Low-Delay Joint Source-Channel Coding with Side Information at the Decoder

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***Abstract*—This paper deals with *distributed joint source-channel coding* (DJSCC) of analog signals over impulsive noise channel. DJSCC, and distributed source coding (DSC), of *analog* sources is commonly realized by quantizing the source and using binary channel codes for coding, i.e., *binning* is realized in the binary domain. To achieve lower delay, we perform binning in the analog domain. Specifically, a single discrete Fourier transform (DFT) code is used both for compression and protection of signal. To do so, parity samples, with respect to a good *systematic DFT code*, are generated, quantized, and transmitted over a noisy channel. To improve the decoding performance, we leverage subspace-based error correction. The performance of the proposed system is analyzed for Gauss-Markov sources over impulsive noise channel.**

I. INTRODUCTION

Motivated by its applications in delay-sensitive sensor networks, we consider a low-delay communications system with two statistically dependent analog signals, $\boldsymbol{x}$ and $\boldsymbol{y}$, in which the encoders do not communicate with each other, whereas the receiver performs *joint decoding*. We focus on the asymmetric scenario where in the compression of $\boldsymbol{x}$ the encoder has no knowledge of $\boldsymbol{y}$ but the decoder knows it, as *side information*.

In practice, lossy DSC systems generally use a quantizer to convert a continuous-valued sequence to a discrete-valued one, and then apply Slepian-Wolf coding in the binary field [1]–[5], where binning is usually done by using capacity-achieving LDPC and turbo codes. Although such an scheme is nearly optimal when code-length goes to infinity, it implies excessive decoding delay due to long code-length and iterative decoding. The other extreme case, i.e., zero delay source-channel coding, can be achieved through the use of analog mapping [6]–[9]. These schemes have lower complexity but do not benefit from the advantages of digital communications as they use analog communications; they are also far from the theoretical limits. A third approach is to take the advantage of analog binning and digital communications. In such a framework [10], compression is done before quantization, i.e., the Wyner-Ziv encoder is realized by Slepian-Wolf coding in the *real field* followed by a quantizer. Specifically, the compression is achieved by generating either *syndrome* or *parity* samples of the input sequence with respect to DFT codes, a class of Bose-Chaudhuri-Hocquenghem (BCH) codes in the *real field*. The syndrome or parity samples are then quantized and transmitted over a *noiseless* channel. This implies *separate* source and channel coding.

The *separation theorem* however, is based on several assumptions such as the source and channel coders not being constrained in terms of complexity and delay. It breaks down, for example, for non-ergodic channels and real-time communication. In such cases, it makes sense to integrate the design of the source and channel coder systems, because *joint source-channel coding* (JSCC) performs better given a fixed complexity and/or delay constraints. Likewise, distributed JSCC (DJSCC) is shown to outperform separate distributed source and channel coding in some practical cases [11]. DJSCC has been addressed in [5], [11]–[13], using different binary codes.

The main contribution of this paper is to introduce DJSCC using real field codes. To do so, we use a single DFT code both to compress $\boldsymbol{x}$ and protect it against channel variations. This scheme is advantageous mainly because the correlation channel models the variations between the continuous-valued sources rather than the quantized ones and thus it can be more accurate.[1] Besides, owing to DFT codes, this scheme can exploit temporal correlation typically found in many sources. The proposed scheme maps short source blocks into channel blocks and thus it is well suited to low-delay coding. Another contribution of this paper is to apply subspace-based decoding in the context of DSC which improves the error localization as well as error detection steps. Numerical results, including the mean-squared error (MSE), for DJSCC of Gauss-Markov sequences are presented. While the MSE performance of DJSCC systems with binary codes is limited to the quantization error level, the proposed scheme breaks through this limit.

The rest of this paper is organized as follows. We briefly explain the construction and decoding of DFT codes in Section II, and apply and modify subspace error localization to DSC in Section III. We introduce DJSCC based on DFT codes in Section IV, and evaluate the proposed system by performing simulation in Section V. Section VI concludes the paper.

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[1]A relevant work can be found in [14] where it is shown that, in distributed compressed sensing scenarios, exploiting the correlation statistics in the recovery process leads to performance gains.

II. Systematic Real BCH-DFT codes

A. Encoding

A BCH-DFT code [15] is a BCH code over real or complex field whose parity-check matrix $\boldsymbol{H}$ is defined based on the DFT matrix. $\boldsymbol{H}$ is a null space of $\boldsymbol{G}$, the generator matrix of the code. An (n, k) BCH-DFT code inserts $n-k$ cyclically adjacent zeros in the spectrum of any codevector, and thus it is capable of correcting up to $t = \lfloor \frac{n-k}{2} \rfloor$ errors [15]–[18]. From a *frame theory* point of view, BCH-DFT codes are the well-known *harmonic* frames. A *systematic* DFT code is a code whose generator matrix $\boldsymbol{G}$ includes the identity matrix of size k as a submatrix. To form the generator matrix for a systematic, real BCH-DFT code we can right multiply $\boldsymbol{G}$ by $\boldsymbol{G}_k^{-1}$, where $\boldsymbol{G_k}$ is a subframe of $\boldsymbol{G}$ that includes k rows of $\boldsymbol{G}$ [18]. These rows can be chosen arbitrarily, resulting in $\binom{n}{k}$ systematic frames for an (n, k) DFT frame. We have proved [19, Theorem 7] that when using these systematic frames for error correction, the mean-squared reconstruction error is minimized when the systematic rows are chosen as evenly as possible. This implies $n - \lfloor \frac{n}{k} \rfloor k$ systematic rows with successive circular distance $\lceil \frac{n}{k} \rceil$. In the extreme scenario, where the systematic rows are equally spaced, the systematic frame is *tight*. This is realized only when n is an integer multiple of k. Such a frame lends itself well to minimize reconstruction error [20]. In this paper, we use these optimal frames for encoding. Also, hereafter, we use "DFT code" and "real BCH-DFT code" interchangeably.

B. Decoding

To do decoding, the extension of the Peterson-Gorenstein-Zierler (PGZ) algorithm to the real field [15] can be applied. This algorithm comprises three major steps, i.e., to find the number, location, and magnitude of errors; these are usually called error *detection*, error *localization*, and error *calculation*. To this end, we need to find the syndrome of "error." Then, the exact value of errors is determined using the PGZ algorithm, if the number of errors is within the capacity of the code and there is no quantization. In the presence of quantization, the decoding becomes an estimation problem. Then, it is necessary to modify the PGZ algorithm to detect errors reliably [15]. The above algorithm further needs to be tailor-made for DSC, both for the syndrome-based and parity-based approaches, as explained in [10]. In the remainder of this paper, we first improve the decoding algorithm and then extend parity-based DSC to DJSCC.

III. Modified Subspace Decoding

A. Error Localization

We first apply *subspace* error localization [16], rather than *coding-theoretic* approach, to the decoding algorithms in [10]. Subspace approach is more general than coding theoretic one in the sense that it can use up to $t+1-\nu$ degrees of freedom to localize ν errors, compared to just one degree of freedom in coding the theoretic method. Hence, it is capable of improving the error localization both for the syndrome- and parity-based DSC similar to that in channel coding [16].

Let $\boldsymbol{s}_e = [s_1, s_2, \ldots, s_{n-k}]$ be the syndrome of error, perturbed by quantization error, as defined in [10, eq.(5), (14)]. We can form the syndrome matrix

$$\boldsymbol{S}_m = \begin{bmatrix} s_1 & s_2 & \ldots & s_{d-m+1} \\ s_2 & s_3 & \ldots & s_{d-m+2} \\ \vdots & \vdots & \ddots & \vdots \\ s_m & s_{m+1} & \ldots & s_d \end{bmatrix}, \tag{1}$$

where $d \triangleq n-k$. We set $m = t+1$,[2] and eigen-decompose the covariance matrix $\boldsymbol{R} = \boldsymbol{S}_m \boldsymbol{S}_m^H$. This results in two sets of vectors corresponding to two orthogonal subspaces, namely, the *error subspace* and *noise subspace*. The first set of vectors, which is composed of the ν eigenvectors corresponding to the ν largest eigenvalues of $\boldsymbol{R}$, forms a *spanning basis* for the error subspace [16], [21]. Hence, the noise subspace is spanned by the remaining $m-\nu$ eigenvectors. The vectors spanning the noise subspace are use to localize errors by applying the MUSIC- or ESPRIT-like algorithms,[3] as detailed in [16]. We use the MUSIC-based approach in this paper.

Error localization can be further improved for parity-based DSC [10] as transmitted parity samples are noise-free and thus the error locations are restricted in the codevectors. Therefore, we can exclude the set of roots corresponding to the location of the parity samples. In this context, again it makes sense to use a systematic code with evenly-spaced parity samples so as to optimize the location of error-free and error-prone samples in the codevectors. For example, in an optimal $(10, 5)$ systematic code parity samples can only be in odd (even) positions while data samples are placed in even (odd) positions. Apart from keeping the effective range of parity samples as small as possible, which improves the decoding performance [18], such a code maximizes the distance between the error-prone roots of the code; hence, it helps decrease the probability of incorrect decision.

B. Error Detection

For error detection, we first find an empirical threshold θ based on eigendecomposition of $\boldsymbol{R}$ when there is no error. Let $\lambda_{\max}$ denote the largest eigenvalue of $\boldsymbol{R}$. We find θ such that

$$\Pr(\lambda_{\max} < \theta) \geq p_d, \tag{2}$$

where p_d is the desired probability of correct detection. In practice, where errors can happen, we estimate the number of errors by finding the number of eigenvalues of $\boldsymbol{R}$ greater than θ. This one step estimation is better than the original estimation in the PGZ algorithm where the last column and row of $\boldsymbol{S}_m$ are removed until we come up with a non-singular matrix [15], [24]. The improvement comes from incorporating

[2] Although $\nu+1 \leq m \leq d-\nu+1$, the best result is achieved for $m = t+1$ [16].

[3] The MUltiple SIgnal Classification (MUSIC) [22] and Estimation of Signal Parameters via Rotational Invariant Techniques (ESPRIT) [23] are subspace-based techniques for *multiple frequency component* estimation and *direction-of-arrival* estimation.

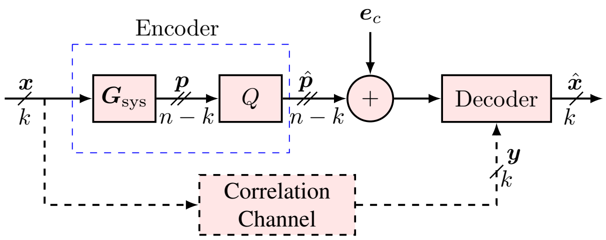

Fig. 1. The DJSCC using DFT codes. $\boldsymbol{G}_{\mathrm{sys}}$ represents the generator matrix of a systematic code.

all syndrome samples, rather than some of them, for the decision making.

IV. Distributed Joint Source and Channel Coding

The concept of lossy DSC and Wyner-Ziv coding using DFT codes is explained in [10], both for the syndrome and parity approaches. This is mainly motivated by taking advantage of modeling the correlation between the analog sources before quantizing them [10]. That is, given $\boldsymbol{x}$ and $\boldsymbol{y}$, two sequences of i.i.d. random variables $x_1 \dots x_n$, and $y_1 \dots y_n$, the $\boldsymbol{x}$-$\boldsymbol{y}$ dependency is defined by $y_i = x_i + e_i$, where e_i is a real-valued i.i.d. random variable, independent of x_i. This model captures any variation of $\boldsymbol{x}$ and can be used to model correlation between $\boldsymbol{x}$ and $\boldsymbol{y}$ precisely. Particularly, $\boldsymbol{e}$ can have the *Gaussian* or *Gaussian-Erasure* distributions [25], [26].

In this section, we extend the parity-based Wyner-Ziv coding of analog sources to the case where errors in the transmission are allowed. Thus, we introduce distributed JSSC of analog correlated sources in the analog domain. Specifically, we consider transmission corrupted by *impulsive noise*. This model is motivated by implementation of wireless sensor networks in power substations [27], [28]. The impulsive noise is prevalent in power substations since it is created by partial discharges, corona noise and electrical arcs, hosted by high-voltage equipment such as transformers, bushings, power lines, circuit breakers and switch-gear [28]. The magnitude of the impulses is assumed to have a Gaussian distribution; hence, the Gaussian-Erasure channel is used to model the transmission channel, as well.

A. Coding and Compression

To compress and protect $\boldsymbol{x}$, the encoder generates parity sequence $\boldsymbol{p}$ of $n-k$ samples, with respect to a good systematic DFT code. The parity is then quantized and transmitted over a noisy channel, as shown in Fig. 1. To keep the dynamic range of parity samples as small as possible, we make use of optimal systematic DFT codes, proposed in [19]. This increases the efficiency of the system for a fixed number of precision bits. Using an (n, k) DFT code a total compression ration of $k : (n-k)$ is achieved. Obviously, if $n < 2k$ compression is possible. However, since there is little redundancy the end-to-end distortion could be high. Conversely, a code with $n > 2k$ expands input sequence by adding *soft redundancy* to protect it in a noisy channel.

B. Decoding

Let $\tilde{\boldsymbol{p}} = \hat{\boldsymbol{p}} + \boldsymbol{e}_c$, be the received parity vector which is distorted by quantization error $\boldsymbol{q}$ ($\hat{\boldsymbol{p}} = \boldsymbol{p}+\boldsymbol{q}$) as well as channel error $\boldsymbol{e}_c$. Also, let $\boldsymbol{y} = \boldsymbol{x} + \boldsymbol{e}_v$ denote side information where $\boldsymbol{e}_v$ represents the error due to the "virtual" correlation channel. The objective of the decoder is to estimate the input sequence from the received parity and side information. Although we only need to determine $\boldsymbol{e}_v$, effectively it is required to find both $\boldsymbol{e}_v$ and $\boldsymbol{e}_c$. From an error correction point of view, this is equal to finding the error vector $\boldsymbol{e} = [\boldsymbol{e}_v \;\; \boldsymbol{e}_c]^T$ that affects the codevector $[\boldsymbol{x} \;\; \boldsymbol{p}]^T$. Hence, to find the syndrome of error at the decoder, we append the parity $\tilde{\boldsymbol{p}}$ to the side information $\boldsymbol{y}$ and form $\tilde{\boldsymbol{z}}$, a valid codevector perturbed by quantization and channel errors. Without quantization ($\boldsymbol{q} = \boldsymbol{0}$)

$$\boldsymbol{z} = \begin{bmatrix} \boldsymbol{y} \\ \tilde{\boldsymbol{p}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{p} \end{bmatrix} + \begin{bmatrix} \boldsymbol{e}_v \\ \boldsymbol{e}_c \end{bmatrix} = \boldsymbol{G}_{\mathrm{sys}}\boldsymbol{x} + \boldsymbol{e}, \quad (3)$$

and, multiplying both sides by $\boldsymbol{H}$, we obtain

$$\boldsymbol{s}_z = \boldsymbol{s}_e, \quad (4)$$

where $\boldsymbol{s}_z \equiv \boldsymbol{H}\boldsymbol{z}$ and $\boldsymbol{s}_e \equiv \boldsymbol{H}\boldsymbol{e}$. It should be emphasized that in this case ($\boldsymbol{q} = \boldsymbol{0}$), error vector can be determined exactly, as long as the number of errors is not greater than t. In practice, quantization is also involved and we have

$$\tilde{\boldsymbol{z}} = \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{p} \end{bmatrix} + \begin{bmatrix} \boldsymbol{e}_v \\ \boldsymbol{e}_c \end{bmatrix} + \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{q} \end{bmatrix} = \boldsymbol{G}_{\mathrm{sys}}\boldsymbol{x} + \boldsymbol{e} + \boldsymbol{q}'. \quad (5)$$

Thus,

$$\boldsymbol{s}_{\tilde{z}} = \boldsymbol{s}_e + \boldsymbol{s}_{q'}, \quad (6)$$

in which $\boldsymbol{s}_{q'} \equiv \boldsymbol{H}\boldsymbol{q}'$. That is, we obtain a distorted version of the syndrome of error. Knowing the syndrome of error, we use the error detection and localization algorithm, explained in Section III, to find and correct error.

Although the extension of parity-based DSC to DJSCC is straightforward, it is not clear how to do this for syndrome-based DSC. This is because, in a syndrome-based DSC with noisy transmission, the decoder can only form $\boldsymbol{s}_{e_v} + \boldsymbol{e}_c$, where $\boldsymbol{s}_{e_v}$ is the difference between the transmitted syndrome and syndrome of side information, i.e., $\boldsymbol{s}_{e_v} = \boldsymbol{s}_y - \boldsymbol{s}_x$, as it was in the DSC [10]. However, with $\boldsymbol{s}_{e_v} + \boldsymbol{e}_c$ the rank of the syndrome matrix $\boldsymbol{S}_t$ is not necessarily equal to ν, even if quantization error is assumed to be zero. Therefore, the PGZ and subspace-based methods fail to find the number and location of errors.

V. Simulation Results

To evaluate the performance of the proposed systems we perform simulations over a Gauss-Markov source with mean 0, variance 1, and correlation coefficient 0.9. Parity samples are generated using the $(10, 5)$ DFT code, quantized with a 6-bit uniform quantizer, and transmitted over an impulsive noise channel; the effective range of the input sequences is assumed to be $[-4, 4]$. The "virtual" correlation channel and transmission channel altogether insert up to t errors generated by $\mathcal{N}(0, \sigma_e^2)$. The decoder detects, localizes, and decodes errors. To measure the end-to-end distortion, we compare

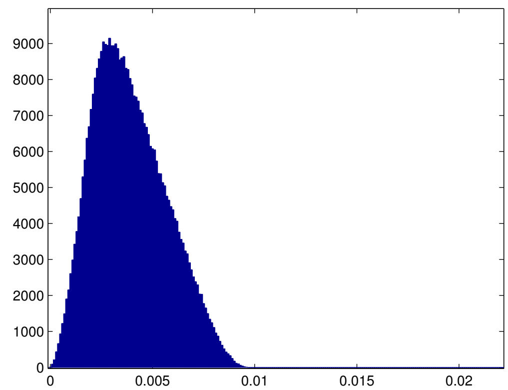

Fig. 2. Histogram of $\lambda_{\max}(\boldsymbol{R})$ for a quantized $(10,5)$ DFT code. Given $p_d = 90\%$, we get $\theta = 0.0065$.

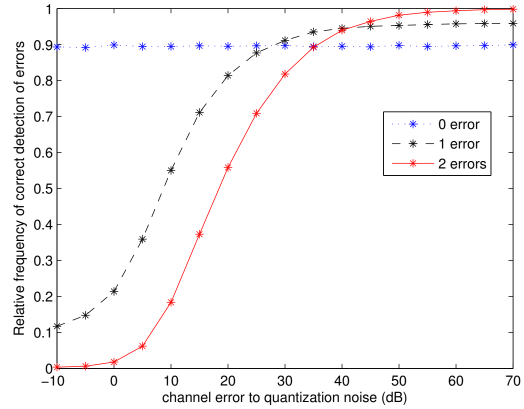

Fig. 3. Relative frequency of correct estimation of the number of errors for a $(10,5)$ DFT code.

the MSE between transmitted and reconstructed sequences. For each channel-error-to-quantization-noise ratio (CEQNR), defined as σ_e^2/σ_q^2, we use 2×10^5 input samples.

Simulation results are plotted in Fig. 3 - Fig. 6, by varying CEQNR. Before doing so, based on Fig. 2, the threshold $\theta = 0.0065$ is fixed for $p_d = 90\%$; it is used to estimate ν in Fig. 3. Note that this threshold varies depending on the quantization. The estimated number is then used to find the location of errors in Fig. 4, both for the PGZ and subspace methods.[4] Next, the output of Fig. 4, for subspace method, is fed to the last step to find the magnitude of errors and correct them. The MSE is compared against the quantization error level, the ideal case in the lossy source coding based on binary codes; though, this ideal case is not necessarily attainable, even using capacity-approaching codes [29]. To put our results in perspective, we also calculate the MSE assuming perfect error localization; it gives 0, 6.5×10^{-5}, and 1.8×10^{-4} respectively for 0, 1, and 2 errors, in any CEQNR. This implies that there is still room to improve the MSE performance of the proposed system, given a better solution for error localization. It also indicates the performance gap between this DFT code and binary codes in the ideal case. Expectedly, for the same number of errors, high rate codes have better performance. As an example, in Fig. 6 we show the MSE performance of a systematic $(12,5)$ code constructed based on [19, Theorem 7]; $\theta = 0.0115$ is used for error detection.

Seeing that we do not use the ideal Slepian-Wolf coding assumption, the gap between performance of our schemes and Wyner-Ziv rate-distortion function is more than usual. However, it should be noted that capacity-approaching channel codes may introduce significant delay if one strives to approach the capacity of the channel with a very low probability of transmission error. Hence, those are out of the question for delay-sensitive systems. In that case, it would be best to use

[4]It is worth mentioning that if the amplitude of errors is fixed, as assumed in [16], the results improves considerably. For one thing, at the CEQNR of 20dB the probability of correct localization becomes 1.

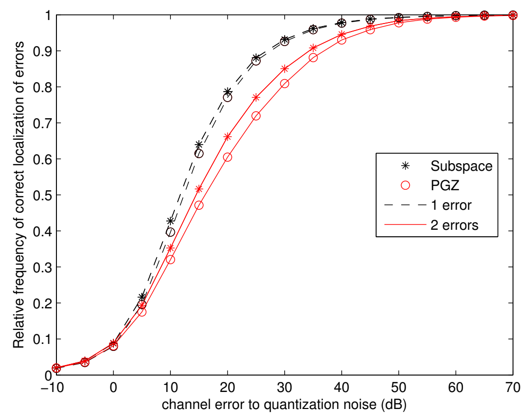

Fig. 4. Relative frequency of correct localization of errors, corresponding to Fig. 3, for the PGZ and subspace methods.

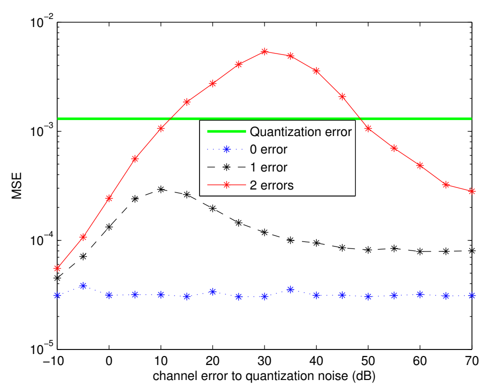

Fig. 5. Reconstruction error for the subspace-based error localization.

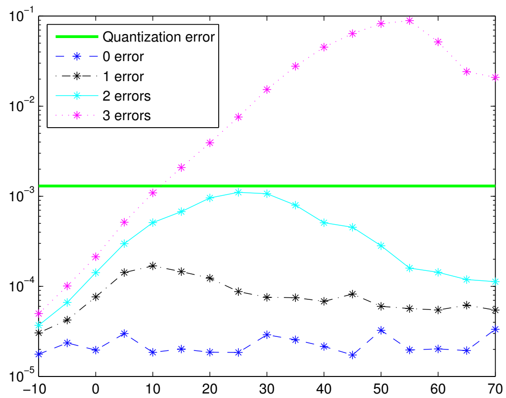

Fig. 6. Reconstruction error for a $(12, 5)$ DFT code.

channel codes of low rate and focus on achieving a very low probability of error. The system we introduced is a low-delay system which works well with reasonably high-rate codes. Finally, the proposed scheme for DJSCC, and also parity-based DSC, can be easily extended to rate-adaptive system, by puncturing some parity samples. Rate-adaptive systems are popular in transmission of non-ergodic data, like video [30].

VI. Conclusion

We have studied a low-delay scheme for lossy joint source-channel coding with side information at the decoder. Unlike the common approach where compression and channel coding are done after quantization we perform them before quantizing the sources. This introduces a new framework for DJSCC in which binning is done in the real field and through the use of a single DFT code. In addition to adopting the subspace-based error localization to the context of DSC based on DFT codes, we introduced a subspace-based approach for error detection. Numerical results show the efficacy of the proposed scheme, especially for impulsive channels and relatively sparse errors. To further improve the MSE, one should come up with a better algorithm for error localization.

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