

The Optimised Local Renyi Entropy-Based Shrinkage Algorithm for Sparse TFD Reconstruction

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- Time-frequency distributions (TFDs) are useful tools for non-stationary signals analysis. However, due to the presence of unwanted cross-terms useful information extraction from TFDs has proven to be a challenging task, especially in the case of noise-corrupted real-life signals. One way to suppress the cross-terms is by employing compressive sensing methods that enforce sparsity in the resulting TFD.
- In this work, we have developed a sparse reconstruction algorithm that reconstructs a TFD from a small sub-set of signal samples in the ambiguity domain. The algorithm utilises the information from both the short-term and the narrow-band Rényi time-frequency entropies, while its parameters are optimised using evolutionary meta-heuristic methods.
- Results are presented for both synthetic and real-life signals in noise, and compared to the state-of-the-art sparse reconstruction algorithms.

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Time-Frequency Signal Analysis

- The Wigner-Ville Distribution (WVD) is the most commonly used method for TFD calculation defined as

$$W_z(t, f) = \int_{-\infty}^{\infty} z\left(t + \frac{\tau}{2}\right) z^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau, \quad (1)$$

which introduces wanted components (auto-terms) and highly oscillatory unwanted components (cross-terms).

- The cross-terms can be suppressed in the WVD post-processing by applying a low-pass filter to the ambiguity function (AF):

$$A_z(\nu, \tau) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W_z(t, f) e^{j2\pi(f\tau - \nu t)} dt df, \quad (2)$$

which leaves the auto-terms positioned at the AF origin and filters out the cross-terms positioned through the rest of the domain:

$$\mathcal{A}_z(\nu, \tau) = g(\nu, \tau) A_z(\nu, \tau), \quad (3)$$

where $g(\nu, \tau)$ is the AF filter kernel.

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The Compressive Sensing (CS) Methods

- The cross-term suppression can be achieved with the sparse reconstruction. Eq. (3) can be rewritten in the matrix form:

$$\boldsymbol{\vartheta}_z(t, f) = \boldsymbol{\psi}^H \cdot \mathbf{A}'_z(\nu, \tau), \quad (4)$$

where $\boldsymbol{\vartheta}_z(t, f)$ is the sparse TFD, or the solution matrix, $\boldsymbol{\psi}^H$ is the Hermitian transpose of the domain transformation matrix representing the 2D Fourier transform equivalent to (2), and $\mathbf{A}'_z(\nu, \tau)$ is the CS-AF, or the observation matrix, which is a $N'_\tau \times N'_\nu$ rectangle containing the AF samples belonging to the auto-terms.

- The rest of the AF is calculated in a way which produces the sparsest TFD. This is an optimization problem with the ℓ_0 -norm-based regularization function:

$$\boldsymbol{\vartheta}_z^{\ell_0}(t, f) = \arg \min_{\boldsymbol{\vartheta}_z(t, f)} \|\boldsymbol{\vartheta}_z(t, f)\|_0, \quad (5)$$

subject to: $\|\boldsymbol{\vartheta}_z(t, f) - \boldsymbol{\psi}^H \mathbf{A}'_z(\nu, \tau)\|_2^2 \leq \epsilon,$

where ϵ is a user-defined solution tolerance.

The Local Rényi Entropies

METHODS

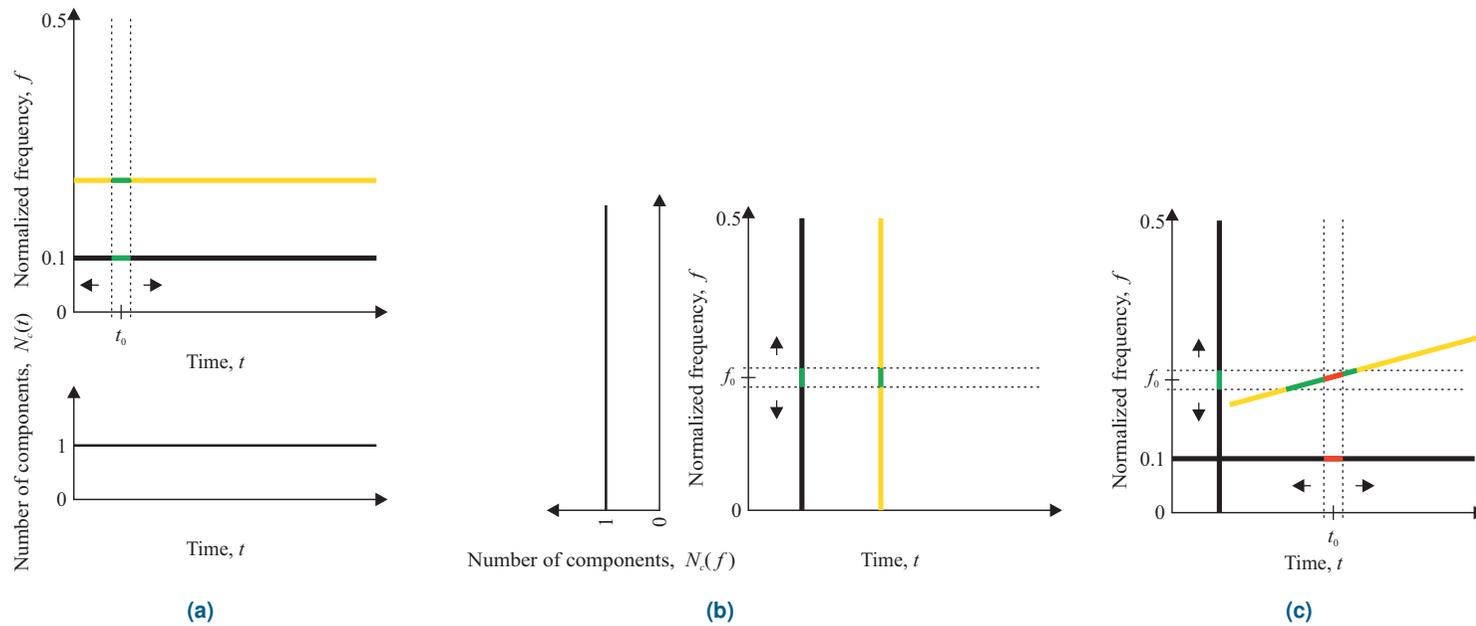


Figure 1: (a) Short-term Rényi entropy; (b) narrow-band Rényi entropy; (c) both local entropies on one-component signal.

The Local Rényi Entropy Based Shrinkage Algorithm for Sparse TFD Reconstruction

- The proposed shrinkage algorithm is based on the Two-step iterative shrinkage/thresholding (TwIST) algorithm:

$$[\vartheta_z^{\ell_0}(t, f)]^{[n+1]} = (1 - \alpha)[\vartheta_z^{\ell_0}(t, f)]^{[n-1]} + (\alpha - \beta)[\vartheta_z^{\ell_0}(t, f)]^{[n]} + \beta \cdot \text{shrink}\left\{[\vartheta_z^{\ell_0}(t, f)]^{[n]} + \psi^H\left(\mathbf{A}'_z(\nu, \tau) - \psi[\vartheta_z^{\ell_0}(t, f)]^{[n]}\right)\right\}, \quad (6)$$

where α and β are user-defined TwIST relaxation parameters.

- shrink*{·} operator is based on the **short-term** and the **narrow-band Rényi entropies** which give information on the number of signal components in each time- or frequency-slice, $N_c(t)$ or $N_c(f)$, respectively.

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- CS-AF filtering concentrates mainly on the auto-terms; hence, the obtained sparse TFD has auto-terms with larger non-negative energy surface than cross-terms.
- The shrinkage algorithm leaves samples belonging to $N_c(t)$ or $N_c(f)$ largest surfaces in time- or frequency-slice.
- Parameters δ_t/δ_f control the number of samples left in the final time-/frequency-slice.
- The algorithm performance is controlled by the percentage of utilization of each Rényi entropy information, controlled by the parameter p :

$$\varsigma_z(t, f) = p \cdot \varsigma_z^t(t, f) + (1 - p) \cdot \varsigma_z^f(t, f), \quad (7)$$

where $\varsigma_z^t(t, f)$ and $\varsigma_z^f(t, f)$ are TFDs obtained by the proposed shrinkage performed over time- or frequency-slices, respectively.

Considered Test Signals

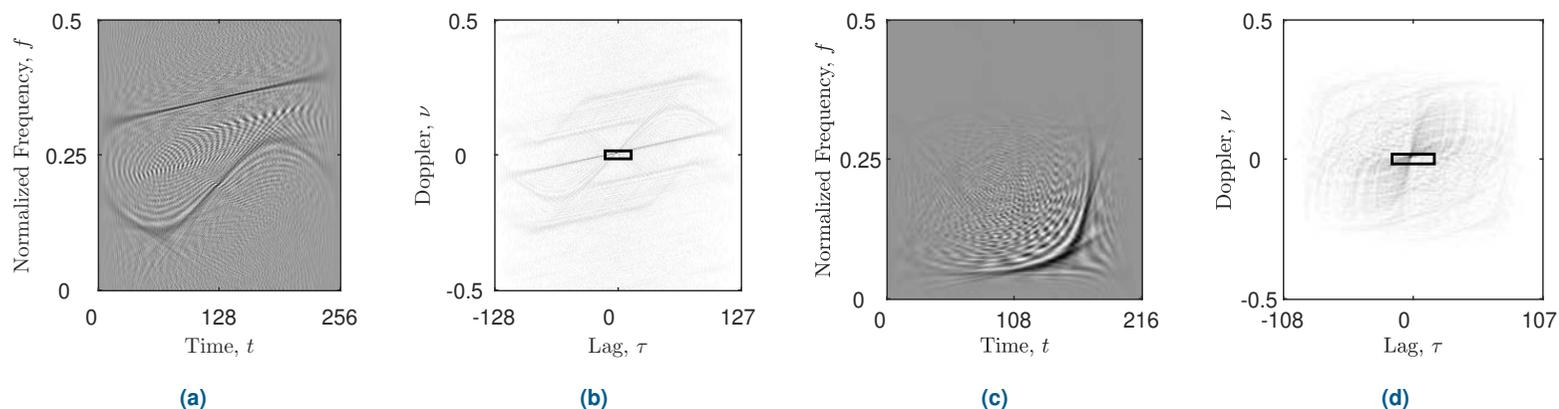


Figure 2: WVD and its respective AF of: (a),(b) z_s ; (c),(d) z_r . The automatically selected CS-AF area has been marked by a rectangle.

- z_s - synthetic signal composed of linear and sinusoidal FM components embedded in additive white Gaussian noise with signal-to-noise ratio = 3 dB.
- z_r - real-life gravitational signal (<https://lsc.ligo.org>)
- The reconstruction performance has been compared to the following state-of-the-art reconstruction algorithms: TwIST, Sparse reconstruction by separable approximation (SpARSA) and Split augmented Lagrangian shrinkage algorithm (SALSA).

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Parameters Optimization

- We have used the multi-objective optimization method based on the Particle swarm optimization (MOPSO) method; a stochastic optimization algorithm inspired by nature and social behaviour between birds in swarms.

Objectives which need to be minimized:

- mean squared errors between the local number of components (obtained by the short-term and the narrow-band Rényi entropy) in the starting and reconstructed TFDs, $MSE_{t,f}$ - preserve components resolution and consistency
- the number of regions with continuously-connected AF samples, N_r - preserves components connectivity

For the proposed algorithm, a multi-objective problem is formalized as:

$$\begin{aligned} \min \{ & MSE_t, MSE_f, N_r(\alpha, \beta, p, \delta_t, \delta_f) \}, \\ \text{s.t. } & \alpha, p, \delta_t, \delta_f \in [0, 1], \beta \in [0, 2\alpha]. \end{aligned} \quad (8)$$

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RESULTS

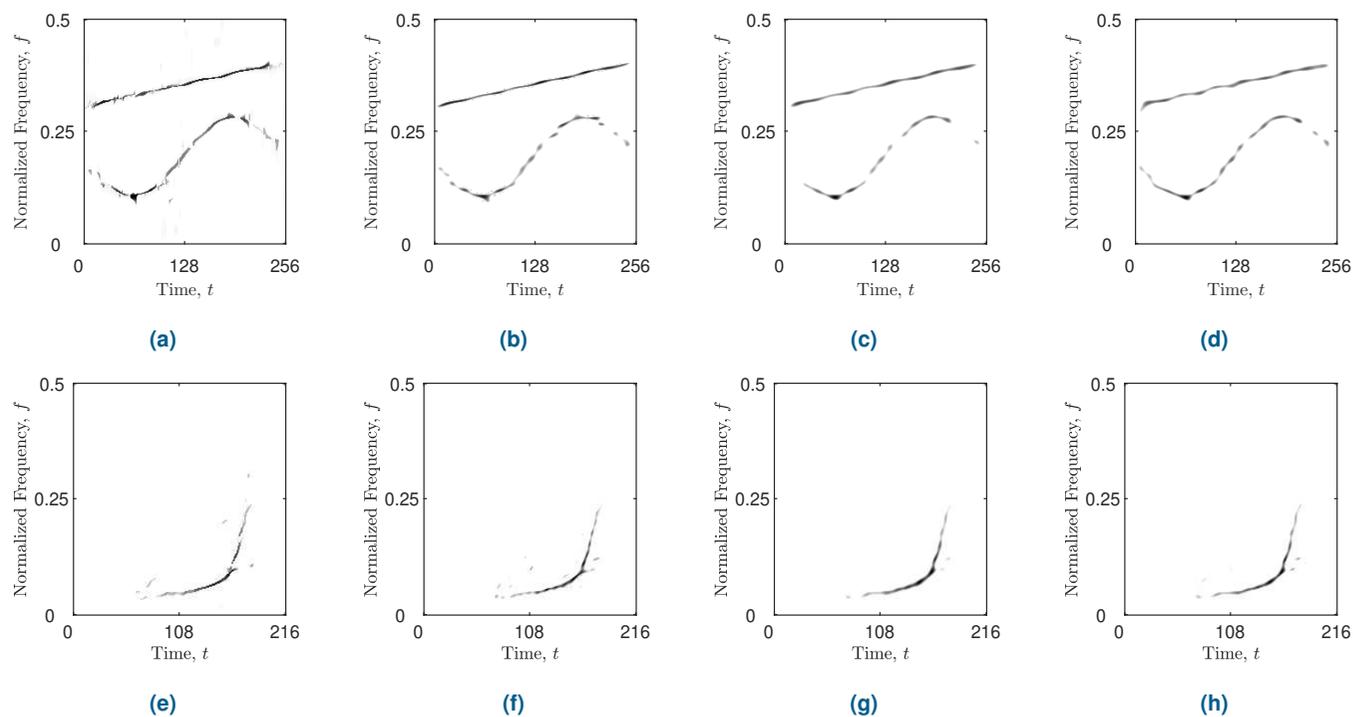


Figure 3: Reconstructed sparse TFDs of: (a) z_S with the proposed algorithm; (b) z_S with the TwIST algorithm; (c) z_S with the SpaRSA algorithm; (d) z_S with the SALSA algorithm; (e) z_r with the proposed algorithm; (f) z_r with the TwIST algorithm; (g) z_r with the SpaRSA algorithm; (h) z_r with the SALSA algorithm.

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Table 1: Comparison with the state-of-the-art algorithms. The bold values indicate the best performing/fastest reconstruction algorithm.

| | Rényi | | TwIST | | SpaRSA | | SALSA | |
|---------|--------------------|--------------------|---------------|--------|--------------|--------------|----------|--------|
| | $p = 0.816$ | $p = 1$ | z_s | z_r | z_s | z_r | z_s | z_r |
| | $\delta_t = 0.010$ | $\delta_t = 0.913$ | | | | | | |
| | $\delta_t = 0.948$ | $\delta_t = 0.823$ | | | | | | |
| MSE_t | 0.0170 | 0.0052 | 0.0132 | 0.0194 | 0.0204 | 0.0339 | 0.0211 | 0.0218 |
| MSE_f | 0.0110 | 0.0048 | 0.0423 | 0.0074 | 0.0396 | 0.0111 | 0.0205 | 0.0077 |
| N_r | 17 | 11 | 18 | 21 | 6 | 4 | 5 | 7 |
| $t[s]$ | 0.165 | 0.381 | 0.191 | 0.25 | 0.138 | 0.112 | 0.604 | 0.232 |

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- By utilizing both local Rényi entropies simultaneously, the proposed algorithm reduces inaccuracies of each entropy when analysing signals with components having different FM modulations.
- The proposed algorithm achieves competitive results when compared to the state-of-the-art sparse reconstruction algorithms, providing the best compromise between the objective functions and the algorithm execution time.

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