

HIGHLIGHTS

- Asymptotic **Karhunen–Loève integral expansion of cyclostationary (CS) processes** and connection to their Cramér–Loève representation.
- Extension of classical stationary Wiener filtering results.
- Unified theoretical analysis** of smoothing, filtering and prediction of CS processes.
- Quantification of **minimum mean squared error and achievable synchronous gain** in terms of coherence statistics.

Let $\{x(n) \in \mathbb{C}\}_{n \in \mathbb{Z}}$ be a zero-mean, proper and second-order random process with autocorrelation function

$$R_x(n, m) \triangleq E[x(n+m)x^*(n)].$$

Types of processes:

Wide-sense stationary (WSS): $R_x(n, m) \equiv R_x(m)$.

Cyclostationary (CS): $R_x(n, m) \equiv R_x(n+lp, m) \quad \forall l \in \mathbb{Z}$.

CRAMÉR–LOÈVE (CL) EXPANSION

$$x(n) = \int_0^1 e^{j2\pi fn} dv_x(f)$$

$$dv_x(f) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} x(n) e^{-j2\pi fn} \triangleq \text{CL}\{x(n)\}(f). \quad (1)$$

Spectral correlation:

$$S_X(\alpha, f) d\alpha df \triangleq E[dv_x(f) dv_x^*(f - \alpha)].$$

> **WSS processes** have orthogonal increments:

$$S_X^{(WSS)}(\alpha, f) = S_X(f) \delta(\alpha),$$

where $S_X(f) df \triangleq E[|dv_x(f)|^2]$ is the power spectral density (PSD).

> **CS processes** display spectral lines:

$$S_X^{(CS)}(\alpha, f) \triangleq \sum_{k=0}^{P-1} S_X^{(k/P)}(f) \delta(\alpha - \frac{k}{P}),$$

where

$$S_X^{(k/P)}(f) \triangleq \frac{1}{P} \sum_{n=0}^{P-1} \sum_{m \in \mathbb{Z}} R_x(n, m) e^{-j2\pi(\frac{kn}{P} + fm)}$$

is the *cyclic PSD*.

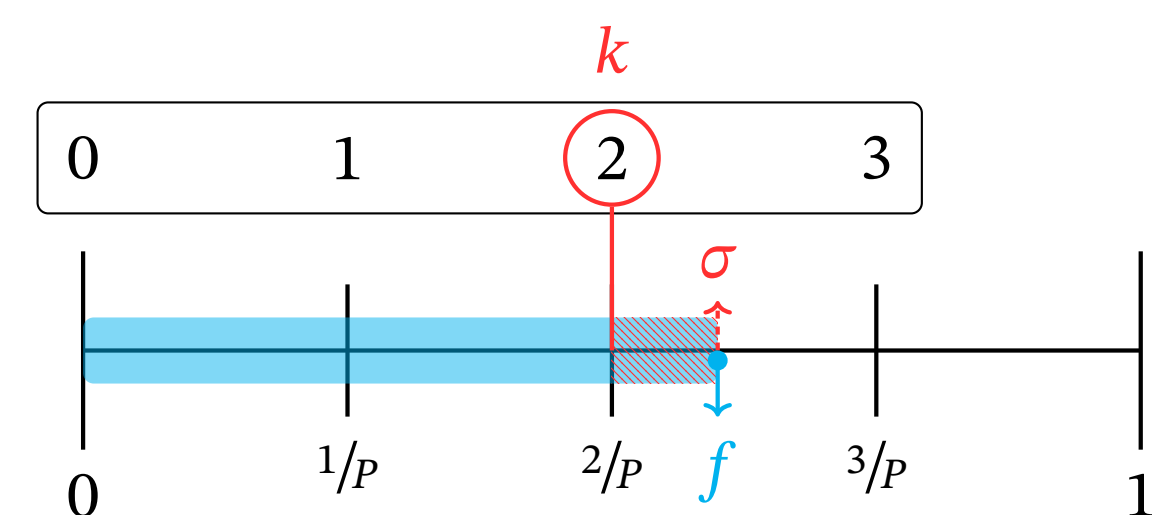
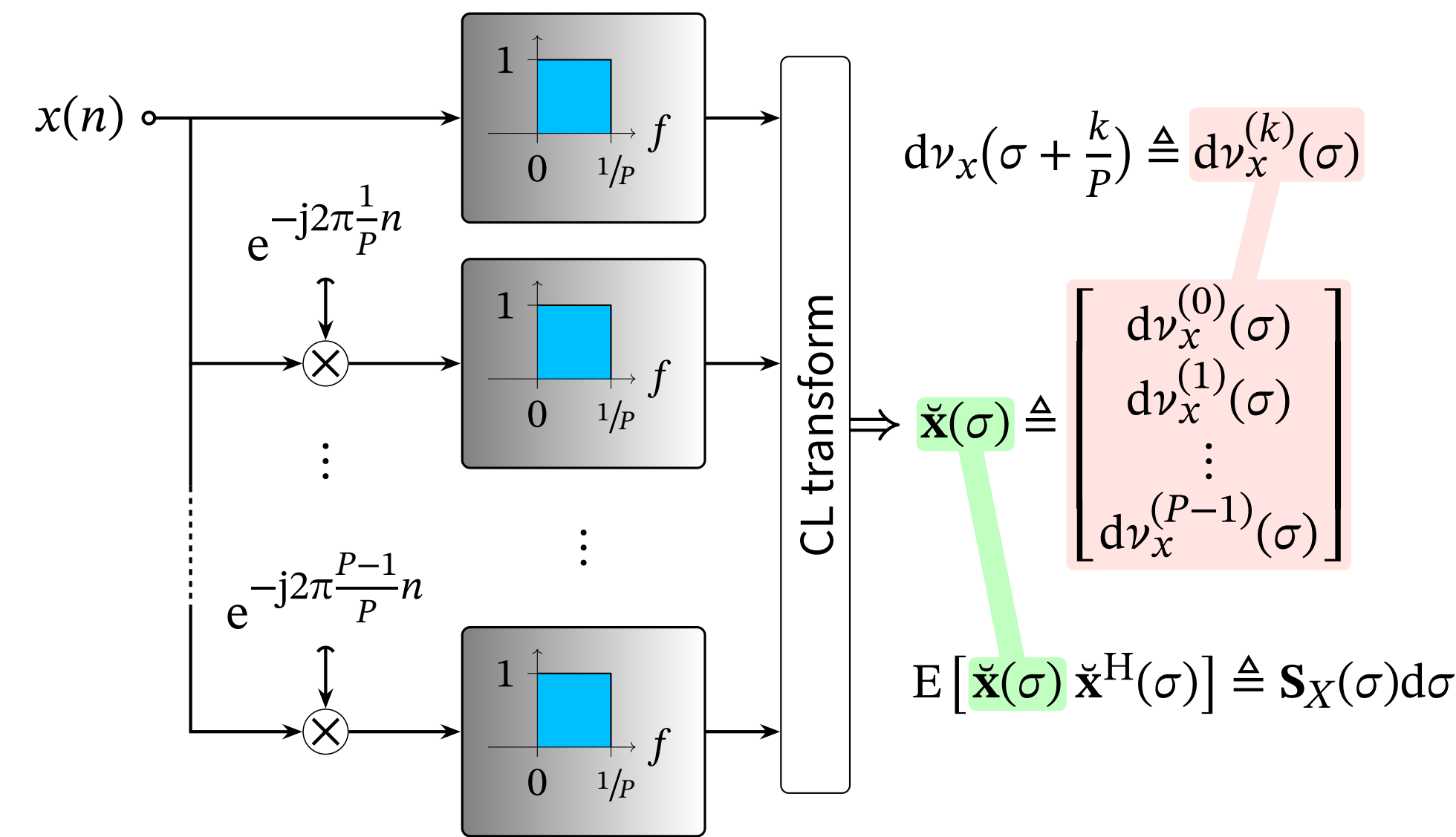


Figure 1. Spectral domain segmentation: $f \triangleq \sigma + k/P$.

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Figure 2. Gladyshev decomposition (harmonic series representation).



KARHUNEN–LOÈVE (KL) EXPANSION

$$x(n) = \int_0^1 \phi(n, \lambda) d\xi_x(\lambda) \quad (2)$$

$$d\xi_x(\lambda) = \lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=-\frac{N}{2}}^{\frac{N}{2}-1} x(n) \phi^*(n, \lambda) \triangleq \text{KL}\{x(n)\}(\lambda).$$

Basis $\{\phi(n, \lambda)\}$ solves the following eigenequation:

$$\sum_{l \in \mathbb{Z}} R_x(l, k-l) \phi(l, \lambda) = S_X(\lambda) \phi(k, \lambda),$$

where $S_X(\lambda) d\lambda \triangleq E[|d\xi_x(\lambda)|^2]$ is the *KL spectrum* of $\{x(n)\}$.

> KL basis of WSS processes is $\{\phi_{WSS}(n, \lambda) \triangleq e^{j2\pi n \lambda}\}$.

THEOREM 1 – KL basis of CS processes

The Karhunen–Loève eigenbasis of a P -periodic cyclostationary process is

$$\phi_{CS}^{(p)}(n, \sigma) = \sum_{q=0}^{P-1} [\mathbf{B}_X(\sigma)]_{q,p} e^{j2\pi(\sigma + \frac{q}{P})n}. \quad (3)$$

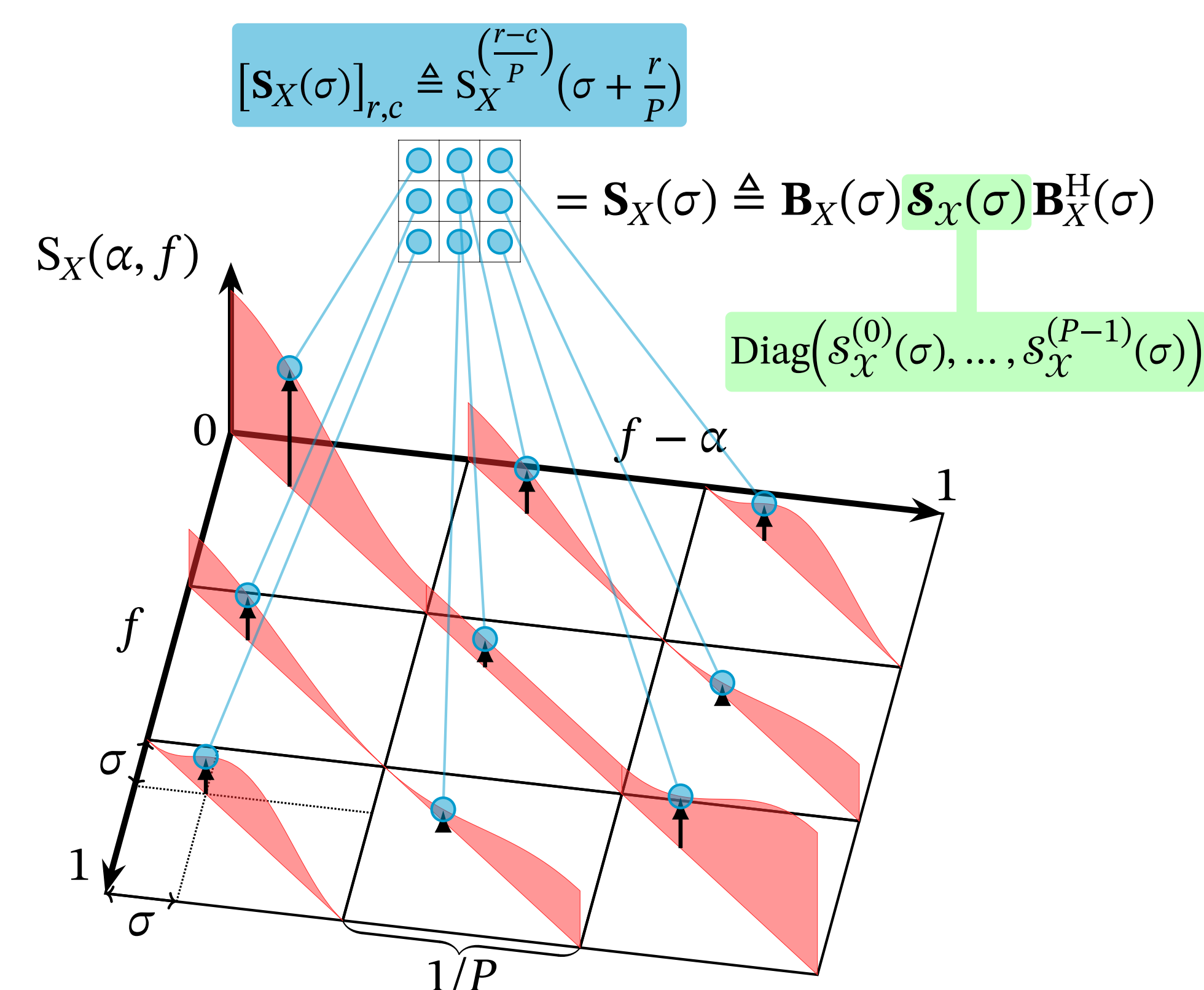


Figure 3. Construction of the cyclic spectrum matrix (CSM).

COROLLARY 1: KL–CL connection

The KL and CL spectral representations of a CS process are related through the following inequality:

$$\tilde{\mathbf{x}}(\sigma) = \mathbf{B}_X^H(\sigma) \mathbf{x}(\sigma), \quad (4)$$

where $\tilde{\mathbf{x}}(\sigma) \triangleq [d\xi_x^{(0)}(\sigma), \dots, d\xi_x^{(P-1)}(\sigma)]^T$.

Optimalities of the KL representation:

Signal model:

$$x(n) = d(n - \varepsilon) + z(n) \Rightarrow \begin{cases} \{d(n)\}: \text{digital PAM signal.} \\ \{z(n)\}: \text{additive white Gaussian noise.} \\ \varepsilon \sim \mathcal{U}[0, \Delta]: \text{synchronization reliability.} \end{cases}$$

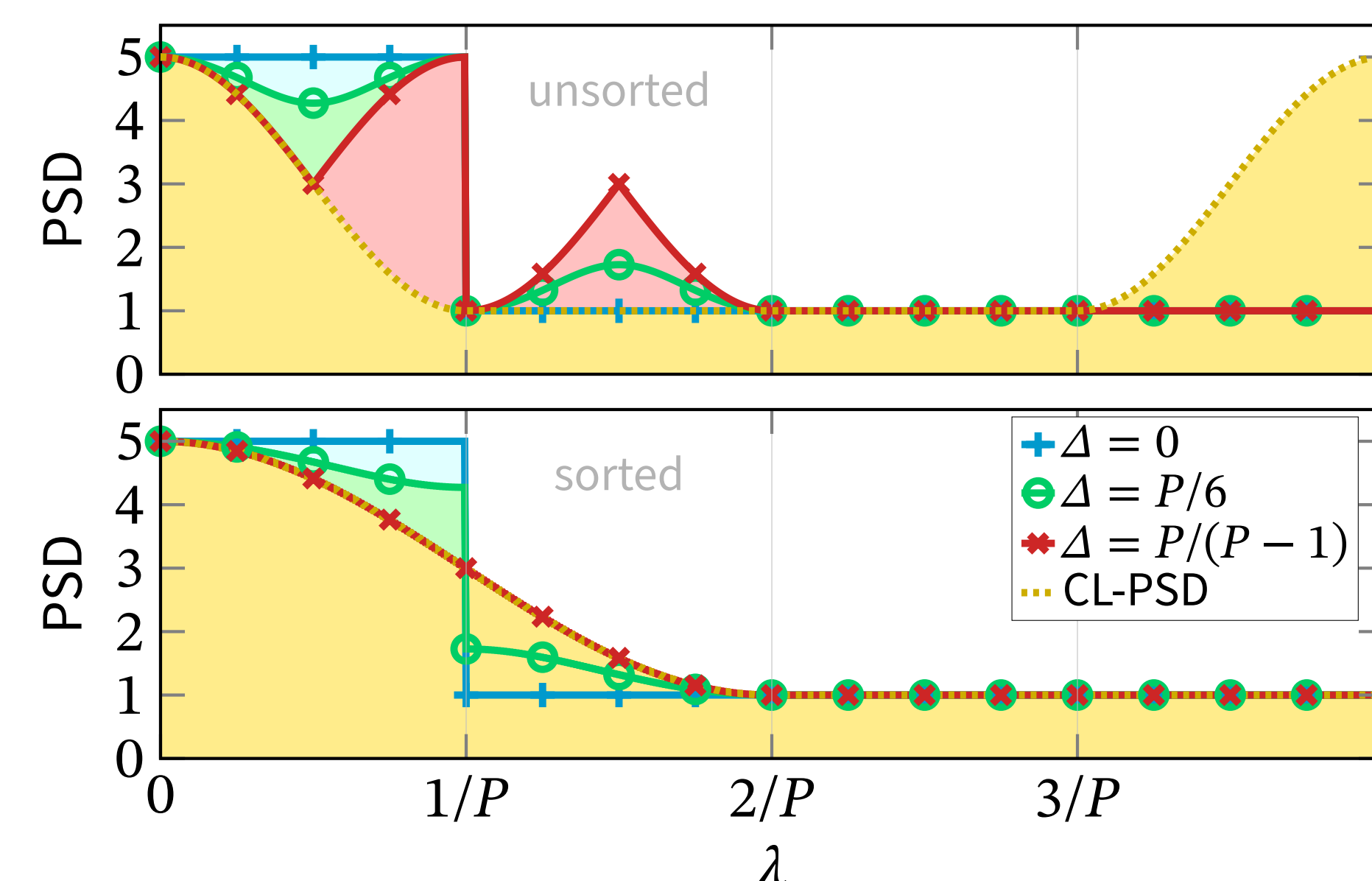


Figure 4. Optimal energy compaction of the KL representation.

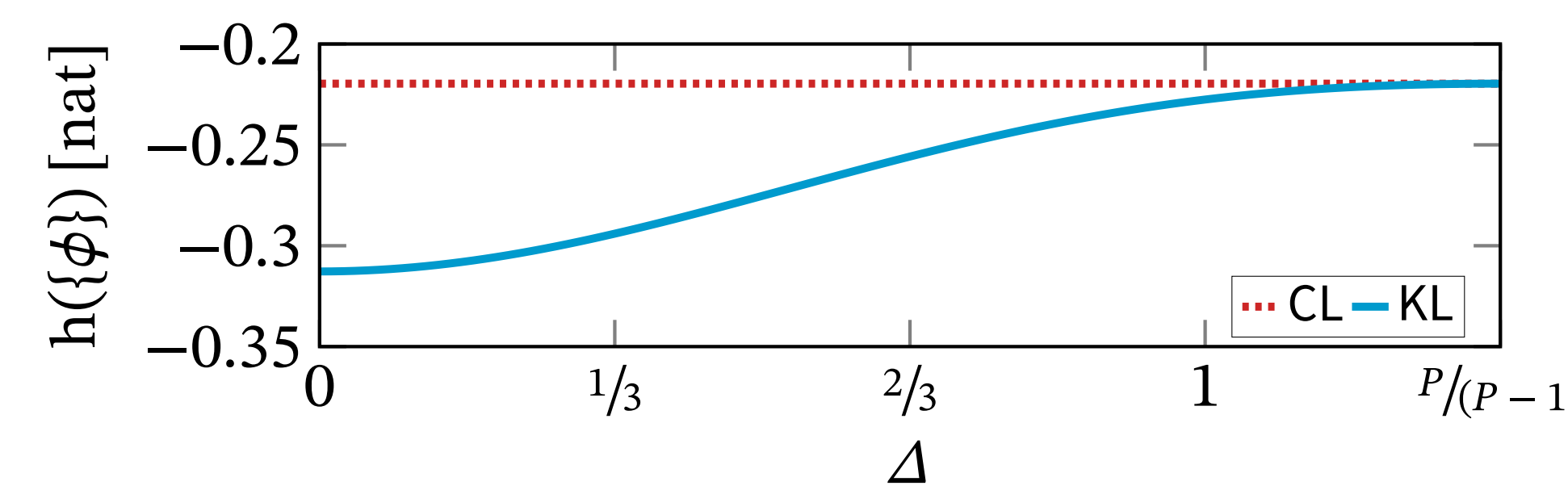


Figure 5. Minimum representation entropy of the KL representation.

CYCLIC WIENER FILTERING

Smoothing

THEOREM 2 – Cyclic Wiener filter in the KL domain

The (noncausal) cyclic Wiener filter is equivalent to the KL Wiener filter.

> The FRESH implementation can be expressed as a multiplicative filter in the KL domain: $\mathcal{W}_p(\sigma) = E[d\xi_d^{(p)}(\sigma) d\xi_x^{(p)*}(\sigma)] / E[|d\xi_x^{(p)}(\sigma)|^2]$.

> Minimum MSE:

$$\text{MMSE}_{nc} = \int_0^{1/P} \text{Tr}[\mathbf{S}_D(\sigma)(\mathbf{I}_P - \mathbf{C}_{DX}(\sigma)\mathbf{C}_{DX}^H(\sigma))] d\sigma, \quad (5)$$

where $\mathbf{C}_{DX}(\sigma) \triangleq \mathbf{S}_D^{-1/2}(\sigma) E[\tilde{\mathbf{d}}(\sigma) \tilde{\mathbf{x}}^H(\sigma)] \mathbf{S}_X^{-1/2}(\sigma)$ is the *coherence matrix*.

> High SNR regime: $\text{MMSE}_{nc} \xrightarrow{\text{SNR} \rightarrow \infty} B/\text{SNR}$, where $S_D(\lambda)$ is defined for $\lambda \in [0, B)$.

Filtering

> Derived using the *Guo–Shamai–Verdú theorem*:

$$\begin{aligned} \text{MMSE}_c(\text{SNR}) &= E[\text{MMSE}_{nc}(\Gamma \sim \mathcal{U}[0, \text{SNR}])] \\ &= -\frac{1}{\text{SNR}} \int_0^{1/P} \ln|\mathbf{I}_P - \mathbf{C}_{DX}(\sigma)\mathbf{C}_{DX}^H(\sigma)| d\sigma. \end{aligned} \quad (6)$$

> High SNR regime: $\text{MMSE}_c(\text{SNR}) \xrightarrow{\text{SNR} \rightarrow \infty} B \frac{\ln \text{SNR}}{\text{SNR}} + O(1/\text{SNR})$.

Prediction

> MMSE of one-step prediction of $\{x(n)\}$:

$$\text{MMSE}_p = \exp \int_0^{1/P} \ln|\mathbf{S}_X(\sigma)| d\sigma. \quad (7)$$

> High SNR regime: $\text{MMSE}_p(\text{SNR}) \xrightarrow{\text{SNR} \rightarrow \infty} A/\text{SNR}^{(1-B)}$.

> Synchronous gain (\propto spectral flatness):

$$\zeta_p = \frac{\text{MMSE}_p}{\text{MMSE}_{\text{WSS}, p}} = \exp \int_0^{1/P} \ln|\bar{\mathbf{C}}_X(\sigma)| d\sigma, \quad (8)$$

where $\bar{\mathbf{C}}_X(\sigma) \triangleq (\mathbf{I}_P \circ \mathbf{S}_X^{-1/2}(\sigma)) \mathbf{S}_X(\sigma) (\mathbf{I}_P \circ \mathbf{S}_X^{-1/2}(\sigma))$ is the *spectral coherence matrix*.

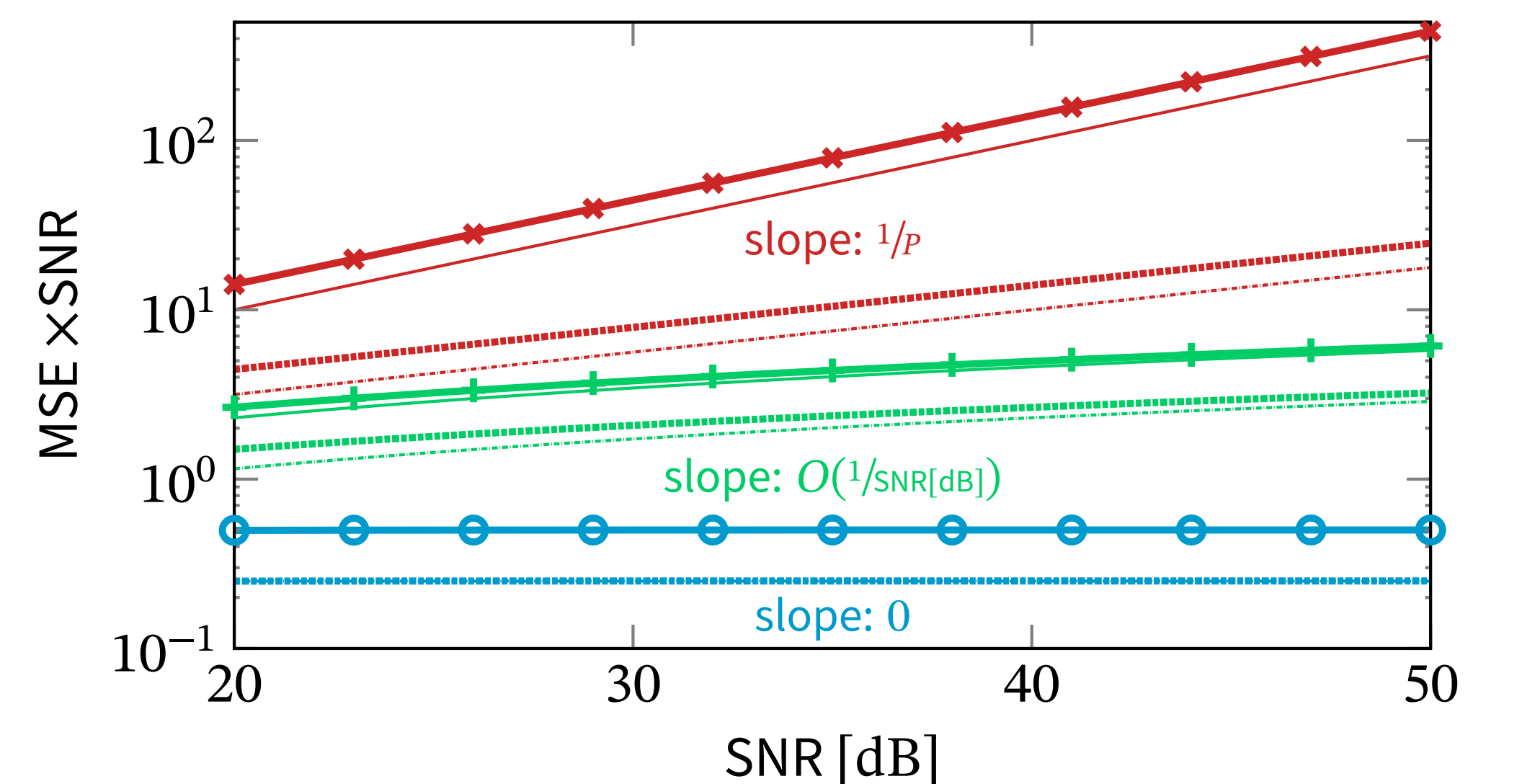
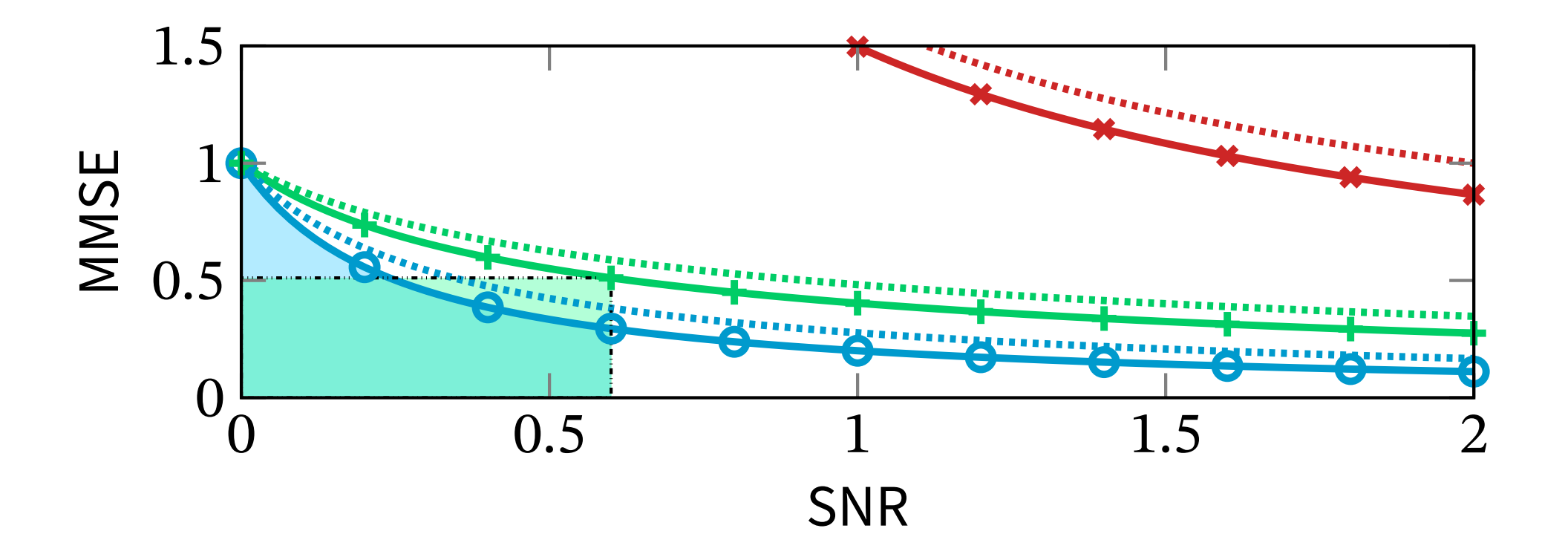


Figure 6. MMSE and synchronous gain illustrations.

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