

Distributed Lossy Source Coding Using BCH-DFT Codes

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February 11, 2014

Overview

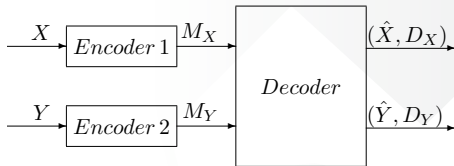
- 1 Introduction and Background
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 - Summary
 - Future Research Directions



Distributed Source Coding

Problem Statement

- ▶ Distributed source coding



A communication system with

- ▶ Two separate, **correlated** signals (X and Y)
- ▶ The sources cannot communicate with each other; thus, encoding is done **independently** or in a distributed manner
- ▶ The receiver, however, can perform **joint decoding**

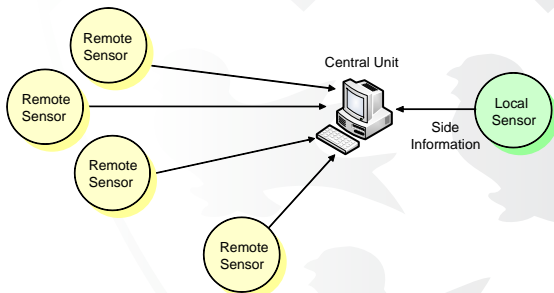
Motivation and Applications

Why DSC?

- ▶ Reduce the data required for storage/transmission
- ▶ Increase battery life (eliminate power consumption for communication)
- ▶ Low complexity encoders (shift the complexity to the decoder)

Applications

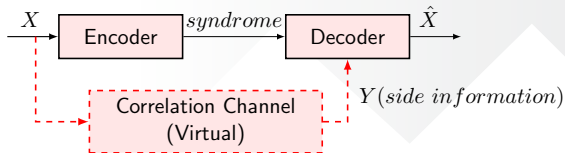
- ▶ Sensor networks
- ▶ Low complexity video coding



Practical Code Construction

Lossless DSC (Slepian-Wolf Coding)

- ▶ DSC is essentially a **channel coding problem** (view Y as corrupted version of discrete-valued X)



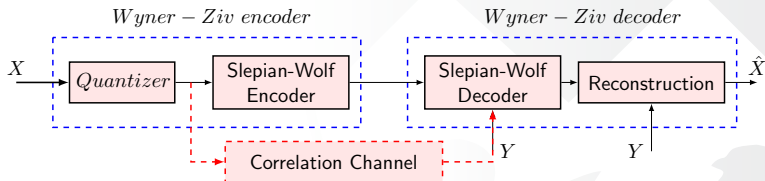
- ▶ The channel code design and its rate depends on the correlation channel
- ▶ The correlation is usually modeled as a BSC
- ▶ Capacity-approaching channel codes (LDPC and Turbo codes) are asymptotically optimal

Practical Code Construction

Lossy DSC

What if the sources are **continuous-valued**?

Conventional Approach

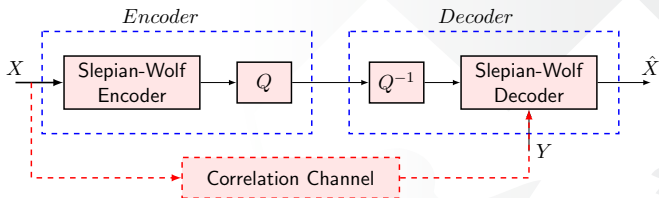


- ▶ There are *quantization loss* and *binning loss*
- ▶ Correlation between real-valued signals is translated to binary domain which can bring about further loss

Lossy DSC in the Real Field

Q: How can we better model the virtual correlation channel?

► The Proposed Framework



► Motivations

- More realistic correlation channel model
- Lower delay and complexity

[J1] M. Vaezi and F. Labeau, "Distributed source-channel coding based on real-field BCH codes," IEEE Trans. Signal Process., Jan. 2014.

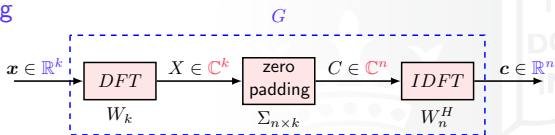
[C1] —, "Improved modeling of the correlation between continuous-valued sources in LDPC-based DSC," In Proc. Asilomar 2012.

[C2] —, "Least squares solution for error correction on the real field using quantized DFT codes," In Proc. EUSIPCO 2012.

[C3] —, "Distributed lossy source coding using real-number codes," In Proc. VTC-Fall 2012.

BCH-DFT Codes as Channel Codes

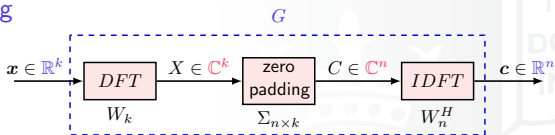
Encoding



- ▶ G consists of k columns from the IDFT matrix (W_n^H)
- ▶ The remaining $n - k$ columns of the IDFT matrix form H

BCH-DFT Codes as Channel Codes

Encoding



Decoding: let $r = c + e$ where e has $\nu \leq t$ nonzero elements at $1 \leq i_1, \dots, i_\nu \leq n$ with magnitudes $e_{i_1}, \dots, e_{i_\nu}$.

- ▶ Compute the syndrome of error ($s = Hr = He$)
- ▶ Form the below syndrome matrix for $m = \lfloor \frac{d}{2} \rfloor$

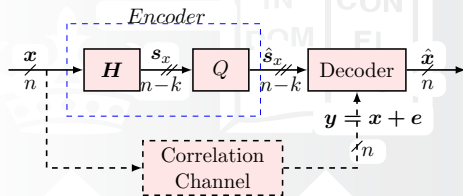
$$S_m = \begin{bmatrix} s_1 & s_2 & \dots & s_{d-m+1} \\ s_2 & s_3 & \dots & s_{d-m+2} \\ \vdots & \vdots & \ddots & \vdots \\ s_m & s_{m+1} & \dots & s_d \end{bmatrix}$$

- ▶ Decoding algorithms have the following major steps:
 1. **Detection** (determine the **number** of errors; $\nu \leq \lfloor \frac{d}{2} \rfloor$)
 2. **Localization** (find the **location** of errors; i_1, \dots, i_ν)
 3. **Estimation** (calculate the **magnitude** of errors; $e_{i_1}, \dots, e_{i_\nu}$)

Proposed Lossy DSC Based on BCH-DFT Codes

Syndrome Approach

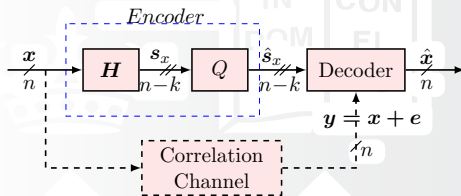
- ▶ The decoder computes s_x
- ▶ The encoder finds $s_e = s_y - s_x$
($\tilde{s}_e = s_y - \hat{s}_x = s_e - q$)
- ▶ Compression ratio is $n : n - k$



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Correlation model

$$Y = X + E, \quad E \sim \begin{cases} \mathcal{N}(0, \sigma_0^2) & \text{w.p. } p_0, \\ \mathcal{N}(0, \sigma_1^2) & \text{w.p. } p_1, \\ 0 & \text{w.p. } 1 - p_0 - p_1, \end{cases}$$

in which $\sigma_1^2 = \sigma_i^2 + \sigma_0^2$, $\sigma_i^2 \gg \sigma_0^2$, and $p_0 + p_1 \leq 1$.

- ▶ $p_0 = 1$ or $p_1 = 1 \implies$ Gaussian correlation model
- ▶ $p_0 + p_1 = 1 \implies$ Gaussian-Bernoulli-Gaussian (GBG) model
- ▶ $p_0 + p_1 < 1, p_0 p_1 = 0 \implies$ Gaussian-Erasure (GE) model

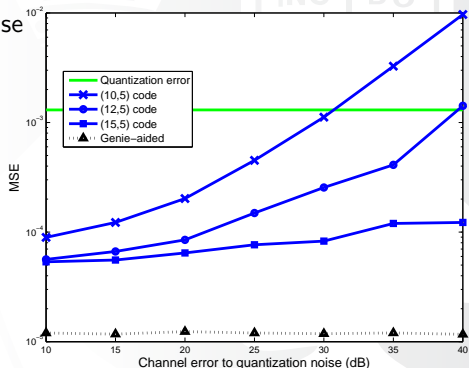
Numerical Results

- ▶ Channel-error-to-quantization-noise ratio (CEQNR)

$$\text{CEQNR} \triangleq \frac{\sigma_i^2}{\sigma_q^2},$$

where $\sigma_q^2 = \frac{\Delta^2}{12}$.

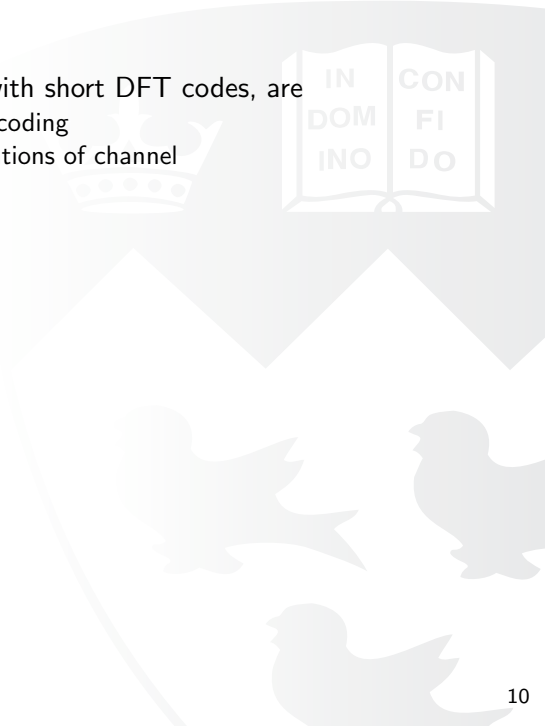
- ▶ Gauss-Markov source X with $\sigma_X = 1$, $\rho = 0.9$
- ▶ GE correlation model with $p_1 = 0.04$



Rate-Adaptive DSC

The proposed schemes, with short DFT codes, are

- ▶ Suitable for low-delay coding
- ▶ Vulnerable to the variations of channel

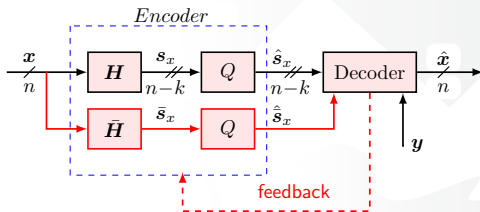


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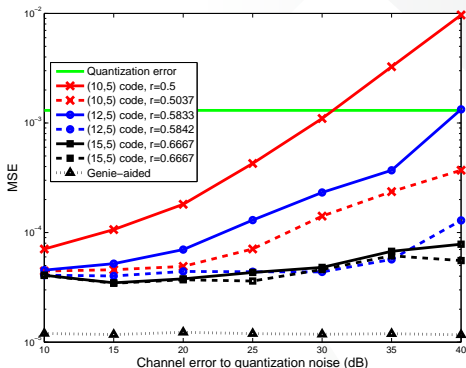
Solution: Rate-adaptive DSC with feedback



Rate-Adaptive DSC

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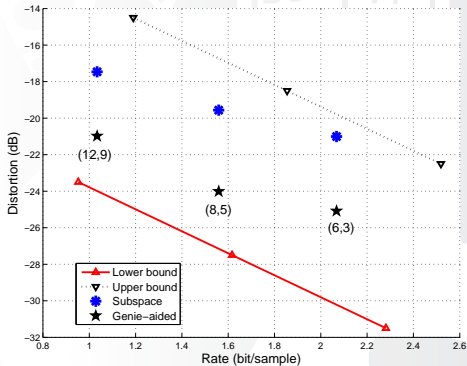
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Rate-Distortion Performance

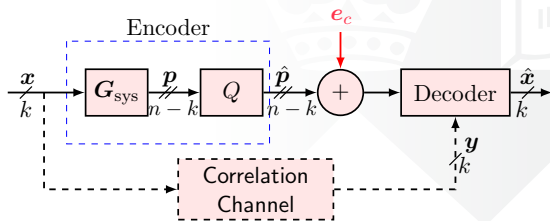
Parameters:

- ▶ Gauss-Markov source X with $\sigma_X = 1$, $\rho = 0.9$
- ▶ GBG correlation model with $p_1 = 0.04$, $\sigma_0 = 0.05\sigma_e$
- ▶ CEQNR = 25dB (or $\sigma_0 = 0.1282$ and $\sigma_e = 2.5647$ for $b = 4$)
- ▶ $\underline{R}_{X|Y}^{\text{GBG}}(D) = \sum_{j=0}^1 p_j R_{X|Y, s_j}(D)$
- ▶ $\bar{R}_{X|Y}^{\text{GBG}}(D) = R_{X|Y, s_1}(D)$



Other Contributions

Distributed Joint Source-Channel Coding



- ▶ Parity-based DSC
- ▶ Distributed joint source-channel coding
- ▶ Systematic DFT frames and their properties

[J2] M. Vaezi and F. Labeau, "Systematic DFT frames: Principle, eigenvalues structure, and applications," IEEE Trans. Signal Process., Aug. 2013.

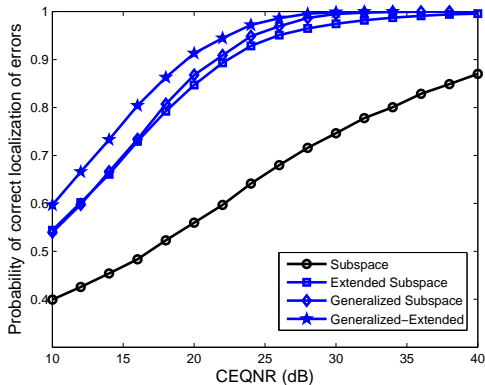
[C4] —, "Low-delay joint source-channel coding with side information at the decoder," In Proc. DSP 2013.

[C5] —, "Systematic DFT frames: Principle and eigenvalues structure," In Proc. ISIT 2012.

Other Contributions

Generalized Subspace-Based Error Localization

- ▶ Classical decoding with subspace-based approach
- ▶ Improved decoding based on extra syndromes
 - ▶ **Extended Subspace:**
Increase the number of vectors in the noise subspace
 - ▶ **Generalized Subspace:**
Utilize different syndrome matrices for one code



[J3] M. Vaezi and F. Labeau, "Generalized and extended subspace algorithms for error correction with quantized DFT codes," IEEE Trans. Commun., Dec. 2013.

[C6] —, "Extended subspace error localization for rate-adaptive distributed source coding," In Proc. ISIT 2013.

Summary of Contributions

- ▶ A new framework for lossy DSC
 - ▶ Syndrome approach
 - ▶ Parity approach
- ▶ Distributed joint source-channel coding
- ▶ Systematic DFT frames
- ▶ Rate-adaptive DSC
- ▶ Improved decoding for BCH-DFT codes
- ▶ Generalized encoding for BCH-DFT codes

Future Research Directions

There are several avenues for future work, mainly revolving around improving the decoding algorithm for DFT codes or extending the developed algorithms to other codes, or fields.

- ▶ Improving Error localization (Rate-Distortion) Performance
- ▶ Generalized Decoding for DCT and DST Codes
- ▶ Lossy DSC Using Oversampled Filter Banks
- ▶ Parametric Frequency Estimation
- ▶ Spectral Compressive Sensing



Thank You 😊





Backup Slides



Rate Region

Lossless DSC (Slepian-Wolf coding)

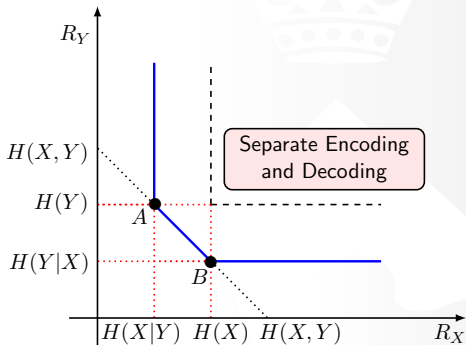
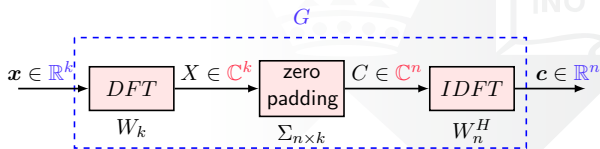


Figure: Achievable rate regions for the Slepian-Wolf coding (solid lines) and separate encoding with separate decoding (dashed lines).

BCH-DFT Codes

Encoding

- ▶ Encoding scheme for an (n, k) real BCH-DFT



- ▶ G consists of k columns from the IDFT matrix (W_n^H)
- ▶ Σ inserts $d = n - k$ **successive zeros** in the transform domain
- ▶ H takes $n - k$ columns of W_n^H corresponding to zeros of Σ
- ▶ The error correction capacity is $t = \lfloor \frac{d}{2} \rfloor = \lfloor \frac{n-k}{2} \rfloor$

Example: The $(6,3)$ DFT code

$$G = \begin{pmatrix} 1 & 0 & 0 \\ \frac{2}{3} & \frac{2}{3} & \frac{-1}{3} \\ 0 & 1 & 0 \\ \frac{-1}{3} & \frac{2}{3} & \frac{2}{3} \\ 0 & \frac{3}{3} & 1 \\ \frac{2}{3} & \frac{-1}{3} & \frac{2}{3} \end{pmatrix}$$

Error Correction in DFT Codes

- ▶ Decoding algorithms for a BCH-DFT code
 1. **Detection** (to determine the **number** of errors; $\nu \leq t = \lfloor \frac{n-k}{2} \rfloor$)
 2. **Localization** (to find the **location** of errors; i_1, \dots, i_ν)
 3. **Estimation** (to calculate the **magnitude** of errors; $e_{i_1}, \dots, e_{i_\nu}$)

$$\mathbf{s} = H\mathbf{r} = H(\mathbf{c} + \mathbf{e}) = H\mathbf{e},$$

$$s_m = \frac{1}{\sqrt{n}} \sum_{p=1}^{\nu} e_{i_p} X_p^{\alpha-1+m}, \quad m = 1, \dots, d = n - k,$$

and $X_p = e^{\frac{j2\pi}{n}i_p}$, $p = 1, \dots, \nu$.

$$\mathbf{S}_t = \begin{bmatrix} s_1 & s_2 & \dots & s_t \\ s_2 & s_3 & \dots & s_{t+1} \\ \vdots & \vdots & \ddots & \vdots \\ s_t & s_{t+1} & \dots & s_{2t-1} \end{bmatrix}$$

Error Correction in DFT Codes

Performance with Perfect Error Localization

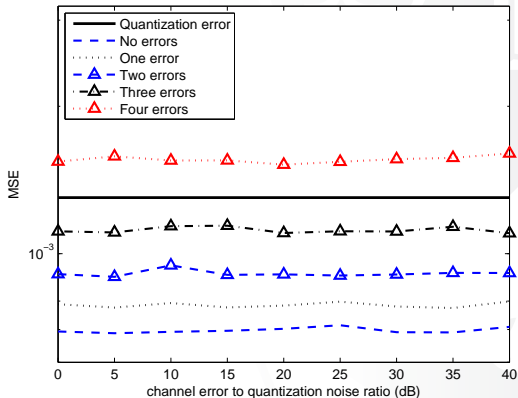


Figure: The MSE performance of LS estimation for a (17, 9) DFT code with *perfect error localization* for different error patterns.

Error Correction in DFT Codes

Subspace-Based Approach

1. Form the *error-locator matrix* of order m as

$$V_m = \begin{bmatrix} 1 & 1 & \dots & 1 \\ X_1 & X_2 & \dots & X_\nu \\ \vdots & \vdots & \ddots & \vdots \\ X_1^{m-1} & X_2^{m-1} & \dots & X_\nu^{m-1} \end{bmatrix}.$$

2. Define the syndrome matrix (for $m = \lceil \frac{d}{2} \rceil$) by

$$\begin{aligned} S_m &= V_m D V_{d-m+1}^T \\ &= \begin{bmatrix} s_1 & s_2 & \dots & s_{d-m+1} \\ s_2 & s_3 & \dots & s_{d-m+2} \\ \vdots & \vdots & \ddots & \vdots \\ s_m & s_{m+1} & \dots & s_d \end{bmatrix}. \end{aligned}$$

where D is a diagonal matrix of size ν with nonzero diagonal elements $d_p = \frac{1}{\sqrt{n}} e_{i_p} X_p^\alpha, p = 1, \dots, \nu$.

Error Correction in DFT Codes

Subspace-Based Approach

3. Eigen-decompose the covariance matrix $R_m = S_m S_m^H$

$$R_m = [U_e \ U_n] \begin{bmatrix} \Delta_e & \mathbf{0} \\ \mathbf{0} & \Delta_n \end{bmatrix} [U_e \ U_n]^H,$$

- ▶ Δ_e and Δ_n contain the ν largest and $m - \nu$ smallest eigenvalues
 - ▶ U_e and U_n contain the eigenvectors corresponding to Δ_e and Δ_n
 - ▶ The columns in U_e span the *channel-error subspace* spanned by V_m thus, $U_e^H U_n = \mathbf{0} \Rightarrow V_m^H U_n = \mathbf{0}$
4. Let $\mathbf{v} = [1, x, x^2, \dots, x^{m-1}]^T$ where x is a complex variable, then

$$F(x) \triangleq \sum_{j=1}^{m-\nu} \mathbf{v}^H \mathbf{u}_{n,j} = \sum_{j=1}^{m-\nu} \sum_{i=0}^{m-1} f_{ji} x^i.$$

$F(x)$ is sum of $m - \nu$ polynomials $\{f_{ji}\}_{j=1}^{m-\nu}$ of order $m - 1$.

Error Correction in DFT Codes

Subspace-Based Approach



Figure: Subspace method: graphical representation

Error Correction in DFT Codes

Subspace-Based Approach

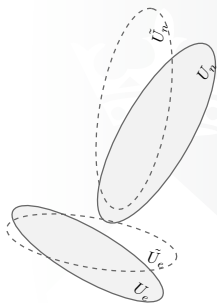


Figure: Subspace method: graphical representation

Error Correction in DFT Codes

Subspace-Based Approach

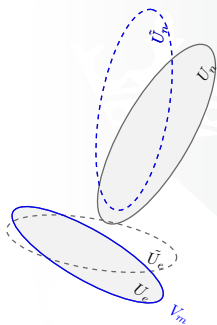


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Error Correction in DFT Codes

Subspace-Based Approach

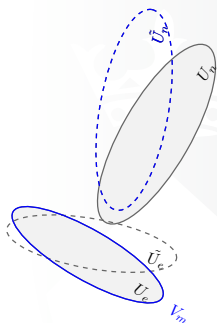


Figure: Subspace method: graphical representation

Subspace vs. coding-theoretic method

There are $m - \nu = \lceil \frac{d}{2} \rceil - \nu$ polynomials rather than just one, and they have higher degrees of freedom

⇒ Subspace method performs better than the coding-theoretic approach

Extended Subspace Decoding

Motivation

Main idea:

Increasing the dimension of the estimated noise subspace \Rightarrow the number of polynomials with linearly independent coefficients and/or their degree grow.

Construction:

The extended syndrome matrix S'_m is defined for $d' > d$, and similar to S_m it is decomposable as

$$S'_m = V_m D V_{d'-m+1}^T.$$

To form S'_m we need d' syndrome samples while we only have d samples.

$$s'_m = \frac{1}{\sqrt{n}} \sum_{p=1}^{\nu} e_{i_p} X_p^{\alpha-1+m}, \quad m = 1, \dots, d',$$

Extended Subspace Decoding

Extended Syndrome

$$s'_m = \begin{cases} s_m, & 1 \leq m \leq d, \\ \bar{s}_{m-d}, & d < m \leq d', \end{cases}$$

where $\bar{s} = \bar{H}e$, is the **extended syndrome** of error.

Recal: \bar{H} consists of those k columns of the IDFT matrix of order n not used in H (used in G).

Q:

How can we compute \bar{s} ?

Let us try

$$\bar{H}r = \bar{H}c + \bar{H}e \neq \bar{H}e$$

So to have $\bar{H}r = \bar{s}$, either $\bar{H}c$ must vanish or we should remove it.

Extended Subspace Decoding

Extended Syndrome

- ▶ $\bar{H}\mathbf{c} = \mathbf{0}$ could happen in the special case of rate $\frac{1}{2}$ codes when all error indices are even
- ▶ In general, we need to find a way to remove $\bar{H}\mathbf{c}$

We exploit the gain from the extended subspace decoding by transmitting extra samples \Rightarrow Rate-adaptive DFT codes

1. Rate-adaptive DSC (syndrome & parity approaches)
2. Rate-adaptive channel coding
3. Rate-adaptive distributed joint source-channel coding

Generalized Error Localization

Subspace Approach

1. Eigen-decompose the covariance matrix

$$R_m = S_m S_m^H, \quad m = \lceil \frac{d}{2} \rceil = \lceil \frac{n-k}{2} \rceil$$

$$R_m = [U_e \ U_n] \begin{bmatrix} \Delta_e & \mathbf{0} \\ \mathbf{0} & \Delta_n \end{bmatrix} [U_e \ U_n]^H,$$

- ▶ The columns in U_e span *channel-error subspace* spanned by V_m . Thus,
 $U_e^H U_n = \mathbf{0} \Rightarrow V_m^H U_n = \mathbf{0}$

2. Let $\mathbf{v} = [1, x, x^2, \dots, x^{m-1}]^T$ where x is a complex variable, then

$$F(x) \triangleq \sum_{j=1}^{m-\nu} \mathbf{v}^H \mathbf{u}_{n,j} = \sum_{j=1}^{m-\nu} \sum_{i=0}^{m-1} f_{ji} x^i.$$

$\Rightarrow F(x)$ is sum of $m - \nu$ polynomials.

Figure: Subspace approach



U_n

U_e

Generalized Error Localization

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\tilde{U}_e
 U_e

Figure: Subspace approach

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$\Rightarrow F(x)$ is sum of $m - \nu$ polynomials.



Figure: Subspace approach

Generalized Subspace-Based

$$S_m^{[i]} \triangleq \begin{bmatrix} S_{\lceil 0 \rceil_n} & S_{\lceil i \rceil_n} & \cdots & S_{\lceil i(d-m) \rceil_n} \\ S_{\lceil i \rceil_n} & S_{\lceil 2i \rceil_n} & \cdots & S_{\lceil i(d-m+1) \rceil_n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{\lceil i(m-1) \rceil_n} & S_{\lceil im \rceil_n} & \cdots & S_{\lceil i(d-1) \rceil_n} \end{bmatrix},$$
$$= V_m^{[i]} D V_{d-m+1}^{[i]T}$$

Algorithm

1. Eigendecompose $S_m^{[i]} S_m^{[i]H}$ to find $U_e^{[i]}, U_q^{[i]}$
2. Since the columns in $U_e^{[i]}$ and $V_m^{[i]}$ span the same subspace,
 $U_e^{[i]H} U_n^{[i]} = \mathbf{0} \Rightarrow V_m^{[i]H} U_n^{[i]} = \mathbf{0} \quad \forall i \in \mathcal{P}_n$
3. Define

$$\Gamma(x) \triangleq \sum_{i \in \mathcal{P}_n} F^{[i]}(x) = \sum_{i \in \mathcal{P}_n} \sum_{j=1}^{m-\nu} \sum_{k=0}^{m-1} f_{jk}^{[i]} x^{ki},$$

and use it for error localization.

Example 1

Consider the $(10, 5)$ code, for which $\mathcal{P}_n = \{1, 3, 7, 9\}$. Then we have

$$S_3^{[1]} = \begin{bmatrix} s_1 & s_2 & s_3 \\ s_2 & s_3 & s_4 \\ s_3 & s_4 & s_5 \end{bmatrix}, S_3^{[3]} = \begin{bmatrix} s_1 & s_4 & s_7 \\ s_4 & s_7 & s_{10} \\ s_7 & s_{10} & s_3 \end{bmatrix},$$
$$S_3^{[7]} = \begin{bmatrix} s_1 & s_8 & s_5 \\ s_8 & s_5 & s_2 \\ s_5 & s_2 & s_9 \end{bmatrix}, S_3^{[9]} = \begin{bmatrix} s_1 & s_{10} & s_9 \\ s_{10} & s_9 & s_8 \\ s_9 & s_8 & s_7 \end{bmatrix}.$$

Example 2

- ▶ $(11, 3)$ code; $n = 11 \implies \mathcal{P}_n = \{1, \dots, 10\}$
- ▶ We can have 10 syndrome matrices for each $d' \in [8, \dots, 11]$
- ▶ For $d' = 11$, these matrices share the same elements only with different arrangements, e.g.,

$$S_6'^{[2]} = \begin{bmatrix} s_1 & s_3 & s_5 & s_7 & s_9 & s_{11} \\ s_3 & s_5 & s_7 & s_9 & s_{11} & s_2 \\ s_5 & s_7 & s_9 & s_{11} & s_2 & s_4 \\ s_7 & s_9 & s_{11} & s_2 & s_4 & s_6 \\ s_9 & s_{11} & s_2 & s_4 & s_6 & s_8 \\ s_{11} & s_2 & s_4 & s_6 & s_8 & s_{10} \end{bmatrix},$$

and

$$S_6'^{[9]} = \begin{bmatrix} s_1 & s_{10} & s_8 & s_6 & s_4 & s_2 \\ s_{10} & s_8 & s_6 & s_4 & s_2 & s_{11} \\ s_8 & s_6 & s_4 & s_2 & s_{11} & s_9 \\ s_6 & s_4 & s_2 & s_{11} & s_9 & s_7 \\ s_4 & s_2 & s_{11} & s_9 & s_7 & s_5 \\ s_2 & s_{11} & s_9 & s_7 & s_5 & s_3 \end{bmatrix}.$$

Rate-Adaptive DSC

The proposed schemes, with short DFT codes, are

- ▶ Suitable for low-delay coding
- ▶ Vulnerable to the variations of channel



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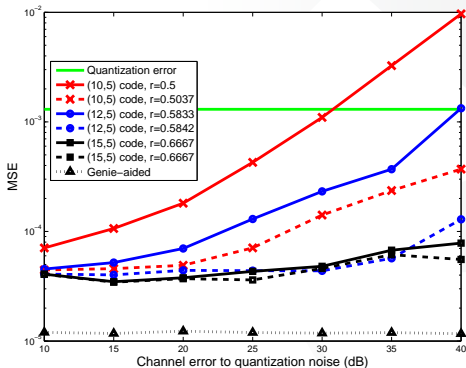
- ▶ Define \bar{H} such that $[H_{n-k \times n}^T | \bar{H}_{k \times n}^T] = W_n^H$
- ▶ Algorithm:
 1. **Decoder:** Request for extra syndrome samples if $\hat{\nu} \geq t$
 2. **Encoder:** Transmit $\bar{s}_x = \bar{H}x$ sample by sample
 3. **Decoder:** Compute $\bar{s}_y = \bar{H}y = \bar{s}_x + \bar{s}_e$ and $\bar{s}_e = \bar{s}_y - \bar{s}_x$
 4. **Decoder:** Append \bar{s}_e to s_e and use the *extended subspace decoding*

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