Unary adaptive subtraction of joint multiple models with complex wavelet frames

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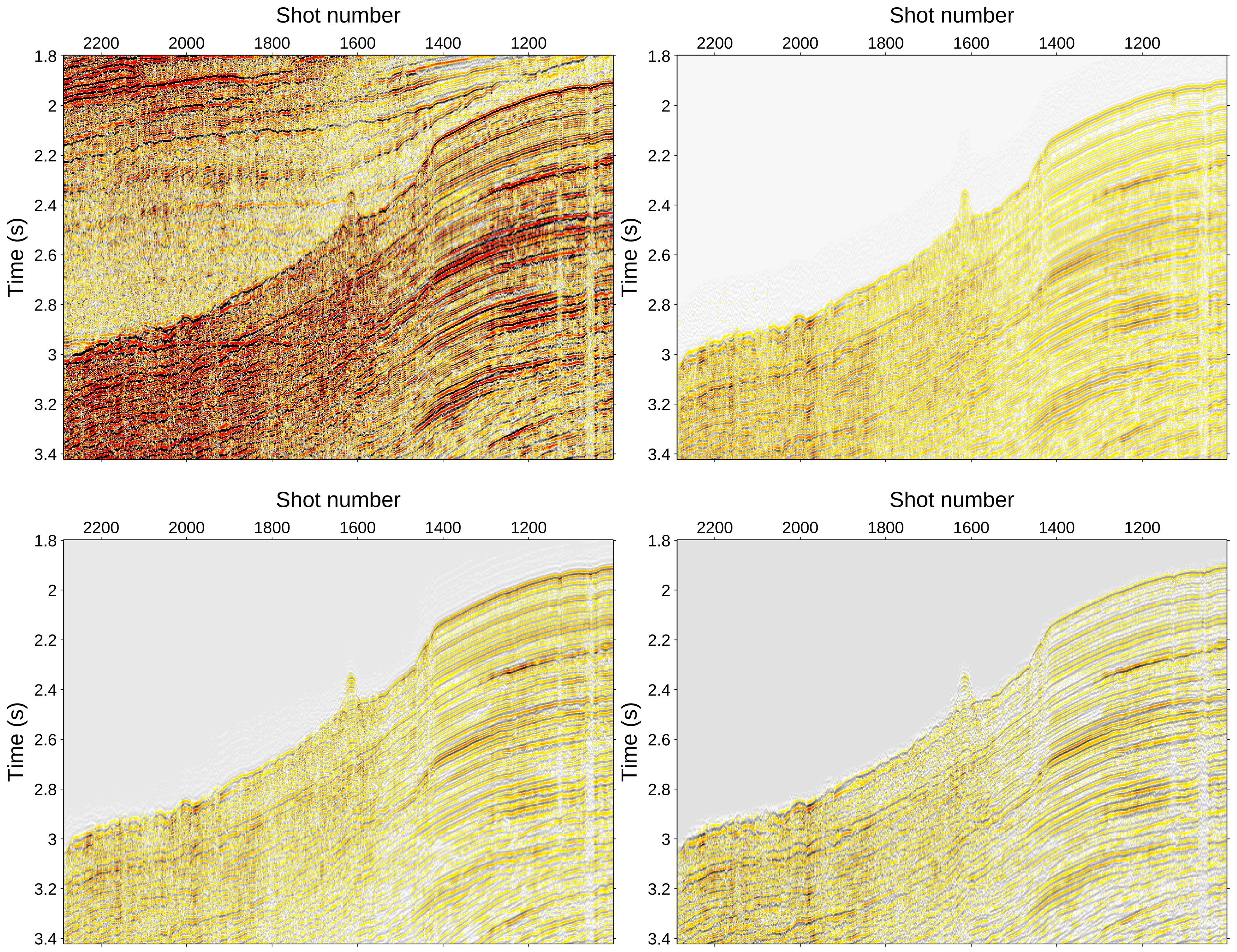
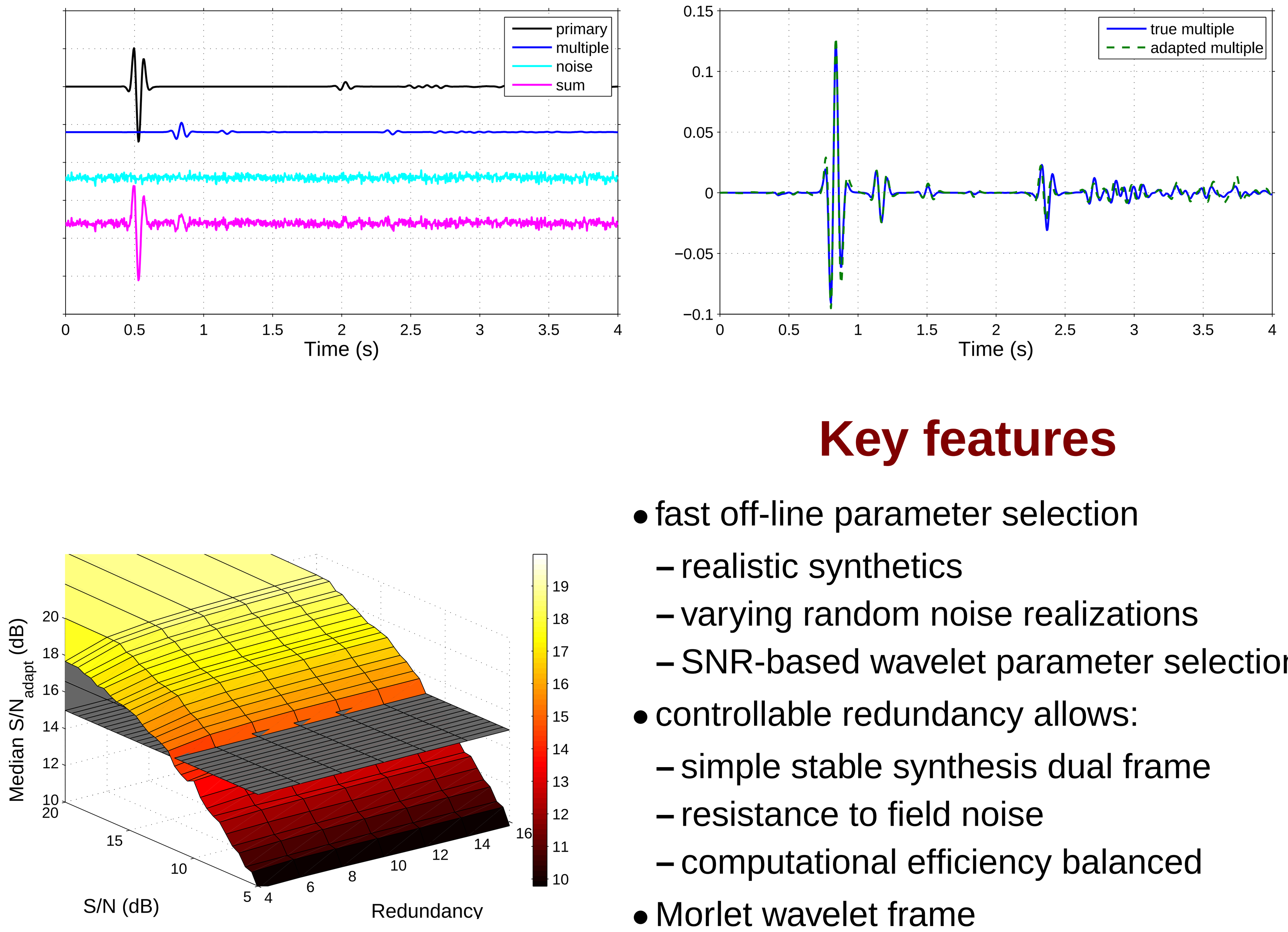
TaM0: Non-stationary, wavelet-based, adaptive multiple removal
TaM1: “Complex” wavelet transform + simple one-tap (unary) filter
TaM2: Redundancy selection: noise robustness and processing speed
TaM3: Smooth adaptation to adaptive joint multiple model filtering

Motivation: Multiple model data



Data and three multiple models, common offset plane (need for a model-based, non-stationary, adaptive multiple filtering).

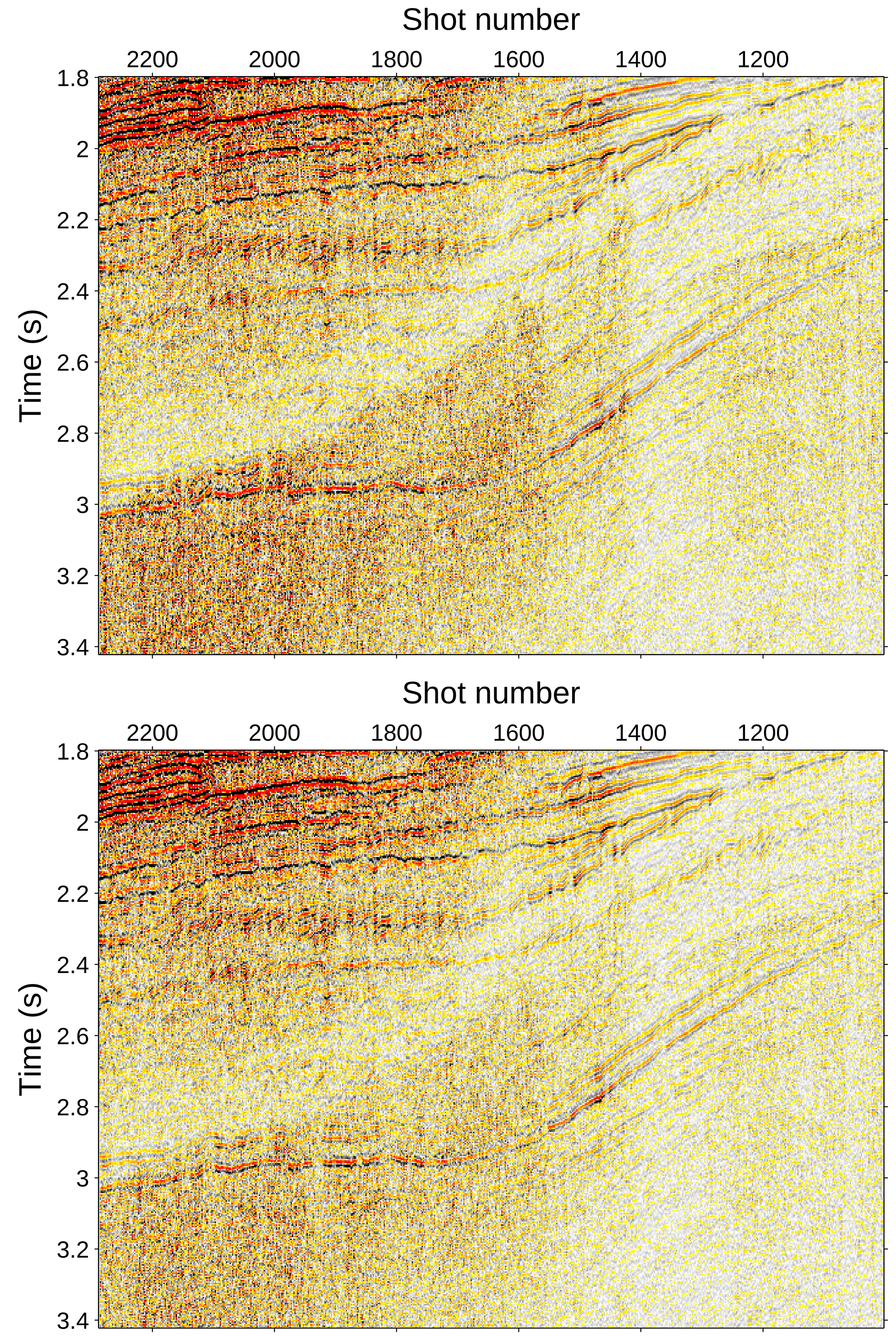
Redundancy selection



Key features

- fast off-line parameter selection
  - realistic synthetics
  - varying random noise realizations
  - SNR-based wavelet parameter selection
- controllable redundancy allows:
  - simple stable synthesis dual frame
  - resistance to field noise
  - computational efficiency balanced
- Morlet wavelet frame
  - approximately analytic
  - sliding window processing along scales

Results: field data multiple filtering



Subtraction results: (top) model 3 (bottom) joint multi-model multiple removal. Some multiples better attenuated around 3s, random noises reduced.

Complex wavelet frame decomposition

- Complex Morlet wavelet definition:

$$\psi(t) = \pi^{-1/4} e^{-i\omega_0 t} e^{-t^2/2}, \quad \omega_0\text{: central frequency} \tag{1}$$

- Discretized time r, octave j, voice v:

$$\psi^v_{r,j}[n] = \frac{1}{\sqrt{2^{j+v/V}}}\psi\left(\frac{nT - r2^j b_0}{2^{j+v/V}}\right), \quad b_0\text{: sampling at scale zero} \tag{2}$$

- Time-scale analysis:

$$\mathbf{d} = d^v_{r,j} = \langle d[n], \psi^v_{r,j}[n]\rangle = \sum_n d[n]\overline{\psi^v_{r,j}[n]} \tag{3}$$

Unary filter estimation

- Windowed adaptation: complex a_{opt} compensates local delay/amplitude mismatches:

$$\mathbf{a}_{\mathrm{opt}} = \underset{\{a_k\}(k\in K)}{\arg\min} \left\| \mathbf{d} - \sum_k a_k \mathbf{x}_k \right\|^2 \tag{4}$$

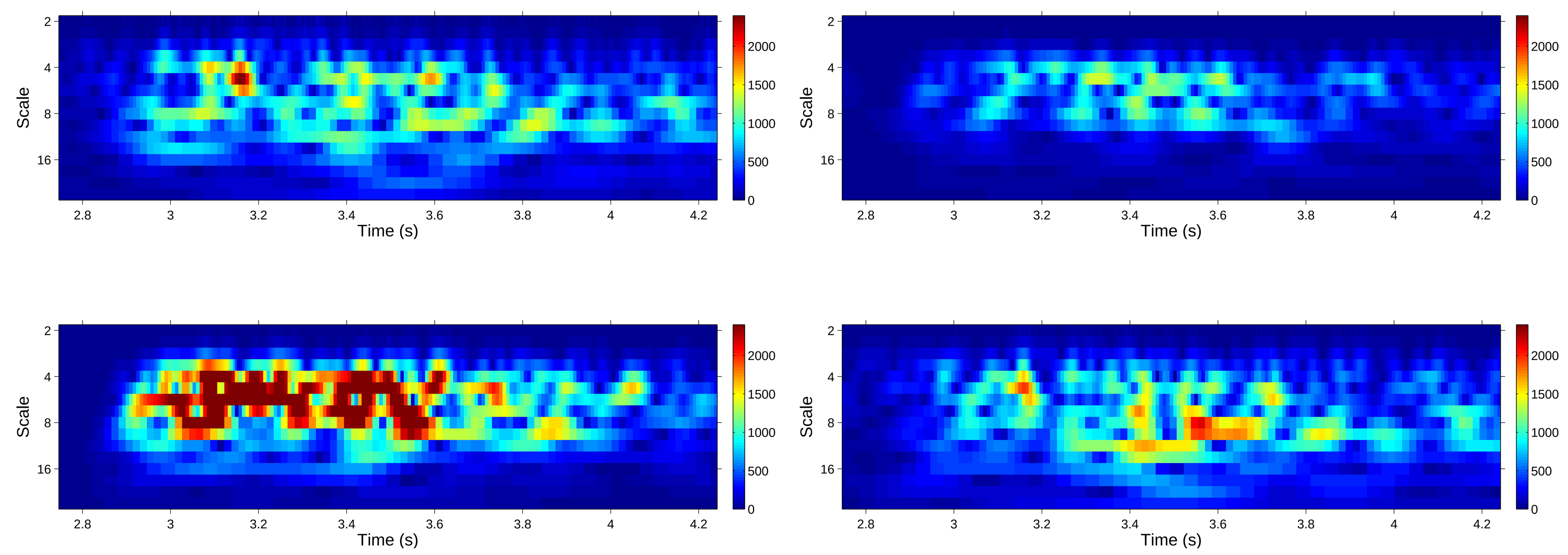
- Vector Wiener equations for complex signals:

$$\langle \mathbf{d}, \mathbf{x}_m\rangle = \sum_k a_k \langle \mathbf{x}_k, \mathbf{x}_m\rangle \tag{5}$$

- Time-scale synthesis:

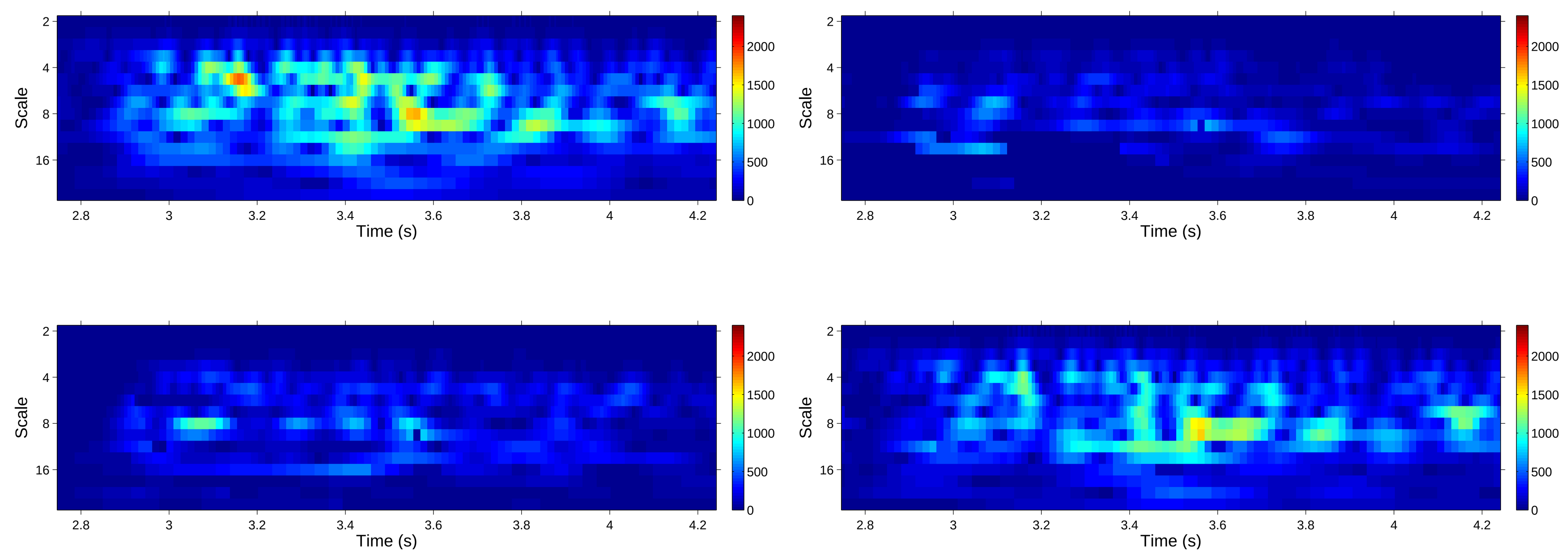
$$\hat{d}[n] = \sum_r \sum_{j,v} \hat{d}^v_{r,j} \widetilde{\psi}^v_{r,j}[n] \tag{6}$$

Time-scale data and model trace representations



Data and model trace Morlet wavelet scalograms.

Complex wavelet domain adaptation



Adapted joint and individual model trace Morlet wavelet scalograms.

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SEG Annual Meeting, Las Vegas, Nevada, USA, 4-9 November 2012