
Inverse Eigenvalue Problems in Wireless Communications



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Introduction



- Matrix construction problems arise in theory of wireless communication
- Many papers have appeared in *IEEE Trans. on Information Theory*
- We view these constructions as *inverse eigenvalue problems*
 - Provides new insights
 - Suggests new tools for solution
 - Offers new and interesting inverse eigenvalue problems

References: [Rupf-Massey 1994; Vishwanath-Anantharam 1999; Ulukus-Yates 2001; Rose 2001; Viswanath-Anantharam 2002; Anigstein-Anantharam 2003; . . .]

Code-Division Multiple Access (CDMA)



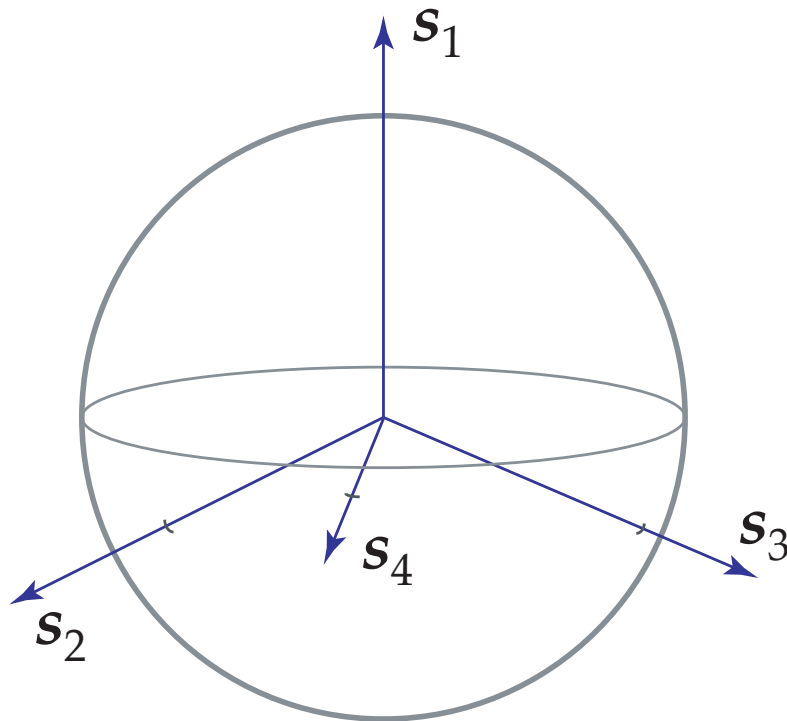
- A CDMA system allows many users to share a wireless channel
- Channel is modeled as a vector space of dimension d
- Each of N users receives a unit-norm signature vector \mathbf{s}_k ($N > d$)
- Each user's information is encoded in a complex number b_k
- In each transmission interval, a user sends $b_k \mathbf{s}_k$
- Each user may have a different power level w_k
- Base station receives superposition $\sum_{k=1}^N b_k \sqrt{w_k} \mathbf{s}_k + \mathbf{v}$, where \mathbf{v} is additive noise
- The base station must extract all b_k from the d -dimensional noisy observation

Reference: [Viterbi 1995]

Example



- 🦉 Intuition: the signature vectors should be well separated for the system to perform well



$$\frac{1}{3} \begin{bmatrix} 0 & 0 & \sqrt{6} & -\sqrt{6} \\ 0 & 2\sqrt{2} & -\sqrt{2} & -\sqrt{2} \\ 3 & -1 & -1 & -1 \end{bmatrix}$$

Optimal CDMA Signatures



- For clarity, suppose the noise is a white, Gaussian random process
- Form the weighted signature matrix

$$X = [\sqrt{w_1} \mathbf{s}_1 \quad \sqrt{w_2} \mathbf{s}_2 \quad \dots \quad \sqrt{w_N} \mathbf{s}_N]$$

- One performance measure is *total weighted squared correlation* (TWSC)

$$\text{TWSC}(X) \stackrel{\text{def}}{=} \|X^* X\|_F^2 = \sum w_j w_k |\langle \mathbf{s}_j, \mathbf{s}_k \rangle|^2$$

- Minimizing TWSC is (often) equivalent to finding X for which

$$XX^* = \frac{\sum w_k}{d} \mathbf{I}_d \quad \text{and} \quad \text{diag}(X^* X) = (w_1, \dots, w_N)$$

- Thus X is row-orthogonal with specified column norms

References: [Rupf-Massey 1994; Vishwanath-Anantharam 1999, 2002]

Connection with Tight Frames



- An *α -tight frame* is a collection $\{\mathbf{x}_k\}$ of N vectors in \mathbb{C}^d such that

$$\sum_{k=1}^N |\langle \mathbf{y}, \mathbf{x}_k \rangle|^2 = \alpha \|\mathbf{y}\|_2^2 \quad \text{for all } \mathbf{y} \text{ in } \mathbb{C}^d$$

- α -tight frames generalize orthonormal systems
- Designing tight frames with specified norms \equiv Designing optimal CDMA signatures under white noise
- Tight frames also arise in signal processing, harmonic analysis, physics,
...

Spectral Properties of Tight Frames



• The *frame synthesis matrix* is defined as $X \stackrel{\text{def}}{=} [\mathbf{x}_1 \quad \dots \quad \mathbf{x}_N]$

• Observe that the tight frame condition can be written

$$\frac{\mathbf{y}^*(XX^*)\mathbf{y}}{\mathbf{y}^*\mathbf{y}} = \alpha \quad \text{for all } \mathbf{y} \text{ in } \mathbb{C}^d$$

• Four equivalent definitions of a tight frame:

- The rows of X are orthogonal
- The d singular values of X are identical
- The d non-zero eigenvalues of X^*X are identical
- The Gram matrix X^*X is a scaled rank- d orthogonal projector

Structural Constraints on Frame Vectors



- Prescribed Euclidean norms
 - This is the CDMA signature design problem
- Low peak-to-average-power ratio
 - Components of each vector should have similar moduli
- Low cross-correlations $|\langle \mathbf{x}_j, \mathbf{x}_k \rangle|$ between each pair
 - Vectors in tight frames can have large pairwise correlations
 - Preferable for all vectors to be well separated
- Components drawn from a finite alphabet
 - Fundamental problem in communications engineering
 - One common alphabet is $\mathcal{A} = \{(\pm 1 \pm i)/\sqrt{2}\}$
- . . .
- . . .

Inverse Singular Value Problems



- ✚ Let \mathcal{S} be a collection of “structured” $d \times N$ matrices
- ✚ Let \mathcal{X} be the collection of $d \times N$ matrices with singular values $\sigma_1, \dots, \sigma_d$
- ✚ Find a matrix in the intersection of \mathcal{S} and \mathcal{X}
- ✚ If problem is not soluble, find a matrix in \mathcal{S} that is closest to \mathcal{X} with respect to some norm
- ✚ General numerical approaches are available
- ✚ Inverse eigenvalue problems defined similarly for the $N \times N$ Gram matrix

References: [Chu 1998, Chu-Golub 2002]

Algorithms



Finite-step methods

- Useful for simple structural constraints
- Fast and easy to implement
- Always succeed

Alternating projection methods

- Good for more complicated structural constraints
- Slow but easy to implement
- May fail

Projected gradient or coordinate-free Newton methods

- Difficult to develop; not good at repeated eigenvalues
- Fairly fast but hard to implement
- May fail

Finite-Step Methods



- Goal: construct tight frame X with squared column norms w_1, \dots, w_N
- Equivalent to Schur-Horn Inverse Eigenvalue Problem
 - Gram matrix X^*X has diagonal w_1, \dots, w_N
 - Gram matrix has d non-zero eigenvalues, all equal to $\sum w_k/d$
 - Diagonal must majorize eigenvalues: $0 \leq w_j \leq \sum w_k/d$ for all j

Basic Idea

- Start with diagonal matrix of eigenvalues
- Apply sequence of $(N - 1)$ plane rotations [Chan-Li 1983]

$$\begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \longmapsto \begin{bmatrix} 0.4000 & 0.4323 & -0.2449 \\ 0.4323 & 0.7000 & 0.1732 \\ -0.2449 & 0.1732 & 0.9000 \end{bmatrix}$$

- Extract the frame X with rank-revealing QR [Golub-van Loan 1996]

Finite-Step Methods



Equal Column Norms

- Start with arbitrary Hermitian matrix whose trace is $\sum w_k$
- Apply $(N - 1)$ plane rotations [Bendel-Mickey 1978, GvL 1996]

$$\begin{bmatrix} 0.6911 & 1.1008 & -1.0501 \\ 1.1008 & 1.8318 & -0.9213 \\ -1.0501 & -0.9213 & -0.5229 \end{bmatrix} \mapsto \begin{bmatrix} 0.6667 & -1.4933 & -0.5223 \\ -1.4933 & 0.6667 & 1.4308 \\ -0.5223 & 1.4308 & 0.6667 \end{bmatrix}$$

- Extract the frame X with rank-revealing QR factorization

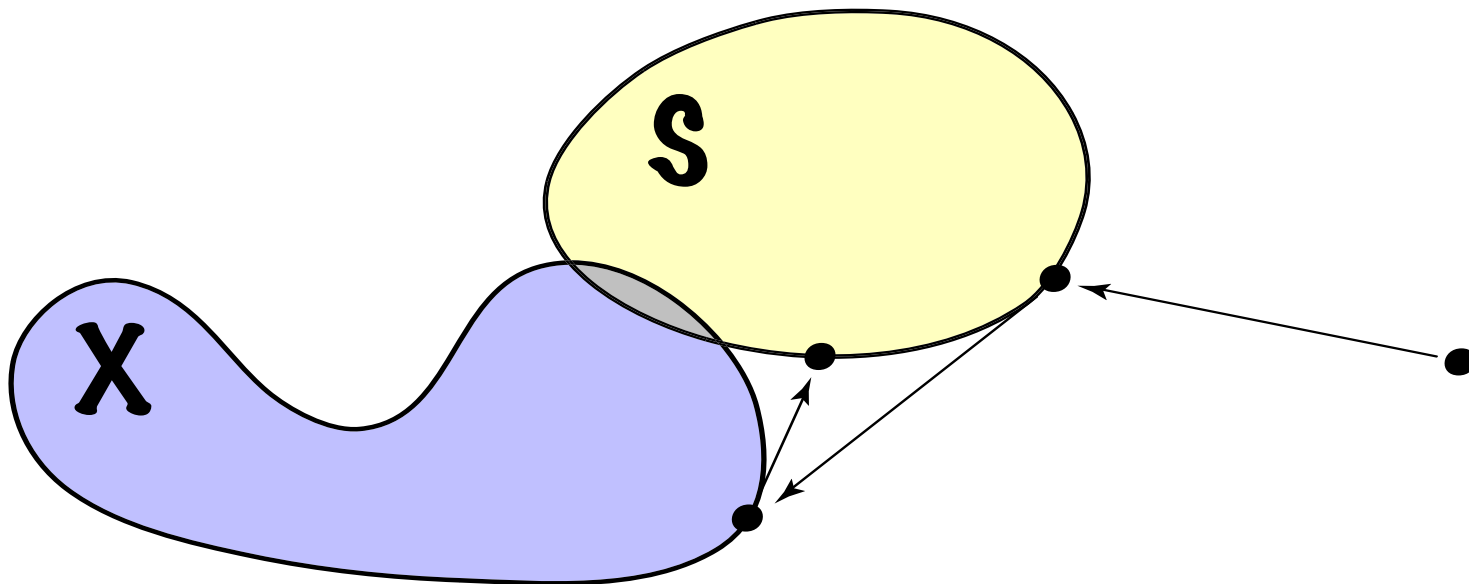
One-Sided Methods

- Can use Davies-Higham method [2000] to construct tight frames with equal column norms directly
- We have extended Chan-Li to construct tight frames with arbitrary column norms directly [TDH 2003, DHSuT 2003]

Alternating Projections



- Let \mathcal{S} be the collection of matrices that satisfy the structural constraint
- Let \mathcal{X} be the collection of α -tight frames
- Begin with an arbitrary matrix
- Find the nearest matrix that satisfies the structural constraint
- Find the nearest matrix that satisfies the spectral constraint. . .



Literature on Alternating Projections



Theory

- Subspaces [J. Neumann 1933; Diliberto-Straus 1951; Wiener 1955; . . .]
- Convex sets [Cheney-Goldstein 1959]
- Descent algorithms [Zangwill 1969; R. Meyer 1976; Fiorot-Huard 1979]
- Corrected [Dykstra 1983; Boyle-Dykstra 1985; Han 1987]
- Information divergences [Csiszár-Tusnády 1984]
- Recent surveys [Bauschke-Borwein 1996; Deutsch 2001]

Practice

- Signal recovery and restoration [Landau-Miranker 1961; Gerchberg 1973; Youla-Webb 1982; Cadzow 1988; Donoho-Stark 1989; . . .]
- Schur-Horn IEP [Chu 1996]
- Nearest symmetric diagonally dominant matrix [Raydan-Tarazaga 2000]
- Nearest correlation matrix [Higham 2002]

Nearest Frames & Gram Matrices



- To implement the alternating projection, one must compute the tight frame or tight frame Gram matrix nearest a given matrix
- For analytic simplicity, we use the Frobenius norm

Theorem 1. *Suppose that Z has polar decomposition $R\Theta$. The matrix Θ is a tight frame nearest to Z . If Z has full rank, the nearest matrix is unique.*

Theorem 2. *Let Z be a Hermitian matrix, and let the columns of U be an orthonormal basis for an eigenspace associated with the d algebraically largest eigenvalues. Then UU^* is a rank- d orthogonal projector closest to Z . The nearest projector is unique if and only if $\lambda_d(Z) > \lambda_{d+1}(Z)$.*

References: [Horn-Johnson 1985]

Nearest Matrix with Specified Column Norms



Consider the structural constraint set

$$\mathcal{S} = \{S \in \mathbb{C}^{d \times N} : \|s_k\|_2^2 = w_k\}$$

Proposition 1. *Let Z be an arbitrary matrix. A matrix in \mathcal{S} is closest to Z if and only if*

$$s_k = \begin{cases} w_k z_k / \|z_k\|_2 & \text{for } z_k \neq \mathbf{0} \\ w_k u_k & \text{for } z_k = \mathbf{0}, \end{cases} \quad \text{and}$$

where u_k is an arbitrary unit vector. If the columns of Z are all non-zero, then the solution to the nearness problem is unique.

Convergence for Fixed Column Norms



Theorem 3. [THSt 2003] *Suppose that S_0 has full rank and non-zero columns. Perform an alternating projection between \mathcal{S} and \mathcal{X} . The sequence of iterates either converges in norm to a full-rank fixed point of the algorithm or it has a continuum of accumulation points that are all full-rank fixed points of the algorithm.*

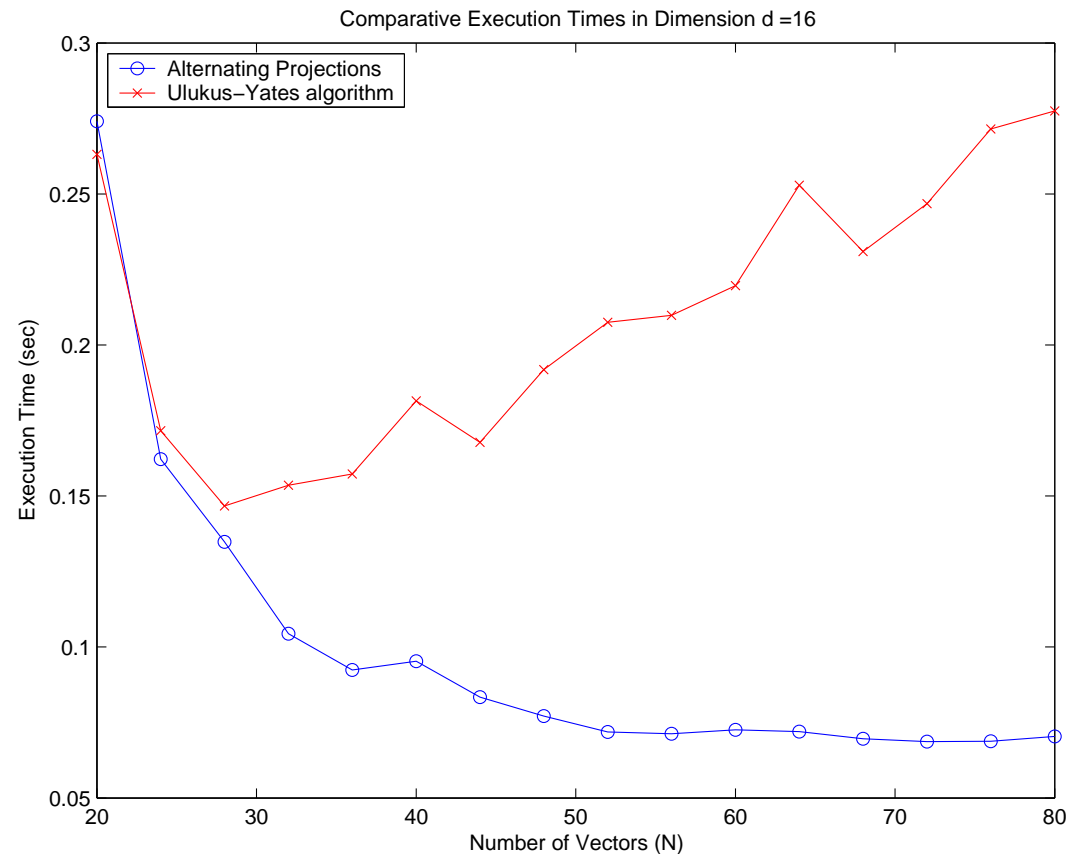
Theorem 4. [THSt 2003] *The full-rank stationary points of the alternating projection between \mathcal{S} and \mathcal{X} are precisely the full-rank matrices in \mathcal{S} whose columns are all eigenvectors of SS^* . That is, $SS^*S = S\Lambda$ where Λ is diagonal and positive.*

- Each fixed point may be identified as union of tight frames for mutually orthogonal subspaces of \mathbb{C}^d [Ulukus-Yates 2001; Benedetto-Fickus 2002; Anigstein-Anantharam 2003]

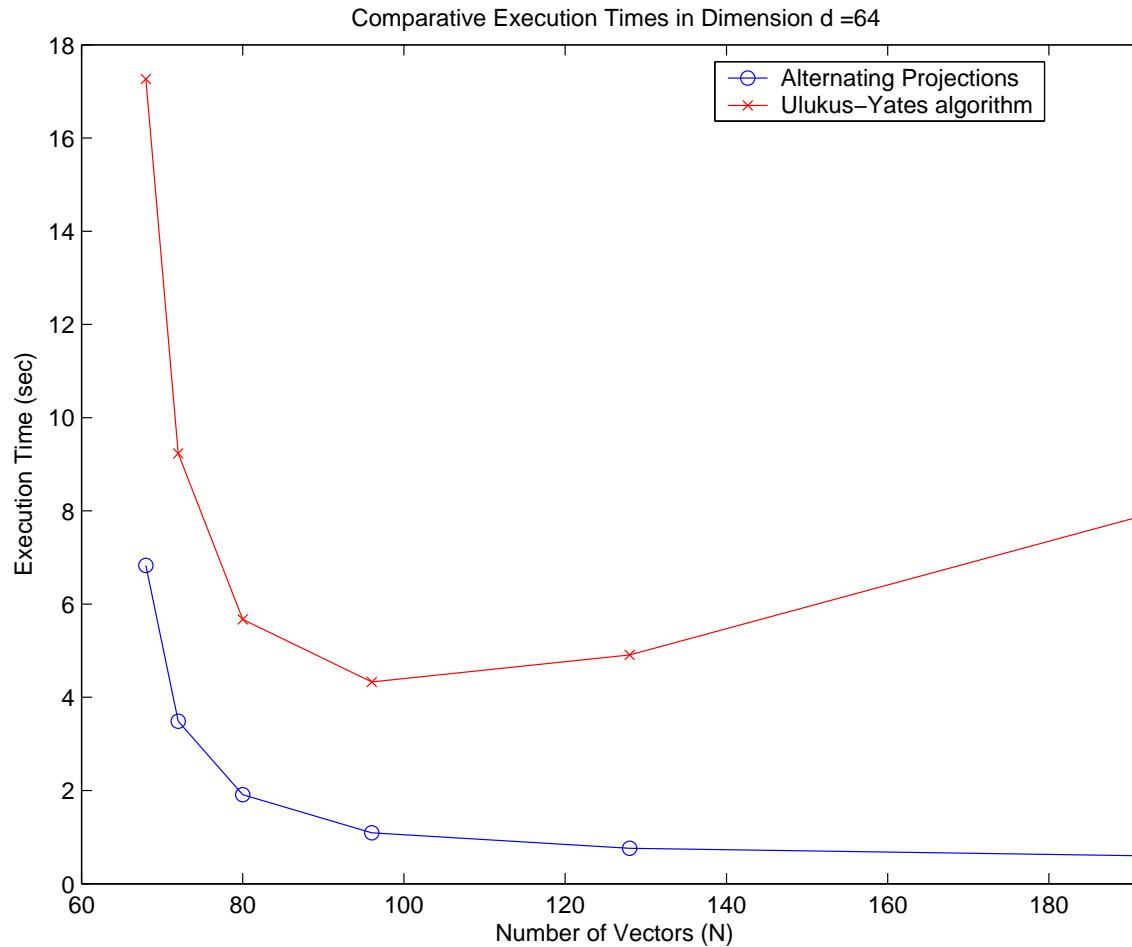
Alternating Projections vs. Ulukus-Yates



- Other algorithms have been proposed for constructing tight frames with specified column norms, eg. [Ulukus-Yates 2001]



Alternating Projections vs. Ulukus-Yates



Peak-to-Average-Power Ratio



- In communications applications, it is practical for the vectors to have components with similar moduli
- Define the *peak-to-average-power ratio* of a vector \mathbf{v} in \mathbb{C}^d to be

$$\text{PAR}(\mathbf{v}) \stackrel{\text{def}}{=} \frac{\max_j |v_j|^2}{\sum_j |v_j|^2 / d}$$

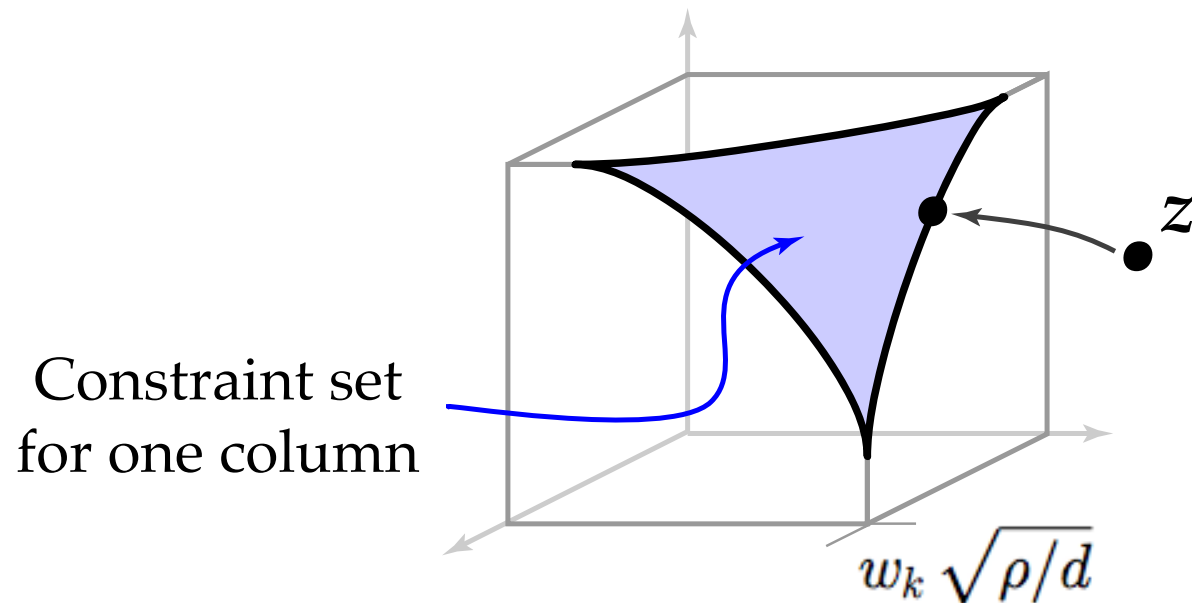
- Note that $1 \leq \text{PAR}(\mathbf{v}) \leq d$
 - The lower extreme corresponds to equal-modulus vectors
 - The upper bound occurs only for scaled canonical basis vectors

The PAR Constraint



- Let ρ be the maximum allowable PAR
- Suppose the frame vectors have norms w_1, \dots, w_N
- The constraint set becomes

$$\mathcal{S} = \{S \in \mathbb{C}^{d \times N} : \text{PAR}(\mathbf{s}_k) \leq \rho \text{ and } \|\mathbf{s}_k\|_2^2 = w_k\}$$



Optimal Grassmannian Frames



- An interesting (and difficult) problem is to construct a unit-norm tight frame with minimally correlated vectors
- For any $d \times N$ matrix Z with unit-norm columns

$$\max_{m \neq n} |\langle z_j, z_k \rangle| \geq \sqrt{\frac{N-d}{d(N-1)}}.$$

- The matrices that meet the bound are called *optimal Grassmannian (tight) frames*
- Each pair of columns has identical cross-correlation $|\langle z_j, z_k \rangle|$
- They do not exist for most combinations of d and N
- Closely related to “packings in Grassmannian manifolds”

References: [Conway-Hardin-Sloane 1996; StH 2003, SuTDH 2003]

Constructing Optimal Grassmannian Frames



- Let $\mu = \sqrt{(N-d)/(d(N-1))}$
- Consider the constraint sets

$$\mathcal{S} = \{S \in \mathbb{C}^{N \times N} : S = S^*; \quad \text{diag } S = \mathbf{e}; \quad |s_{jk}| \leq \mu\}$$

$$\mathcal{X} = \{X \in \mathbb{C}^{N \times N} : X = X^*; \quad \lambda(X) = (\underbrace{N/d, \dots, N/d}_d, 0, \dots, 0)\}$$

- Any matrix in $\mathcal{S} \cap \mathcal{X}$ is an optimal Grassmannian frame
- Empirically, an alternating projection between \mathcal{S} and \mathcal{X} appears to find optimal Grassmannian frames when they exist

Reference: [TDHSt 2003, DHSST 2003]

Tight Frames vs. Grassmannian Frames



Tight frame:

$$X = \begin{bmatrix} -0.6669 & -0.3972 & 0.9829 & 0.1984 & 0.5164 & -0.3540 \\ 0.6106 & 0.4999 & -0.0761 & 0.5205 & 0.4776 & -0.9341 \\ 0.4272 & -0.7696 & 0.1676 & 0.8305 & -0.7108 & -0.0470 \end{bmatrix}$$
$$X^*X = \begin{bmatrix} 1.0000 & 0.2414 & -0.6303 & 0.5402 & -0.3564 & -0.3543 \\ 0.2414 & 1.0000 & -0.5575 & -0.4578 & 0.5807 & -0.2902 \\ -0.6303 & -0.5575 & 1.0000 & 0.2947 & 0.3521 & -0.2847 \\ 0.5402 & -0.4578 & 0.2947 & 1.0000 & -0.2392 & -0.5954 \\ -0.3564 & 0.5807 & 0.3521 & -0.2392 & 1.0000 & -0.5955 \\ -0.3543 & -0.2902 & -0.2847 & -0.5954 & -0.5955 & 1.0000 \end{bmatrix}$$

Grassmannian frame:

$$X = \begin{bmatrix} -0.1619 & -0.6806 & 0.1696 & 0.3635 & -0.4757 & 0.3511 \\ 0.6509 & 0.1877 & -0.4726 & 0.2428 & -0.5067 & -0.0456 \\ -0.2239 & 0.0391 & -0.4978 & -0.5558 & -0.1302 & 0.6121 \end{bmatrix}$$
$$X^*X = \begin{bmatrix} 1.0000 & 0.4472 & -0.4472 & 0.4472 & -0.4472 & -0.4472 \\ 0.4472 & 1.0000 & -0.4472 & -0.4472 & 0.4472 & -0.4472 \\ -0.4472 & -0.4472 & 1.0000 & 0.4472 & 0.4472 & -0.4472 \\ 0.4472 & -0.4472 & 0.4472 & 1.0000 & -0.4472 & -0.4472 \\ -0.4472 & 0.4472 & 0.4472 & -0.4472 & 1.0000 & -0.4472 \\ -0.4472 & -0.4472 & -0.4472 & -0.4472 & -0.4472 & 1.0000 \end{bmatrix}$$

Conclusions



- Wireless is a timely application
- It yields inverse eigenvalue problems and matrix nearness problems
- Tight frames generalize orthogonal bases and have other applications
- The linear algebra community may be able to contribute significantly

Papers



- [THSt] “Inverse eigenvalue problems, alternating minimization and optimal CDMA signature sequences.” *Proceedings of IEEE International Symposium on Information Theory*. July 2003.
- [TDHSt] “CDMA signature sequences with low peak-to-average ratio via alternating minimization.” To appear at Asilomar, November 2003.
- [TDH] “Finite-step algorithms for constructing optimal CDMA signature sequences.” Submitted, April 2003.
- [DHSuT] “Generalized finite algorithms for constructing Hermitian matrices with prescribed diagonal and spectrum.”
- [TDHSt] “An alternating projection method for designing structured tight frames.” In preparation.
- [SuTDH] “Necessary conditions for existence of optimal Grassmannian frames.” In preparation.
- [DHSST] “Grassmannian packings via alternating projections.” In preparation.

For More Information. . .



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