Joint Source-Channel Coding for Correlated Gaussian Sources Over a Gaussian MAC with Side Information

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Abstract— **We consider the transmission of correlated Gaussian sources over a Gaussian multiple access channel (GMAC) with side information. Three joint source-channel coding schemes: Amplify and Forward (AF), Separation based (SB) and a coding scheme developed by Lapidoth and Tinguely (LT) are studied. Various methods are proposed to effectively utilize the side information with these schemes such that the sum of the distortions is minimized. The performance of the three schemes is also compared. It is found that AF is the best at low SNR but the worst under high SNR. Also, decoder side information is more useful than encoder side information.**

Keywords: Gaussian multiple access channel, side information, joint source-channel coding, correlated sources.

I. Introduction

Sensor nodes are often deployed for monitoring a random field. The observations made by the sensor nodes need to be transmitted to a fusion node. Since energy is a scarce resource on a sensor node, and data transmission is energy intensive, it is important to compress information transmitted as much as possible.

Due to the spatial proximity of the nodes, sensor observations from the random field are correlated. These correlations can be exploited to compress data. Furthermore, the sensor nodes often relay the observations from their neighbors, apart from transmitting their own data. Hence side information may be available at each node which can be used to compress the transmitted data. The side information may also be available because each node is listening when other nodes are transmitting through a MAC.

The sensor nodes often transmit their observations to the fusion center (or a cluster head) over a Multiple Access Channel (MAC). The received symbol may be a superposition of the transmitted symbols corrupted by additive white Gaussian noise (AWGN). This then is the well known Gaussian MAC (GMAC) which can be studied in the context of sensor networks in [6], [7], [16]. In this paper we consider transmission of correlated Gaussian sources over a GMAC with the aid of side information.

In the following we survey the related literature. Wyner and Ziv [18] obtained the rate distortion function for source coding with side information at the decoder. Cover, El Gamal and Salehi [2] provided sufficient conditions for transmitting losslessly discrete correlated observations over a discrete MAC. They also show that unlike for independent sources, source-channel separation does not hold in this system. Reference [15] extends the result in [2] and obtains sufficient conditions for lossy transmission of correlated sources over a MAC with side information.

The capacity region of the GMAC with independent inputs is available in [3]. The distributed correlated Gaussian source coding problem is discussed in [9], [17]. Exact rate region for two sources is provided in [17]. Capacity region of GMAC with feedback is obtained in [10]. The GMAC with correlated jointly Gaussian input is studied in [11]. A coding scheme for transmission of discrete correlated sources over a GMAC is developed in [13]. In [8] one necessary and two sufficient conditions for transmitting a jointly Gaussian source over a GMAC are provided. It is shown that the amplify and forward scheme is optimal below a certain SNR determined by source correlations. The performance of the schemes given in [8] is compared with that of Separation based scheme in [14]. GMAC under received power constraints is studied in [5] and it is shown that the source-channel separation holds in this case. The transmission of Gaussian sources over orthogonal Gaussian channels is discussed in [12].

Side information aware coding strategies for a CEO kind of system are discussed in [4]. Statistical knowledge of the side information available at the decoder is used in quantization and communication in addition to estimation at the decoder. It is shown that these strategies lead to significant performance gains over the scheme where side information is used only in estimation.

When limited to a MAC, our setup is more general than the system in [4] as we also have encoder side information. Also, we consider a general MAC while [4] considers orthogonal channels. Our results can also be interpreted in the framework of cooperative communication.

This paper makes the following contributions. From our general results in [15] we obtain conditions for transmission of correlated sources under various assumptions on availability of side information. These conditions are specialized for transmission of Gaussian sources over a GMAC with side information. We also compare three joint source-channel coding schemes in [14] under the availability of side information. We propose techniques which effectively use the side information to lower the sum of the distortions achievable.

The paper is organized as follows. Section II presents the model and the general result on a MAC with side information provided in [15]. Section III specializes the

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result to Gaussian sources over a Gaussian MAC. It also presents three joint source-channel coding schemes with side information. Section IV compares the three schemes. Section V concludes the paper.

II. Transmission of correlated sources over a MAC

In this section we consider the transmission of memoryless dependent sources, through a memoryless multiple access channel. The sources and/or the channel input/output alphabets can be discrete or continuous. Furthermore, side information may be available at the encoders and the decoder. Thus our system is very general and covers many systems studied over the years as special cases ([15]).

We consider two sources (U_1, U_2) and side information random variables Z_1, Z_2, Z with a known joint distribution $F(u_1, u_2, z_1, z_2, z)$. Side information Z_i is available to encoder $i,\ i = 1, 2$ and the decoder has side information Z. The side information is available to the encoders and the decoder causally. The encoders at the two users do not communicate with each other except via the side information. The random vector sequence $\{(U_{1n}, U_{2n}, Z_{1n}, Z_{2n}, Z_n), n \geq 1\}$ formed from the source outputs and the side information with distribution F is independent identically distributed (*iid*) in time. The sources transmit their code words X_i's to a single decoder through a memoryless multiple access channel. The channel output Y has distribution $p(y|x_1, x_2)$ if x_1 and x_2 are transmitted at that time. The decoder receives Y and also has access to the side information Z. It uses Y and Z to estimate the sensor observations U_i as $\hat{U}_i,\ i = 1, 2$.

It is of interest to find encoders and a decoder such that $\{U_{1n}, U_{2n}, n \geq 1\}$ can be transmitted over the given MAC with $E[d_i(U_i, \hat{U}_i)] \leq D_i,\ i = 1, 2$ where d_i are non-negative distortion measures and D_i are the given distortion constraints. If the distortion measures are unbounded we assume that $u_i^*,\ i = 1, 2$ exist such that $E[d_i(U_i, u_i^*)] < \infty,\ i = 1, 2$. If the channel alphabets are from an infinite set then there is also a transmit power constraint.

Source channel separation does not hold for this system.

From [15], it is possible to transmit the above sources over the MAC with given distortions if there exist r.v.s (W_1, W_2, X_1, X_2) such that

$$\begin{aligned} I(U_1, Z_1; W_1|W_2, Z) &< I(X_1; Y|X_2, W_2, Z), \\ I(U_2, Z_2; W_2|W_1, Z) &< I(X_2; Y|X_1, W_1, Z), \\ I(U_1, U_2, Z_1, Z_2; W_1, W_2|Z) &< I(X_1, X_2; Y|Z) \end{aligned} \tag{1}$$

where $X_1 \leftrightarrow W_1 \leftrightarrow (U_1, Z_1) \leftrightarrow (U_2, Z_2) \leftrightarrow W_2 \leftrightarrow X_2$ ($X \leftrightarrow Y \leftrightarrow Z$ denotes that $\{X, Y, Z\}$ forms a Markov chain) and a decoder g exists such that $g(Y, Z) = (\hat{U}_1, \hat{U}_2)$ and $E[d_i(U_i, \hat{U}_i)] \leq D_i,\ i = 1, 2$.

Let for a sequence $\{a_n, n = 1, 2...\}$, a^n denote $(a_1, a_2 ... a_n)$. The encoding scheme used in proving (1) involves distributed vector quantization (W_1^n, W_2^n) of the sources (U_1^n, U_2^n) and the side information Z_1^n, Z_2^n followed by a correlation preserving mapping to the channel code words (X_1^n, X_2^n). The decoding approach involves first decoding (W_1^n, W_2^n) and then obtaining estimate $(\hat{U}_1^n, \hat{U}_2^n)$ as a function of (W_1^n, W_2^n) and the decoder side information Z^n.

These conditions can be specialized to the cases with the side information only at the encoder and only at the decoder (by taking Z (respectively, (Z_1, Z_2)) independent of other random variables.

In the next section we specialize these result to the Gaussian sources.

III. Gaussian sources over a GMAC with side information

In a Gaussian MAC the channel output Y_n at time n is given by $Y_n = X_{1n} + X_{2n} + N_n$ where X_{1n} and X_{2n} are the channel inputs at time n and N_n is a Gaussian random variable independent of X_{1n} and X_{2n}, with $E[N_n] = 0$ and $var(N_n) = \sigma^2$. We will also assume that (U_{1n}, U_{2n}) is jointly Gaussian with mean zero, variances $\sigma_i^2,\ i = 1, 2$ and correlation ρ. The distortion measure will be Mean Square Error (MSE). The power constraints are $E[X_i^2] \leq P_i,\ i = 1, 2$.

Side information Z_i is available at encoder $i,\ i = 1, 2$ and Z is available at the decoder. One use of the side information Z_i at the encoders is to increase the correlation between the sources. It is known that if $Y_1, Y_2, ...Y_q$ and $X_1, X_2 ... X_p$ have a joint normal distribution then the functions $f(Y_1, Y_2, ...Y_q), g(X_1, X_2 ... X_p)$ having maximum correlations among themselves are linear (see [1]). It is also known from Lemma 3 of [13] that for jointly Gaussian inputs with correlation ρ the maximum correlation achievable between the jointly Gaussian channel inputs is ρ. Furthermore, the operations on Gaussian random vectors like projections, innovations etc give linear combinations as the solution. This motivates us to take appropriate linear combinations $L_i = a_i U_i + b_i Z_i,\ i = 1, 2$ of (U_i, Z_i) at encoder i. When side information is available at the decoder it is used to estimate the sources and also it can reduce the rates through the channel (as can be seen in (1)). In the following we propose techniques to extend the three schemes given in [14] with various assumptions on the availability of side information. The three schemes studied in [14] were: Amplify and Forward (AF), Separation Based (SB) approach and a coding scheme given by Lapidoth and Tinguely (LT)([8]).

A. AF with side information

In AF, without the side information, the channel codes X_i are just scaled source symbols U_i. Since (U_1, U_2) are themselves jointly Gaussian, (X_1, X_2) will be jointly Gaussian and retain the dependence of inputs (U_1, U_2). The scaling is done to ensure $E[{X_i}^2] = P_i, i = 1, 2$. For the single user case this coding is optimal. At the decoder inputs U_1 and U_2 are directly estimated from Y as $\hat{U}_i = E[U_i|Y], i = 1, 2$.

When side information is available at the decoder or/and at the encoders we modify the scheme as discussed below.

1) Side information at encoders only: Linear combination of the source outputs and side information $L_i = a_i U_i + b_i Z_i,\ i = 1, 2$ is amplified to X_i to meet the power constraints and sent over the channel. These linear combinations

can increase the correlation between the channel alphabets. However a distortion may be incurred in estimating the sources from L_i. Thus the optimal $a_i s$ and $b_i s$ selected may not give the highest possible correlation between L_1 and L_2. Hence we find the linear combinations, which minimize the sum of distortions. For this we consider the following optimization problem:
Minimize

$$D(a_1, b_1, a_2, b_2) = E[(U_1 - \hat{U}_1)^2] + E[(U_2 - \hat{U}_2)^2] \quad (2)$$

subject to

$$E[X_1^2] \leq P_1,\ E[X_2^2] \leq P_2$$

where

$$\hat{U}_1 = E[U_1|Y],\ \hat{U}_2 = E[U_2|Y].$$

2) Side information at Decoder only: In this case X_i is scaled U_i and the decoder side information Z is used in estimating (U_1, U_2) from (Y_1, Y_2). Since Z is correlated with the sources it can help in getting better estimate of the sources and the distortions can be lowered. The optimal estimation rule is

$$\hat{U}_1 = E[U_1|Y, Z],\ \hat{U}_2 = E[U_2|Y, Z]. \quad (3)$$

The corresponding conditional variances give the distortions.

3) Side information at both Encoder and Decoder: : Linear combinations of the sources L_i are amplified to get X_i as above and sent over the channel. This increases the correlations and the decoder side information Z is used to get better estimates of the sources. To find the optimal linear combination, we solve an optimization problem similar to (2) with $\hat{U}_1 = E[U_1|Y, Z],\ \hat{U}_2 = E[U_2|Y, Z]$.

B. SB with side information

In SB, without side information, the jointly Gaussian sources are vector quantized to W_1^n and W_2^n. The quantized outputs are Slepian-Wolf encoded. This produces code words, which are (asymptotically) independent. These independent code words are encoded to capacity achieving independent Gaussian channel codes (X_1^n, X_2^n). The scheme is modified to incorporate side information as follows:

1) SB with encoder side information: Find (L_1, L_2) from (U_1, U_2) and (Z_1, Z_2). For a given (L_1, L_2), we use the coding-decoding scheme described above. The linear combinations L_1 and L_2 are obtained which minimize (2) through this coding-decoding scheme.

2) SB with decoder side information: (U_1^n, U_2^n) are vector quantized to W_1^n and W_2^n at rates (R_1, R_2). The quantized outputs are Slepian-Wolf encoded. These are then mapped to independent channel codewords. The availability of the side information Z at the decoder reduces the rates (R_1, R_2) at which the vector quantizers operate. (R_1, R_2) are found from (1) with independent X_1, X_2. Side information Z^n is also used at the decoder in finding $(\hat{U}_1^n, \hat{U}_2^n)$ from (W_1^n, W_2^n).

3) SB with both encoder and decoder side information: We combine the techniques given above. Optimal (L_1, L_2) are found; vector quantized and Slepian-Wolf encoded. At the decoder Z is used to reduce the distortion.

C. LT with side information

In LT, without side information ([8]), (U_1^n, U_2^n) are vector quantized to 2^{nR_1}, 2^{nR_2} vectors $(\tilde{U}_1^n, \tilde{U}_2^n)$ where R_1 and R_2 are the rates of the quantizers. Also, W_1^n, W_2^n are 2^{nR_1} and 2^{nR_2}, n length code words obtained independently with distributions $\mathcal{N}(0,1)$. For each $\tilde{u}_i^n$, we pick the codeword w_i^n that is closest to it. This way we obtain Gaussian codewords W_1^n, W_2^n which retain the correlations of (U_1^n, U_2^n). X_1^n and X_2^n are obtained by scaling W_1^n, W_2^n to satisfy the transmit power constraints. (U_1, U_2, W_1, W_2) are (approximately) jointly Gaussian with covariance matrix given in [8].

The scheme is modified to incorporate side information:

1) LT with encoder side information: For a given (L_1, L_2), we use the encoding-decoding scheme described above by replacing (U_1^n, U_2^n) by (L_1^n, L_2^n). The linear combinations L_1 and L_2 are obtained which minimize (2) through this encoding-decoding scheme.

2) LT with decoder side information: The sources are coded into jointly Gaussian code words in the same way as in the no side information case. The rates at which the vector quantizers operate are a function of the side information at the decoder and are obtained from (1). This side information is also used in estimating (U_1, U_2) from (W_1, W_2).

3) LT with encoder and decoder side information: We combine the techniques given in III-C.1 and III-C.2 to obtain a good coding scheme for this case. The side information Z_1, Z_2 and Z are used effectively as in the case presented in III-B.3.

IV. Comparison of the schemes with side information

We provide the comparison of the three schemes for $U_1, U_2 \sim \mathcal{N}(0,1)$ and correlation ρ. Also we take the side information with a specific structure which seems natural in this set up. Let $Z_1 = s_1 U_2 + V_1$ and $Z_2 = s_2 U_1 + V_2$, where $V_1, V_2 \sim \mathcal{N}(0,1)$ and are independent of each other and independent of the sources, and s_1 and s_2 are constants that can be interpreted as the side channel SNR. This can also be interpreted in the framework of co-operative communication where Z_1 and Z_2 represent the co-operation between the encoders. We also take $Z = (Z_1, Z_2)$.

We consider the symmetric case: $P_1 = P_2 = P$, $s_1 = s_2$, $D_1 = D_2$. The channel noise variance $\sigma_N^2 = 1$. Thus P can be interpreted as the channel SNR.

Consider the AF scheme. Fig. 1 gives the minimum sum of distortions achieved for different channel SNRs under various assumptions on the availability of the side information. It can be seen from the figure that decoder only side information is much more useful than encoder only side information. The reduction in distortion is directly proportional to the quality of the side information (i.e., the side channel SNR). The encoder only side information case shows marginal improvement over the no side information case. This is somewhat different from the case of orthogonal Gaussian channels ([12]), where the encoder only side information is not useful at all. It is also found that when side information is provided at the decoder, providing it at the encoders also does not help much as seen in Fig. 1. Thus the critical information is the side information at the decoder. This is consistent with the findings in [4].

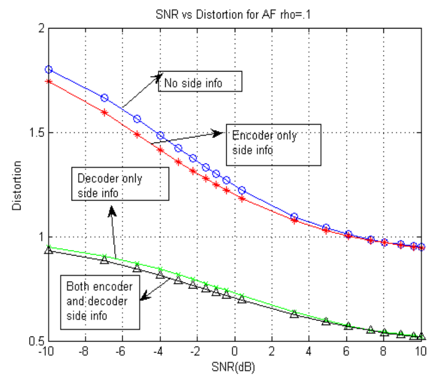

Fig. 1. SNR vs distortion performance for AF, $s_1 = s_2 = 1$, $\rho = .1$

Consider the SB. Fig. 2 gives the SNR vs distortion performance of the scheme under various assumptions on the availability of the side information. It can be seen from the figure that in this case also, the decoder only side information is much more useful than the encoder only side information. In fact the encoder only side information shows no improvement at this ρ. At larger ρ (results not provided here due to lack of space) there is a marginal improvement due to the increased correlations. It is also found that when side information is provided at the decoder, providing it also at the encoder does not help much as seen in figure Fig. 2.

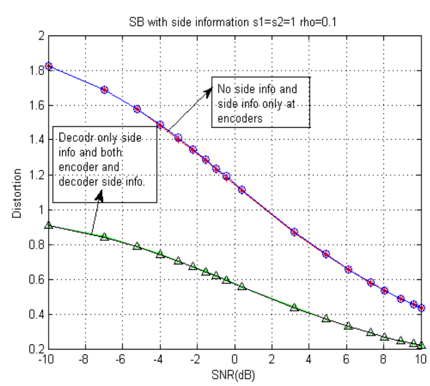

Fig. 2. SNR vs distortion performance for SB, $s_1 = s_2 = 1$ $\rho = .1$

Consider the LT. Fig. 3 gives the SNR vs distortion performance of the schemes under various assumptions on the availability of the side information. The encoder only side information case shows marginal improvement over the no side information case. The other conclusions remain the same as for the above two cases.

From Figs. 1-3 it is also found that for the encoder only side information LT performs better than SB under all SNRs and all ρ. This conclusion is similar to the no side information case ([14]). AF performs better than both the schemes for low SNR's.

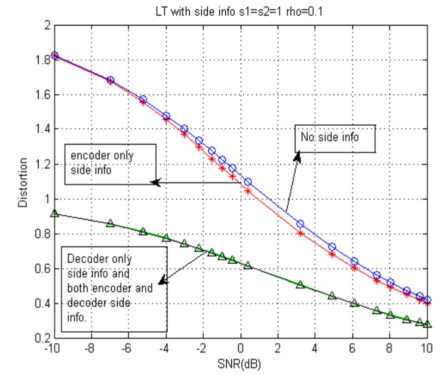

Fig. 3. SNR vs distortion performance for LT, $s_1 = s_2 = 1$ $\rho = .1$

Decoder-only side information was briefly treated in [14]. However, there it was used only for estimation at the decoder (and not also for determining the communication rates at the encoders, as done now). Compared to the results in [14], now we find that the decoder-only side information is much more effective. It is also seen that SB becomes better than LT when the quality of the side information provided at the decoder is improved. The same effect is found when side information is fed to both encoders and the decoder. In the symmetric case this cut-off (where SB takes over LT) side channel SNR is a function of ρ. Fig. 4 plots the sum of distortions vs the side channel SNR $s_1 = s_2 = s$ and gives the cut-off side channel SNR above which the SB is optimal when $\rho = 0.5$. This cut-off is valid for all channel SNR's. SB becomes optimal because the estimation efficiency and the communication rates can be improved in SB when the quality of the side information improves.

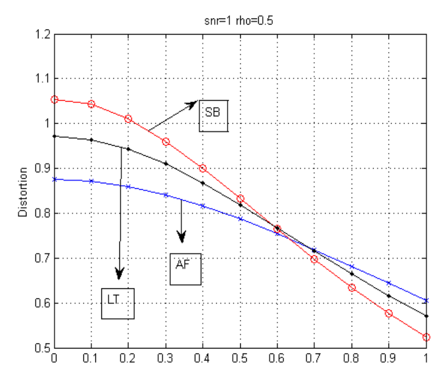

Fig. 4. Distortion vs side information power, SNR=0dB, $\rho = .5$

Consider the asymmetric case where $P_1 \neq P_2$. First we study the AF scheme. Let $s_1 = s_2 = 0.5$ and $\rho = 0.5$. The optimal $a_i^*, b_i^*,\ i = 1, 2$ and the minimum sum of distortions (D_{min}) achievable is given in Table I.

From Table I we observe that the side information Z_1 is not used ($b_1^* = 0$) when the difference between P_1 and P_2 is large. This is because, as power P_2 is larger, the quality of information about U_2 reaching the decoder is high. However, for small P_1, b_2^* is non-zero i.e. the side information Z_2 sent

TABLE I

DISTORTIONS ACHIEVED FOR AF (ASSYMETRIC CASE) AND OPTIMAL LINEAR COMBINATIONS, $\rho = 0.5$

P_1	P_2	a_1^*	b_1^*	a_2^*	b_2^*	D_{min}
0.1	10	0.3162	0	3.03	0.3952	0.7727
1	10	1	0	3.0662	0.3113	0.6663
3	10	1.7321	0	3.1005	0.2131	0.5996
5	10	2.2361	0	3.1216	0.1467	0.5728
7	10	2.6458	0	3.1368	0.0952	0.5589
8	10	2.8267	0.0070	3.1428	0.0737	0.5544
9	10	2.99	0.0222	3.1980	0.0547	0.5509

to encoder 2 is found useful at the decoder.

The optimal a_i^*, b_i^* $i = 1, 2$ obtained also depend on s_1, s_2 and ρ. If s_1, s_2 are large (i.e, the side information quality is good) then $b_i s$ are larger. For example, if $s_1 = s_2 = 10$, the first row of Table I changes to $\{a_1^*, b_1^*, a_2^*, b_2^*\} = \{.2018, .0162, 1.866, .1779\}$. This optimal linear combination yields a $D_{min} = 0.6183$ as compared to the no side information case of 0.7913. For $s_1 = s_2 = 0.5$ and $\rho = 0.1$, the linear combinations are tabulated in Table II.

TABLE II

DISTORTIONS ACHIEVED FOR AF (ASSYMETRIC CASE) AND OPTIMAL LINEAR COMBINATIONS, $\rho = 0.1$

P_1	P_2	a_1^*	b_1^*	a_2^*	b_2^*	D_{min}
0.1	10	0.3095	0.0468	3.1491	0.1614	1.0590
0.5	10	0.7012	0.0580	3.1490	0.1621	1.0348
5	10	2.2327	0.0517	3.1544	0.1097	0.9667
10	10	3.3158	0.0670	3.1580	0.0670	0.9474

It is concluded from Table II that at lower ρ the side information is more useful because it can increase the correlations.

Based on computations not provided here due to the lack of space, we conclude that for the SB and LT schemes in the asymmetric case, the optimal linear combinations are symmetric i.e, $a_1 = a_2$ and $b_1 = b_2$. However the a_1, b_1 chosen depend on (P_1, P_2, s_1, s_2) and the rates of transmission through the channel are asymmetric.

The general conclusions (based on above computations and [14]) are summarized as follows

- Decoder only side information is much more useful than encoder only side information. Encoder only side information helps marginally if at all. The reduction in distortion is propotional to the side information quality.
- AF is optimal at low SNR with or without side information.
- Distortions in AF do not go to zero, when channel SNR is increased, with or without side information. Distortions in both SB and LT go to zero at high channel SNR. Therefore, at high enough SNR AF is the worst. This is because of the interference between the two users.
- LT is always better than SB in the no side information case. But with side information SB is sometimes better than LT.
- In the asymmetric case, when the difference between powers are large, encoder side information is more useful at lower ρ and at higher side channel SNR.

V. CONCLUSIONS

In this paper we have discussed the transmission of correlated Gaussian sources over a GMAC under various assumptions on the availability of the side information. Schemes for utilizing the side information in three joint source-channel coding schemes are studied and the performance of the schemes are compared. It is found that the SB approach performs better under the assumption of high quality side information at the decoder and this finding motivates the use of SB in network scenarios.

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