{n} \log \Delta_{S,m} \leq \mathbb{E}_{\pi_{x^n(m)}(x)} [D(\bar{P}_{Z|X} \| P_{Z|X})] + o(1). \quad (62)$$

We next observe that

$$\frac{1}{n} \sum_{t \in \{1, \dots, n\}: x_t(\tilde{M})=x} P_{\tilde{Z}_t}(z) = \frac{1}{n} \sum_{t \in \{1, \dots, n\}: x_t(\tilde{M})=x} \mathbb{1}\{\tilde{Z}_t = z\} \quad (63)$$

$$= \frac{1}{n} \sum_{t \in \{1, \dots, n\}} \mathbb{1}\{x_t(\tilde{M}) = x, \tilde{Z}_t = z\} \quad (64)$$

$$= \pi_{x^n(m)\tilde{Z}^n}(x, z) \quad (65)$$

$$= \pi_{x^n(m)}(x) \bar{P}_{Z|X}(z|x) + o(1), \quad (66)$$

where the last equation holds by the type-condition (48a).

From the definition of  $\beta_n$  and by combining (56), (62), and (66), we obtain:

$$-\frac{1}{n} \log \beta_n$$

$$\leq -\frac{1}{n} \log \Pr \left[ \hat{\mathcal{H}} = 0 \mid \mathcal{H} = 1, M = m \right] \quad (67)$$

$$\leq \sum_x \pi_{x^n(m)}(x) \sum_z \bar{P}_{Z|X}(z|x) \frac{\bar{P}_{Z|X}(z|x)}{Q_{Z|X}(z|x)} + \mathbb{E}_{\pi_{x^n(m)}} \left[ D(\bar{P}_{Z|X} \| P_{Z|X}) \right] + o(1) \quad (68)$$

$$\leq \sum_x \pi_{x^n(m)}(x) D(\bar{P}_{Z|X}(\cdot|x) \| Q_{Z|X}(\cdot|x)) + o(1) \quad (69)$$

$$\leq \sum_x \mathbb{E}_M[\pi_{x^n(M)}(x)] D(\bar{P}_{Z|X}(\cdot|x) \| Q_{Z|X}(\cdot|x)) + o(1), \quad (70)$$

where the last step holds by (47).

The desired converse is then immediately established by considering the accumulation point of the increasing block-lengths  $\{n_i\}$ , and by using definition (18).

#### IV. CONCLUSION AND FUTURE DIRECTIONS

We established the strong converse for a memoryless ISAC problem with bi-static radar when the sensing performance is measured in terms of the largest exponential decay rates of the detection error probabilities under the two hypotheses. Notice that our model also includes as special case the setups where the receiver has perfect or imperfect channel-state information by including this state-information as part of the output.

Interesting future research directions include extensions to mono-static radar systems where the transmitter can apply closed-loop encodings depending also on past generalized feedback systems or systems with memory. Analyzing other sensing criteria is also of interest, such as the estimation error when the distribution of the state-sequence depends on a single continuous-valued parameter as for example the Doppler shift in a radar application.

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