Multicoding Schemes for Interference Channels

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Abstract—The best known inner bound for the two-user discrete memoryless interference channel is the Han–Kobayashi rate region. The coding schemes that achieve this region are based on rate-splitting and superposition coding. In this paper, we develop a multicoding scheme to achieve the same rate region. A key advantage of the multicoding nature of the proposed coding scheme is that it can be naturally extended to more general settings, such as when encoders have state information or can overhear each other. In particular, we extend our coding scheme to characterize the capacity region of the state-dependent deterministic Z-interference channel when noncausal state information is available at the interfering transmitter. We specialize our results to the case of the linear deterministic model with ON/OFF interference, which models a wireless system where a cognitive transmitter is noncausally aware of the times it interferes with a primary transmission. For this special case, we provide an explicit expression for the capacity region and discuss some interesting properties of the optimal strategy. We also extend our multicoding scheme to find the capacity region of the deterministic Z-interference channel when the signal of the interfering transmitter can be overheard at the other transmitter (also known as unidirectional partial cribbing).

Index Terms—Interference channel, multicoding, Z-interference channel, partial cribbing, state information.

I. INTRODUCTION

THE discrete memoryless interference channel (DM-IC) is the canonical model for studying the effect of interference in wireless systems. The capacity of this channel is only known in some special cases e.g. class of deterministic ICs [3], [4], strong interference conditions [5]–[7], degraded conditions [8], [9] and a class of semideterministic ICs [10]. Characterizing the capacity region in the general case has been one of the long standing open problems in information theory. The best known achievable rate region is the so-called Han-Kobayashi scheme, which can be achieved by using schemes that are based on the concepts of rate-splitting and superposition coding [11], [12]. Rate-splitting refers to the technique of splitting the message at a transmitter into a common and a private part, where the common part is decoded at all the receivers and the private part is decoded only at the intended receiver. The two parts of the message are then combined into a single signal using superposition coding, first introduced in [13] in the context of the broadcast channel. In all the special cases where the capacity is known, the Han-Kobayashi region equals the capacity region. However, it has been very recently shown that this inner bound is not tight in general [14].

The first result we present in this paper is to show that the Han-Kobayashi region can be achieved by a multicoding scheme. This scheme does not involve any explicit rate-splitting. Instead, the codebook at each encoder is generated as a multicodebook, i.e. there are multiple codewords corresponding to each message, and the encoder chooses one by checking an appropriate joint typicality condition. The auxiliary random variable in this scheme is not explicitly associated with a designated part of the message to be decoded at both receivers.[1] It's role is reminiscent of the encoding for state-dependent channels in [16], and the alternative proof of Marton's achievable rate region for the broadcast channel given in [17]. A key advantage of the multicoding nature is that the new scheme requires almost no change to be applicable to setups in which the canonical interference channel model is augmented to incorporate additional node capabilities such as cognition and state-dependence, while extending the original Han-Kobayashi scheme to such setups requires one to have a multicoding structure at each level of the superposition coding, along with having to change the decoding procedure significantly. We demonstrate this by providing schemes for the aforementioned augmented settings that are nearly identical to the new achievability scheme for the canonical interference channel.

The first setting we consider is when the interference channel is state-dependent and the state-information is available non-causally to one of the transmitters (cognitive transmitter). We know that for a point-to-point state-dependent channel with non-causal state information at the encoder, the optimal achievability scheme due to Gelfand and Pinsker uses multicoding at the encoders. Hence, for state-dependent

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[1] A similar idea, combined with the block-Markov operation of backward encoding, has been recently used in [15] to develop an achievability scheme called distributed-decode-forward for broadcast traffic on relay networks.

interference channels with noncausal state information at the encoders too, we would like to use the idea of multicoding. Since the new achievability scheme that we present for the canonical interference channel already involves multicoding, it requires almost no change to be applicable to the state-dependent setting; the only modification that needs to happen is that the encoder now includes the state sequence in the joint typicality check that it performs. Note that extending the original Han-Kobayashi scheme to this setting on the other hand would require to generate multiple superposition codebooks, each corresponding to a possible realization of the state sequence. In this paper, we focus for simplicity on the case when the state-information is available only at one transmitter, and the cross-link from the other transmitter is weak enough to be ignored, giving rise to the so called Z-interference channel topology. We are able to prove the optimality of the new scheme for this setup when the interference is deterministic. Note however that as mentioned earlier the multicoding-based scheme for the canonical interference channel can be appied near-verbatim even for the general state-dependent interference channel with noncausal state information at the transmitters. The reason we focus on the deterministic Z-interference channel is that we are able to also prove a converse in this case and therefore obtain an exact capacity characterization.

We then specialize our capacity characterization for the state-dependent deterministic Z-interference channel to the case where the channels are governed by the linear deterministic model of [18]. In the recent literature, this model has proven extremely useful for approximating the capacity of wireless networks and developing insights for the design of optimal communication strategies. We consider a linear deterministic Z-interference channel, in which the state of the channel denotes whether the interference link is present or not. When the transmitters are base-stations and the receivers are end-users, this can model the scenario where one of the transmitters is cognitive, for example it can be a central controller that knows when the other Tx-Rx pair will be scheduled to communicate on the same frequency band. When the two Tx-Rx pairs are scheduled to communicate on the same frequency band, this gives an interference channel; when they communicate on different frequency bands each pair gets a clean channel free of interference. Moreover, the cognitive transmitter can know the schedule ahead of time, i.e. the times at which its transmission will be interfering with the second Tx-Rx pair. For this special case, we identify auxiliary random variables and provide an explicit expression for the capacity region. This explicit capacity characterization allows us to identify interesting properties of the optimal strategy. In particular, with single bit level for the linear deterministic channels (which would imply low to moderate SNR for the corresponding Gaussian channels), the sum rate is maximized when the interfering transmitter remains silent (transmits 0's) at times when it interferes with the second transmission. It then treats these symbols as stuck to 0 and performs Gelfand-Pinsker coding. The second transmitter observes a clean channel at all times and communicates at the maximal rate of 1 bit per channel use. This capacity characterization also reveals that when all nodes are provided with the state

information the sum-capacity cannot be further improved. Thus, for this channel, the sum-capacity when all nodes have state information is the same as that when only the interfering encoder has state information.

State-dependent interference channels where the state information is known only to some of the transmitters have received a lot of attention recently, which we mention in this paragraph. Given the inherent difficulty of the problem, works such as [19]–[22] have considered special cases and proposed particular coding schemes. However, exact capacity characterizations have proven difficult. Another line of related work has been the study of cognitive state-dependent ICs [23]–[26]. Here, the term "cognitive" is usually used to mean that the cognitive transmitters know not only the state of the channel but also messages of other transmitters. Note that this assumption is significantly stronger than assuming state information at the transmitter as we do here.

The second setting we consider is when one of the transmitters has the capability to overhear the signal transmitted by the other transmitter, which can be used to induce cooperation between the two transmitters. This is different from having orthogonal communication links (or conferencing) between the encoders, as studied in [27]. Instead, overhearing exploits the natural broadcasting nature of the wireless medium to establish cooperation without requiring any dedicated resources. A variety of different models have been used to capture overhearing [28]–[30], and are known by different names such as cribbing, source cooperation, generalized feedback, cognition etc. We use "partial cribbing" to model the overhearing, in which some deterministic function of the signal transmitted by the non-cognitive transmitter is available at the cognitive transmitter in a strictly causal fashion. Again, for simplicity, we focus on the case of the Z-interference channel, where the cross-link between the non-cognitive transmitter and its undesired receiver is weak enough to be ignored. For this setting, we develop a simple achievability scheme by combining our multicoding-based scheme with block-Markov coding and show that it is optimal for deterministic configurations.

Finally, to further illustrate the point that simple schemes can be obtained for augmented scenarios, we describe two extensions which introduce even more complexity in the model. In the first extension, a third message is introduced in the state-dependent Z-interference channel, which is to be communicated from the interfering transmitter to the interfered receiver. The second extension combines the state-dependent Z-IC and the Z-IC with unidirectional partial cribbing. In both extensions, we are able to obtain simple optimal schemes by naturally extending the multicoding-based achievability schemes.

Organization: We describe the models considered in this paper formally in Section II. The alternate achievability scheme that achieves the Han-Kobayashi region is presented in Sections III. Section IV describes the results concerning the state-dependent setup and section V describes the results concerning the cribbing setup. The two extensions are described in Section VI and we end the paper with a short discussion in Section VII.
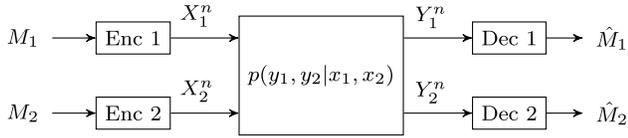
Fig. 1.   Two-User Discrete Memoryless Interference Channel (DM-IC).

II. MODEL

Capital letters, small letters and capital calligraphic letters denote random variables, realizations and alphabets respectively. The tuple $(x(1), x(2), \ldots, x(n))$ and the set $\{a, a+1, \ldots, b\}$ are denoted by x^n and $[a : b]$ respectively, and $\mathcal{T}_\epsilon^{(n)}$ stands for the ϵ-strongly typical set of length-n sequences.

We now describe the channel models considered in this paper.

A. Canonical Interference Channel

The two-user discrete memoryless interference channel $p_{Y_1, Y_2 | X_1, X_2}(y_1, y_2 | x_1, x_2)$ is depicted in Fig. 1. Each sender $j \in \{1, 2\}$ wishes to communicate a message M_j to the corresponding receiver.

A $(n, 2^{nR_1}, 2^{nR_2}, \epsilon)$ code for the above channel consists of the encoding and decoding functions:

$$f_{j,i} : [1 : 2^{nR_j}] \to \mathcal{X}_j, \quad j \in \{1, 2\}, 1 \leq i \leq n,$$
$$g_j : \mathcal{Y}_j^n \to [1 : 2^{nR_j}], \quad j \in \{1, 2\},$$

such that

$$\Pr\left\{g(Y_j^n) \neq M_j\right\} \leq \epsilon, \quad j \in \{1, 2\},$$

where M_1 and M_2 are assumed to be distributed uniformly in $[1 : 2^{nR_1}]$ and $[1 : 2^{nR_2}]$ respectively. A rate pair (R_1, R_2) is said to be *achievable* if for every $\epsilon > 0$, there exists a $(n, 2^{nR_1}, 2^{nR_2}, \epsilon)$ code for sufficiently large n. The capacity region is defined to be the closure of the achievable rate region.

B. State-Dependent Z-Interference Channel

The state-dependent Z-interference channel (S-D Z-IC), described by $p(y_1 | x_1, s)p(y_2 | x_1, x_2, s)$ and memoryless state $p(s)$, is depicted in Fig. 2. The states are assumed to be known noncausally at encoder 1. Each sender $j \in \{1, 2\}$ wishes to communicate a message M_j at rate R_j to the corresponding receiver. For this setting, a $(n, 2^{nR_1}, 2^{nR_2}, \epsilon)$ code consists of the encoding and decoding functions:

$$f_{1,i} : [1 : 2^{nR_1}] \times \mathcal{S}^n \to \mathcal{X}_1, \quad 1 \leq i \leq n,$$
$$f_{2,i} : [1 : 2^{nR_2}] \to \mathcal{X}_2, \quad 1 \leq i \leq n,$$
$$g_j : \mathcal{Y}_j^n \to [1 : 2^{nR_j}], \quad j \in \{1, 2\},$$

such that

$$\Pr\left\{g(Y_j^n) \neq M_j\right\} \leq \epsilon, \quad j \in \{1, 2\}.$$

The probability of error, achievable rate pairs (R_1, R_2) and the capacity region are defined in a similar manner as before.
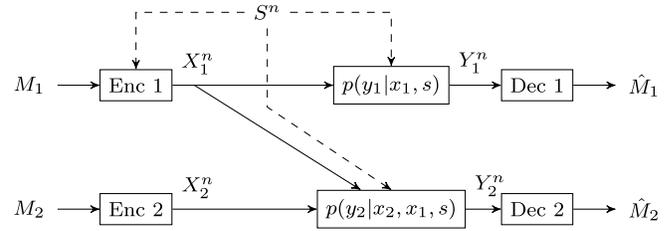
Fig. 2.   The State-Dependent Z-Interference Channel (S-D Z-IC).
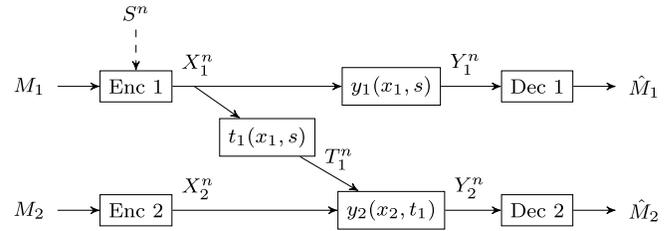
Fig. 3.   The Injective Deterministic S-D Z-IC.
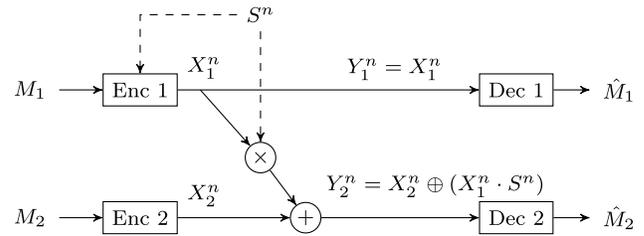
Fig. 4.   The Modulo-Additive S-D Z-IC. All channel inputs and outputs take values in the same finite alphabet $\mathcal{X}$. The state S is Ber(λ).

A special case of the S-D Z-IC, which is the injective deterministic S-D Z-IC, is depicted in Fig. 3. The channel output Y_1 is a deterministic function $y_1(X_1, S)$ of the channel input X_1 and the state S. At receiver 2, the channel output Y_2 is a deterministic function $y_2(X_2, T_1)$ of the channel input X_2 and the interference T_1, which is assumed to be a deterministic function $t_1(X_1, S)$. We also assume that if x_2 is given, $y_2(x_2, t_1)$ is an injective function of t_1, i.e. there exists some function g such that $t_1 = g(y_2, x_2)$.

We consider a special case of the injective deterministic S-D Z-IC in detail, which is the modulo-additive S-D Z-IC, depicted in Fig. 4. All channel inputs and outputs come from a finite alphabet $\mathcal{X} = \{0, 1, \ldots, |\mathcal{X}| - 1\}$. The channel has two states. In state $S = 0$, there is no interference while in state $S = 1$, the cross-link is present. When the cross-link is present, the output at receiver 2 is the modulo-$|\mathcal{X}|$ sum of X_2 and X_1. For all other cases, the output is equal to the input. We can describe this formally as:

$$Y_1 = X_1,$$
$$Y_2 = X_2 \oplus (S \cdot X_1).$$

Assume that the state S is i.i.d. Ber(λ). A generalization of this model that incorporates multiple levels is also considered subsequently.
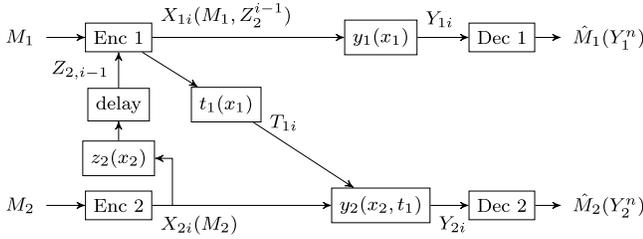
Fig. 5. Injective Deterministic Z-Interference Channel with Unidirectional Partial Cribbing.

C. Z-Interference Channel With Partial Cribbing

The discrete memoryless deterministic Z-interference channel is depicted in Fig. 5. The channel output Y_1 is a deterministic function $y_1(X_1)$ of the channel input X_1. At receiver 2, the channel output Y_2 is a deterministic function $y_2(X_2, T_1)$ of the channel input X_2 and the interference T_1, which is assumed to be a deterministic function $t_1(X_1)$. We also assume that if x_2 is given, $y_2(x_2, t_1)$ is an injective function of t_1, i.e. there exists some function g such that $t_1 = g(y_2, x_2)$. Each sender $j \in \{1, 2\}$ wishes to communicate a message M_j at rate R_j to the corresponding receiver.

We assume that encoder 1 can overhear the signal from transmitter 2 *strictly causally*, which is modeled as partial cribbing with a delay [31]. The partial cribbing signal, which is a function of X_2 is denoted by Z_2. So X_{1i} is a function of (M_1, Z_2^{i-1}) and X_{2i} is a function of M_2.

A $(n, 2^{nR_1}, 2^{nR_2}, \epsilon)$ code for this setting consists of

$$f_{1,i} : [1 : 2^{nR_1}] \times \mathcal{Z}_2^{i-1} \to \mathcal{X}_1, \quad 1 \le i \le n,$$
$$f_{2,i} : [1 : 2^{nR_2}] \to \mathcal{X}_2, \quad 1 \le i \le n,$$
$$g_j : \mathcal{Y}_j^n \to [1 : 2^{nR_j}], \quad j \in \{1, 2\},$$

such that

$$\Pr\left\{ g(Y_j^n) \ne M_j \right\} \le \epsilon, \quad j \in \{1, 2\}.$$

The probability of error, achievable rate pairs (R_1, R_2) and the capacity region are defined in a similar manner as before.

III. CANONICAL INTERFERENCE CHANNEL

A. Preliminaries

The currently best known achievable rate region for the 2-user DM-IC was provided by Han and Kobayashi in [11], using a scheme based on rate-splitting and superposition coding. An alternative achievable rate region that included the Han-Kobayashi rate region was proposed in [12], using another scheme that used rate-splitting and superposition coding. Using the terminology introduced in [32], the encoding in [11] can be described as employing *homogeneous* superposition coding, while that in [12] can be described as employing *heterogeneous* superposition coding. It was then proved in [33] that the two regions are, in fact, equivalent and given by the following compact representation (see also [34], [35]).

Theorem 1 (Han-Kobayashi Region): A rate pair (R_1, R_2) is achievable for the DM-IC $p(y_1, y_2|x_1, x_2)$ if

$$R_1 < I(X_1; Y_1|U_2, Q),$$
$$R_2 < I(X_2; Y_2|U_1, Q),$$
$$R_1 + R_2 < I(X_1; Y_1|U_1, U_2, Q) + I(X_2, U_1; Y_2|Q),$$
$$R_1 + R_2 < I(X_1, U_2; Y_1|U_1, Q) + I(X_2, U_1; Y_2|U_2, Q),$$
$$R_1 + R_2 < I(X_1, U_2; Y_1|Q) + I(X_2; Y_2|U_1, U_2, Q),$$
$$2R_1 + R_2 < I(X_1; Y_1|U_1, U_2, Q) + I(X_2, U_1; Y_2|U_2, Q)$$
$$+ I(X_1, U_2; Y_1|Q),$$
$$R_1 + 2R_2 < I(X_2; Y_2|U_1, U_2, Q) + I(X_1, U_2; Y_1|U_1, Q)$$
$$+ I(X_2, U_1; Y_2|Q), \quad (1)$$

for some pmf $p(q)p(u_1, x_1|q)p(u_2, x_2|q)$, where $|\mathcal{U}_1| \le |\mathcal{X}_1| + 4$, $|\mathcal{U}_2| \le |\mathcal{X}_2| + 4$ and $|\mathcal{Q}| \le 4$.

B. Outline of the New Achievability Scheme

We first describe the alternative achievability scheme informally and discuss the similarities and differences with the existing achievability schemes. The later subsections describe and analyze the scheme formally.

Encoder j, where $j \in \{1, 2\}$ prepares two codebooks:

- A transmission multicodebook,[2] which is a set of codewords $\{x_j^n(\cdot, \cdot)\}$ formed using the transmission random variable X_j. This set is partitioned into a number of bins (or subcodebooks), where the bin-index corresponds to the message,
- A coordination codebook which is a set of codewords $\{u_j^n(\cdot)\}$ formed using the auxiliary random variable U_j.

Given a message, one codeword x_j^n from the corresponding bin in the transmission multicodebook is chosen so that it is jointly typical with some codeword u_j^n in the coordination codebook. The codeword x_j^n so chosen forms the transmission codeword.

At a decoder, the desired message is decoded by using joint typicality decoding, which uses the coordination codebook and the transmission multicodebook of the corresponding encoder and the coordination codebook of the other encoder. Thus, a receiver makes use of the interference via its knowledge of the coordination codebook at the interfering transmitter.

From the above description, it can be seen that the coordination codebook does not carry any explicit part of the message. Its purpose is to ensure that the transmission codeword from a given bin is well-chosen, i.e. it is beneficial to the intended receiver and also the unintended receiver. To the best of our knowledge, this is the first time an auxiliary random variable (which is not the time-sharing random variable) appears in one of the best known achievability schemes without being explicitly associated with any message.

C. Achievability Scheme

Choose a pmf $p(u_1, x_1)p(u_2, x_2)$ and $0 < \epsilon' < \epsilon$.

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[2]The term "multicodebook" refers to the fact that there are multiple codewords corresponding to each message.

Codebook Generation:

- Encoder 1 generates a coordination codebook consisting of $2^{nR_{1c}}$ codewords[3] $u_1^n(l_{1c})$, $l_{1c} \in [1 : 2^{nR_{1c}}]$ i.i.d. according to $\prod_{i=1}^n p(u_{1i})$. It also generates a transmission multicodebook consisting of $2^{n(R_1+R_{1p})}$ codewords $x_1^n(m_1, l_{1p})$, $m_1 \in [1 : 2^{nR_1}]$, $l_{1p} \in [1 : 2^{nR_{1p}}]$ i.i.d. according to $\prod_{i=1}^n p(x_{1i})$.
- Similarly, encoder 2 generates a coordination codebook consisting of $2^{nR_{2c}}$ codewords $u_2^n(l_{2c})$, $l_{2c} \in [1 : 2^{nR_{2c}}]$ i.i.d. according to $\prod_{i=1}^n p(u_{2i})$. It also generates a transmission multicodebook consisting of $2^{n(R_2+R_{2p})}$ codewords $x_2^n(m_2, l_{2p})$, $m_2 \in [1 : 2^{nR_2}]$, $l_{2p} \in [1 : 2^{nR_{2p}}]$ i.i.d. according to $\prod_{i=1}^n p(x_{2i})$.

Encoding:

- To transmit message m_1, encoder 1 finds a pair (l_{1c}, l_{1p}) such that

$$(u_1^n(l_{1c}), x_1^n(m_1, l_{1p})) \in \mathcal{T}_{\epsilon'}^{(n)}$$

and transmits $x_1^n(m_1, l_{1p})$. If it cannot find such a pair, it transmits $x_1^n(m_1, 1)$.
- Similarly, to transmit message m_2, encoder 2 finds a pair (l_{2c}, l_{2p}) such that

$$(u_2^n(l_{2c}), x_2^n(m_2, l_{2p})) \in \mathcal{T}_{\epsilon'}^{(n)}$$

and transmits $x_2^n(m_2, l_{2p})$. If it cannot find such a pair, it transmits $x_2^n(m_2, 1)$.

The codebook generation and encoding process are illustrated in Fig. 6.

Decoding:

- Decoder 1 finds the unique $\hat{m}_1$ such that

$$(u_1^n(l_{1c}), x_1^n(\hat{m}_1, l_{1p}), u_2^n(l_{2c}), y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$$

for some (l_{1c}, l_{1p}, l_{2c}). If none or more than one such $\hat{m}_1$ are found, then decoder 1 declares error.
- Decoder 2 finds the unique $\hat{m}_2$ such that

$$(u_2^n(l_{2c}), x_2^n(\hat{m}_2, l_{2p}), u_1^n(l_{1c}), y_2^n) \in \mathcal{T}_{\epsilon}^{(n)}$$

for some (l_{2c}, l_{2p}, l_{1c}). If none or more than one such $\hat{m}_2$ are found, then decoder 2 declares error.

Discussion: Before providing the formal analysis of the probability of error to show that the coding scheme described above achieves the Han-Kobayashi region, we discuss the connection between the new scheme and the scheme from [12] which motivates the equivalence of their rate regions.

Consider the set of codewords used at encoder 1. While this set resembles a multicodebook, it can be reduced to a standard codebook (one codeword per message) by stripping away the codewords in each bin that are not jointly typical with any of the u_1^n codewords, and therefore are never used by the transmitters. In other words, after we generate the multicodebook in Fig. 6, we can form a smaller codebook by only keeping one codeword per message which is jointly

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[3] Though there is no notion of a common message or a private message in this achievability scheme, we use the subscripts c and p to convey if the corresponding random variables are used for decoding at all destinations or only the desired destination respectively.
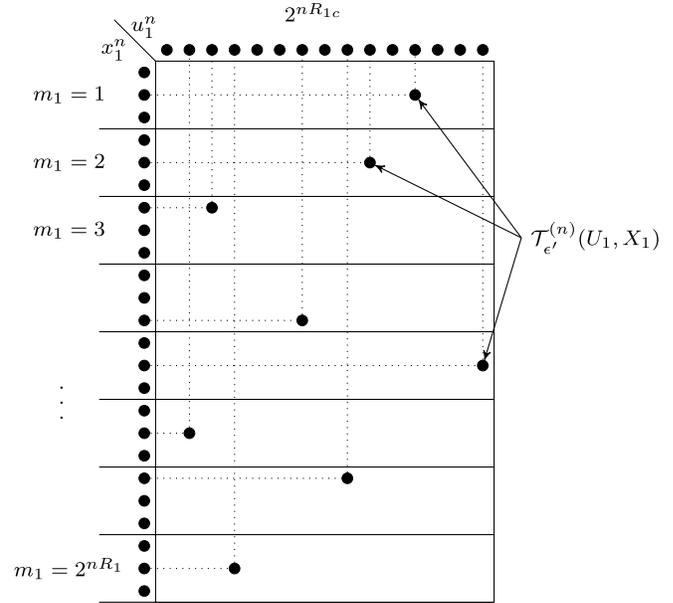
Fig. 6. Codebook Generation and Encoding at Encoder 1. Each dot along either of the axes represents a codeword. The independently generated x_1^n codewords, lined up along the vertical axis in the figure, are binned into 2^{nR_1} bins. The independently generated coordination codewords u_1^n are lined up along the horizontal axis. A pair (x_1^n, u_1^n) being jointly typical is represented by horizontal and vertical dotted lines, originating from the respective codewords and meeting in a dot. To transmit message m_1, a jointly typical pair (x_1^n, u_1^n) is sought where x_1^n falls into the m_1-th bin, and then x_1^n is transmitted.

typical with one of the u_1^n codewords (i.e., those codewords highlighted in Fig. 6). Note that this reduced codebook indeed has a superposition structure. Each of the 2^{nR_1} remaining codewords x_1^n is jointly typical with one of the $2^{nR_{1c}}$ u_1^n codewords, and when n is large there will be exactly $2^{n(R_1-R_{1c})}$ x_1^n codewords that are typical with each u_1^n codeword, i.e., these $2^{n(R_1-R_{1c})}$ x_1^n codewords will look as if they were generated i.i.d. from $p(x_1|u_1)$. Therefore, the u_1^n codewords can be indeed thought as the cloud centers in this superposition codebook and x_1^n's as the satellite codewords. Therefore, our multicodebook construction can be viewed as an equivalent way to generate a superposition codebook as in [33]. This reveals that both the codebook structure and the decoding in our scheme are similar to that in the Han-Kobayashi scheme and therefore the two achievable rate regions are, not surprisingly, equal.

However, note that for broadcast channels, combining Marton coding (which employs multicoding) [17] with Gelfand-Pinsker coding (which also employs multicoding) is more straightforward than combining superposition coding with Gelfand-Pinsker coding. The former has been shown to be optimal in some cases [36]. Since our codebook construction for the interference channel also has the flavor of multicoding, extending this construction to setups where multicoding is required is also quite straightforward. As mentioned in the introduction, we exploit this to develop simple achievability schemes for more general setups described in later sections.

Probability of Error: Due to the symmetry of the code, the average probability of error $P(\mathcal{E})$ is equal to $P(\mathcal{E}|M_1, M_2)$, so we can assume $(M_1, M_2) = (1, 1)$ and analyze $P(\mathcal{E}|1, 1)$. Let $(L_{1c}, L_{1p}, L_{2c}, L_{2p})$ denote the indices chosen during encoding by encoder 1 and encoder 2.

We now define events that cover the event of error in decoding message m_1:

$$\mathcal{E}_1 \triangleq \{(U_1^n(l_{1c}), X_1^n(1, l_{1p})) \notin \mathcal{T}_{\epsilon'}^{(n)} \text{ for all } l_{1c}, l_{1p}\},$$

$$\mathcal{E}_2 \triangleq \{(U_1^n(L_{1c}), X_1^n(1, L_{1p}), U_2^n(L_{2c}), Y_1^n) \notin \mathcal{T}_{\epsilon}^{(n)}\},$$

$$\mathcal{E}_3 \triangleq \{(U_1^n(L_{1c}), X_1^n(m_1, l_{1p}), U_2^n(L_{2c}), Y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$$
$$\text{for some } m_1 \neq 1, \text{ for some } l_{1p}\},$$

$$\mathcal{E}_4 \triangleq \{(U_1^n(L_{1c}), X_1^n(m_1, l_{1p}), U_2^n(l_{2c}), Y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$$
$$\text{for some } m_1 \neq 1, \text{ for some } l_{1p}, l_{2c}\},$$

$$\mathcal{E}_5 \triangleq \{(U_1^n(l_{1c}), X_1^n(m_1, l_{1p}), U_2^n(L_{2c}), Y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$$
$$\text{for some } m_1 \neq 1, \text{ for some } l_{1p}, l_{1c}\},$$

$$\mathcal{E}_6 \triangleq \{(U_1^n(l_{1c}), X_1^n(m_1, l_{1p}), U_2^n(l_{2c}), Y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$$
$$\text{for some } m_1 \neq 1, \text{ for some } l_{1c}, l_{1p}, l_{2c}\}.$$

Consider also the event $\mathcal{E}_1'$, analogous to $\mathcal{E}_1$, which is defined as follows.

$$\mathcal{E}_1' \triangleq \{(U_2^n(l_{2c}), X_2^n(1, l_{2p})) \notin \mathcal{T}_{\epsilon'}^{(n)} \text{ for all } l_{2c}, l_{2p}\}.$$

Since an error for m_1 occurs only if at least one of the above events occur, we use the union bound to get the following upper bound on the average probability of error in decoding m_1:

$$P(\mathcal{E}_1) + P(\mathcal{E}_1') + P(\mathcal{E}_2 \cap \mathcal{E}_1^c \cap \mathcal{E}_1'^c)$$
$$+ P(\mathcal{E}_3) + P(\mathcal{E}_4) + P(\mathcal{E}_5) + P(\mathcal{E}_6).$$

By the mutual covering lemma [37, Ch. 8], $P(\mathcal{E}_1) \to 0$ as $n \to \infty$ if

$$R_{1p} + R_{1c} > I(U_1; X_1) + \delta(\epsilon'), \qquad (2)$$

where $\delta(\epsilon') \to 0$ as $\epsilon' \to 0$.

Similarly, we get that $P(\mathcal{E}_1') \to 0$ as $n \to \infty$ if

$$R_{2p} + R_{2c} > I(U_2; X_2) + \delta(\epsilon'). \qquad (3)$$

By the conditional typicality lemma, $P(\mathcal{E}_2 \cap \mathcal{E}_1^c \cap \mathcal{E}_1'^c)$ tends to zero as $n \to \infty$.

For $P(\mathcal{E}_3) \to 0$, we can use the packing lemma from [37, Ch. 3] to get the condition

$$R_1 + R_{1p} < I(X_1; U_1, U_2, Y_1) - \delta(\epsilon), \qquad (4)$$

where $\delta(\epsilon) \to 0$ as $\epsilon \to 0$.

For $P(\mathcal{E}_4) \to 0$, we can again use the packing lemma to get the condition

$$R_1 + R_{1p} + R_{2c} < I(X_1, U_2; U_1, Y_1) - \delta(\epsilon). \qquad (5)$$

For $P(\mathcal{E}_5) \to 0$, we apply the multivariate packing lemma from the Appendix as shown in (54) to get the condition

$$R_1 + R_{1p} + R_{1c} < I(U_1; X_1) + I(U_1, X_1; U_2, Y_1) - \delta(\epsilon). \qquad (6)$$

Finally, for $P(\mathcal{E}_6) \to 0$ as $n \to \infty$, another application of the multivariate packing lemma as shown in (55) gives the condition

$$R_1 + R_{1p} + R_{1c} + R_{2c} < I(U_1; X_1) + I(U_2; Y_1)$$
$$+ I(U_1, X_1; U_2, Y_1) - \delta(\epsilon). \qquad (7)$$

A similar analysis leads to the following additional conditions for the probability of error in decoding m_2 to vanish as $n \to \infty$.

$$R_2 + R_{2p} < I(X_2; U_2, U_1, Y_2) - \delta(\epsilon), \qquad (8)$$

$$R_2 + R_{2p} + R_{1c} < I(X_2, U_1; U_2, Y_2) - \delta(\epsilon), \qquad (9)$$

$$R_2 + R_{2p} + R_{2c} < I(U_2; X_2) + I(U_2, X_2; U_1, Y_2)$$
$$- \delta(\epsilon), \qquad (10)$$

$$R_2 + R_{2p} + R_{2c} + R_{1c} < I(U_2; X_2) + I(U_1; Y_2)$$
$$+ I(U_2, X_2; U_1, Y_2) - \delta(\epsilon). \qquad (11)$$

Hence the probability of error vanishes as $n \to \infty$ if the conditions (2)-(11) are satisfied. For the sake of brevity, let us first denote the RHS of the conditions (2)-(11) by $a, b, c, d, e, f, g, h, i, j$ respectively (ignoring the $\delta(\epsilon')$ and $\delta(\epsilon)$ terms).

We then note the following relations among these terms which can be proved using the chain rule of mutual information, the Markov chains $U_1 - X_1 - (U_2, X_2, Y_1, Y_2)$ and $U_2 - X_2 - (U_1, X_1, Y_1, Y_2)$ and the independence of (U_1, X_1) and (U_2, X_2).

$$e - a \leq \min\{c, d\},$$
$$f - a \leq d \leq f,$$
$$c \leq e \leq f,$$
$$i - b \leq \min\{g, h\},$$
$$j - b \leq h \leq j,$$
$$g \leq i \leq j. \qquad (12)$$

We now employ Fourier-Motzkin elimination on the conditions (2)-(11) and $R_{1c}, R_{1p}, R_{2c}, R_{2p} \geq 0$ to eliminate $R_{1c}, R_{1p}, R_{2c}, R_{2p}$. The set of relations (12) can be used to simplify this task by recognizing redundant constraints. At the end, we get the following achievable region:

$$R_1 < e - a,$$
$$R_2 < i - b,$$
$$R_1 + R_2 < c + j - a - b,$$
$$R_1 + R_2 < d + h - a - b,$$
$$R_1 + R_2 < f + g - a - b,$$
$$2R_1 + R_2 < c + h + f - 2a - b,$$
$$R_1 + 2R_2 < d + g + j - a - 2b. \qquad (13)$$

Using the same facts as those used to prove (12), we can show that the above region is the same as the Han-Kobayashi region. For the sake of completeness, we show this explicitly in Appendix I.

Then, by including a time-sharing random variable Q, we get that the following region is achievable:

$$R_1 < I(X_1; Y_1 | U_2, Q),$$
$$R_2 < I(X_2; Y_2 | U_1, Q),$$
$$R_1 + R_2 < I(X_1; Y_1 | U_1, U_2, Q) + I(X_2, U_1; Y_2 | Q),$$
$$R_1 + R_2 < I(X_1, U_2; Y_1 | U_1, Q) + I(X_2, U_1; Y_2 | U_2, Q),$$
$$R_1 + R_2 < I(X_1, U_2; Y_1 | Q) + I(X_2; Y_2 | U_1, U_2, Q),$$
$$2R_1 + R_2 < I(X_1; Y_1 | U_1, U_2, Q) + I(X_2, U_1; Y_2 | U_2, Q)$$
$$+ I(X_1, U_2; Y_1 | Q),$$
$$R_1 + 2R_2 < I(X_2; Y_2 | U_1, U_2, Q) + I(X_1, U_2; Y_1 | U_1, Q)$$
$$+ I(X_2, U_1; Y_2 | Q), \qquad (14)$$

for pmf $p(q)p(u_1, x_1|q)p(u_2, x_2|q)$. This region is identical to the region in (1). ∎

IV. STATE-DEPENDENT INTERFERENCE CHANNELS

In this section, we focus on the particular setup of the state-dependent Z-interference channel (S-D Z-IC) with noncausal state information at the interfering transmitter, as depicted in Fig. 2. We provide a simple achievability scheme for this setup, that is obtained by modifying only slightly the achievability scheme that we have developed for the general interference channel. The modification, apart from the choice of pmf, is simply that the informed encoder now includes the observed state sequence when it performs the joint typicality encoding, the rest of the scheme description remains the same. This scheme is shown to be optimal for the deterministic case. The auxiliary random variable used for encoding at the interfering transmitter now implicitly captures some part of the message as well as some part of the state sequence realization.

We mention here that the advantages of multicoding in terms of getting simple achievability schemes are not restricted to the deterministic Z-setups. They hold for general setups, and the reason we focus on the deterministic Z-setups is that we can prove converses, which suggests the merits of the new scheme. The achievability scheme can also be viewed as a generalization of the schemes presented in [22] and [38].

After characterizing the capacity region of the deterministic S-D Z-IC, we investigate a special case in detail: the modulo-additive S-D Z-IC. The modulo-additive channel is motivated by the linear deterministic model which has gained popularity over the recent years for studying wireless networks [18]. For this case (which can be thought of as a linear deterministic model with only one *bit level*), we obtain an explicit description of the capacity region and furthermore, show that the capacity region is also achieved by the standard Gelfand-Pinsker coding over the first link and treating interference as noise over the second link. Following this, the modulo-additive S-D Z-IC with multiple levels is considered and some discussion is provided about the capacity region and the performance of simple achievability schemes.

To summarize, this section contains the following contributions:

- An achievable rate region for the S-D Z-IC,
- Capacity region of the injective deterministic S-D Z-IC,

- Modulo-additive S-D Z-IC: optimality of treating interference-as-noise and other properties.

A. Results for the State-Dependent Channel

The following theorem provides an inner bound to the capacity region of the S-D Z-IC in Fig. 2.

Theorem 2: A rate pair (R_1, R_2) is achievable for the S-D Z-IC in Fig. 2 if

$$R_1 < I(U; Y_1 | Q) - I(U; S | Q),$$
$$R_2 < I(X_2; Y_2 | V, Q),$$
$$R_2 < I(V, X_2; Y_2 | Q) - I(V; S | Q),$$
$$R_1 + R_2 < I(U; Y_1 | Q) + I(V, X_2; Y_2 | Q)$$
$$- I(U; S | Q) - I(U, S; V | Q), \qquad (15)$$

for some pmf $p(q)p(u, v|s, q)p(x_1|u, v, s, q)p(x_2|q)$.

For the injective deterministic S-D Z-IC, we can identify natural choices for the auxiliary random variables in Theorem 2 that, in fact, yield the capacity region. This result is stated in the following theorem.

Theorem 3: The capacity region of the injective deterministic S-D Z-IC in Fig. 3 is the set of rate pairs (R_1, R_2) that satisfy

$$R_1 \leq H(Y_1 | S, Q),$$
$$R_2 \leq H(Y_2 | T_1, Q),$$
$$R_2 \leq H(Y_2 | Q) - I(T_1; S | Q),$$
$$R_1 + R_2 \leq H(Y_1 | T_1, S, Q) + H(Y_2 | Q) - I(T_1; S | Q), \qquad (16)$$

for some pmf $p(q)p(x_1|s, q)p(x_2|q)$, where $|\mathcal{Q}| \leq 4$.

Remark 1: Note that the capacity region remains unchanged even if the first receiver is provided with the state information. The proof of this theorem is presented in subsection IV-C.

B. Proof of Theorem 2

Fix $p(u, v|s)p(x_1|u, v, s)p(x_2)$ and choose $0 < \epsilon' < \epsilon$.

Codebook Generation:

- Encoder 2 generates 2^{nR_2} codewords $x_2^n(m_2), m_2 \in [1 : 2^{nR_2}]$ i.i.d. according to $p(x_2)$.
- Encoder 1 generates $2^{n(R_1+R_1')}$ codewords $u^n(m_1, l_1)$ i.i.d. according to $p(u)$, where $m_1 \in [1 : 2^{nR_1}]$ and $l_1 \in [1 : 2^{nR_1'}]$. Encoder 1 also generates $2^{nR_2'}$ codewords $v^n(l_2), l_2 \in [1 : 2^{nR_2'}]$ i.i.d. according to $p(v)$.

Encoding:

- To transmit message m_2, encoder 2 transmits $x_2^n(m_2)$.
- Assume that the message to be transmitted by encoder 1 is m_1. After observing s^n, it finds a pair (l_1, l_2) such that $(u^n(m_1, l_1), v^n(l_2), s^n) \in \mathcal{T}_{\epsilon'}^{(n)}$. Then it transmits x_1^n, which is generated i.i.d. according to $p(x_1|u, v, s)$.

Decoding:

- Decoder 1 finds a unique $\hat{m}_1$ such that $(u^n(\hat{m}_1, l_1), y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$ for some l_1.
- Decoder 2 finds a unique $\hat{m}_2$ such that $(x_2^n(\hat{m}_2), v^n(l_2), y_2^n) \in \mathcal{T}_{\epsilon}^{(n)}$ for some l_2.

Probability of Error: Due to the symmetry of the code, the average probability of error $\mathsf{P}(\mathcal{E})$ is equal to $\mathsf{P}(\mathcal{E}|M_1, M_2)$, so we can assume $(M_1, M_2) = (1, 1)$ and analyze $\mathsf{P}(\mathcal{E}|1, 1)$. Let (L_1, L_2) denote the pair of indices chosen by encoder 1 such that $(U^n(1, L_1), V^n(L_2), S^n) \in \mathcal{T}_{\epsilon'}^n$.

We now define events that cover the error event:

$$\mathcal{E}_1 \triangleq \{(U^n(1, l_1), V^n(l_2), S^n) \notin \mathcal{T}_{\epsilon'}^{(n)} \text{ for all } l_1, l_2\},$$

$$\mathcal{E}_2 \triangleq \{(U^n(1, L_1), Y_1^n) \notin \mathcal{T}_\epsilon^{(n)}\},$$

$$\mathcal{E}_3 \triangleq \{(U^n(m_1, l_1), Y_1^n) \in \mathcal{T}_\epsilon^{(n)} \text{ for some } m_1 \neq 1, l_1\},$$

$$\mathcal{E}_4 \triangleq \{(X_2^n(1), V^n(L_2), Y_2^n) \notin \mathcal{T}_\epsilon^{(n)}\},$$

$$\mathcal{E}_5 \triangleq \{(X_2^n(m_2), V^n(l_2), Y_2^n) \in \mathcal{T}_\epsilon^{(n)} \text{ for some } m_2 \neq 1, l_2\}.$$

Since an error occurs only if at least one of the above events occur, we have the following upper bound on the average probability of error:

$$\mathsf{P}(\mathcal{E}) \leq \mathsf{P}(\mathcal{E}_1) + \mathsf{P}(\mathcal{E}_2 \cap \mathcal{E}_1^c) + \mathsf{P}(\mathcal{E}_3) + \mathsf{P}(\mathcal{E}_4 \cap \mathcal{E}_1^c) + \mathsf{P}(\mathcal{E}_5).$$

Similar to the proof of the mutual covering lemma [37, Ch. 8], we can show that $\mathsf{P}(\mathcal{E}_1) \to 0$ as $n \to \infty$ if

$$R_1' > I(U; S) + \delta(\epsilon'), \tag{17}$$
$$R_2' > I(V; S) + \delta(\epsilon'), \tag{18}$$
$$R_1' + R_2' > I(U; S) + I(U, S; V) + \delta(\epsilon'), \tag{19}$$

where $\delta(\epsilon') \to 0$ as $\epsilon' \to 0$.

By the conditional typicality lemma [37, Ch. 2], $\mathsf{P}(\mathcal{E}_2 \cap \mathcal{E}_1^c)$ and $\mathsf{P}(\mathcal{E}_4 \cap \mathcal{E}_1^c)$ both tend to zero as $n \to \infty$.

By the packing lemma [37, Ch. 3], for $\mathsf{P}(\mathcal{E}_3) \to 0$, we require

$$R_1 + R_1' < I(U; Y_1) - \delta(\epsilon), \tag{20}$$

and for $\mathsf{P}(\mathcal{E}_5) \to 0$, we require

$$R_2 < I(X_2; Y_2|V) - \delta(\epsilon), \tag{21}$$
$$R_2 + R_2' < I(V, X_2; Y_2) - \delta(\epsilon), \tag{22}$$

where $\delta(\epsilon) \to 0$ as $\epsilon \to 0$. Hence, $\mathsf{P}(\mathcal{E}) \to 0$ if (17), (18), (19), (20), (21), (22) are satisfied. Allowing coded-time sharing with a time-sharing random variable Q and eliminating R_1', R_2' via Fourier-Motzkin elimination, we obtain the region (15). ∎

C. Proof of Theorem 3

Achievability follows from Theorem 2 by choosing $U = Y_1$ and $V = T_1$. These choices are valid since encoder 1 knows (M_1, S^n), which determines T_1^n and Y_1^n. We now prove the converse.

Given a sequence of codes that achieves reliable communication (i.e. $P_e^{(n)} \to 0$ as $n \to \infty$) at rates (R_1, R_2), we have, by Fano's inequality:

$$H(M_1|Y_1^n) \leq n\epsilon_n,$$
$$H(M_2|Y_2^n) \leq n\epsilon_n,$$

where $\epsilon_n \to 0$ as $n \to \infty$.

Using these, we can establish an upper bound on R_1 as follows,

$$\begin{aligned}
nR_1 &= H(M_1) \\
&= H(M_1|S^n) \\
&\leq I(M_1; Y_1^n|S^n) + n\epsilon_n \\
&\leq H(Y_1^n|S^n) + n\epsilon_n \\
&\leq \sum_{i=1}^n H(Y_{1i}|S_i) + n\epsilon_n.
\end{aligned}$$

A simple upper bound on R_2 is established in the following:

$$\begin{aligned}
nR_2 &= H(M_2) \\
&= H(M_2|T_1^n) \\
&\leq I(M_2; Y_2^n|T_1^n) + n\epsilon_n \\
&\leq H(Y_2^n|T_1^n) + n\epsilon_n \\
&\leq \sum_{i=1}^n H(Y_{2i}|T_{1i}) + n\epsilon_n.
\end{aligned}$$

For the second upper bound on R_2, consider the following:

$$\begin{aligned}
nR_2 &= H(M_2) \\
&= H(M_2) + H(Y_2^n|M_2) - H(Y_2^n|M_2) \\
&= H(Y_2^n) + H(M_2|Y_2^n) - H(Y_2^n|M_2) \\
&\leq \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - H(Y_2^n|M_2) \\
&\overset{(a)}{=} \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - H(T_1^n|M_2) \\
&\overset{(b)}{=} \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - H(T_1^n) \\
&\leq \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - I(T_1^n; S^n) \\
&= \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - H(S^n) + H(T_1^n|S^n) \\
&\leq \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - H(S^n) + \sum_{i=1}^n H(T_{1i}|S_i) \\
&\overset{(c)}{=} \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - \sum_{i=1}^n H(S_i) + \sum_{i=1}^n H(T_{1i}|S_i) \\
&= \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n - \sum_{i=1}^n I(T_{1i}; S_i)
\end{aligned}$$

$$\tag{23}$$

where step (a) follows by the injectivity property, step (b) follows because T_1^n is independent of M_2, and step (c) follows because S^n is an i.i.d. sequence.
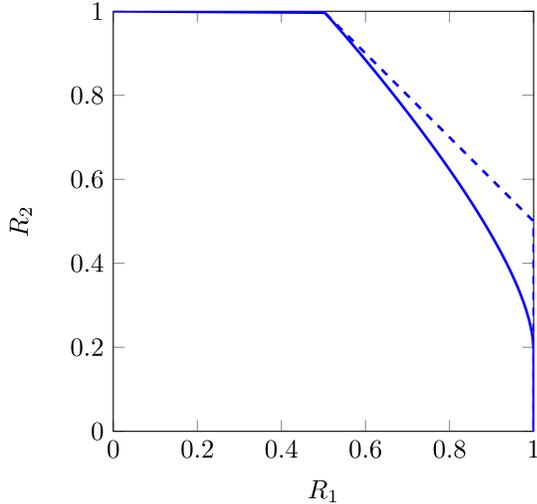
Fig. 7. Capacity Region with $\mathcal{X} = \{0, 1\}$ and S i.i.d. $\text{Ber}\left(\frac{1}{2}\right)$. The dotted line shows the capacity region when all nodes have state information. Note that the maximal sum-rate of 1.5 bits/channel use is achievable with state information only at the interfering Tx.

We now establish an upper bound on the sum-rate.

$$
\begin{aligned}
&n(R_1 + R_2) \\
&= H(M_1|S^n) + H(M_2) \\
&\leq I(M_1; T_1^n, Y_1^n|S^n) + n\epsilon_n + H(Y_2^n) + H(M_2|Y_2^n) \\
&\quad - H(Y_2^n|M_2) \\
&\leq I(M_1; T_1^n, Y_1^n|S^n) + n\epsilon_n + H(Y_2^n) + n\epsilon_n - H(Y_2^n|M_2) \\
&\overset{(a)}{\leq} H(T_1^n, Y_1^n|S^n) + H(Y_2^n) - H(T_1^n|M_2) + 2n\epsilon_n \\
&\overset{(b)}{=} H(T_1^n, Y_1^n|S^n) + H(Y_2^n) - H(T_1^n) + 2n\epsilon_n \\
&= H(Y_1^n|S^n, T_1^n) + H(Y_2^n) - I(T_1^n; S^n) + 2n\epsilon_n \\
&\overset{(c)}{\leq} \sum_{i=1}^{n} H(Y_{1i}|S_i, T_{1i}) + \sum_{i=1}^{n} H(Y_{2i}) - \sum_{i=1}^{n} I(T_{1i}; S_i) + 2n\epsilon_n
\end{aligned}
$$

where as before, steps (a), (b) and (c) follow because of injectivity property, independence of T_1^n and M_2, and i.i.d. state respectively.

From the four bounds established in this section, we can complete the converse by introducing an independent time-sharing random variable Q uniformly distributed on $[1 : n]$ and defining $X_1, T_1, S, X_2, Y_1, Y_2$ to be $X_{1Q}, T_{1Q}, S_Q, X_{2Q}, Y_{1Q}, Y_{2Q}$ respectively. ∎

D. Example: Modulo-Additive State-Dependent Z-Interference Channel

Theorem 4: The capacity region of the modulo-additive S-D Z-IC in Fig. 4 is given by the convex closure of the rate pairs (R_1, R_2) satisfying

$$
\begin{aligned}
R_1 &< (1 - \lambda) \log |\mathcal{X}| + \lambda H(\boldsymbol{p}), \\
R_2 &< \log |\mathcal{X}| - H(\lambda \boldsymbol{p} + (1 - \lambda)\boldsymbol{\delta}_0), \quad (24)
\end{aligned}
$$

for some $\boldsymbol{p} \in \mathcal{P}_{\mathcal{X}}$, where $\mathcal{P}_{\mathcal{X}}$ denotes the probability simplex corresponding to $\mathcal{X}$, $H(\boldsymbol{p})$ stands for the entropy of the pmf $\boldsymbol{p}$ and $\boldsymbol{\delta}_0$ denotes the pmf that has unit mass at 0.

The capacity region when $\mathcal{X} = \{0, 1\}$ and S is i.i.d. $\text{Ber}\left(\frac{1}{2}\right)$ is shown in Figure 7.

Proof of Theorem 4: Consider the capacity region stated in Theorem 3. Let $\boldsymbol{p}_{1,0}$, $\boldsymbol{p}_{1,1}$ and $\boldsymbol{p}_2$, all in $\mathcal{P}_{\mathcal{X}}$, be used to denote the pmf's $p(x_1|s = 0, q)$, $p(x_1|s = 1, q)$ and $p(x_2|q)$ respectively. Evaluating each of the constraints in (16) gives us the following expression for the capacity region:

$$
\begin{aligned}
R_1 &< (1 - \lambda)H(\boldsymbol{p}_{1,0}) + \lambda H(\boldsymbol{p}_{1,1}), \\
R_2 &< H(\boldsymbol{p}_2), \\
R_2 &< H\left((1 - \lambda)\boldsymbol{p}_2 + \lambda \widetilde{\boldsymbol{p}}\right) + \lambda H(\boldsymbol{p}_{1,1}) \\
&\quad - H\left(\lambda \boldsymbol{p}_{1,1} + (1 - \lambda)\boldsymbol{\delta}_0\right), \\
R_1 + R_2 &< (1 - \lambda)H(\boldsymbol{p}_{1,0}) + H\left((1 - \lambda)\boldsymbol{p}_2 + \lambda \widetilde{\boldsymbol{p}}\right) \\
&\quad + \lambda H(\boldsymbol{p}_{1,1}) - H\left(\lambda \boldsymbol{p}_{1,1} + (1 - \lambda)\boldsymbol{\delta}_0\right),
\end{aligned}
$$
$$\tag{25}$$

where $\widetilde{\boldsymbol{p}} \in \mathcal{P}_{\mathcal{X}}$ is a pmf that is defined as

$$
\widetilde{\boldsymbol{p}}(k) = \sum_{i=0}^{|\mathcal{X}|-1} \boldsymbol{p}_{1,1}(i)\boldsymbol{p}_2(k - i), \quad 0 \leq k \leq |\mathcal{X}| - 1,
$$

and $k - i$ should be understood to be $(k - i) \bmod |\mathcal{X}|$.

Firstly, we note that $\boldsymbol{p}_{1,0}$ should be chosen as the pmf of the uniform distribution to maximize $H(\boldsymbol{p}_{1,0})$, thus maximizing the RHS of the constraints in (25). Similarly, $\boldsymbol{p}_2$ should also be chosen to be the pmf of the uniform distribution. Then, we can also remove the first constraint on R_2, since it is rendered redundant by the other constraint on R_2. Thus, the capacity region is given by the convex closure of (R_1, R_2) satisfying

$$
\begin{aligned}
R_1 &< (1 - \lambda) \log(|\mathcal{X}|) + \lambda H(\boldsymbol{p}_{1,1}), \\
R_2 &< \log(|\mathcal{X}|) + \lambda H(\boldsymbol{p}_{1,1}) - H\left(\lambda \boldsymbol{p}_{1,1} + (1 - \lambda)\boldsymbol{\delta}_0\right), \\
R_1 + R_2 &< (2 - \lambda) \log(|\mathcal{X}|) + \lambda H(\boldsymbol{p}_{1,1}) \\
&\quad - H\left(\lambda \boldsymbol{p}_{1,1} + (1 - \lambda)\boldsymbol{\delta}_0\right), \quad (26)
\end{aligned}
$$

for $\boldsymbol{p}_{1,1} \in \mathcal{P}_{\mathcal{X}}$.

For any $\boldsymbol{p}$, the region in (24) is contained in the region in (26) for $\boldsymbol{p}_{1,1} = \boldsymbol{p}$. Hence, the convex closure of (24) is contained in the convex closure of (26).

However, also note that the region in (26) for any $\boldsymbol{p}_{1,1}$ is contained in the convex hull of two regions, one obtained by setting $\boldsymbol{p} = \boldsymbol{p}_{1,1}$ in (24) and the other obtained by setting $\boldsymbol{p} = \boldsymbol{\delta}_0$ in (24). Hence, the convex closure of (26) is also contained in the convex closure of (24). This concludes the proof of Theorem 4. ∎

Remark 2: The optimal sum-rate $(2 - \lambda) \log |\mathcal{X}|$ is achieved by choosing $\boldsymbol{p} = \boldsymbol{\delta}_0$. This corresponds to setting the transmitted symbols of the first transmitter to 0 when $S = 1$ so that it does not interfere with the second transmission. The first transmitter then treats these symbols as stuck to 0 and performs Gelfand-Pinsker coding. The second transmitter transmits at rate $\log(|\mathcal{X}|)$ bits/channel use. It can be easily verified that this is also the optimal sum-rate when all nodes are provided with the state information. Thus, for this channel, the sum-capacity when all nodes have state information is the same as that when only encoder 1 has state information.

Remark 3: Finally, we note that there is also another way to achieve the capacity region of the modulo additive S-D Z-IC.
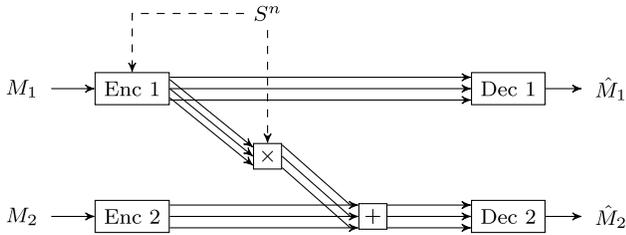
Fig. 8. The Modulo-Additive S-D Z-IC wit multiple bit levels.

For this, first recall that to get the capacity region expression in Theorem 3, we set the auxiliary random variables U and V in the expression in Theorem 2 to Y_1 and T_1 respectively. Another choice, which corresponds to standard Gelfand-Pinsker coding for the first transmitter-receiver pair and treating interference as noise at the second receiver is to choose $V = \phi$ in Theorem 2. This gives us the following achievable region:

$$R_1 < I(U; Y_1|Q) - I(U; S|Q),$$
$$R_2 < I(X_2; Y_2|Q), \tag{27}$$

for some pmf $p(q)p(u|s, q)p(x_1|u, s, q)p(x_2|q)$. We can now see that for the modulo-additive S-D Z-IC, the capacity region is also achieved by making the following choices in the above region: $p(u|s = 0)$ to be the uniform pmf over $\mathcal{X}$, $p(u|s = 1)$ to be $\boldsymbol{p}$, $p(x_1|u, s)$ to be δ_u (i.e. $X_1 = U$) and $p(x_2)$ to be the uniform pmf over $\mathcal{X}$. Thus, the capacity region of the modulo-additive S-D Z-IC can also be achieved by treating interference as noise at the second receiver.

E. Multiple-Level Modulo-Additive S-D Z-IC

The linear deterministic model introduced in [18] consists of multiple *bit levels* that roughly correspond to bits communicated at different power levels. The modulo-additive S-D Z-IC that we looked at in the previous subsection is a special case in which the number of levels is one. Extending the model to have multiple bit levels raises some interesting questions which we consider in this subsection.

More specifically, consider the model depicted in Fig. 8, which can be thought of as three copies of the model in Fig. 4, which are however related by the common state affecting them. For simplicity, we restrict attention to the case when the alphabet on each level, denoted by $\mathcal{X}$, is the binary alphabet, i.e. $\{0, 1\}$, and the state is Ber(0.5). Let L denote the number of bit levels.

This model also falls under the injective-deterministic setup for which we have completely characterized the capacity region. So the capacity region can be easily computed, as we indeed do in the following. This evaluation also allows us to immediately compare the capacity region with the rates achieved by some straightforward achievability schemes that we can employ. In particular, consider the following two simple achievability schemes:

- "Separation": The simplest strategy one can employ is to separately consider each level and communicate over it independently of the other levels. This gives us that the
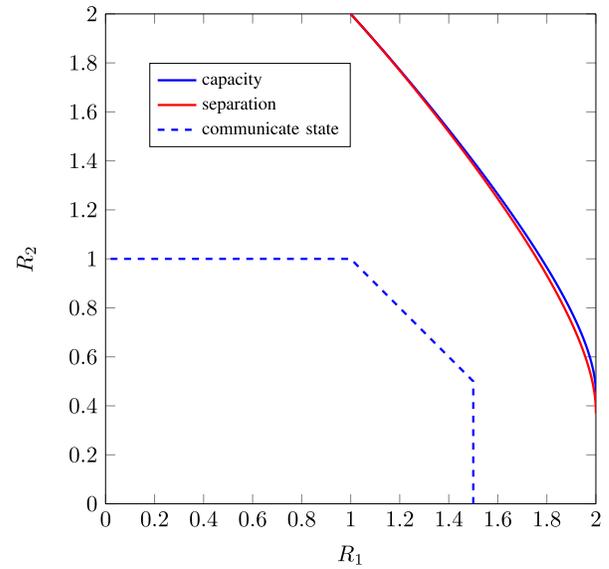
Fig. 9. Comparison of the different rate regions for 3-level binary modulo-additive S-D Z-IC.

rate pairs (R_1, R_2) satisfying

$$R_1 < \frac{L}{2} + \sum_{i=1}^{L} \frac{1}{2}H(\boldsymbol{p}_i),$$
$$R_2 < L - \sum_{i=1}^{L} H\left(\boldsymbol{p}_i + \delta_0\right), \tag{28}$$

for some $\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_L \in \mathcal{P}_{\mathcal{X}}$ are achievable.

- "Communicate state": Alternatively, by noticing that strictly better rates could have been achieved if decoder 2 also had access to the state information, we can reserve one level to communicate the state from encoder 1 to decoder 2. This is done by ensuring that encoder 1 transmits a 1 on this reserved level whenever the state is 1, and encoder 2 constantly transmits a 0 on this level. The nodes communicate on the remaining levels keeping in mind that now decoder 2 also has state information. Note that while no communication can happen between encoder 2 and decoder 2 on the reserved level, encoder 1 can still communicate with decoder 1 at rate 0.5 on this level by treating it as a channel with stuck bits (bit equals 1 whenever state equals 1). This strategy provides us the following achievable region:

$$R_1 < \frac{L}{2} + \frac{1}{2}H(\boldsymbol{p}),$$
$$R_2 < L - 1 - \frac{1}{2}H(\boldsymbol{p}), \tag{29}$$

for some $\boldsymbol{p} \in \mathcal{P}_{\mathcal{X}^{L-1}}$.

We can expect that the suboptimality of reserving one level for communicating the state should become relatively small as the number of levels increases i.e. at high SNR. This is corroborated by the numerical analysis, shown in Figs. 9 and 10, in which we can see that there is a marked improvement in the rates achieved by this scheme relative to the capacity region as we increase the number of levels
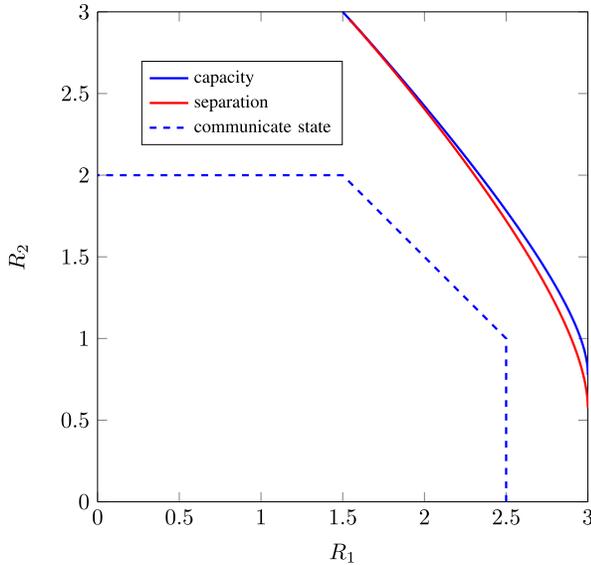
Fig. 10. Comparison of the different rate regions for 3-level binary moduloadditive S-D Z-IC.

from 2 to 3. Indeed, since all the levels are affected by the same state, the entropy of the state becomes small compared to the communication rates as the SNR increases, so it is not a big overhead to explicitly communicate the state to decoder 2 at high SNR. However, at low SNR, the figures show that the overhead incurred is quite high due to which this approach is significantly suboptimal, while the simple scheme of treating the levels separately results in achieving very close to the entire capacity region.

V. INTERFERENCE CHANNELS WITH PARTIAL CRIBBING

In this section, we focus on deterministic Z-interference channels when the interfering transmitter can overhear the signal transmitted by the other transmitter after it passes through some channel. This channel is also modeled as a deterministic channel, dubbed as *partial cribbing* in [31]. Deterministic models, in particular linear deterministic models [18], have gained popularity due to the observation that they are simpler to analyze and are provably close in performance to Gaussian models.

There have been quite a few very sophisticated achievability schemes designed for interference channels with causal cribbing encoders, however optimality of the achievable rate regions has not been addressed. In the most general interference channel model with causal cribbing [29], each encoder needs to split its message into four parts: a common part to be sent cooperatively, a common part to be sent non-cooperatively, a private part to be sent cooperatively and a private part to be sent non-cooperatively. Further, because of the causal nature of cribbing, achievability schemes usually involve block-Markov coding, so that each encoder also needs to consider the cooperative messages of both encoders from the previous block. Motivated by the alternative achievability scheme we have presented earlier for the general interference channel, we present a simple optimal achievability scheme that minimizes the rate-splitting that is required. Specifically, while

encoder 2 only splits its message into a cooperative and non-cooperative private part, encoder 1 does not perform any rate-splitting at all. Encoder 2 needs to perform rate-splitting so that the partial cribbing can be exploited, but other than that, the achievability scheme is the same as the one we have developed for the canonical interference channel, except that the codewords are now generated conditioned on the cribbed sequence from the previous block. By focusing on the specific configuration of the Z-interference channel, we are able to prove the optimality of an achievability scheme that is simpler than the highly involved achievability schemes for the general case that are currently known.

A. Result for Partial Cribbing

Theorem 5: The capacity region of the injective deterministic Z-interference channel with unidirectional partial cribbing, depicted in Fig. 5, is given by the convex closure of (R_1, R_2) satisfying

$$
\begin{aligned}
R_1 &\leq H(Y_1|W), \\
R_2 &\leq \min\left(H(Y_2), H(Y_2, Z_2|T_1, W)\right), \\
R_1 + R_2 &\leq H(Y_1|T_1, W) + \min\left(H(Y_2), H(Y_2, Z_2|W)\right),
\end{aligned}
\tag{30}
$$

for $p(w)p(x_1|w)p(x_2|w)$, where W is an auxiliary random variable whose cardinality can be bounded as $|\mathcal{W}| \leq |\mathcal{Y}_2| + 3$.

The proof of this theorem is presented below.

B. Proof of Theorem 5

Achievability: Choose a pmf $p(w)p(u_d, u_c, x_1|w)$ $p(x_2, z_2|w)$ and $0 < \epsilon' < \epsilon$, where for the sake of generality, we use the auxiliary random variables U_d and U_c. In the injective deterministic case at hand, they can be set to Y_1 and T_1 respectively.

Codebook Generation: The communication time is divided into B blocks, each containing n channel uses, and an independent random code is generated for each block $b \in [1 : B]$. Whenever it is clear from the context, we suppress the dependence of codewords on b to keep the notation simple. The messages in block B are fixed apriori, so a total of $B - 1$ messages are communicated over the B blocks. The resulting rate loss can be made as negligible as desired by choosing a sufficiently large B.

We split R_2 as $R_2' + R_2''$, which corresponds to the split of message 2 into two parts, one that will be sent cooperatively by both transmitters to receiver 2 and the other non-cooperatively only by transmitter 2 to receiver 2. For each block b, let $m_{2,b}' \in [1 : 2^{nR_2'}]$ and $m_{2,b}'' \in [1 : 2^{nR_2''}]$. For each block $b \in [1 : B]$, we generate $2^{nR_2'}$ codewords w^n i.i.d. according to $p(w)$.

- For each w^n in block b, we generate $2^{nR_2'}$ codewords $\left\{z_2^n(w^n, m_{2,b}')\right\}$ i.i.d. according to $p(z_2|w)$. Then for each (w^n, z_2^n), we generate $2^{nR_2''}$ codewords $\left\{x_2^n(w^n, z_2^n, m_{2,b}'')\right\}$ i.i.d. according to $p(x_2|z_2, w)$.
- For each w^n in block b, we generate 2^{nR_c} codewords $\left\{u_c^n(w^n, l_c)\right\}$ i.i.d. according to $p(u_c|w)$, where

$l_c \in [1 : 2^{nR_c}]$. We also generate $2^{n(R_1 + R_d)}$ codewords $\{u_d^n(m_{1,b}, l_d)\}$ i.i.d. according to $p(u_d)$, where $m_{1,b} \in [1 : 2^{nR_1}]$ and $l_d \in [1 : 2^{nR_d}]$.[4]

Encoding: Let us assume for now that as a result of the cribbing, encoder 1 knows $m'_{2,b-1}$ at the end of block $b - 1$. Then in block b, both encoders can encode $m'_{2,b-1}$ using $w^n(m'_{2,b-1})$ where w^n is from the code for block b.

- To transmit message $m_{1,b}$, encoder 1 finds a pair (l_d, l_c) such that

$$(w^n(m'_{2,b-1}), u_c^n(w^n, l_c), u_d^n(m_{1,b}, l_d)) \in \mathcal{T}_{\epsilon'}^{(n)}.$$

  It transmits x_1^n that is generated i.i.d. according to $p(x_1|w, u_d, u_c)$.

- To transmit message $m_{2,b} = (m'_{2,b}, m''_{2,b})$, encoder 2 encodes $m'_{2,b}$ as $z_2^n(w^n, m'_{2,b})$ and then transmits $x_2^n(w^n, z_2^n, m''_{2,b})$.

We fix apriori the messages in block B to be $m_{1,B} = 1$, $m'_{2,B} = 1$ and $m''_{2,B} = 1$. Also, to avoid mentioning edge cases explicitly, whenever $m_{1,0}, m'_{2,0}$ or $m''_{2,0}$ appear, we assume that all are fixed to 1.

Decoding:

- *Encoder 1:* At the end of block b, assuming it has already decoded $m'_{2,b-1}$ at the end of block $b - 1$, encoder 1 decodes $m'_{2,b}$ by finding the unique $\hat{m}'_{2,b}$ such that the sequence z_2^n it has observed via cribbing is equal to $z_2^n(w^n, \hat{m}'_{2,b})$.

- *Decoder 1:* In each block b, decoder 1 finds the unique $\hat{m}_{1,b}$ such that $(u_d^n(m_{1,b}, l_d), y_1^n) \in \mathcal{T}_{\epsilon}^{(n)}$ for some l_d.

- *Decoder 2:* Decoder 2 performs backward decoding as follows:

  – In block B, decoder 2 finds a unique $m'_{2,B-1}$ such that the condition (31) is satisfied for some l_c.

$$(w^n(\hat{m}'_{2,B-1}), z_2^n(w^n, 1), x_2^n(w^n, z_2^n, 1),$$
$$u_c^n(w^n, l_c), y_2^n) \in \mathcal{T}_{\epsilon}^{(n)} \tag{31}$$

  – In block b, assuming $m'_{2,b}$ has been decoded correctly, it finds the unique $(\hat{m}'_{2,b-1}, \hat{m}''_{2,b})$ such that the condition (32) is satisfied for some l_c.

$$(w^n(\hat{m}'_{2,b-1}), z_2^n(w^n, m'_{2,b}), x_2^n(w^n, z_2^n,$$
$$\hat{m}''_{2,b}), u_c^n(w^n, l_c), y_2^n) \in \mathcal{T}_{\epsilon}^{(n)} \tag{32}$$

Probability of Error: To get a vanishing probability of error, we can impose the conditions described in the following list.

- Similar to the proof of the mutual covering lemma [37, Ch. 8], we can show that the following conditions are sufficient for the success of encoding at the first transmitter:

$$R_d > I(U_d; W) + \delta(\epsilon'), \tag{33}$$
$$R_d + R_c > I(U_d; U_c, W) + \delta(\epsilon'). \tag{34}$$

- For the decoding at encoder 1 to succeed:

$$R'_2 < H(Z_2|W) - \delta(\epsilon). \tag{35}$$

[4]Note that the u_d^n codewords are generated independently of the w^n codewords.

- For decoding at decoder 1 to succeed:

$$R_1 + R_d < I(U_d; Y_1) - \delta(\epsilon). \tag{36}$$

- For the backward decoding at decoder 2 to succeed, it is sufficient that the following conditions are satisfied:

$$R''_2 < I(X_2; Y_2|W, U_c, Z_2) - \delta(\epsilon), \tag{37}$$
$$R''_2 + R_c < I(U_c, X_2; Y_2|W, Z_2) - \delta(\epsilon), \tag{38}$$
$$R'_2 + R''_2 + R_c < I(W, U_c, X_2; Y_2) - \delta(\epsilon). \tag{39}$$

Noting that $R'_2 + R''_2 = R_2$, eliminating (R_d, R_c, R'_2, R''_2) from (33)-(39) via Fourier-Motzkin elimination, and substituting $U_d = Y_1$ and $U_c = T_1$, we get the achievable region in (30) with the following additional bound on R_1:

$$R_1 < H(Y_1|W, T_1) + H(Y_2|W, Z_2).$$

To conclude the proof of achievability, we show that this bound is rendered redundant by $R_1 < H(Y_1|W)$ which can be proved by the following chain of inequalities:

$$H(Y_1|W, T_1) + H(Y_2|W, Z_2)$$
$$\geq H(Y_1|W, T_1) + H(Y_2|W, X_2)$$
$$= H(Y_1|W, T_1) + H(T_1|W, X_2)$$
$$= H(Y_1|W, T_1) + H(T_1|W)$$
$$= H(Y_1, T_1|W)$$
$$\geq H(Y_1|W).$$

Converse: We now establish the converse. By Fano's inequality, we have the following two relations that are satisfied by any sequence of codes that achieve reliable communication:

$$H(M_1|Y_1^n) \leq n\epsilon_n, \quad H(M_2|Y_2^n) \leq n\epsilon_n,$$

where $\epsilon_n \to 0$ as $n \to \infty$.

First, an upper bound on R_1 is established in (40).

$$nR_1 = H(M_1)$$
$$= H(M_1|Z_2^n)$$
$$\leq I(M_1; Y_1^n|Z_2^n) + n\epsilon_n$$
$$\leq H(Y_1^n|Z_2^n) + n\epsilon_n$$
$$\leq \sum_{i=1}^n H(Y_{1i}|Z_2^{i-1}) + n\epsilon_n$$
$$= \sum_{i=1}^n H(Y_{1i}|W_i) + n\epsilon_n, \tag{40}$$

where $W_i \triangleq Z_2^{i-1}$.

Next, we establish two bounds on R_2, the first one in (41) as follows:

$$nR_2 = H(M_2)$$
$$\leq I(M_2; Y_2^n) + n\epsilon_n$$
$$\leq H(Y_2^n) + n\epsilon_n$$
$$\leq \sum_{i=1}^n H(Y_{2i}) + n\epsilon_n, \tag{41}$$

and the second one in (42) below:

$$
\begin{aligned}
nR_2 &= H(M_2|M_1) \\
&= H(M_2, Z_2^n|M_1) \\
&= H(Z_2^n|M_1) + H(M_2|M_1, Z_2^n) \\
&\overset{(a)}{=} H(Z_2^n|M_1) + H(M_2|M_1, Z_2^n, T_1^n) \\
&\le H(Z_2^n|M_1) + I(M_2; Y_2^n|M_1, Z_2^n, T_1^n) + n\epsilon_n \\
&\le H(Z_2^n) + H(Y_2^n|Z_2^n, T_1^n) + n\epsilon_n \\
&\le \sum_{i=1}^{n} H(Z_{2i}|W_i) + \sum_{i=1}^{n} H(Y_{2i}|W_i, T_{1i}, Z_{2i}) + n\epsilon_n, \\
&\overset{(b)}{=} \sum_{i=1}^{n} H(Z_{2i}|W_i, T_{1i}) + \sum_{i=1}^{n} H(Y_{2i}|W_i, T_{1i}, Z_{2i}) \\
&\quad + n\epsilon_n, \\
&= \sum_{i=1}^{n} H(Y_{2i}, Z_{2i}|W_i, T_{1i}) + n\epsilon_n, \quad (42)
\end{aligned}
$$

where step (a) follows because T_1^n is a function of X_1^n which is a function of (M_1, Z_2^n), and step (b) follows because $Z_{2i} - W_i - T_{1i}$.

Finally, we establish two bounds on the sum-rate, the first one in (43) below:

$$
\begin{aligned}
n(R_1 &+ R_2) \\
&= H(M_1|Z_1^n) + H(M_2, Z_2^n) \\
&= H(M_1, T_1^n|Z_2^n) + H(Z_2^n) + H(M_2|Z_2^n) \\
&= H(T_1^n|Z_2^n) + H(M_1|T_1^n, Z_2^n) + H(Z_2^n) + H(M_2|Z_2^n) \\
&\overset{(a)}{\le} H(Y_2^n|X_2^n, Z_2^n) + I(M_1; Y_1^n|T_1^n, Z_2^n) + H(Z_2^n) \\
&\quad + I(M_2; Y_2^n|Z_2^n) + n\epsilon_n \\
&\le H(Y_2^n|X_2^n, Z_2^n) + H(Y_1^n|T_1^n, Z_2^n) + H(Z_2^n) \\
&\quad + H(Y_2^n|Z_2^n) - H(Y_2^n|M_2, Z_2^n) + n\epsilon_n \\
&= H(Y_2^n|X_2^n, Z_2^n) + H(Y_1^n|T_1^n, Z_2^n) + H(Z_2^n) \\
&\quad + H(Y_2^n|Z_2^n) - H(Y_2^n|M_2, X_2^n, Z_2^n) + n\epsilon_n \\
&\overset{(b)}{=} H(Y_2^n|X_2^n, Z_2^n) + H(Y_1^n|T_1^n, Z_2^n) + H(Z_2^n) \\
&\quad + H(Y_2^n|Z_2^n) - H(Y_2^n|X_2^n, Z_2^n) + n\epsilon_n \\
&= H(Y_1^n|T_1^n, Z_2^n) + H(Z_2^n) + H(Y_2^n|Z_2^n) + n\epsilon_n \\
&= H(Y_1^n|T_1^n, Z_2^n) + H(Y_2^n, Z_2^n) + n\epsilon_n \\
&\le \sum_{i=1}^{n} H(Y_{1i}|T_{1i}, W_i) + \sum_{i=1}^{n} H(Y_{2i}, Z_{2i}|W_i) + n\epsilon_n, \\
&\quad (43)
\end{aligned}
$$

where step (a) uses the fact that $H(T_1^n|Z_2^n) \le H(Y_2^n|X_2^n, Z_2^n)$, which is proved below:

$$
\begin{aligned}
H(T_1^n|Z_2^n) &\le H(T_1^n) \\
&= H(Y_2^n|X_2^n) \\
&= H(Y_2^n|X_2^n, Z_2^n),
\end{aligned}
$$

and step (b) follows because $M_2 - (X_2^n, Z_2^n) - Y_2^n$.
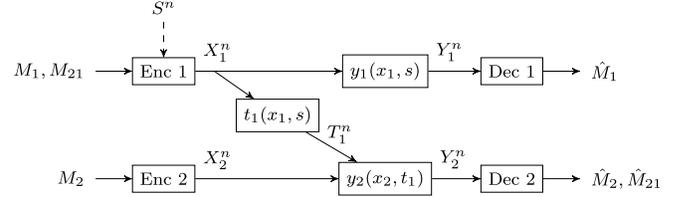
Fig. 11. The Injective Deterministic S-D Z-C.

The second bound on the sum-rate is established in (44) as follows:

$$
\begin{aligned}
n(R_1 &+ R_2) \\
&= H(M_1, T_1^n|Z_2^n) + H(M_2) \\
&\le H(T_1^n|Z_2^n) + H(M_1|T_1^n, Z_2^n) + I(M_2; Y_2^n) + n\epsilon_n \\
&\le H(Y_2^n|X_2^n, Z_2^n) + I(M_1; Y_1^n|T_1^n, Z_2^n) + H(Y_2^n) \\
&\quad - H(Y_2^n|M_2) + n\epsilon_n \\
&\le H(Y_2^n|X_2^n, Z_2^n) + H(Y_1^n|T_1^n, Z_2^n) + H(Y_2^n) \\
&\quad - H(Y_2^n|X_2^n, Z_2^n) + n\epsilon_n \\
&= H(Y_1^n|T_1^n, Z_2^n) + H(Y_2^n) + n\epsilon_n \\
&\le \sum_{i=1}^{n} H(Y_{1i}|T_{1i}, W_i) + \sum_{i=1}^{n} H(Y_{2i}) + n\epsilon_n. \quad (44)
\end{aligned}
$$

In (40)-(44), we can introduce a time-sharing random variable Q uniformly distributed on $[1 : n]$. Defining W to be (W_Q, Q) and (X_1, X_2, Y_1, Y_2) to be $(X_{1Q}, X_{2Q}, Y_{1Q}, Y_{2Q})$, we get the required bounds on the rates.

We also require the Markov relationship $X_1 - W - X_2$ to be satisfied. Since W_i is chosen to be Z_2^{i-1}, we immediately have $X_{1i} - W_i - X_{2i}$ and hence $X_1 - W - X_2$. Finally, the bound on the cardinality of W can be established using the standard convex cover method. ∎

VI. EXTENSIONS

A. State-Dependent Z-Channel

The result in Theorem 3 can be extended easily to Z-channels in which transmitter 1 also wishes to communicate a message M_{21} at rate R_{21} to receiver 2, as shown in Fig. 11.

Theorem 6: The capacity region of the injective deterministic state-dependent Z-channel is the set of rate pairs (R_1, R_{21}, R_2) that satisfy

$$
\begin{aligned}
R_1 &\le H(Y_1|S, Q), \\
R_2 &\le H(Y_2|T_1, Q), \\
R_{21} &\le H(T_1|S, Q), \\
R_1 + R_{21} &\le H(T_1, Y_1|S, Q), \\
R_2 + R_{21} &\le H(Y_2|Q) - I(T_1; S|Q), \\
R_1 + R_2 + R_{21} &\le H(Y_1|T_1, S, Q) + H(Y_2|Q) - I(T_1; S|Q),
\end{aligned}
$$

for some pmf $p(q)p(x_1|s, q)p(x_2|q)$, where $|\mathcal{Q}| \le 6$.

The achievability scheme for this case is similar to the achievability scheme for the Z-IC described in Section IV-C except that now the v^n codewords at encoder 1 are also binned, and this bin-index corresponds to the message M_{21}, that is to be communicated from transmitter 1 to receiver 2. The converse can be established by following similar steps as the converse for the Z-IC.
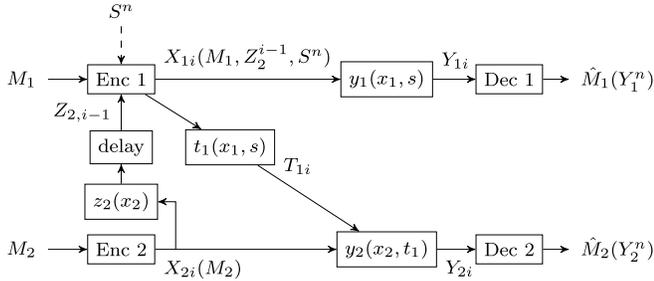
Fig. 12. State-Dependent Injective Deterministic Z-Interference Channel with Unidirectional Partial Cribbing.

Remark 4: Since broadcast channel and multiple-access channel are special cases of the Z-channel, Theorem 6 also provides the capacity region for the deterministic broadcast channel and the injective deterministic multiple-access channel.

B. State-Dependent Injective Deterministic Z-IC With Unidirectional Partial Cribbing

To illustrate further the advantages of the multicoding scheme, we consider a model that combines the state-dependent Z-IC and the Z-IC with unidirectional partial cribbing, as depicted in Fig. 12. We can combine the achievability schemes for the two component setups from Sections IV-C and V-B in a straightforward manner to get an achievability scheme for this setup. It turns out that this is capacity-achieving, resulting in the following theorem.

Theorem 7: The capacity region of the channel in Fig. 12 is given by the convex closure of rate pairs (R_1, R_2) satisfying

$$
\begin{aligned}
R_1 &< H(Y_1|W, S) \\
R_2 &< H(Y_2, Z_2|T_1, W) \\
R_2 &< \min(H(Y_2), H(Y_2, Z_2|W)) - I(T_1; S|W) \\
R_1 + R_2 &< H(Y_1|W, T_1, S) + \min(H(Y_2), H(Y_2, Z_2|W)) \\
&\quad - I(T_1; S|W)
\end{aligned}
$$

for pmf of the form $p(w)p(x_2|w)p(x_1|w, s)$.

The proof of the converse combines ideas from the converse proofs we have presented for the state-only case and the cribbing-only case.

VII. Discussion

Note that there is one difference between the multicoding-based achievability scheme for the canonical interference channel and the achievability schemes for the settings in Sections IV and V. For the former, the codebook associated with the auxiliary random variable U is used at both receivers during decoding, whereas for the cribbing setup, the codebook associated with auxiliary random variable U_d is only used at the desired receiver, while that associated with the auxiliary random variable U_c is only used at the undesired receiver. One way to understand this dichotomy is to observe similarities with the inner bound for broadcast channel which combines Marton coding and superposition coding, given in [37, Proposition 8.1] which involves three auxiliary random variables U_0, U_1, U_2. Here, the random variable U_0 is used at both receivers during decoding, while U_1 and U_2 are used only at the respective receivers. Now for the deterministic cribbing

setup that we have considered, we can think that in the optimal scheme, U_0 can be set to be the empty random variable ϕ, and U_1 and U_2 correspond to U_d and U_c respectively, i.e., there is no superposition coding, only Marton coding is used (with the distinction from usual Marton coding that the set of U_c^n codewords is not binned). The situation is similar for deterministic and semideterministic broadcast channels where $U_0 = \phi$ is optimal too. On the other hand, the Han-Kobayashi scheme employing superposition coding can be thought of as setting U_2 to ϕ, and U_0 and U_1 correspond to U and X respectively (no Marton coding, only superposition coding). The key observation is that in the Han-Kobayashi scheme, it is not necessary to think of U as encoding a part of the message explicitly, which can be exploited to view the superposition coding instead in a manner resembling Marton coding, as we have shown in Section III (again with the distinction from usual Marton coding that the set of codewords corresponding to the auxiliary random variable is not binned). This clarifies the dichotomy mentioned at the beginning of this paragraph. Alternatively, we can understand both ways of decoding in a unified manner, as in [39].

Acknowledgment

Appendix I
Equivalence to Han-Kobayashi Region

We show that the region in (13) is equivalent to the Han-Kobayashi region.

- Consider the upper bound on R_1:

$$
\begin{aligned}
e - a &= I(U_1, X_1; U_2, Y_1) \\
&\overset{(a)}{=} I(X_1; U_2, Y_1) \\
&\overset{(b)}{=} I(X_1; Y_1|U_2),
\end{aligned}
\tag{45}
$$

where step (a) follows since $U_1 - X_1 - (U_2, Y_1)$ is a Markov chain, and step (b) follows since X_1 is independent of U_2.

- Similarly,

$$
i - b = I(X_2; Y_2|U_1).
\tag{46}
$$

- Consider the first upper bound on the sum-rate $c + j - a - b$:

$$
\begin{aligned}
&c + j - a - b \\
&= I(X_1; U_1, U_2, Y_1) + I(U_2; X_2) + I(U_1; Y_2) \\
&\quad + I(U_2, X_2; U_1, Y_2) - I(U_2; X_2) - I(U_1; X_1) \\
&\overset{(a)}{=} I(X_1; U_2, Y_1|U_1) + I(U_1; Y_2) + I(U_2, X_2; U_1, Y_2) \\
&\overset{(b)}{=} I(X_1; U_2, Y_1|U_1) + I(U_1; Y_2) + I(X_2; U_1, Y_2) \\
&\overset{(c)}{=} I(X_1; U_2, Y_1|U_1) + I(U_1; Y_2) + I(X_2; Y_2|U_1) \\
&\overset{(d)}{=} I(X_1; Y_1|U_1, U_2) + I(X_2, U_1; Y_2),
\end{aligned}
\tag{47}
$$

where step (a) follows by the chain rule of mutual information, step (b) follows by the Markov chain $U_2 - X_2 - (U_1, Y_2)$, step (c) follows since U_1 and X_2 are

independent and step (d) follows by the independence of U_2 and (U_1, X_1).

- By similar steps, $f + g - a - b =$

$$I(X_1, U_2; Y_1) + I(X_2; Y_2|U_1, U_2). \qquad (48)$$

- The remaining upper-bound on the sum-rate $d + h - a - b$ can be simplified as follows:

$$
\begin{aligned}
&d + h - a - b \\
&= I(X_1, U_2; U_1, Y_1) + I(X_2, U_1; U_2, Y_2) \\
&\quad - I(U_1; X_1) - I(U_2; X_2) \\
&= I(X_1, U_2; Y_1|U_1) + I(X_2, U_1; Y_2|U_2), \qquad (49)
\end{aligned}
$$

which follows by the chain rule of mutual information and the independence of (U_1, X_1) and (U_2, X_2).

- The upper bound on $2R_1 + R_2$ can be simplified as follows:

$$
\begin{aligned}
&c + h + f - 2a - b \\
&= I(X_1; U_1, U_2, Y_1) + I(X_2, U_1; U_2, Y_2) + I(U_1; X_1) \\
&\quad + I(U_2; Y_1) + I(U_1, X_1; U_2, Y_1) - 2I(U_1; X_1) \\
&\quad - I(U_2; X_2) \\
&\overset{(a)}{=} I(X_1; U_2, Y_1|U_1) + I(X_2, U_1; Y_2|U_2) + I(U_2; Y_1) \\
&\quad + I(U_1, X_1; U_2, Y_1) \\
&\overset{(b)}{=} I(X_1; U_2, Y_1|U_1) + I(X_2, U_1; Y_2|U_2) + I(U_2; Y_1) \\
&\quad + I(X_1; Y_1|U_2) \\
&\overset{(c)}{=} I(X_1; Y_1|U_1, U_2) + I(X_2, U_1; Y_2|U_2) \\
&\quad + I(X_1, U_2; Y_1), \qquad (50)
\end{aligned}
$$

where step (a) holds by the chain rule of mutual information and the independence of U_1 and (U_2, X_2), step (b) follows by $U_1 - X_1 - (U_2, Y_1)$ and the independence of X_1

and U_2, and step (c) follows by the chain rule of mutual information and the independence of U_2 and (U_1, X_1).

- Finally, $d + g + j - a - 2b$ can be similarly shown to be equal to

$$I(X_2; Y_2|U_1, U_2) + I(X_1, U_2; Y_1|U_1) + I(X_2, U_1; Y_2). \qquad (51)$$

APPENDIX II
MULTIVARIATE PACKING LEMMA

Lemma 1: Consider the following four assumptions.

(A) Let $\{U, X_1, X_2, \ldots, X_K, Y\}$ be random variables that have some joint distribution $p_{U, X_1, X_2, \ldots, X_K, Y}$.

(B) Let $(\tilde{U}^n, \tilde{Y}^n) \sim p(\tilde{u}^n, \tilde{y}^n)$ be a pair of arbitrarily distributed sequences.

(C) For each $j \in [1 : K]$, let $\{X_j^n(m_j), \ m_j \in \mathcal{A}_j\}$, where $|\mathcal{A}_j| \leq 2^{nR_j}$, be random sequences each distributed according to $\prod_{i=1}^{n} p_{X_j|U}(x_{ji}|\tilde{u}_i)$.

(D) For each $j \in [1 : K]$ and each m_j, assume that $X_j^n(m_j)$ is pairwise conditionally independent of $(\ldots, X_{j-1}^n(m_{j-1}), X_{j+1}^n(m_{j+1}), \ldots, \tilde{Y}^n)$ given $\tilde{U}^n$ for all $(\ldots, m_{j-1}, m_{j+1}, \ldots)$, but arbitrarily dependent on other $X_j^n(\cdot)$ sequences.

Then there exists $\delta(\epsilon)$ that tends to zero as $\epsilon \to 0$ such that

$$
\begin{aligned}
&\mathsf{P}((\tilde{U}^n, X_1^n(m_1), X_2^n(m_2), \ldots, X_K^n(m_K), \tilde{Y}^n) \in \mathcal{T}_\epsilon^{(n)} \\
&\qquad \text{for some } m_1 \in \mathcal{A}_1, m_2 \in \mathcal{A}_2, \ldots, m_K \in \mathcal{A}_K)
\end{aligned}
$$

tends to 0 as $n \to \infty$ if

$$\sum_{j=1}^{K} R_j < \sum_{j=1}^{K} H(X_j|U) - H(X_1, X_2, \ldots, X_K|U, Y) - \delta(\epsilon). \qquad (52)$$

$$
\begin{aligned}
&\mathsf{P}\left(\left(\tilde{U}^n, \{X_j^n(\tilde{m}_j)\}_{j=1}^{K}, \tilde{Y}^n\right) \in \mathcal{T}_\epsilon^{(n)}\right) \\
&= \sum_{(\tilde{u}^n, \tilde{y}^n) \in \mathcal{T}_\epsilon^{(n)}} p(\tilde{u}^n, \tilde{y}^n) \mathsf{P}\left(\left(\tilde{U}^n, X_1^n(m_1), X_2^n(m_2), \ldots, X_K^n(m_K), \tilde{Y}^n\right) \in \mathcal{T}_\epsilon^{(n)} \middle| \tilde{U}^n = \tilde{u}^n, \tilde{Y}^n = \tilde{y}^n\right) \\
&\overset{(a)}{=} \sum_{(\tilde{u}^n, \tilde{y}^n) \in \mathcal{T}_\epsilon^{(n)}} p(\tilde{u}^n, \tilde{y}^n) \mathsf{P}\left(\left(\tilde{u}^n, X_1^n(m_1), X_2^n(m_2), \ldots, X_K^n(m_K), \tilde{y}^n\right) \in \mathcal{T}_\epsilon^{(n)} \middle| \tilde{U}^n = \tilde{u}^n\right) \\
&\overset{(b)}{=} \sum_{(\tilde{u}^n, \tilde{y}^n) \in \mathcal{T}_\epsilon^{(n)}} p(\tilde{u}^n, \tilde{y}^n) \sum_{T_\epsilon^{(n)}(X_1, X_2, \ldots, X_K|\tilde{u}^n, \tilde{y}^n)} p(x_1^n, \ldots, x_K^n|\tilde{u}^n) \\
&\overset{(c)}{=} \sum_{(\tilde{u}^n, \tilde{y}^n) \in \mathcal{T}_\epsilon^{(n)}} p(\tilde{u}^n, \tilde{y}^n) \sum_{T_\epsilon^{(n)}(X_1, X_2, \ldots, X_K|\tilde{u}^n, \tilde{y}^n)} \prod_{j=1}^{K} p(x_j^n|\tilde{u}^n) \\
&\leq \sum_{(\tilde{u}^n, \tilde{y}^n) \in \mathcal{T}_\epsilon^{(n)}} p(\tilde{u}^n, \tilde{y}^n) \left| T_\epsilon^{(n)}\left(X_1, X_2, \ldots, X_K|\tilde{u}^n, \tilde{y}^n\right) \right| \prod_{j=1}^{K} 2^{-n(H(X_j|U) - \delta(\epsilon))} \\
&\leq \sum_{(\tilde{u}^n, \tilde{y}^n) \in \mathcal{T}_\epsilon^{(n)}} p(\tilde{u}^n, \tilde{y}^n) 2^{n(H(X_1, \ldots, X_K|U, Y) + \delta(\epsilon))} \prod_{j=1}^{K} 2^{-n(H(X_j|U) - \delta(\epsilon))} \\
&= 2^{n(H(X_1, \ldots, X_K|U, Y) + \delta(\epsilon))} \prod_{j=1}^{K} 2^{-n(H(X_j|U) - \delta(\epsilon))}. \qquad (53)
\end{aligned}
$$

Proof: The proof follows on similar lines as that of the packing lemma in [37, Ch. 3].

Consider a fixed tuple $(\tilde{m}_1, \tilde{m}_2, \ldots, \tilde{m}_K)$. The chain of inequalities resulting in (53), as shown at the bottom of the previous page, bounds the probability of $(\tilde{U}^n, \{X_j^n(\tilde{m}_j)\}_{j=1}^K, \tilde{Y}^n)$ being jointly typical, where (*a*), (*b*) and (*c*) follow from assumptions (C) and (D). Then we can apply the union bound over all possible tuples $(\tilde{m}_1, \tilde{m}_2, \ldots, \tilde{m}_K)$ to get the condition (52). ∎

Example 1: For the case $U = \phi$ and random variables X_1, X_2, Y, the condition (52) can be expressed as follows:

$$R_1 + R_2 < H(X_1) + H(X_2) - H(X_1, X_2|Y) - \delta(\epsilon)$$
$$= I(X_1; X_2) + I(X_1, X_2; Y) - \delta(\epsilon). \quad (54)$$

Example 2: For the case $U = \phi$ and random variables X_1, X_2, X_3, Y, the condition (52) can be expressed as follows:

$$R_1 + R_2 + R_3 < H(X_1) + H(X_2) + H(X_3)$$
$$- H(X_1, X_2, X_3|Y) - \delta(\epsilon)$$
$$= I(X_1; X_2) + I(X_3; Y)$$
$$+ I(X_1, X_2; X_3, Y) - \delta(\epsilon). \quad (55)$$

REFERENCES

[1] R. Kolte, A. Özgür, and H. Permuter, "Deterministic Z-interference channels with unidirectional partial cribbing," in *Proc. 48th Annu. Conf. Inf. Sci. Syst.*, Mar. 2014, pp. 1–6.
[2] R. Kolte, A. Özgür, and H. Permuter, "The capacity region of a class of deterministic state-dependent Z-interference channels," in *Proc. IEEE Int. Symp. Inf. Theory*, Jun./Jul. 2014, pp. 656–660.
[3] A. El Gamal and M. Costa, "The capacity region of a class of deterministic interference channels," *IEEE Trans. Inf. Theory*, vol. 28, no. 2, pp. 343–346, Mar. 1982.
[4] H.-F. Chong, M. Motani, and H. K. Garg, "The capacity region of a class of interference channels," in *Proc. IEEE Int. Symp. Inf. Theory*, Jun. 2007, pp. 2856–2860.
[5] H. Sato, "The capacity of the Gaussian interference channel under strong interference," *IEEE Trans. Inf. Theory*, vol. 27, no. 6, pp. 786–788, Nov. 1981.
[6] M. Costa and A. El Gamal, "The capacity region of the discrete memoryless interference channel with strong interference (corresp.)," *IEEE Trans. Inf. Theory*, vol. 33, no. 5, pp. 710–711, Sep. 1987.
[7] S. T. Chung and J. M. Cioffi, "The capacity region of frequency-selective Gaussian interference channels under strong interference," *IEEE Trans. Commun.*, vol. 55, no. 9, pp. 1812–1821, Sep. 2007.
[8] R. Benzel, "The capacity region of a class of discrete additive degraded interference channels," *IEEE Trans. Inf. Theory*, vol. 25, no. 2, pp. 228–231, Mar. 1979.
[9] N. Liu and S. Ulukus, "The capacity region of a class of discrete degraded interference channels," *IEEE Trans. Inf. Theory*, vol. 54, no. 9, pp. 4372–4378, Sep. 2008.
[10] H.-F. Chong and M. Motani, "The capacity region of a class of semi-deterministic interference channels," *IEEE Trans. Inf. Theory*, vol. 55, no. 2, pp. 598–603, Feb. 2009.
[11] T. Han and K. Kobayashi, "A new achievable rate region for the interference channel," *IEEE Trans. Inf. Theory*, vol. 27, no. 1, pp. 49–60, Jan. 1981.
[12] H.-F. Chong, M. Motani, and H. K. Garg, "A comparison of two achievable rate regions for the interference channel," in *Proc. Inf. Theory Appl. Workshop*, Feb. 2006, pp. 6–10.
[13] T. Cover, "Broadcast channels," *IEEE Trans. Inf. Theory*, vol. 18, no. 1, pp. 2–14, Jan. 1972.
[14] C. Nair, L. Xia, and M. Yazdanpanah, "Sub-optimality of the Han–Kobayashi achievable region for interference channels," *CoRR*, vol. 1502, no. 02589, pp. 1–8, Feb. 2015. [Online]. Available: http://arxiv.org/abs/1502.02589

[15] S. H. Lim, K. T. Kim, and Y.-H. Kim, "Distributed decode-forward for multicast," in *Proc. IEEE Int. Symp. Inf. Theory*, Jun./Jul. 2014, pp. 636–640.
[16] S. I. Gel'fand and M. S. Pinsker, "Coding for channel with random parameters," *Problems Control Inf. Theory*, vol. 9, no. 1, pp. 19–31, 1980.
[17] A. El Gamal and E. van der Meulen, "A proof of Marton's coding theorem for the discrete memoryless broadcast channel (Corresp.)," *IEEE Trans. Inf. Theory*, vol. 27, no. 1, pp. 120–122, Jan. 1981.
[18] A. S. Avestimehr, S. N. Diggavi, and D. N. C. Tse, "Wireless network information flow: A deterministic approach," *IEEE Trans. Inf. Theory*, vol. 57, no. 4, pp. 1872–1905, Apr. 2011.
[19] L. Zhang, J. Jiang, and S. Cui, "Gaussian interference channel with state information," *IEEE Trans. Wireless Commun.*, vol. 12, no. 8, pp. 4058–4071, Aug. 2013.
[20] S. Ghasemi-Goojani and H. Behroozi, "On the achievable rate-regions for state-dependent Gaussian interference channel," *CoRR*, vol. 1301, no. 5535, pp. 1–18, Jan. 2013.
[21] R. Duan, Y. Liang, and S. S. Shitz, "On the capacity region of Gaussian interference channels with state," in *Proc. IEEE Int. Symp. Inf. Theory*, Jul. 2013, pp. 1097–1101.
[22] R. Duan, Y. Liang, A. Khisti, and S. S. Shitz, "State-dependent Gaussian Z-channel with mismatched side-information and interference," in *Proc. IEEE Inf. Theory Workshop*, Sep. 2013, pp. 1–5.
[23] S. Rini, D. Tuninetti, and N. Devroye, "New inner and outer bounds for the memoryless cognitive interference channel and some new capacity results," *IEEE Trans. Inf. Theory*, vol. 57, no. 7, pp. 4087–4109, Jul. 2011.
[24] A. Somekh-Baruch, S. Shamai (Shitz), and S. Verdu, "Cognitive interference channels with state information," in *Proc. IEEE Int. Symp. Inf. Theory*, Jul. 2008, pp. 1353–1357.
[25] R. Duan and Y. Liang, "Gaussian cognitive interference channels with state," in *Proc. IEEE Int. Symp. Inf. Theory*, Jul. 2012, pp. 1822–1826.
[26] M. Kazemi and A. Vosoughi, "On the capacity of the state-dependent cognitive interference channel," in *Proc. IEEE Int. Symp. Inf. Theory*, Jul. 2013, pp. 2044–2048.
[27] I.-H. Wang and D. N. C. Tse, "Interference mitigation through limited transmitter cooperation," *IEEE Trans. Inf. Theory*, vol. 57, no. 5, pp. 2913–2940, May 2011.
[28] V. Prabhakaran and P. Viswanath, "Interference channels with source cooperation," *IEEE Trans. Inf. Theory*, vol. 57, no. 1, pp. 156–186, Jan. 2011.
[29] S. Yang and D. Tuninetti, "Interference channel with generalized feedback (a.k.a. with source cooperation): Part I: Achievable region," *IEEE Trans. Inf. Theory*, vol. 57, no. 5, pp. 2686–2710, May 2011.
[30] M. Cardone, D. Tuninetti, R. Knopp, and U. Salim. (Jul. 2012). "On the capacity of the two-user Gaussian causal cognitive interference channel." [Online]. Available: https://arxiv.org/abs/1207.5319
[31] H. Asnani and H. H. Permuter, "Multiple-access channel with partial and controlled cribbing encoders," *IEEE Trans. Inf. Theory*, vol. 59, no. 4, pp. 2252–2266, Apr. 2013.
[32] L. Wang, E. Şaşoğlu, B. Bandemer, and Y.-H. Kim, "A comparison of superposition coding schemes," in *Proc. IEEE Int. Symp. Inf. Theory*, Istanbul, Turkey, Jul. 2013, pp. 2970–2974.
[33] H.-F. Chong, M. Motani, H. K. Garg, and H. El Gamal, "On the Han–Kobayashi region for the interference channel," *IEEE Trans. Inf. Theory*, vol. 54, no. 7, pp. 3188–3195, Jul. 2008.
[34] G. Kramer, "Review of rate regions for interference channels," in *Proc. Int. Zurich Seminar Commun.*, 2006, pp. 162–165.
[35] K. Kobayashi and T. Han, "A further consideration on the HK and the CMG regions for the interference channel," in *Proc. Inf. Theory Appl. Workshop*, Jan./Feb. 2007, pp. 1–7.
[36] A. Lapidoth and L. Wang, "The state-dependent semideterministic broadcast channel," *IEEE Trans. Inf. Theory*, vol. 59, no. 4, pp. 2242–2251, Apr. 2013.
[37] A. El Gamal and Y.-H. Kim, *Network Information Theory*. New York, NY, USA: Cambridge Univ. Press, 2012.
[38] V. R. Cadambe, S. A. Jafar, and S. Vishwanath, "The capacity region of a class of deterministic Z channels," in *Proc. IEEE Int. Symp. Inf. Theory*, Jun./Jul. 2009, pp. 2634–2638.
[39] B. Bandemer, A. El Gamal, and Y.-H. Kim, "Simultaneous nonunique decoding is rate-optimal," in *Proc. 50th Annu. Allerton Conf. Commun., Control, Comput. (Allerton)*, Oct. 2012, pp. 9–16.

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