Enhancing the Robustness of Distributed Compression Using Ideas from Channel Coding

Peiyu Tan and Jing Li (Tiffany)
Electrical and Computer Engineering Department
Lehigh University, Bethlehem, 18015
{pet3,jingli}@ece.lehigh.edu

***Abstract*— We investigate the self error resilience of practical distributed source coding (DSC) approaches at the presence of residual transmission errors. It is firstly shown that the existing *asymmetric syndrome-former inverse-syndrome-former framework* (ASIF), although simple, general and optimal for the noiseless-channel case, is not sustainable to transmission errors. The vulnerability stems from the underlying *binning approach*. Using ideas from channel coding, we illuminate a subtle relation between the *binning approach* and the *parity approach*, and demonstrate, through the examples of convolutional codes, how the former can be transformed to the latter for stronger self error resilience. Simulation results confirm that the new scheme is much more robust and less error-sensitive than the existing ASIF scheme.**

I. Introduction

Consider multiple physically-separated non-communicating sources sending statistically-correlated data to a common destination. Using the binning argument, Slepian and Wolf established the achievable rate region for distributed compression (but joint de-compression) [1]. Succeeding research reveals that practical solutions to distributed source coding (DSC) lie in channel codes. Excellent formulations using powerful linear channel codes, and particularly low density parity check (LDPC) codes (e.g. [2]- [4]) and turbo codes (e.g. [5]- [9]), have been developed, some of which are shown to be (asymptotically) optimal.

A majority body of the work considers noiseless channels. Implicit in this model is the assumption that perfect channel coding is performed at the edge of the transmission channel/network. However, practical channel codes are imperfect. The existence of residual errors could therefore compromise the efficiency of the source coding mechanism.

This paper concerns the error resilient capability of a general and efficient Slepian-Wolf coding approach, formerly known as the *asymmetric SF-ISF framework* (ASIF) [9]. By exploiting the syndrome former (SF) and inverse syndrome former (ISF) of a linear channel code, the ASIF approach is shown to be capable of converting any linear channel code to an asymmetric Slepian-Wolf code (i.e. general), and, if the channel code is capacity-approaching on the virtual channel characterized by the source correlation, then the resulting Slepian-Wolf code can get arbitrarily close to the corner points of the Slepian-Wolf boundary (i.e. optimal) [9]. Unlike the existing joint source-channel coding strategies [10]- [12] which considers the joint design of Slepian-Wolf compression and error protection and which explicitly allocate rate for the purpose of error protection, here we are primarily interested in the "intrinsic" error resilient capability, or the robustness, of the approach. Specifically, we wish to investigate the sensitivity of ASIF to the (residual) transmission errors and, without explicitly allocating rate to error protection nor sacrificing the simplicity and optimality of the scheme, to improve its self error resilience.

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As will be discussed in detail later on, ASIF is based on the idea of code binning where compression is achieved by mapping long sequences in the bin/coset to short bin-indexes/syndromes. The binning practice is intrinsically vulnerable to transmission errors, since any residual error in the bin-index results in a shift of the search space to a wrong bin, making the decoding errors uncontrollable. By treating syndromes as a special type of parity bits and introducing simple modifications to the source decoder, we show how the *binning approach* can be transformed to the *parity approach* for improved self error resilience. For readability, we discuss ASIF using simplest generalizable examples of convolutional codes, but our results generalize to all the convolutional and convolutional based codes such as turbo codes.

The remainder of the paper is organized as follows. Section II reviews the background of DSC and presents the system model of ASIF. Section III evaluates the robustness of ASIF and proposes improved decoding strategies along with simulation examples. Section IV concludes the paper.

II. Background

A. System Model

We consider asymmetric DSC, where two memoryless binary symmetric sources X and Y are correlated by a virtual binary symmetric channel (BSC) with a cross-over probability $p_y = P(Y \neq X)$. In a noiseless-channel DSC setup, Y is assumed to be compressed at full rate and losslessly available at the joint decoder, and X is compressed as much as possible: $R_x \rightarrow H(X|Y)$; see Figure 1. In the context of imperfect transmission, without loss of generality, let us assume that Y is also losslessly available at the decoder. This is because the residual transmission errors in Y can be factored into the correlation model. For example, a system with an error rate of p_e for Y is equivalent to one that has a zero transmission error for Y but an inter-source correlation of $P(Y \neq X) = p'_y$, where $p'_y = p_y + p_e - p_y p_e$. For the other source X, we assume that its compressed version, S, experiences a residual

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error probability of p_s. Hence, the system model of interest comprises a source X, which will be compressed using ASIF, transmitted over a BSC(p_s), and decoded with side information Y, whose correlation with X is characterized by BSC(p_y).

B. The Binning Approach and the Parity Approach

The fundamental idea of code binning [1] is to uniformly group the 2^n sequences from source X^n, each of length n, into $2^{(n-k)}$ bins each indexed with a length $(n-k)$ bin-index sequence. Thus a compression ratio of $n:(n-k)$ is achieved by transmitting the bin-index instead of the original sequence. At the decoder, the bin-index will be used to locate the bin and the side information Y^n will be used to identify the specific sequence in the bin. In practice, bins are often constructed using an (n,k) linear channel code, where source sequences X^n are taken as virtual codewords, cosets as bins and syndromes as bin-indexes [9]. For this reason, the *binning approach* is also referred to as the *syndrome approach*. For lossless transmission, the binning approach can achieve the Slepian-Wolf limit ($R_x \geq H(X|Y)$, $R_y \geq H(Y)$) with zero-distortion, provided that the (n,k) channel code in use is capacity-achieving on the virtual channel [1].

Aside from the binning approach, the *parity approach* has also been widely used in the practice of asymmetric DSC. Consider an (n,k) systematic linear channel code. A compression ratio of $k:(n-k)$ can be achieved by encoding source X^k using the channel code, and sending the parity bits instead of the systematic bits. The decoder will take Y^k as noisy systematic bits and perform channel decoding to recover X^k. The parity approach is conceptually simpler than the binning approach; but the candidate code that will guarantee a limit-approaching compression performance is less obvious.

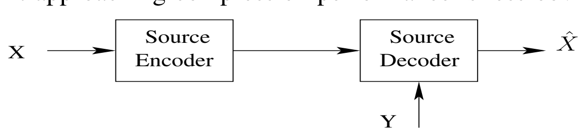

Fig. 1. Asymmetric distributed source coding

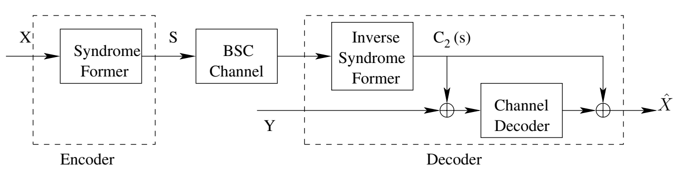

Fig. 2. System model for the ASIF scheme.

C. ASIF

The asymmetric SF-ISF framework proposed in [9] presents an explicit implementation of the binning approach, and is therefore optimal. The syndrome former and inverse syndrome former are modules that map the codeword space $\{X^n\}$ to the syndrome space $\{S^{(n-k)}\}$ and vice versa. Specifically, the syndrome former finds the bin-index or syndrome for the source sequence or a codeword; and the inverse syndrome former assigns an *arbitrary* source sequence within that bin to a given syndrome sequence or bin-index. As shown in Figure 2, the source encoder is simply the SF module, and the source decoder consists of the matching ISF and the original channel decoder. In the plot, S denotes the syndrome sequence (output of SF) and $c2(s)$ denotes an arbitrary codeword c associated with syndrome sequence s (output of ISF).

A detailed discussion on constructing SF-ISF pairs for different codes can be found in [9]. For convolutional code with rate k/n and generator matrix G, the SF can be implemented via an $n/(n-k)$ linear sequential circuit specified by an $n \times (n-k)$ transfer matrix H^T with rank $(n-k)$ subject to $GH^T = 0_k$, where 0_k is the k-by-k all-zero matrix. The matching ISF, $(H^{-1})^T$, can be obtained by taking the left inverse of the syndrome former, H^T, i.e. $(H^{-1})^T H^T = I_{n-k}$, where I_{n-k} is an identity matrix with rank $(n-k)$.

For a given code, there are more than one valid pair of SF and ISF. The exact formulations of these SF-ISFs usually depend on the code and therefore lack a common form. One exception to the latter is what we referred to as the *universal* SF-ISF pair. For a rate k/n convolutional code with generator matrix $G(D)$ consisting of $k \times n$ generator polynomials, divide the generator matrix into into a $k \times k$ square part $P(D)$ in the left and a $k \times (n-k)$ part $Q_(D)$ in the right: $G(D) = [P(D), Q(D)]$. The universal SF-ISF pair takes the form of

$$\text{SF:} \qquad H^T = \begin{bmatrix} P^{-1}Q \\ I \end{bmatrix}_{n\times(n-k)}, \qquad (1)$$

$$\text{ISF:} \qquad (H^{-1})^T = \begin{bmatrix} \mathbf{0}, I \end{bmatrix}_{(n-k)\times n}, \qquad (2)$$

where $\mathbf{0}$ and I denote the all-zero matrix and the identity matrix, respectively. One interesting property of this universal SF-ISF pair is that, for a given length $n-k$ syndrome, the ISF always finds, in the respective bin, a sequence whose first k bits are zeros and the latter $n-k$ bits are the syndrome itself.

III. Robustness of ASIF in Noisy Environments

The binning approach is inherently vulnerable to errors, since any error in the syndrome will result in a shift of the bin in which the decoder searches for the correct sequence x^n. Hence, although the side information y^n may help locate the correct relative position within a bin, there is no way to recover the correct sequence in a wrong bin.

To examine the impact of syndrome errors (and bin shifts) on the performance of ASIF, we conduct a test on a rate 1/2 recursive systematic convolutional (RSC) code with generator matrix $G = [1, \frac{1\oplus D^2 \oplus D^3 \oplus D^4}{1\oplus D \oplus D^4}]$. We start with the simple universal "systematic" SF-ISF construction in (1) and (2):

$$\text{SF}: \qquad H^T = \begin{bmatrix} \frac{1\oplus D^2\oplus D^3\oplus D^4}{1\oplus D\oplus D^4} \\ 1 \end{bmatrix}, \qquad (3)$$

$$\text{ISF}: \qquad (H^{-1})^T = \begin{bmatrix} 0, & 1 \end{bmatrix}. \qquad (4)$$

A. ASIF Using Systematic SF-ISF Pair

The first question we ask is, when residual transmission errors exist in the syndrome but the source decoder has no knowledge of it or no means of exploiting this knowledge, how severely will the performance be impaired? The situation corresponds to "blind" source decoding where the input to the ISF module (see Figure 2) is considered noiseless and

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the input to the Channel Decoder module is treated as a BSC(p_y) corrupted codeword. We tested two strong correlation cases with $p_y = 0.005$ and 0.01. The normalized distortions of the recovered sequences, x^n, obtained using computer simulation, are listed in Table I. For convenience, we refer to this scheme as "ASIF-S", where "S" stands for "systematic" SF. We observe that with error-free syndrome transmission (i.e $p_s = 0$), the source decoder is capable of near-lossless recovery of x^n with a normalized distortion of 10^{-5} or less. However, the distortion rises rapidly as soon as errors appear in the syndromes: at a small percentage of syndrome error $p_s = 0.5\%$, the distortion has already increased by more than 2 magnitudes.

TABLE I

RESULTS FOR ASIF-S, BLIND DECODING

Distortion	$p_s = 0$	.005	.010	.015	.020
$p_y = .005$	4.006e-6	2.455e-3	5.07e-3	7.31e-3	1.05e-2
$p_y = .010$	1.628e-5	2.66e-3	5.135e-3	7.57e-3	1.0135e-2

TABLE II

RESULTS FOR ASIF-S, p_s KNOWN TO THE DECODER

Distortion	$p_s = 0$	.005	.010	.015	.020
$p_y = .005$	3.5679e-6	2.525e-3	5.527e-3	7.62e-3	1.054e-2
$p_y = .010$	1.4787e-5	2.485e-3	5.065e-3	7.905e-3	1.023e-2

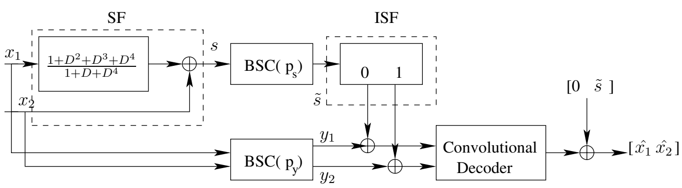

Fig. 3. ASIF using a systematic syndrome former (ASIF-S).

We suspect that the (virtual) channel mismatch contributes in part to the large distortion. To rectify this, in our second test, we equip the source decoder with p_s, the residual error rate of the syndromes.Using a simple analysis on ASIF-S, it is easy to show that the input to the Channel Decoder module remains to be a BSC corrupted codeword, but now the crossover probability becomes $(\frac{1}{2}p_s + p_y - \frac{1}{2}p_s p_y)$ instead of p_y. We expect the source decoder to benefit from the correctly-adjusted crossover probability; but the simulation results demonstrate no observable improvement; see Table II.

Comparing the results in Tables I and II, we see that the distortion levels in both cases are to the same order as p_s for $p_s > 0$ (more precisely, when a rate k/n code is used, the distortions are approximately $(n-k)/n$ of p_s). This phenomenon becomes easy to explain when we redraw ASIF in Figure 2 using the actual channel code and the SF-ISF pair. As shown in the equivalent system diagram in Figure 3, although the knowledge of p_s contributes to better decoding results from the convolutional channel decoder, the final result from the source decoder is the sum of the convolutional decoder output and the ISF output, $[0, \tilde{s}]$. The involvement of the syndrome, $\tilde{S}$, brings back the error rate. A more rigorous analysis of the distortion level can be obtained by working through the validity proof of ASIF:

When syndrome transmission is noiseless ($p_s = 0$), the side information y is viewed as a noisy version of source x: $y = x \oplus n_y$, where n_y follows Bernoulli distribution with $P(n_y = 1) = p_y$. Assume x is associated with the syndrome sequence s: $x \stackrel{\triangle}{=} c_1(s)$. The SF module in the source encoder (see Figure 2) will thus map (compress) x to s, and the ISF in the source decoder will map s back to a sequence in that bin, $c_2(s)$. The input to the Channel Decoder module in Figure 2 [9]:

$$\begin{aligned} y \oplus c_2(s) &= (x \oplus n_y) \oplus c_2(s) \\ &= \underbrace{c_1(s) \oplus c_2(s)}_{c_3(0)} \oplus n_y, \end{aligned} \tag{5}$$

where $c_3(0)$ denotes a valid codeword of the channel code (since it has the all-zeros syndrome). Hence, if the channel code is powerful enough to combat the noise n_y, it will recover $c_3(0)$ with a vanishing error probability. Since $c_3(0) = c_1(s) \oplus c_2(s) = x \oplus c_2(s)$, adding the ISF output $c_2(s)$ back to $c_3(0)$ at the end of the source decoder yields the original sequence: $\hat{x} = c_3(0) + c_2(s) = x \oplus c_2(s) \oplus c_2(s) = x$.

However, at the presence of the syndrome noise ($p_s > 0$), the output from the ISF becomes $c_2'(s \oplus n_s)$, where $P(n_s = 1) = p_s$. Thus, Equation (5) becomes:

$$\begin{aligned} y \oplus c_2(s \oplus n_s) &= x \oplus n_y \oplus c_2'(s \oplus n_s) \\ &= \underbrace{c_1(s) \oplus c_2(s)}_{c_3(0)} \oplus n_y \oplus n_s' \end{aligned} \tag{6}$$

where n_s' is the output from the ISF with input n_s. When the universal ISF, $(H^{-1})^T = [0, 1]$, is used, we have $n_s' = [0, n_s]$ (for convenience, we assume they are represented in row vectors). The final decoder result is affected in two ways. First, the channel decoder needs to combat a combination of two types of noise, n_y and n_s', to recover $c_3(0)$. Second, the output of the source decoder, $\hat{x} = c_3(0) \oplus c_2'(s \oplus n_s) = c_1(s) \oplus n_s' = x \oplus [0, n_s]$, now yields a noisy version of the original source sequence, and the distortion is dominated by n_s which has non-zero probability p_s.

B. New Scheme

The experiments in the previous subsection indicate that ASIF is sensitive to syndrome errors, largely due to the module-2 addition after the channel decoder. Below we propose an improved decoding strategy that can considerably improve the robustness of the system. The idea is motivated by the distributed source coding procedure for LDPC codes.

Let us provide a quick overview of the LDPC Slepian-Wolf formulation. An (n, k) LDPC code is described by an $m \times n$ parity-check matrix H, where $m = n - k$, and decoded using the well-known message-passing decoding algorithm. In the context of DSC, source encoding is performed by multiplying the source sequence x^n with H, i.e. H assumes the role of the syndrome former in Figure 2. Although it is also possible to explicitly construct a matching ISF and perform source decoding as depicted in Figure 2, a popular approach is to first construct an *extended* parity check matrix, H_{ext}, by concatenating an $m \times m$ identity matrix to the original parity check matrix H: $H_{ext} = [H_{m \times n}, I_m]$, and subsequently apply the message-passing algorithm on H_{ext} to recover a valid codeword $[x^n, s^m]$ from the noisy version $[y^n, \tilde{s^m}]$. By incorporating the syndrome sequence in channel decoding, this latter decoding strategy can efficiently combat the errors in the syndrome.

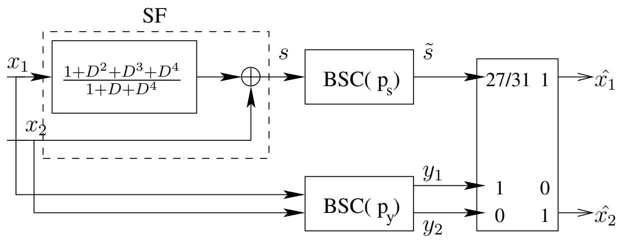

Fig. 4. New scheme using a systematic syndrome former (NEW-S).

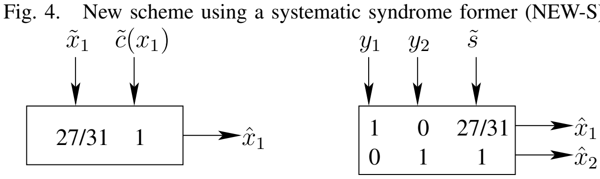

Fig. 5. Comparison of the channel decoders in ASIF-S and NEW-S.

At first sight, it appears that the above LDPC-DSC formulation relies on the unique features of an LDPC code (random parity check matrix and message-passing decoding), and is therefore hard to generalize. For example, how does the Berlekamp-Massey decoding algorithm of the RS code make use of the syndrome information? A closer look reveals that the fundamental idea behind it is in fact general. From the coding theory, one realizes that syndromes can also be viewed as a special type of parity bits. Hence, the LDPC-DSC formulation can be interpreted in two ways: the binning approach using an (n, k) LDPC code, and the parity approach using an $(2n-k, n)$ low-density generator-matrix (LDGM) code. (An LDGM code is a special type of linear-time encodable LDPC codes whose parity check matrix comprises an random sparse matrix on the left and an identity matrix on the right.) This suggests that the binning approach can be naturally transformed to the parity approach (and vice versa), and the latter may be more robust to residual transmission errors.

Now consider our previous example of convolutional codes. The syndrome former can be taken as a special class of convolutional codes with input x^n, output s^{n-k}, generator matrix H^T and rate $n/(n-k) > 1$. That is, s^{n-k} can be viewed as *convolutionally coded* bits, or simply, parity bits, for x^n. The decoder can then treat $[y^n, \hat{s}^{n-k}]$ as a noisy copy of the codeword $[x^n, s^{n-k}]$ from an *extended* systematic convolutional code with input x^n, generator matrix $[I, H^T]$ and rate $n/(2n-k) < 1$.

Using the same example in Figure 3, we plot in Figure 4 the corresponding new scheme. Since a "systematic" syndrome former is used, we refer to it as "NEW-S".

We see that the original ASIF scheme in Figure 3 is a typical binning approach based on a rate 1/2 (or k/n in general) convolutional code, whereas the modified scheme in Figure 4 can be viewed as a parity approach using a rate 2/3 (or $n/(2n-k)$ in general) convolutional code. The differences of the channel decoders in the two schemes are illustrated in Figure 5. Like the LDPC-DSC formulation, the new scheme efficiently incorporates the syndrome in channel decoding, making the errors in the syndrome as correctable as the difference between sources X and Y.

The simulation results of the modified scheme in Figure 4 is presented in Table III. It appears somewhat surprising that the gains are quite marginal. This however is due to the artifact of the choice of the syndrome former. As we will show later, when a more appropriate SF is used (which leads to a better rate 2/3 (or $n/(2n-k)$ in general) convolutional code, the modified scheme will exhibit considerable gains over the existing scheme.

TABLE III
RESULTS FOR NEW-S

Distortion	$p_s=0$	0.005	0.01	0.015	0.02
$p_y=.005$	3.1808e-6	2.365e-3	2.58e-3	2.54e-3	2.54e-3
$p_y=.010$	1.507e-5	2.49e-3	5.135e-3	5.335e-3	4.905e-3

C. Choice of the Syndrome Former

To see why the "systematic" syndrome former in (1) is not a good choice for the new scheme, consider the generator matrix of the resulting rate $n/(2n-k)$ code:

$$G_{new} = \left[\, I,\, H^T \,\right] = \left[\begin{array}{ccc} I_k, & 0, & P^{-1}Q \\ 0, & I_{n-k}, & I_{n-k} \end{array} \right]_{n\times(2n-k)}. \quad (7)$$

Notice that the data corresponding to the last $n-k$ rows in the generator matrix, i.e. x_{k+1}^n, participate in only one check each. This weak protection makes bit flips in those positions hard to correct. We expect a stronger code would result by eliminating the identity part in the syndrome former. This can be done by multiplying the universal SF in (1) with a non-trivial polynomial $W(D)$. For the example we discussed previously, it is convenient to multiply the SF in (3) with $W(D) = 1 \oplus D \oplus D^4$, which yields a non-systematic SF (and its matching ISF):

$$\text{N-SF}: \quad H^T = \left[\begin{array}{c} 1\oplus D^2 \oplus D^3 \oplus D^4 \\ 1 \oplus D \oplus D^4 \end{array} \right], \quad (8)$$

$$\text{Matching ISF}: \quad (H^{-1})^T = \Big[1\oplus D,\ D \Big]. \quad (9)$$

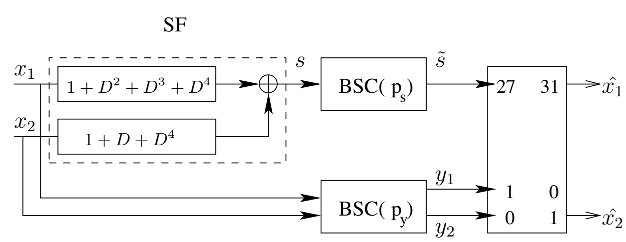

Fig. 6. New scheme using a non-systematic syndrome former (NEW-N).

The system diagram of the new scheme using the non-systematic SF, referred to as "NEW-N", is illustrated in Figure 6). As expected, the simulation results (Table IV) demonstrate strong sustainability to transmission errors. For example, for a syndrome error rate of 10^{-2}, the normalized distortion of the new system stays at a low level of 10^{-4}, which is about 2 magnitude lower than the previous cases.

The encouraging results of the new scheme also motivates us to investigate whether the choice of the SF-ISF pair would also affect the decoder robustness in the original ASIF scheme.

These results, referred to as NEW-S, are listed in Table IV. We observe that different SF-ISF choices affect but slightly the decoder performance in the presence of syndrome errors. Unlike the modified scheme, the non-systematic SF-ISF pair here appears to be (slightly) more sensitive to errors than the systematic SF-ISF.

D. Summary of the Simulation Results

We plot the simulation results discussed previously (Table I-IV) in Figures 7 and 8 for the case of $p_y = 0.005$ and 0.010, respectively. The base channel code we use has a generator matrix $[1, (1 \oplus D^2 \oplus D^3 \oplus D^4)/(1 \oplus D \oplus D^4)]$, which provides a compression ratio of $2:1$. The x-axis denotes the level of the residual errors in syndrome transmission and the y-axis denotes the normalized distortion of the recovered data X. The curves demonstrate that (1) the choice of the SF-ISF pair affects the sensitivity of the decoder to the transmission errors, and is more so with the new scheme than with the existing ASIF scheme, and (2) while the existing ASIF approach is not particularly resistant to the residual errors in the syndromes, the new scheme, which is now based on the parity approach, can be quite robust when used with an appropriate SF (i.e. non-systematic SF).

IV. Conclusion

We have investigated the self error-resilience of the practical binning-based DSC approach at the presence of transmission errors. Using convolutional codes as an illustrating example, we show that the existing ASIF scheme is not sustainable to residual syndrome errors and the vulnerability stems from the underlying binning approach. Motivated by the ideas from channel coding and particularly the LDPC-DSC formulation, a modified source decoding strategy is proposed, which can efficiently combat the residual transmission errors when used with an appropriate syndrome former.

Through absorbing the syndrome sequences in channel decoding, the modified scheme has essentially transformed the binning approach, or the syndrome approach, to the parity approach. From the source coding point of view (i.e. lossless transmission), the binning approach is provenly optimal: it achieves the Slepian-Wolf limit when used with a capacity-approaching channel code. It is also possible to achieve the Slepian-Wolf limit using the parity approach, but what channel code to use is less obvious. On the other hand, when there are residual transmission errors, the parity approach appears to have some advantage over the binning approach. The work in this paper helps illuminate the subtle relation between the binning approach and the parity approach.

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TABLE IV

Results for NEW-N and ASIF-N.

New-N					
Distortion	$p_s = 0$	0.005	0.010	0.015	0.020
$p_y = .005$	3.73e-6	2.017e-4	2.974e-4	3.631e-4	4.68e-4
$p_y = .010$	1.576e-5	3.704e-4	7.613e-4	8.649e-4	1.162e-3
ASIF-N					
Distortion	$p_s = 0$	0.005	0.010	0.015	0.020
$p_y = .005$	3.24e-6	6.935e-3	1.288e-2	1.837e-2	2.287e-2
$p_y = .010$	1.447e-5	6.62e-3	1.300e-2	1.804e-2	2.31e-2

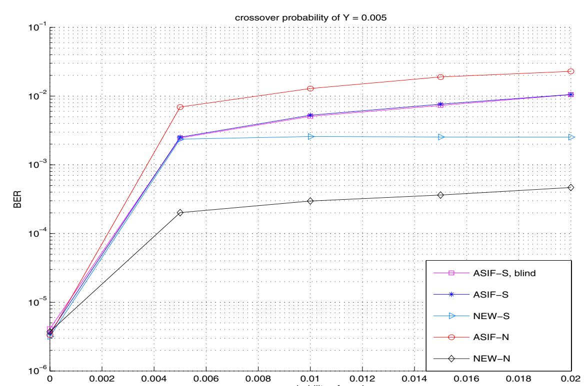

Fig. 7. Performance comparison of different schemes ($p_y = 0.005$)

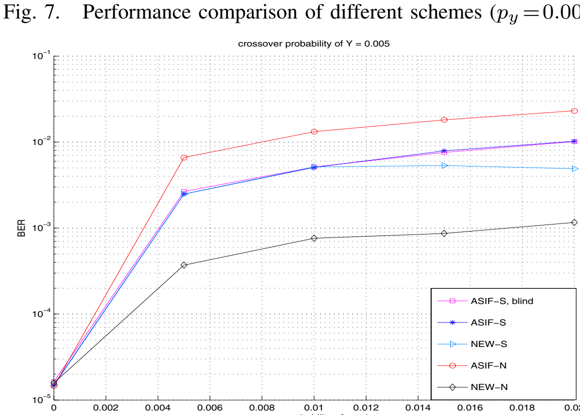

Fig. 8. Performance comparison of different schemes ($p_y = 0.010$)

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