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Correlated Gaussian Sources over Orthogonal Gaussian Channels

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Abstract

We consider the transmission of correlated Gaussian sources over orthogonal Gaussian channels. It is shown that the Amplify and Forward (AF) scheme which simplifies the design of encoders and the decoder, performs close to the optimal scheme even at high SNR. Also, it outperforms a recently proposed scalar quantizer scheme both in performance and complexity. We also study AF when there is side information at the encoders and decoder.

Keywords: Amplify and Forward, Correlated sources, Orthogonal Gaussian channels, Distributed scalar quantizers.

1. INTRODUCTION AND SURVEY

Sensor networks are used in a wide variety of applications due to their ability to operate in environments where human penetration is not possible. These are characterized by inexpensive sensing nodes with limited battery power and storage and hence limited computing and communication capabilities [1]. These sensor nodes may often be deployed for monitoring a random field. Due to the spatial proximity of the sensor nodes, sensor observations are correlated. One often needs to transmit these observations to a fusion center through a Multiple Access Channel (MAC). One standard way to use the MAC is via Time division multiple access (TDMA) or Frequency division multiple access (FDMA) or Code division multiple access (CDMA) ([2], [5]). These protocols although suboptimal are used due to practical considerations. These protocols make MAC a set of parallel orthogonal channels (for CDMA, it happens if we use orthogonal codes). We study transmission of correlated sources through such a system.

Our focus is toward designing simple and energy efficient sensor networks. This problem is addressed in this paper from the point of transmission of correlated Gaussian sources over orthogonal Gaussian channels. There may be side information at the encoders or/and the decoder. Such situations arise when the sensors are observing a Gaussian random field or detecting a change in a random field ([12]). The change is often detected in the mean of sensor observations with the observation noise being Gaussian. In such a scenario we show that the Amplify and Forward (AF) transmission scheme performs close to the optimal scheme and simplifies the sensor node design (transmitter as well as receiver) considerably. We also study its performance with side information. This result is in contrast to the performance of AF in the general GMAC where it is shown ([7], [8]) that AF is optimal only for low SNR and its performance deteriorates increasingly as SNR increases.

In the following we survey the related literature. Cover, El Gamal and Salehi [4] provided sufficient conditions for transmitting losslessly discrete correlated observations over a discrete MAC. They also show that unlike for independent sources, the source-channel separation does not hold for this system. Sufficent conditions for sending bi-variate Gaussian sources over a GMAC are given in [7]. The results of [4] have been extended in [11] to the system with side information and distortion and in [8] to Gaussian sources and Gaussian Multiple Access channel (GMAC).

Lossless transmission of correlated sources over orthogonal channels is addressed in [2]. There it is proved that source-channel separation holds for this system. [15] extends these results to the lossy case and shows that separation holds for the lossy case too. Conditions for separation to hold in multiple access channels are given in [10]. It is shown in [6] that separation holds and uncoded transmission achieves capacity in a Gaussian relay network as the number of relays go to infinity. Distributed scalar quantizers were designed for correlated Gaussian sources and independent Gaussian channels in [14].

This paper makes the following contributions. From the general result in [9] (which extends the result in [11]), we recover the sufficient conditions for transmission over orthogonal channels. In fact for lossless transmission of discrete sources over a discrete alphabet channel we can show that these are the necessary and sufficient conditions for orthogonal channels. As a consequence we obtain that source-channel separation holds for orthogonal channels even with

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side information for lossless transmission. Next we identify an optimal coding scheme for orthogonal Gaussian channels and compare it to the Amplify and Forward (AF) transmission scheme. We show that AF is close to the optimal scheme and also simplifies the sensor node design. We also show that AF outperforms the scheme proposed in [14] in terms of the distortion achieved and the complexity of the encoder, decoder design. We give the performance comparison for multiple sources and with side information also.

The paper is organized as follows. Sufficient conditions for transmission of correlated sources over orthogonal channels with side information are given in Section 2. In Section 3, these conditions are specialized to transmission of correlated Gaussian sources over orthogonal Gaussian channels. The performance of the AF scheme is studied in Section 4. Section 5 gives the performance with side information and Section VI summarizes the results.

2. TRANSMISSION OF CORRELATED SOURCES OVER ORTHOGONAL CHANNELS

We consider transmission of two correlated sources (U_1, U_2) with side information Z_1, Z_2, Z over a system of orthogonal channels (Fig.1). Side information Z_i is available to encoder i, $i \in \{1,2\}$ and the decoder has side information Z. 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 is independent identically distributed (iid) in time. The sources transmit their codewords X_i's to a single decoder through memoryless orthogonal channels having transition probabilities $p(y_1|x_1)$ and $p(y_2|x_2)$. The decoder receives the channel outputs Y_1, Y_2 and also has access to the side information Z. It uses Y_1, Y_2 and Z to estimate the sensor observations U_i as $\hat{U}_i$, $i \in \{1,2\}$.

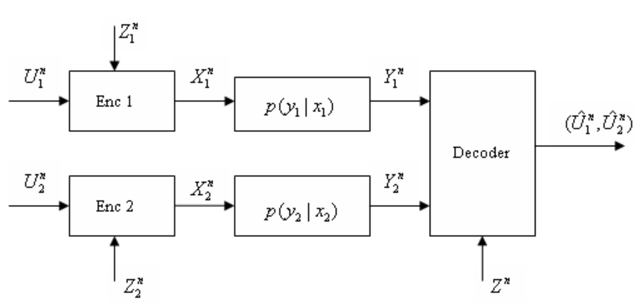

Figure 1: Transmission of correlated sources over orthogonal channels with side information

From the general results in [9] on a MAC with side information we obtain sufficient conditions for transmission (lossless or lossy transmission with given distortions D_1 and D_2)

$$I(U_1, Z_1; W_1|W_2, Z) < I(X_1; Y|X_2, W_2, Z), \quad (1)$$
$$I(U_2, Z_2; W_2|W_1, Z) < I(X_2; Y|X_1, W_1, Z), \quad (2)$$
$$I(U_1, U_2, Z_1, Z_2; W_1, W_2|Z) < I(X_1, X_2; Y|Z). \quad (3)$$

where W_1 and W_2 are auxiliary random variables satisfying the required distortion constraints (that (U_1, U_2) can be recovered from (W_1, W_2) with mean distortions $\leq (D_1, D_2)$) and $X_1 \leftrightarrow W_1 \leftrightarrow (U_1, Z_1) \leftrightarrow (U_2, Z_2) \leftrightarrow W_2 \leftrightarrow X_2$ ($X \leftrightarrow Y \leftrightarrow Z$ will indicate that $\{X, Y, Z\}$ forms a Markov chain).

For the orthogonal channel system $Y = (Y_1, Y_2)$ and the channel transition matrix is $p(y_1, y_2|x_1, x_2) = p(y_1|x_1)p(y_2|x_2)$. Then the conditions (1)-(3) become

$$I(U_1, Z_1; W_1|W_2, Z) < I(X_1; Y_1|W_2, Z) \leq I(X_1; Y_1), \quad (4)$$
$$I(U_2, Z_2; W_2|W_1, Z) < I(X_2; Y_2|W_1, Z) \leq I(X_2; Y_2), \quad (5)$$
$$I(U_1, U_2, Z_1, Z_2; W_1, W_2|Z) < I(X_1, X_2; Y_1, Y_2|Z) \leq I(X_1; Y_1) + I(X_2; Y_2). \quad (6)$$

Using Fano's inequality, for lossless transmission of discrete sources over discrete channels, we can show that outer bounds in (4)-(6) are infact necessary and sufficient conditions. The outer bounds in (4)-(6) are attained if the channel codewords (X_1, X_2) are independent of each other. Also, the distribution of (X_1, X_2) maximizing these bounds are not dependent on the distribution of (U_1, U_2). This implies that source-channel separation holds for this system with side information (Z_1, Z_2, Z) for lossless transmission of discrete sources over a discrete channel. Furthermore, the L.H.S. of the inequalities are simultaneously minimized when W_1 and W_2 are independent. Thus, the source coding (W_1, W_2) on (U_1, Z_1) and (U_2, Z_2) can be done as in Slepian-Wolf coding but also taking into account the fact that the side information Z is available at the decoder.

If we take $W_1 = U_1$ and $W_2 = U_2$ and the side information $(Z_1, Z_2, Z) \perp (U_1, U_2)$ ($X \perp Y$ denotes that X is independent of Y) we can recover the conditions in [2].

3. GAUSSIAN SOURCES AND ORTHOGONAL CHANNELS

Now we consider the transmission of jointly Gaussian sources over orthogonal Gaussian channels. Till Section 5 it will also be assumed that there is no side information Z_1, Z_2, Z.

Now (U_1, U_2) are zero mean jointly Gaussian random variables with variances σ_1^2 and σ_2^2 respectively and correlation ρ. Then $Y_i = X_i + N_i, i = 1,2$ where N_i is Gaussian with zero mean and $\sigma_{N_i}^2$ variance. Also N_1 and N_2 are independent of each other and also of (U_1, U_2).

In this scenario, the R.H.S. of the inequalities in (4)-(6) are maximized by taking $X_i \sim \mathcal{N}(0, P_i),\ i = 1, 2$ independent of each other where P_i is the average transmit power constraint on user i. Then $I(X_i, Y_i) = 0.5log(1 + P_i/\sigma_{N_i}^2),\ i = 1, 2$.

We can specialize the above results to a TDMA, FDMA or CDMA based transmission scheme. The specialization to TDMA is given here. Suppose source 1 uses the channel α fraction of time and user 2, $1-\alpha$ fraction of time. In this case we can use power P_1/α for the first user and $P_2/(1-\alpha)$ for the second user whenever they transmit. The conditions (4)-(6) for the optimal scheme become

$$I(U_1; W_1|W_2) < 0.5\alpha \log\left[1 + \frac{P_1}{\alpha {\sigma_{N_1}}^2}\right], \tag{7}$$

$$I(U_2; W_2|W_1) < 0.5(1-\alpha) \log\left[1 + \frac{P_2}{(1-\alpha){\sigma_{N_2}}^2}\right], \tag{8}$$

$$\begin{aligned} I(U_1, U_2; W_1, W_2) < 0.5\alpha \log&\left[1 + \frac{P_1}{\alpha {\sigma_{N_1}}^2}\right] \\ &+ 0.5(1-\alpha) \log\left[1 + \frac{P_2}{(1-\alpha){\sigma_{N_2}}^2}\right]. \end{aligned} \tag{9}$$

As commented in the last section, for the orthogonal channels an optimal scheme would be to use Slepian-Wolf kind of source coding and then channel coding each source as in a point to point communication. In fact for the Gaussian sources with orthogonal Gaussian channels and no side information, vector quantization of sources followed by Slepian-Wolf coding is an optimal source coding scheme([13]). This followed by iid Gaussian coded sequences with mean 0 and variance $P_i,\ i = 1, 2$ will provide the overall optimal scheme for this system. As in [8], we will call this scheme Separation Based (SB).

In the following we compare the performance of the Amplify and Forward (AF) scheme, which makes the sensor node design simple, with the SB scheme. Unlike in the GMAC there is no interference between the two users when orthogonal channels are used. Therefore, in this case we expect AF to perform quite well.

4. AMPLIFY AND FORWARD SCHEME AND ITS COMPARISON WITH OTHER SCHEMES

We study the performance of Amplify and Forward (AF) scheme in transmitting correlated Gaussian sources over orthogonal channels. For the single user case this scheme is optimal. In AF the source outputs are scaled to meet the power constraints and then transmitted over the orthogonal channels. For the minimum mean square distortion, the decoder calculates the conditional expectations $E[U_1|Y_1, Y_2]$ and $E[U_2|Y_1, Y_2]$. Thus it uses the simplest coding scheme and there is no coding and decoding delay. The distortions incurred are given by the respective conditional variances. The minimum distortions (D_1, D_2) are

$$D_1 = \frac{(\sigma_1 \sigma_{N_1})^2 \left[P_2(1-\rho^2) + \sigma_{N_2}^2\right]}{P_1 P_2 (1-\rho^2) + \sigma_{N_2}^2 P_1 + \sigma_{N_1}^2 P_2 + \sigma_{N_1}^2 \sigma_{N_2}^2}, \tag{10}$$

$$D_2 = \frac{(\sigma_2 \sigma_{N_2})^2 \left[P_1(1-\rho^2) + \sigma_{N_1}^2\right]}{P_1 P_2 (1-\rho^2) + \sigma_{N_2}^2 P_1 + \sigma_{N_1}^2 P_2 + \sigma_{N_1}^2 \sigma_{N_2}^2}. \tag{11}$$

From the (10), (11) we see that as $P_1, P_2 \to \infty$ the distortions D_1, D_2 tend to zero. We also see that D_1 and D_2 are minimum when the average powers used are P_1 and P_2. These conclusions are in contrast to the case of a GMAC where the distortion for the AF does not approach zero as $P_1, P_2 \to \infty$ and the optimal powers needed may not be the maximum average allowed P_1 and P_2([8]).

4.1. Comparison of AF with SB

For comparing the performance of the two schemes we consider the symmetric case where $P_1 = P_2 = P, \sigma_1^2 = \sigma_2^2 = \sigma^2, D_1 = D_2 = D, \sigma_{N_1}^2 = \sigma_{N_2}^2 = \sigma_N^2$. For the GMAC the performances of the two schemes were compared in [8]. It was shown that the distortion achieved by SB tends to zero as the SNR goes to infinity; however that of AF does not. This was because of the interference between the two users at high SNR for AF. Hence AF was found to be sub-optimal for high SNR.

For the present system, the minimum distortions achieved in SB and AF are denoted by $D(SB)$ and $D(AF)$ respectively. σ^2 is taken to be unity without loss of generality. We denote P/σ_N^2 by S. Then $D(SB)$ and $D(AF)$ are

$$D(SB) = \sqrt{\frac{1-\rho^2}{(1+S)^2} + \frac{\rho^2}{(1+S)^4}}, \tag{12}$$

$$D(AF) = \frac{S(1-\rho^2) + 1}{1 + 2S + S^2(1-\rho^2)}. \tag{13}$$

We see from the above equations that when $\rho = 0,\ D(SB) = D(AF) = 1/(1+S)$. At high $S,\ D(AF) \approx 1/S$ and $D(SB) \approx \sqrt{1-\rho^2}/S$. Eventually both $D(SB)$ and $D(AF)$ tend to zero as $S \to \infty$. When $S \to 0$ both $D(SB)$ and $D(AF)$ go to σ^2.

By squaring the equations (12) and (13) we can show that $D(AF) \geq D(SB)$ for all S. But in the following we show that $D(AF)$ is often close to $D(SB)$.

We note that both $D(AF)$ and $D(SB)$ are lower bounded by $S(1-\rho^2)/(1+S)^2$. We denote this by $D(LB)$.

$D(AF)$ is also upper bounded by $(1+S)/[1+S(1-\rho^2)]^2$, which we denote by $D(UB)$. Then,

$$\begin{aligned} D(AF) - D(SB) &\le D(UB) - D(LB) \\ &\le \frac{\rho^2}{S}\left[\frac{1}{(1-\rho^2)^2} + \frac{1}{(1-\rho^2)} + 1\right]. \quad (14) \end{aligned}$$

Then, we see that for large S the difference is small and tends to 0 as $S \to \infty$.

Again, from (13), $D(AF) \le S(1-\rho^2)+1$. This gives,

$$\begin{aligned} D(AF) - D(SB) &\le \frac{S(2+S)(1+S(1-\rho^2))}{(1+S)^2} \\ &\le S + \frac{S}{1+S}. \quad (15) \end{aligned}$$

The R.H.S. is small when S is small. The difference is $O(S)$ as $S \to 0$. $D(AF) - D(SB)$ is less than the minimum of the R.H.S. in (14) and (15). Also,

$$\begin{aligned} D(AF) - D(SB) &\le D(AF) - D(LB) \\ &\le \frac{S^2\rho^2[1+S(1-\rho^2)]}{(1+S)^2(1+2S+S^2(1-\rho^2))} \\ &\le \frac{\rho^2[1+S(1-\rho^2)]}{(1+2S+S^2(1-\rho^2))} \quad (16) \\ &\le \frac{\rho^2}{1+S(1-\rho^2)} \le \rho^2. \end{aligned}$$

From (14), (15) and (16) we conclude that $D(AF) - D(SB)$ is small when S is small or large or whenever ρ is small.

D(AF) and D(SB) are plotted for ρ=0.3 and 0.7 using exact computations in Figs 2 and 3. These figures confirm the theoretical findings.

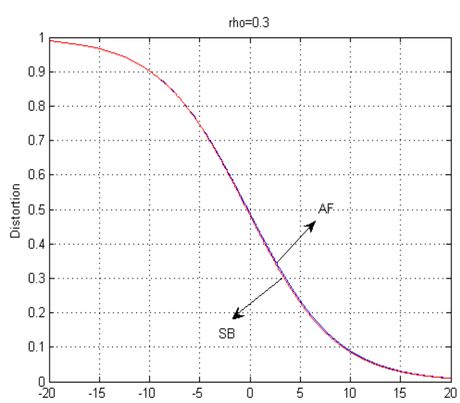

Figure 2: SNR vs distortion performance for $\rho = .3$

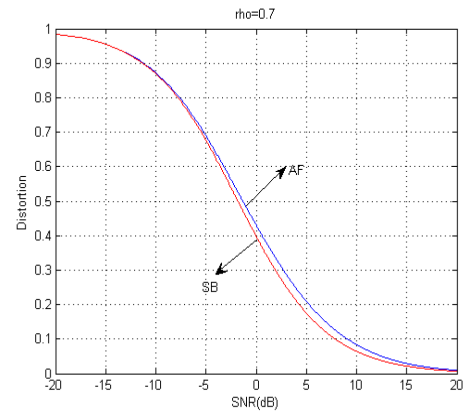

Figure 3: SNR vs distortion performance for $\rho = .7$

4.2. Comparison with distributed scalar quantizers

A distributed scalar quantizer based scheme is proposed in [14]. The main motivation behind this scheme is the use of energy efficient and simple sensor nodes in sensor networks. However their scheme requires a separate design for each channel SNR and correlation between the sources.

We compare the AF based scheme proposed above with the scalar quantizer scheme and show that AF is an ideal candidate for Gaussian sensor networks over orthogonal Gaussian channels. Unlike for the scalar quantizer, for AF the same design caters for all ranges of SNR and correlations. Also, AF encoding and decoding are simpler. We compare AF with the scalar quantizer for the example provided in [14]. In the example the correlation SNR assumed was 13dB which corresponds to a ρ between the sources as 0.957 and the number of levels of the scalar quantizer is 32. The quantizer was optimized for SNR of 10dB. The performance measure in [14] is signal power to distortion ratio (SDR). This is shown in Figure 4. We see that the AF performs better than the scalar quantizer at each SNR.

From Fig 4, we also see that AF performance is close to that of the optimal scheme SB under all SNR's unlike that of the scalar quantizer. We also note that for low SNR, which is often the case in sensor networks, performance of AF is very close to that of SB. Also as noted before, for low ρ, AF performance is close to that of SB.

4.3. Extension to multiple sources

Although the results of the AF and SB are given for two sources, these can be easily extended to the multiple source case. For SB, for the source coding part, the rate region for multiple user case (under a symmetry assumption) is given in [13]. This can be combined with the capacity achieving Gaussian channel codes over each independent channel.

Let N be the number of sources which are jointly Gaus-

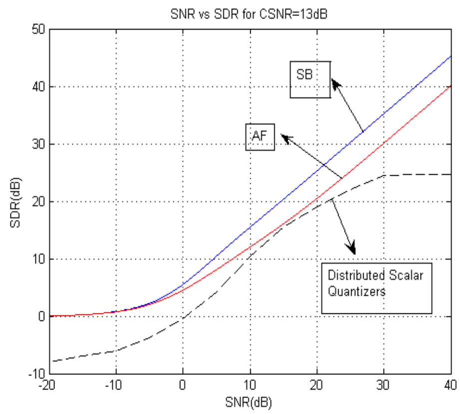

Figure 4: Comparison of AF and distributed scaler quantizer scheme

sian with zero mean and covariance matrix K_U. Let P be the symmetric power constraint. Let K_U have the same structure as given in [13]. Let $C_{UY} = \sqrt{P}[1\rho.....\rho]$ be a $1 \times N$ vector. The minimum distortion achieved by the AF scheme is given as $D(AF) = 1 - C_{UY}(PK_U + \sigma_N^2 I)^{-1}C'_{UY}$.

5. SIDE INFORMATION

Let us consider the case when 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. Then while using SB, the encoding rates at the two sources can be decreased. This can be optimally done (see [3]), if we take appropriate linear combination of (U_i, Z_i) at encoder i and use SB. However we need to recover at the decoder (U_1, U_2) from the linear combinations. This can affect the overall performance.

5.1. AF with side information

5.1.1. Side information at encoders only

A linear combination of the source outputs and side information $L_i = a_iU_i + b_iZ_i,\ i = 1, 2$ is amplified and sent over the channel. We find the linear combinations, which minimize the sum of distortions. For this we consider the following optimization problem:
Minimize

$$D(a_1, b_1, a_2, b_2) = E[(U_1 - \hat{U}_1)^2] + E[(U_2 - \hat{U}_2)^2] \tag{17}$$

subject to $E[X_1^2] \leq P_1,\ E[X_2^2] \leq P_2$
where $\hat{U}_1 = E[U_1|Y_1, Y_2],\ \hat{U}_2 = E[U_2|Y_1, Y_2]$.

5.1.2. Side information at Decoder only

In this case the decoder side information Z is used in estimating (U_1, U_2) from (Y_1, Y_2). The optimal estimation rule is

$$\hat{U}_1 = E[U_1|Y_1, Y_2, Z], \hat{U}_2 = E[U_2|Y_1, Y_2, Z]. \tag{18}$$

5.1.3. Side information at both Encoder and Decoder

Linear combinations of the sources are amplified as above and sent over the channel. To find the optimal linear combination, solve an optimization problem similar to (17) with $(\hat{U}_1, \hat{U}_2)$ as given in (18).

5.2. SB with side information

For a given (L_1, L_2) we use the source-channel coding scheme explained below (7)-(9). The side information Z at the decoder reduces the source rate region. This is also used at the decoder in estimating $(\hat{U}_1, \hat{U}_2)$. The linear combinations L_1 and L_2 are obtained which minimize (17) through this coding-decoding scheme.

5.3. Comparison of AF and SB with side information

We provide the comparison of AF with SB for $U_1, U_2 \sim \mathcal{N}(0, 1)$. Also we take the side information with a specific structure which does look natural in this set up. Let $Z_1 = s_1U_2 + V_1$ and $Z_2 = s_2U_1 + V_2$, 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. We also take $Z = (Z_1, Z_2)$.

We have compared AF and SB with different ρ and s_1, s_2 by explicitly computing the minimum $(D_1 + D_2)/2$ achievable. We take $P_1 = P_2$. Due to lack of space we provide only one case in Fig.5 where $s_1 = s_2 = 0.5$ and $\rho = 0.4$. From the Figure one sees that without side information, the performance of AF and SB is very close for different SNRs. The difference in their performance increases with side information for moderate values of SNR because the effect of the side information is to effectively increase the correlation between the sources. Even for these cases at low and high SNRs the performance of AF is close to that of SB. These observations are in conformity with our conclusions in Section IV.

Our other conclusions, based on computations not presented here are the following. For the symmetric case discussed here, for SB, encoder-only side information reduces the distortion marginally. This happens because a distortion is incurred for (U_1, U_2) while making the linear combinations (L_1, L_2). For the AF we actually see no improvement and the optimal linear combination has $b_1 = b_2 = 0$. For decoder-only side information the performance is improved for both AF and SB as the side information can be used to obtain better estimates of (U_1, U_2). Adding encoder side information further improves the performance only marginally for SB; the AF performance is not improved.

In the asymmetric case some of these conclusions may not be valid.

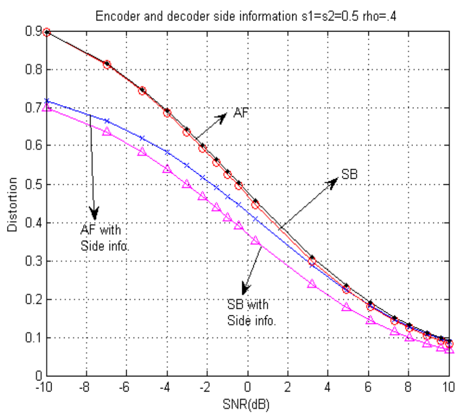

Figure 5: AF and SB with both encoder and decoder side information

6. CONCLUSIONS

From our general results in [9] and [11] we show that source channel separation holds on orthogonal channels even when there is side information for lossless transmission of discrete sources over a discrete channel. We also study Amplify and Forward (AF) joint source-channel coding scheme for Gaussian sources over a GMAC which simplifies the design of sensor nodes. Unlike the GMAC case, in case of transmitting Gaussian sources over orthogonal Gaussian channels the AF can often be close to the optimal scheme. We also show that the AF outperforms the distributed scalar quantizer scheme proposed in [14] in terms of distortion and complexity. Results with side information are also provided.

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