Sparse Random Wavelet Representation & Decomposition

Summary

- Novel method for representing and decomposing 1D signals
- Represent signal in a random wavelet "basis"
- Find representation via Spectral Projected Gradient with L1 minimization (SPGL1)
- Decompose representation into modes via Density-Based Spatial Clustering of Applications with Noise (DBSCAN) or frequency filters

Problem Statement

- Given a 1D signal y, find a sparse representation
- Decompose it into simple modes



Figure 1: Decomposition Visualisation

Wavelet "Basis"



Figure 2: Example real-valued Gabor wavelet with $(\tau, f, \phi; w) = (0.4, 10, 1.26; 0.2).$

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Representation Algorithm

input: $t, y \in \mathbb{R}^N, M \in \mathbb{Z}^+, w, f_{\max} \in \mathbb{R}^+,$	\overline{in}
$r \in]0, 1[$	
Generate $\{\tau_m, f_m, \phi_m\}_{m=1}^M;$	De
Generate M wavelets $g_m \in \mathbb{R}^N$;	Sc
Store wavelets by column in a matrix	Us
$G \in \mathbb{R}^{N \times M};$	ot
Solve	Ex
$x^* = \underset{x \in \mathbb{R}^M}{\arg\min} \ x\ _1 \text{ s.t. } \ Gx - y\ _2 < r\ y\ _2;$	y_k
output: $x^*, G, \{\tau_m, f_m, \phi_m\}_{m=1}^M$	01
• Reconstruct $y \approx Gx^* = \sum_{m=1}^{M} x_m g_m$ • Relative error $\frac{\ Gx^* - y\ _2}{\ u\ }$ is less than r	• A • E 1
$ \mathcal{Y} _2$	

Mathematical Example

Input: $y(t) = y_1(t) + y_2(t) + y_3(t)$ defined by $y_1(t) = \pi t, t \in [0, 5/4]$ $y_2(t) = \cos(40\pi t), t \in [0, 5/4]$ $y_3(t) = \cos\left(\frac{4}{3}\left((2\pi t - 10)^3 - (2\pi - 10)^3 + 20\pi(t - 1)\right)\right)$ $t \in [1, 2].$

Parameters: $f_{\text{max}} = 80, M = 16\,000, r = 5\%$, $w = 0.1 \, \text{s}, \min \, \text{samples} = 3, \epsilon = 0.1, s = 1/80.$

"Synchrosqueezed wavelet transforms: An empirical mode decompositionlike tool"; Daubechies, Lu, & Wu; Applied and Computational Harmonic Analysis, 2011. DOI:10.1016/j.acha.2010.08.002



Figure 3: Segmentation of nonzero wavelets into four modes. Frequency and time-shifts of nonzero wavelets are plotted where colour represents labelling from DBSCAN.

Decomposition Algorithm

nput: $x^*, G, (\tau_m, f_m)_{m=1}^M,$ $\texttt{min_samples} \in \mathbb{Z}^+, \ \epsilon, s \in \mathbb{R}^+$ Define $(\tau_{m_j}, \bar{f}_{m_j})_{j=1}^{\bar{M}'} := \{ (\tau_m, f_m) | x_m^* \neq 0 \};$ cale input points to obtain $(\tau_{m_i}, s \cdot f_{m_i});$ se DBSCAN to label each point by cluster to btain $\{\ell_{m_i}\}$ where $\ell_{m_i} \in \{-1, 0, \cdots, K-1\};$ xtract K modes: $= \sum_{m \in I_k} x_m^* g_m, \ I_k = \{ m_j | \ell_{m_j} = k - 1 \};$ **utput:** $\{y_k\}_{k=1}^{K'}$

Alternatively decompose using known conditions Ex. a band-pass filter could be represented as $= \{ m_j | a < f_{m_j} < b \}$



Figure 4: Learned signal and decomposed modes vs ground truth. Note input was a noisy source (5% Gaussian), and mode 4 was added to mode 1 in the second row.

Input: $y(t) = y_1(t) + y_2(t)$ where $y_1(t)$ is a flute and $y_2(t)$ is a guitar clip around 1.85 s long. **Parameters**: $f_{\text{max}} = 44\,100\,\text{Hz}/16, M = 51\,080,$ $N = 10\,200, r = 8\%, w = 0.03\,\mathrm{s}.$



Flute and Guitar Decomposition



Figure 5: Segmentation via slice at $f = 480 \,\text{Hz}$



Figure 6: Extracted flute and guitar vs original

References

1. Purwins, H. et al. Deep Learning for Audio Signal Processing. CoRR abs/1905.00078. arXiv: 1905.00078 (2019). 2. Hashemi, A. et al. Generalization Bounds for Sparse Random Feature Expansions. 2021. arXiv: 2103.03191. 3. Van den Berg, E. & Friedlander, M. P. Sparse Optimization with Least-Squares Constraints. SIAM Journal on Opti*mization* **21**, 1201–1229 (2011).

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Contact Information

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