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Half-duplex cooperative relay channel Gaussian compression

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Abstract

Utilizing the CS theory and its strong connection to low-density parity-check codes, we provide compressive transmission—a method that uses CS as the channel code and amplitude modulation to transmit multi-level CS random projections directly. This piece concentrates on the compressive cooperation inside a relay channel. Our research focuses on four decode-and-forward (DF) methods—code diversity, receiver diversity, sequential decoding, and concatenated decoding—in a three-terminal half-duplex Gaussian relay channel, and we measure the potential rates for each. To compare the four strategies, we use numerical calculation and virtual experimentation. Additionally, we examine and contrast compressive cooperation with an alternative source channel coding scheme for sparse source transmission. Transmission efficiency and channel adaptation are two areas where collaborative compression shows great potential.

Introduction

"Compressive sensing" (CS) [1,2] is a relatively recent field of study that aims to recover sparse signals with a small number of randomly chosen linear projections. Recently, it has been shown that CS and LDPC codes, a well-known kind of channel coding, are closely associated. [3,4]. When the measurement matrix in CS is employed as the parity-check matrix of an LDPC code, the CS reconstruction approach provided by Baron et al. [5] is virtually identical to Lucy's LDPC decoding algorithm [6]. Given the similarities between CS codes and LDPC codes, we suggest and study compressive transmission, which uses CS codes as channel codes and applies amplitude modulation directly to transmit multi-level CS random projections. Because of its capabilities in both source compression and channel protection, CS may be seen as a hybrid code that combines the two. When sending sparse or compressible data, traditional systems use source coding to compress it first, and then channel coding to protect it over the lossy channel. Compared to the conventional method, compressive transmission offers a number of clear advantages. Thanks to its use of random projections to provide measurements unrelated to the compressible patterns, CS streamlines operations at the transmitter end. Thin signal-gathering devices, such as sensor nodes and single-pixel cameras, may benefit from this [7]. It also makes things last longer. It just takes a little error of one bit to corrupt compressed data. The conventional approach could fail to decode a full coding block or even a data sequence if the channel code isn't strong enough to protect data in an unexpectedly degraded channel. Conversely, since CS random projections operate directly on source bits, errors in individual bits do not impact the overall data quality.

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Model of a Channel

A three-endpoint relay channel operating in half-duplex mode is the subject of this discussion [9]. The letters S, R, and D stand for "source," "relay," and "destination," in that order. Consider the channel gains of three direct connections: (S, D), (S, R), and (R, D). We'll refer to them as csd, csr, and crd, respectively. Assuming equal transit durations between the two endpoints, this research assumes that the relay is positioned along the SD line. As a result of a 2-fold attenuation, the channel gains are csd=1, csr=4, and crd= csd. In a half-duplex configuration, relay R can only receive signals; it cannot transmit them. Because of this, the channel is shared between the two modes of operation, as shown in Figure 1. The time proportion of MAC mode is 1t if the time percentage of BC mode is denoted as t (0t1). When in BC mode, the source emits the symbol x1. The signal could be picked up by both the relay and the receiver. Signals from yr and yd1 have been picked up by the relay and the ultimate destination, respectively.

$$y_r = \sqrt{c_{sr}} x_1 + z_r$$
$$y_{d_1} = \sqrt{c_{sd}} x_1 + z_{d_1}$$

where zr and zd1 are Gaussian noises perceived at R and D

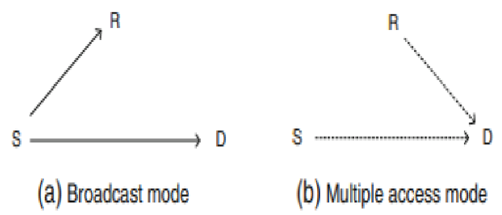

Fig 1 A Three – terminal relay network with R operating in half – duplex mode

At the end of BC mode, the relay generates message w based on its received signals. Then in MAC mode, the source transmits x2 while the relay transmits w simultaneously. The destination receives the superposition of the two signals which can be represented by:

$$y_{d_2} = \sqrt{c_{sd}} x_2 + \sqrt{c_{rd}} w + z_{d_2}$$

where zd2 is the perceived Gaussian noise at D. Finally, the destination D decodes original message from received signals during BC and MAC modes. Assume that random variables Zr, Zd1 and Zd2 , corresponding to the noises zr, zd1 and zd2 , have the same unity energy. Thus, the system resource can be easily characterized by the transmission energy budget E. Denote Es1 , Es2 and Er as the average symbol energy for random variables X1, X2 and W, which correspond to x1, x2 and w, respectively. Then the system constraint can be described by the following inequality:

$$tE_{s_1} + (1-t)(E_{s_2} + E_r) \leq E$$

For clarity of presentation, the following notations are defined as the received signal strength at different links:

$$P_{sd_1} = c_{sd} E_{s_1}, \qquad P_{sr} = c_{sr} E_{s_1}$$
$$P_{sd_2} = c_{sd} E_{s_2}, \qquad P_{rd} = c_{rd} E_r$$

Transmission with compression 3.1 Shift in transmission force via a relay channel For the sake of this study, we represent the original data as bits where the probability is p and the result is 0 for all values between 1 and p. The source is thought of being sparse or compressible when p = 0.5. Segmenting source bits into blocks of length n is done during transmission. In T, we have one source block denoted as u=[u1, u2,..., un]. The source must first create CS measurements in the BC mode using a sparse Rademacher matrix with elements picked from {0, 1, −1} before transmitting u across the relay channel. Here are several ways to represent the transmitted symbols, which are m1 measurements:

$$\mathbf{x}_1 = \sqrt{\alpha_{s_1}} A_1 \mathbf{u}$$

where αs1 is a power scaling parameter to match with sender's power constraint

In MAC mode, the source generates and transmits another m2 measurements using identical/different Rademacher matrix, which can be represented by:

$$\mathbf{x}_2 = \sqrt{\alpha_{s_2}} A_2 \mathbf{u}$$

This article studies DF strategies and leaves compressand-forward (CF) strategies to future

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research. A prerequisite of DF relaying is that the relay can fully decode the messages transmitted by the source in BC mode. With this assumption, the relay can generate new measurements of u and transmits them in MAC mode:

$$\mathbf{w} = \sqrt{\alpha_r} B\mathbf{u}$$

where B is also a Rademacher matrix, and w contains m2 measurements. The power scaling parameters in above equations ensure that:

$$E\left[X_1^2\right] \le E_{s_1}; \quad E\left[X_2^2\right] \le E_{s_2}; \quad E\left[W^2\right] \le E_r$$

Under these power constraints, the corresponding scaling parameters αs1, αs2 and αr can be derived, where the average power of symbol A1u, A2u and Bu are determined by the row weight of corresponding sampling matrix and sparsity probability of u. Since m1 measurements are transmitted in BC mode and m2 measurements are transmitted in MAC mode, the time proportion of BC mode can be calculated as:

$$t = \frac{m_1}{m_1 + m_2}$$

The destination will perform CS decoding from all the measurements received in both modes. The belief propagation algorithm (CS-BP) proposed by Baron et al. [5] is adopted in our system. If the decoding is successful, the transmission rate can be computed by:

$$R = \frac{H(\mathbf{u})}{m_1 + m_2}$$

The cost and time slots for the BC mode and MAC mode, respectively, are determined by m1 and m2, whereas H(u) is the entropy of u. The rate R, given in bits per channel usage, is determined by setting the base of the logarithm in entropy computation to 2. Equation (11) has a relationship between the rate R and the symbol energies Es1, Es2, and Er. The number of measurements required for source recovery may be reduced and the quality of measurements can be improved with an increase in the matching transmission power during compressive transmission via a link channel. Consequently, a greater amount of transmission energy might be used to reach a higher rate. Since just a tiny part of the source vector is used to calculate measurements at the source node, the encoding complexity is quite low in such a compressive transmission system. With L being the average row weight, Q the dimension of the sent message in the belief propagation process, T the iteration number, and M the number of received measurements, the complexity of the belief-propagation based decoding method is O(TMLQ log(Q)) [5].

Numerical study and simulations

In the previous section, we have proposed four DF schemes and formulated their achievable rates. In this section we will first evaluate the four compressive cooperation strategies through both numerical studies and MATLAB simulations, and then comparison between compressive transmission and a conventional scheme based on source compression and binary channel coding is made. In both evaluations, the binary source message with p = 0.1 is considered. As the source is binary, we can evaluate the channel rate with bit rate and characterize the unperfect transmissions with bit error rate (BER). For convenience, instead of information rate we present the results using bit rate:

$$R_b(P) = n/(m_1 + m_2)$$

where n is the block length of u. We set n = 6000 if not otherwise stated. All the results shown in this section are about Rb(P). However, we continue to use notation R(P) when the statement is valid for both rates. Actually, for 0.1-sparse data, the bit rate Rb(P) differs from the information rate R(P) (11) only by a constant coefficient:

$$R(P) = H(p = 0.1) \times R_b(P) \approx 0.469 \times R_b(P)$$

At the end of Section 3, we introduce the notion R ((γ1, P1), ... ,(γk, Pk)) to denote the achievable rate when CS measurements are received from multiple channels. This creates an additional dimension in characterizing channel rates. Without reasonable simplification, we will be unable to compute the optimal rates of different DF schemes even

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through numerical integration. Therefore, we approximate the achievable rate of combined channels with:

$$R((\gamma_1, P_1), \ldots, (\gamma_k, P_k)) \approx \sum_i \gamma_i R(P_i)$$

This approximation is reasonable because otherwise a source needs to do per measurement energy allocation to achieve the optimal performance.

Evaluating compressive cooperation strategies

All potential temporal proportions and transmission powers that meet (4) are considered in the development of the four DF systems that have been suggested. Due to the lack of information about R(P), finding an analytical solution to the optimization issue is challenging. Because of this, we determine the attainable rates of the four DF techniques by numerical integration after obtaining R(P) for compressive transmission through simulations. Any improvement in performance is minimal beyond the ideal row weight Lopt = 2/p, according to Baron et al. [5]. We utilize eight −1's and seven 1's, and we slightly change L to 15. We use amplitude modulation of a single carrier wave for the sake of simplicity. Our findings make it easy to determine the performance of quadrature amplitude modulation (QAM). Rates that may be achieved with direct transmission and the four DF systems are shown in Figure 3. The acronyms codd, recd, succ, and conc stand for the four schemes: code diversity, receiver diversity, sequential decoding, and concatenated decoding. We find that when the channel signal-to-noise ratio (SNR) is low, broadcasting via a relay significantly boosts channel throughput, but this effect is insignificant when the SNR is more than 15 dB.

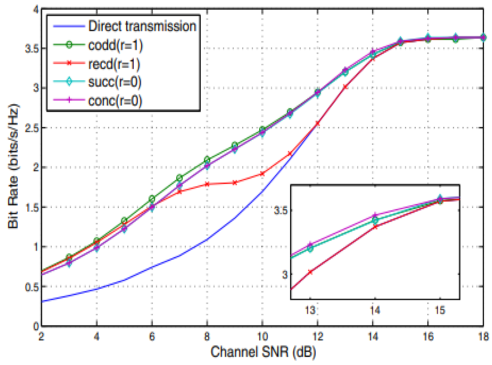

Figure 3 Comparing the bit rates of different DF schemes.

shape when the x-axis is plotted in dB, it is a concave function with respect to P. Considering that R(0) ≥ 0, R(·) is subadditive, i.e.

$$R(P_1) + R(P_2) \geq R(P_1 + P_2)$$

It is possible to deduce from this feature that the rate of code diversity is equal to the rate of receiver diversity. When comparing the code diversity scheme for r = 1 with the two r = 0 schemes, the result is the same as with traditional relay channels. To begin, there is no statistically significant difference in performance between r= 0 and r= 1 methods. Furthermore, when the channel signal-to-noise ratio (SNR) is high, r = 0 schemes are advantageous, but r = 1 schemes are superior in low SNR conditions. At SNRs greater than 13 dB, our numerical findings reveal that r = 0 schemes outperform r = 1 systems in terms of attainable rate. Concatenate decoding seems to outperform consecutive decoding when channel SNR is more than 13 dB, even if the two r = 0 schemes display comparable performance otherwise. Then, in order to assess the disparity between numerical calculations and actual implementations, we run simulations. The following procedure is used to conduct the simulations. To begin, the three methods' optimum parameters, such as the time percentage and energy allocation, are obtained from the numerical analysis. After then, a series of test runs is used to measure the average BER. When the bit error rate (BER) exceeds the reliability level of 10−5, we raise the channel signal-to-noise ratio (SNR) until the BER falls below this threshold. This combination of SNR and rate is shown on

Figure 4. Figure 4 shows a comparison of the maximum numerical rate calculated when r = 0 or 1 with the results of three different DF systems' simulations. The implementation gap for all three approaches is shown to be within 1.4 dB. Throughout the simulation, we find that code diversity maintains a relatively consistent performance at both high and low SNRs, whereas the two r = 0 schemes exhibit a somewhat more variable performance. Furthermore, both r= 0 methods revert to two-hop transmission, with Es2 = 0, when the channel SNR drops below 12 dB. It is prudent to adhere to the code diversity scheme in real-world systems, as r= 0 techniques do not substantially enhance channel rate at high SNR and code diversity is simpler to implement.

Compressive cooperation's BER performance is also assessed. Figure 5 only shows the code diversity scheme's findings as the BER performance of the other two DF schemes is so close. Five different curves have their goal rates calculated at6,8,10,12, and 14 dB. We test several values of the channel SNR and average BER for each goal rate and the corresponding optimum parameters that were derived. As the channel condition degrades from the channel SNR that guarantees dependable transmission, the BER of compressive cooperation does not dramatically rise, according to an intriguing discovery in the figure. Figure 6 shows the usual BER curves of traditional coding and modulation methods, which is drastically different. Compressive transmission seems to be more resilient in the presence of extremely dynamic channels, when exact channel SNR is difficult to ascertain, due to its unique BER feature. Interestingly, channel codes derived from CS measurements may be endlessly created in cases when the source node does not have access to wireless channel status information.

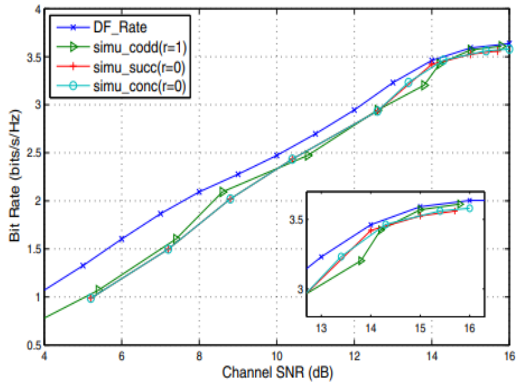

Figure 4 Simulation results of three DF schemes.

delivered until the receiver starts to feel better. As shown in [5], adding more CS measures will increase redundancy and help overcome channel noise. This rateless quality is a huge boon to compressive cooperative communication systems as compared to traditional LDPC codes for channel fluctuation adaptation. The last part of this section compares and contrasts the four DF methods with respect to their computational complexity.

Conclusion

This article suggests a compressive transmission technique employing CS random projections as a combined source-channel code. In this work, we present a three-terminal half-duplex Gaussian relay network by defining and assessing four DF cooperative techniques for compressive transmission research. Through the use of numerical research and simulated workouts, the potential rates of various methods are assessed. For separate source channels, we compared compressive collaboration's compression ratio to that of a conventional coding technique. The proposed compressive cooperation has great potential in the wireless relay channel for a number of reasons, including high transmission efficiency and excellent channel adaption.

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