

INTRODUCTION

WSS signal received by cognitive radar:

$$y(t) = \sum_{k=1}^K c_k e^{j2\pi f_k t/T} + n(t)$$

- c_k 's: zero mean uncorrelated random variables
- $n(t)$: a WSS signal (possibly colored noise).
- $1/T$: the Nyquist sampling rate.
- f_1, \dots, f_k : frequency of interfering signals

Contributions:

- We propose a sub-Nyquist sampling technique: Co-prime Sampling.
- We use atomic norm denoising to detect the frequencies.
- We use *spectral priors* to improve the frequency localization.

COPRIME SAMPLING

Auto-correlation:

$$r_{yy}[k] = E(y(nT)y^*(nT - kT))$$

$$= \sum_{m=1}^K \sigma_m^2 e^{j2\pi f_m k} + r_{nn}[k]$$

- $\sigma_m^2 = E(|c_m|^2)$.
- $r_{nn}[k]$ is the autocorrelation of $n(t)$, and $|r_{nn}[k]| < \eta$.

Coprime Sampling: Sample $y(t)$ using two samplers with rates $1/MT, 1/NT$ Hz

$$x_M[n] = y(MnT),$$

$$x_N[n] = y(NnT)$$

Lemma 1 [2] $\forall 0 \leq k \leq MN - 1, \exists 0 \leq n_1 \leq 2N - 1, 0 \leq n_2 \leq M - 1$, so that $k = Mn_1 - Nn_2$.

Estimating the Auto-Correlation:

1. Find $0 \leq n_1 \leq 2N - 1, 0 \leq n_2 \leq M - 1$, so that $k = Mn_1 - Nn_2$.
2. Compute $\tilde{r}_{yy}[k] = \frac{1}{L} \sum_{l=0}^{L-1} x_M[n_1 + Nl] x_N^*[n_2 + Ml]$
3. Estimate $\tilde{r}_{yy}[-k]$ using $(-n_1, -n_2)$, and refine as $\hat{r}_{yy}[k] = 0.5 \times (\tilde{r}_{yy}[k] + \tilde{r}_{yy}^*[-k])$

RESTRICTED SPECTRAL PRIORS

- **Unconstrained Atomic Set:** $\mathcal{A} \triangleq \{\mathbf{a}(f), f \in [0, 1)\}$ where $\mathbf{a}(f) = [1, e^{j2\pi f}, e^{j2\pi 2f}, \dots, e^{j2\pi(P-1)f}]^T$
- The atomic norm of $\mathbf{x} \in \mathbb{C}^P$: $\|\mathbf{x}\|_{\mathcal{A}} = \inf\{t > 0 | \mathbf{x} \in t\text{conv}(\mathcal{A})\}$

- **Probabilistic Priors:** Band $\mathcal{F}_i \triangleq [f_{i1}, f_{i2})$ contains interfering frequencies w. p. α_i

$$\mathcal{A}_w = \{\mathbf{a}(f)w(f), f \in [0, 1)\}$$

$$w(f) = \alpha_i, \text{ for } f \in \mathcal{F}_i.$$

- **Block Priors:** Only the bands $\mathcal{F} = \bigcup_{i=1}^I \mathcal{F}_i$ are occupied. The corresponding atomic set:

$$\mathcal{A}_p = \{\mathbf{a}(f), f \in \mathcal{F}\}$$

Primal Problem: $\min_{\mathbf{x}} \frac{1}{2} \|\mathbf{r} - \mathbf{x}\|_2^2 + \lambda \|\mathbf{x}\|_{\bar{\mathcal{A}}}$
where $\bar{\mathcal{A}}$ is either \mathcal{A}_w or \mathcal{A}_p , and $\mathbf{r} = [\hat{r}_{yy}[0], \dots, \hat{r}_{yy}[P-1]]^T$, with $P \leq MN$

Dual problem for Probabilistic Priors:

$$\max_{\mathbf{z}} \frac{1}{2} (\|\mathbf{r}\|^2 - \|\mathbf{r} - \mathbf{z}\|^2)$$

$$|\langle \mathbf{a}(f), \mathbf{z} \rangle| \leq \alpha_i \lambda,$$

$$f \in \mathcal{F}_i, i = 1, 2, \dots, I$$

Dual problem for Block Priors:

$$\max_{\mathbf{z}} \frac{1}{2} (\|\mathbf{r}\|^2 - \|\mathbf{r} - \mathbf{z}\|^2)$$

$$|\langle \mathbf{a}(f), \mathbf{z} \rangle| \leq \lambda,$$

$$f \in \mathcal{F}_i, i = 1, 2, \dots, I$$

REFERENCES

- [1] K. V. Mishra, M. Cho, A. Kruger, and W. Xu, "Spectral super-resolution with prior knowledge", IEEE Trans. on Signal Proc., vol. 63, no. 20, pp. 5342-5357, Oct. 2015.
- [2] P. P. Vaidyanathan and Piya Pal, "Sparse Sensing With Co-Prime Samplers and Arrays", IEEE Trans. on Signal Proc., vol. 59, pp. 573-586, Feb. 2011.

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RECASTING THE DUAL PROBLEMS AS SDP

Following [1], for $[f_L, f_H] \subset [0, 1]$, define:

$$\alpha \triangleq \tan(\pi f_L), \beta \triangleq \tan(\pi f_H), d_0 \triangleq -\frac{\alpha\beta + 1}{2}, d_1 \triangleq \frac{1 - \alpha\beta}{4} + j\frac{\alpha + \beta}{4}$$

Furthermore, for Gram matrices $\mathbf{G}_1 \in \mathbb{C}^{P \times P}, \mathbf{G}_2 \in \mathbb{C}^{(P-1) \times (P-1)}$, let

$$\mathcal{L}_{k, f_L, f_H}(\mathbf{G}_1, \mathbf{G}_2) \triangleq \text{tr}(\Theta_k \mathbf{G}_1) + \text{tr}[(d_1 \Theta_{k-1} + d_0 \Theta_k + d_1^* \Theta_{k+1}) \mathbf{G}_2]$$

Θ_k : ones on k th diagonal, and zeros elsewhere. ($k = 0$: the main diagonal, and $k > 0$: upper diagonals.)

Probabilistic Priors:

$$\begin{aligned} & \max_{\mathbf{z}} \|\mathbf{r}\|^2 - \|\mathbf{r} - \mathbf{z}\|^2 \\ & \mathbf{G}_{11}, \mathbf{G}_{12}, \dots, \mathbf{G}_{1I} \succeq 0 \\ & \mathbf{G}_{21}, \mathbf{G}_{22}, \dots, \mathbf{G}_{2I} \succeq 0 \\ & \text{subject to} \\ & \delta_{k_1} = \mathcal{L}_{k_1, f'_{L_1}, f'_{H_1}}(\mathbf{G}_{11}, \mathbf{G}_{21}) \\ & k_1 = 0, \dots, P-1 \\ & \begin{bmatrix} \mathbf{G}_{11} & \frac{1}{\lambda \alpha_1} \tilde{\mathbf{z}}_{\tau_1} \\ \frac{1}{\lambda \alpha_1} \tilde{\mathbf{z}}_{\tau_1}^H & 1 \end{bmatrix} \succeq 0, \\ & \vdots \\ & \delta_{k_I} = \mathcal{L}_{k_I, f'_{L_I}, f'_{H_I}}(\mathbf{G}_{1I}, \mathbf{G}_{2I}) \\ & k_I = 0, \dots, P-1 \\ & \begin{bmatrix} \mathbf{G}_{1I} & \frac{1}{\lambda \alpha_I} \tilde{\mathbf{z}}_{\tau_I} \\ \frac{1}{\lambda \alpha_I} \tilde{\mathbf{z}}_{\tau_I}^H & 1 \end{bmatrix} \succeq 0, \end{aligned}$$

Block Priors:

$$\begin{aligned} & \max_{\mathbf{z}} \|\mathbf{r}\|^2 - \|\mathbf{r} - \mathbf{z}\|^2 \\ & \mathbf{G}_{11}, \mathbf{G}_{12}, \dots, \mathbf{G}_{1I} \succeq 0 \\ & \mathbf{G}_{21}, \mathbf{G}_{22}, \dots, \mathbf{G}_{2I} \succeq 0 \\ & \text{subject to} \\ & \delta_{k_1} = \mathcal{L}_{k_1, f_{L_1}, f_{H_1}}(\mathbf{G}_{11}, \mathbf{G}_{21}) \\ & k_1 = 0, \dots, P-1 \\ & \begin{bmatrix} \mathbf{G}_{11} & \frac{1}{\lambda} \mathbf{z} \\ \frac{1}{\lambda} \mathbf{z}^H & 1 \end{bmatrix} \succeq 0, \\ & \vdots \\ & \delta_{k_I} = \mathcal{L}_{k_I, f_{L_I}, f_{H_I}}(\mathbf{G}_{1I}, \mathbf{G}_{2I}) \\ & k_I = 0, \dots, P-1 \\ & \begin{bmatrix} \mathbf{G}_{1I} & \frac{1}{\lambda} \mathbf{z} \\ \frac{1}{\lambda} \mathbf{z}^H & 1 \end{bmatrix} \succeq 0, \end{aligned}$$

SIMULATION RESULTS

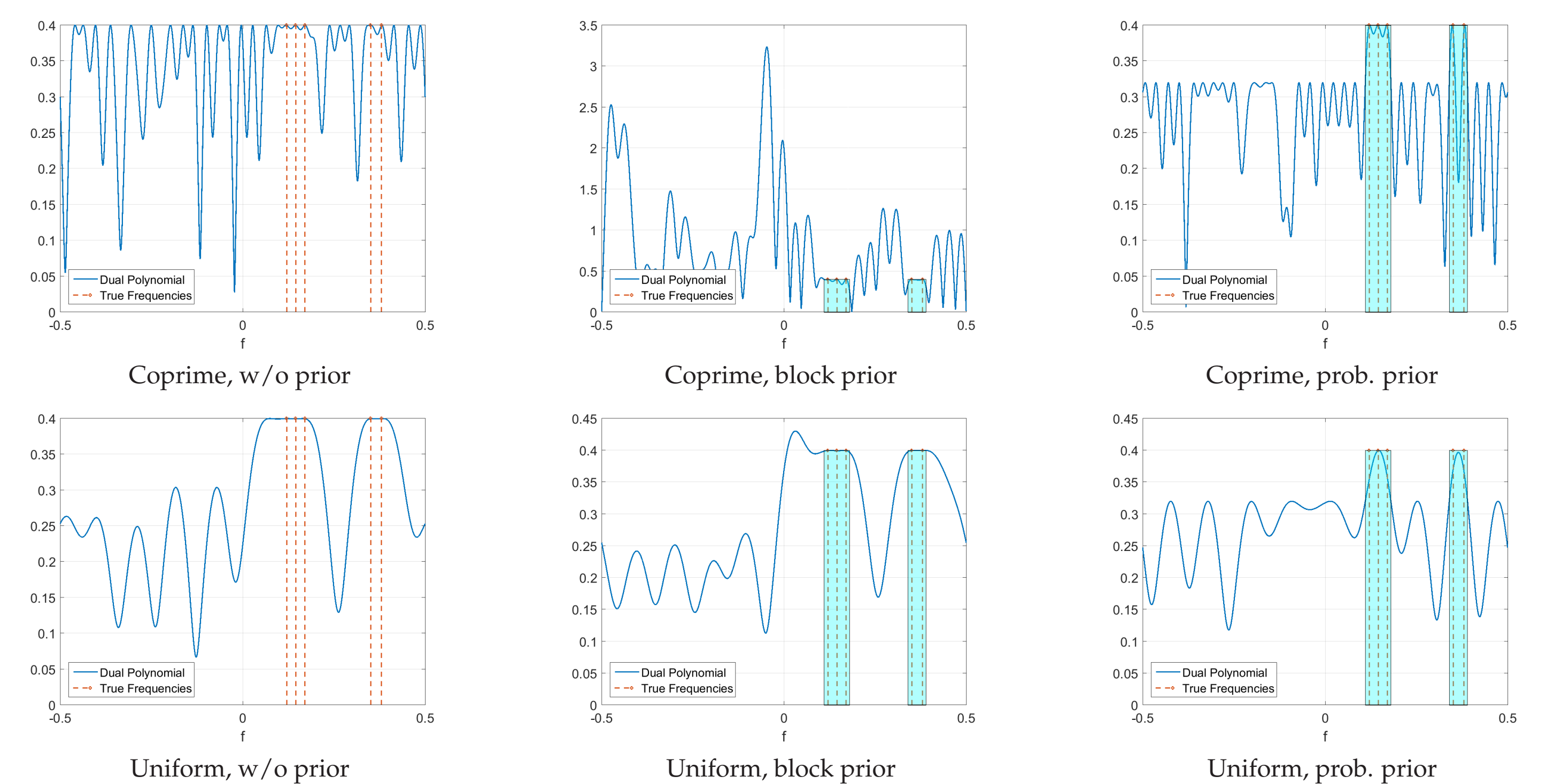


Figure 1. The dual polynomials corresponding to atomic norm denoising, using different samplers and spectral priors, $5 = K < \tilde{M} = 12$, \tilde{M} indicates the block length, and K is the number of spectral lines. We use $L = 20$ blocks

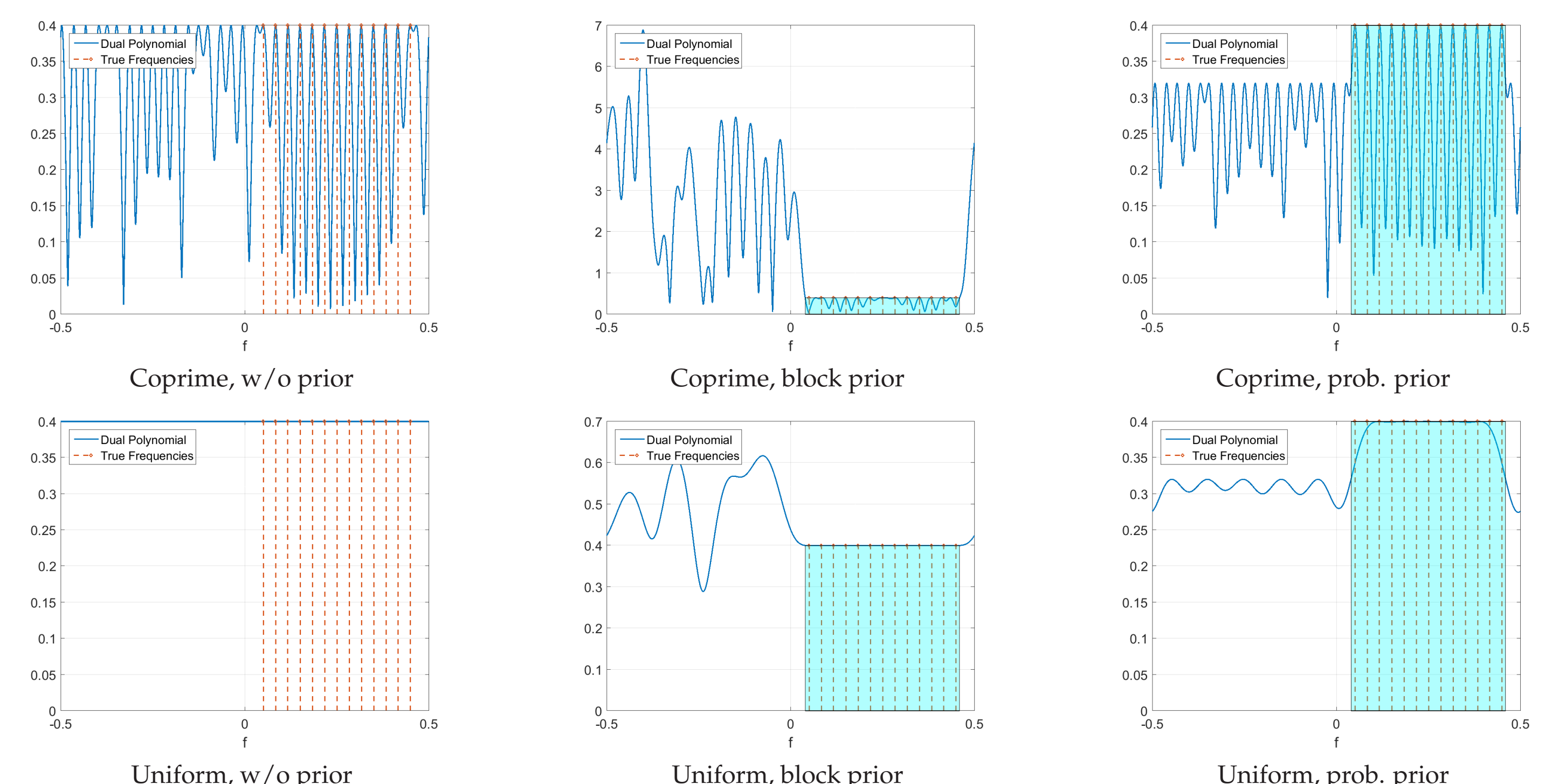


Figure 2. The dual polynomials corresponding to atomic norm denoising, using different samplers and spectral priors, $13 = K > \tilde{M} = 12$