

Systematic DFT Frames: Principle and Eigenvalues Structure

Mojtaba Vaezi and Fabrice Labeau

McGill University



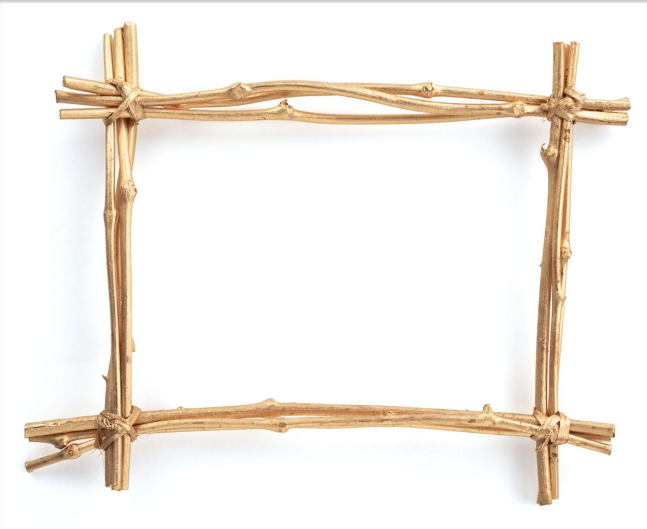
International Symposium on Information Theory
MIT, Cambridge, MA

Thursday, July 5, 2012

Outline

- 1 Introduction
 - Definitions
 - Applications
- 2 Systematic DFT Frames
 - Construction
 - Motivation
 - Performance
- 3 Eigenvalues Structure
 - Extreme eigenvalues
 - Property
- 4 Classification of Systematic Frames
 - Optimality
 - Summary

Frames



Frames

Definition

A spanning family of n vectors $F = \{\mathbf{f}_i\}_{i=1}^n$ in a complex vector space \mathbb{C}^k is called a *frame* if there exist $0 < a \leq b$ such that for any $\mathbf{x} \in \mathbb{C}^k$

$$a\|\mathbf{x}\|^2 \leq \sum_{i=1}^n |\langle \mathbf{x}, \mathbf{f}_i \rangle|^2 \leq b\|\mathbf{x}\|^2, \quad (1)$$

where $\langle \mathbf{x}, \mathbf{f}_i \rangle$ gives the i th coefficient for the frame expansion of \mathbf{x} .

- *frame bounds*, a and b , respectively, ensures that the vectors span the space and the expansion converges
- A frame is *tight* if $a = b$
- Any frame contains a basis, in fact frame are generalization of bases.

Real BCH-DFT Codes

Encoding

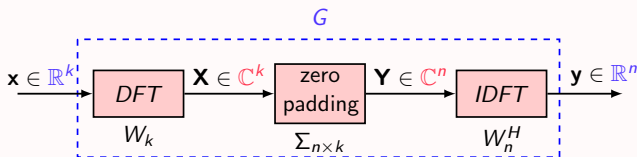


Figure: Real BCH-DFT encoding scheme

$$G = \sqrt{\frac{n}{k}} W_n^H \Sigma W_k, \quad (2)$$

- $\Sigma_{n \times k}$ inserts $n-k$ **consecutive** zeros in the transform domain \implies BCH code
- DFT is used to convert vector $\mathbf{x} \in \mathbb{R}^k$ to a **circularly symmetric** $\mathbf{X} \in \mathbb{C}^k$, guaranteeing a real \mathbf{y}
- Removing the DFT block, we obtain complex BCH-DFT codes

Real BCH-DFT Codes

Applications

Connection to Frame Theory

- The generator matrix G is the **analysis** frame operator; the frame operator is then $G^H G = \frac{n}{k} I_k$
- Complex BCH-DFT codes are **harmonic frames**
- Real BCH-DFT codes are rotated harmonic frames

Real BCH-DFT Codes

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Applications

- Resilience to noise and quantization error
- Resilience to erasures and errors (channel coding)
- Distributed lossy source coding (**new**)

Systematic DFT Frames

Construction

Definition

A **systematic frame** is a frame whose synthesis frame operator

includes identity matrix as a subframe, i.e., $G_{\text{sys}} = \begin{bmatrix} I_k \\ P_{n-k \times k} \end{bmatrix}$

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Note that

- G_k is invertible as it is a frame $\implies G_{\text{sys}}$ exists
- The number of these systematic frames is $\binom{n}{k}$

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Example: A systematic (6,3) DFT code

$$G_{\text{sys}} = \begin{pmatrix} 1 & 0 & 0 \\ \frac{2}{3} & \frac{2}{3} & \frac{-1}{3} \\ 0 & 1 & 0 \\ \frac{-1}{3} & \frac{2}{3} & \frac{2}{3} \\ 0 & 0 & 1 \\ \frac{2}{3} & \frac{-1}{3} & \frac{2}{3} \end{pmatrix}$$

Systematic DFT Frames

Motivation

Applications

- Same applications as other DFT frames
- **Parity-based** distributed source coding

Systematic DFT Frames

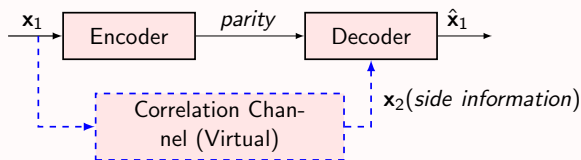
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Distributed source coding

- \mathbf{x}_1 and \mathbf{x}_2 are two separate, **correlated** signals (view \mathbf{x}_2 as corrupted version of \mathbf{x}_1)



Systematic DFT Frames

Optimality condition

Encoding: Let \mathbf{x} be the message vector and $\mathbf{y} = G_{\text{sys}}\mathbf{x}$ represent the codevector. The variance of \mathbf{y} is then given by

$$\begin{aligned}\sigma_y^2 &= \frac{1}{n} \mathbb{E}\{\mathbf{y}^H \mathbf{y}\} = \frac{1}{n} \mathbb{E}\{\mathbf{x}^H G_{\text{sys}}^H G_{\text{sys}} \mathbf{x}\} \\ &= \frac{1}{n} \sigma_x^2 \text{tr}(G_{\text{sys}}^H G_{\text{sys}}) \\ &= \frac{\sigma_x^2}{k} \text{tr}\left((G_k G_k^H)^{-1}\right) \\ &= \sigma_x^2 \frac{1}{k} \sum_{i=1}^k \frac{1}{\lambda_i},\end{aligned}\tag{3}$$

in which $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_k > 0$ are the eigenvalues of $G_k G_k^H$

Systematic DFT Frames

Performance evaluation

The received codevector can be modeled by

$$\hat{\mathbf{y}} = G_{\text{sys}} \mathbf{x} + \mathbf{q}, \quad (4)$$

Linear reconstruction:

$$\hat{\mathbf{x}} = G_{\text{sys}}^\dagger \hat{\mathbf{y}} = \frac{k}{n} G_k G^H \hat{\mathbf{y}} = \mathbf{x} + \frac{k}{n} G_k G^H \mathbf{q}, \quad (5)$$

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Reconstruction error:

$$\begin{aligned} \text{MSE}_{\mathbf{q}} &= \frac{1}{k} \mathbb{E} \{ \|\hat{\mathbf{x}} - \mathbf{x}\|^2 \} = \frac{1}{k} \mathbb{E} \{ \|\mathbf{G}_{\text{sys}}^\dagger \mathbf{q}\|^2 \} \\ &= \frac{1}{k} \mathbb{E} \{ \mathbf{q}^H \mathbf{G}_{\text{sys}}^{\dagger H} \mathbf{G}_{\text{sys}}^\dagger \mathbf{q} \} \\ &= \frac{1}{n} \sigma_q^2 \text{tr} \left(G_k^H G_k \right) = \frac{k}{n} \sigma_q^2, \end{aligned} \quad (6)$$

Systematic DFT Frames

Optimality condition

Q:

Which one of $\binom{n}{k}$ systematic frames results in the best MSE performance?

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$$\begin{aligned} & \underset{\lambda_i}{\text{minimize}} && \sum_{i=1}^k \frac{1}{\lambda_i} \\ & \text{s.t.} && \sum_{i=1}^k \lambda_i = k, \lambda_i > 0 \end{aligned} \tag{7}$$

The constraint comes from the fact (Lemma 1) that all principal diagonal entries of $G_k G_k^H$ are equal to 1.

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Optimal solution: By using Lagrangian method, the optimal eigenvalues are $\lambda_i = 1 \implies$ **tight frames** are the optimal solution

Eigenvalues Structure

Bounds on the extreme eigenvalues

Theorem

For any G_k , a square submatrix of G in (2) in which $n \neq Mk$, the smallest (largest) eigenvalue of $G_k G_k^H$ is *strictly* upper (lower) bounded by 1.

Proof.

Using *Weyl inequalities* we can show that for $n \neq Mk$

$$\lambda_k(G_k^H G_k) \leq \frac{\frac{n}{k} - 1}{\lfloor \frac{n}{k} \rfloor} < 1,$$

then, since $\sum_{i=1}^k \lambda_i = k$, we conclude $\lambda_1(G_k^H G_k) > 1$. □

Eigenvalues Structure

Existence of tight frames

Then, due to the fact that for a tight frame with frame operator $F^H F$, $\lambda_{\min}(F^H F) = \lambda_{\max}(F^H F)$ we conclude

Corollary

*For $n \neq Mk$, where M is a positive integer, **tight** systematic DFT frames **do not** exist.*

- Note that systematic DFT frames are not necessarily tight for $n = Mk$

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For $n \neq Mk$, where M is a positive integer, *tight* systematic DFT frames *do not* exist.

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Q:

What other condition(s) must be met in order to have tight systematic frames?

Eigenvalues Structure

Theorem

Let $\{\lambda_1, \lambda_2, \dots, \lambda_k\}$ be the eigenvalues of a nonsingular $k \times k$ matrix A , then we have

$$\left(\sum_{i=1}^k \frac{1}{\lambda_i}\right) \cdot \left(\prod_{i=1}^k \lambda_i\right) = c, \quad (8)$$

where the constant c is a function of $\text{tr}(A), \dots, \text{tr}(A^{k-1})$.

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where the constant c is a function of $\text{tr}(A), \dots, \text{tr}(A^{k-1})$.

In light of the above theorem, we can see that

$$\underset{\lambda_i}{\text{argmin}} \sum_{i=1}^k \frac{1}{\lambda_i} = \underset{\lambda_i}{\text{argmax}} \prod_{i=1}^k \lambda_i. \quad (9)$$

Classification of Systematic Frames

Alternative optimality condition

$$\begin{aligned} & \underset{\lambda_i}{\text{maximize}} && \prod_{i=1}^k \lambda_i \\ & \text{s.t.} && \sum_{i=1}^k \lambda_i = k, \lambda_i > 0. \end{aligned} \tag{10}$$

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But $\prod_{i=1}^k \lambda_i = \det(G_k G_k^H)$; therefore,

- The “best” submatrix (G_k) is the one with the largest determinant (possibly 1)
- The “worst” submatrix is the one with smallest determinant.

Classification of Systematic Frames

Best frames

Let $\mathcal{I}_{r_k} = \{i_{r_1}, i_{r_2}, \dots, i_{r_k}\}$ be those rows of G used to build G_k , then

$$\begin{aligned} \det(G_k G_k^H) &= \det(V_k V_k^H) = \frac{1}{k^k} \prod_{\substack{1 \leq p < q \leq n \\ p, q \in \mathcal{I}_{r_k}}} |e^{i\theta_p} - e^{i\theta_q}|^2 \\ &= \frac{1}{k^k} \prod_{\substack{1 \leq p < q \leq n \\ p, q \in \mathcal{I}_{r_k}}} 4 \sin^2 \frac{\pi}{n} (q - p). \end{aligned} \tag{11}$$

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When $n = Mk$ and G_k consists of every M th row of G , we get

$$\begin{aligned} \det(V_k V_k^H) &= \frac{2^{k(k-1)}}{k^k} \prod_{r=1}^{k-1} \left(\sin^2 \frac{\pi}{n} Mr \right)^{k-r} \\ &= \frac{2^{k(k-1)}}{k^k} \prod_{r=1}^{k-1} \left(\sin^2 \frac{\pi}{k} r \right)^{k-r} = 1. \end{aligned} \quad (12)$$

Classification of Systematic Frames

Summary of results

Conclusion: The MSE performance of a systematic frame depends on the **position** of data (parity) samples in the codevector, and

- **Best** performance \Leftrightarrow **evenly spaced** data samples
- **Worst** performance \Leftrightarrow **consecutive** data (parity) samples
- Integer oversampling ($n = Mk$) and equally spaced data samples \Leftrightarrow tight systematic frames
- Circular shift and/or reversal of the systematic rows of a systematic frame, does not affect the performance

Classification of Systematic Frames

Numerical example

Table: Eigenvalues structure for two systematic DFT frames with different codeword patterns. A “×” and “–” represent data (systematic) and parity samples.

Code	Codeword pattern	λ_{\min}	λ_{\max}	$\sum_{i=1}^k 1/\lambda_i$	$\prod_{i=1}^k \lambda_i$
(6, 3)	× × × – – –	0.0572	1.9428	19	0.1111
	× × – × – –	0.2546	1.7454	5.5	0.4444
	× × – – × –	0.2546	1.7454	5.5	0.4444
	× – × – × –	1	1	3	1
(7, 5)	× × × × × – –	0.0396	1.4	28.70	0.0827
	× × × × – × –	0.1506	1.4	10.32	0.2684
	× × – × × – ×	0.3110	1.4	7.40	0.4173
	× – × × × – ×	0.3110	1.4	7.40	0.4173

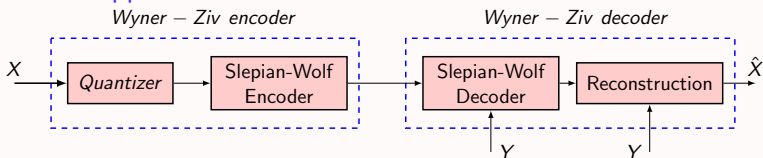
Thank you!

Practical code construction

Lossy DSC with SI at the decoder (Wyner-Ziv coding)

What if the source is a **continuous-valued** sequence? (many practical applications)

- Current approach

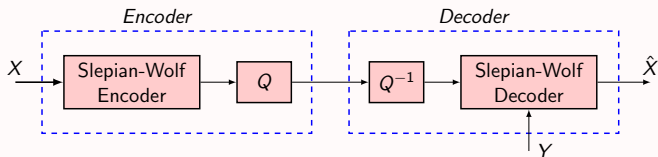


- There are source coding loss (or quantization loss) and channel coding loss (or binning loss)

Practical code construction

Wyner-Ziv coding in the real field

- Alternative approach



- **Similarities and differences**

- There are still coding loss and quantization loss
- Coding is before quantization \Rightarrow error correction in the real field (soft redundancy)

- **Advantages**

- 1 Correlation channel model is more realistic
- 2 Quantization error can be reduced by a factor of coderate (it vanishes if X and Y are completely correlated)
- 3 Better performance w.r.t. delay and complexity

Practical code construction

Wyner-Ziv coding in the real field

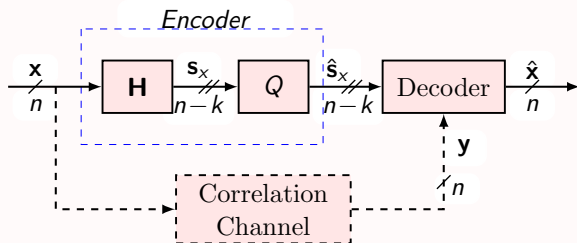


Figure: The Wyner-Ziv coding using DFT codes: Syndrome approach.

Practical code construction

Wyner-Ziv coding in the real field

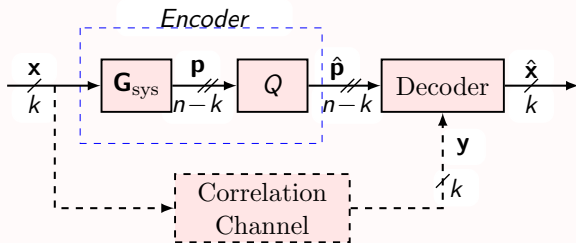


Figure: The Wyner-Ziv coding using DFT codes: Parity approach.