

The tfclusters package

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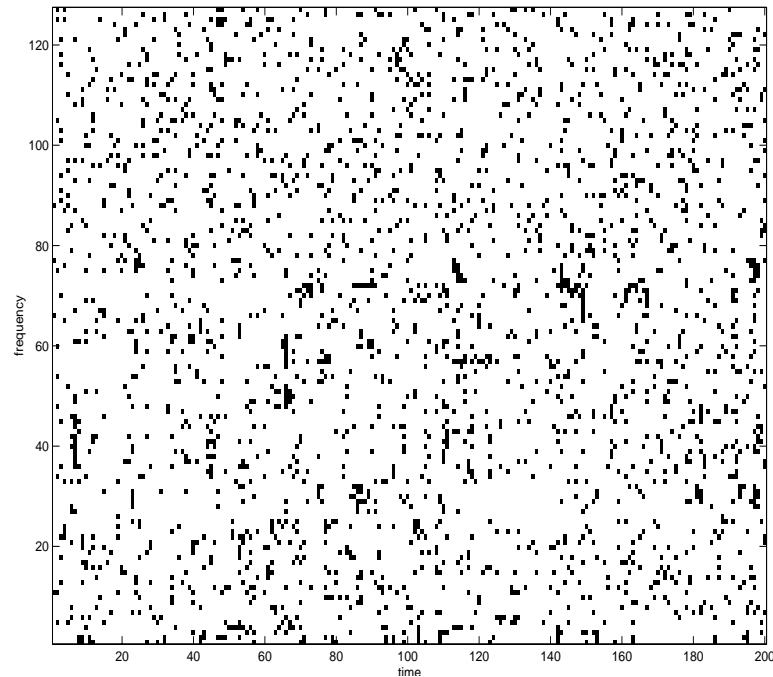
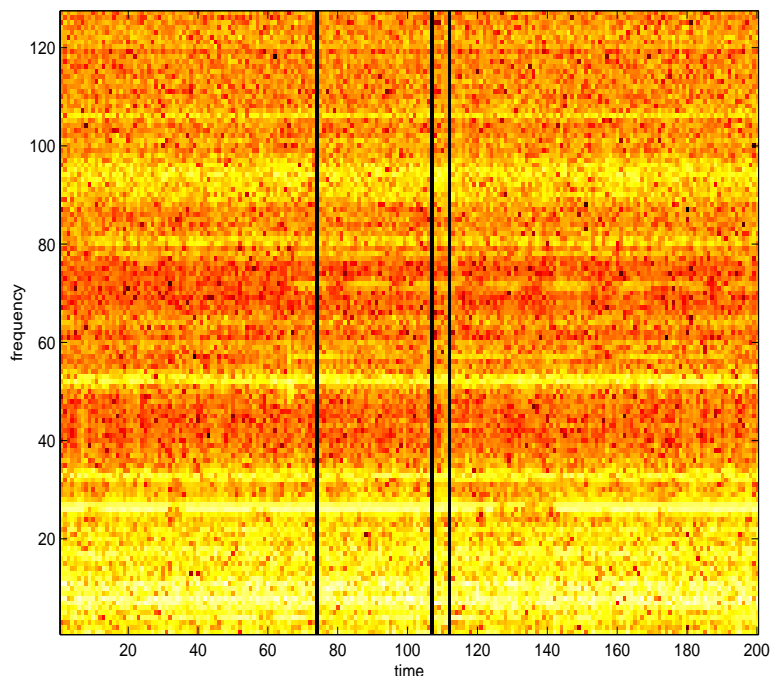


tfclusters

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- Efficient algorithm for detecting unmodeled bursts in Gaussian noise
 - Based on time-frequency power thresholding and clustering analysis. Uses short-time Fourier decomposition.
 - lal implementation completed and tested on E2 data
 - lalwrapper implementation completed (tested only with stand-alone wrapperAPI on fake data)
 - Will work best on white noise, but can handle lines and colored noise (but must be Gaussian)
 - Parallel implementation in DMT for real-time triggers generation

Noise model and first threshold

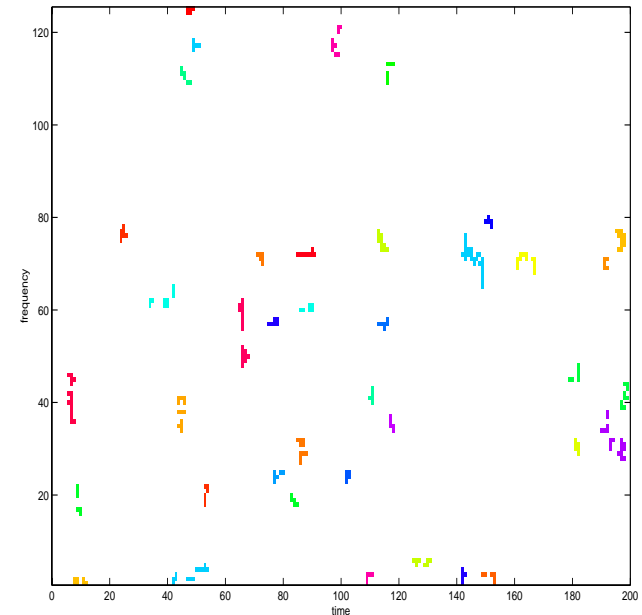
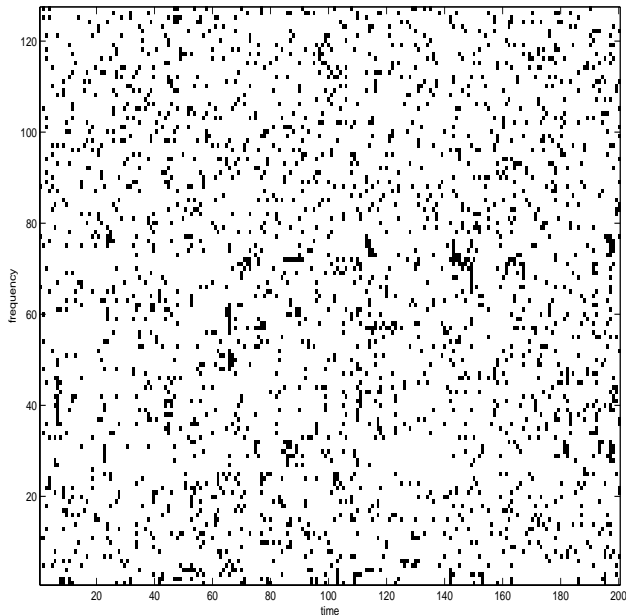
- Threshold spectrogram to get uniform black pixel probability: power threshold from exponential or non-central χ^2



```
void LALComputeSpectrogram(LALStatus*, Spectrogram*, TFPlaneParams*, REAL4TimeSeries*);  
void LALTFCRiceThreshold(LALStatus *, REAL4 *, RiceThresholdParams *);  
void LALGetClusters(LALStatus*, CList*, Spectrogram*, CListDir*);
```

Clustering Analysis (second threshold)

- In white noise, large clusters are exponentially unlikely: threshold on cluster size (number of pixels)
- To increase efficiency, allow close pairs of small clusters



```
void LALGetClusters(LALStatus*, CList*, Spectrogram*, CListDir*);
```

Integrated power (third threshold)

- Reject a fraction of the clusters that would make the first two cuts with just steady-state noise: threshold on
Prob(observed integrated power | cluster size, passed 1st & 2nd cuts)

```
void LALClusterPowerThreshold(LALStatus *, CList*, CList*, CListDir*);
```

- For θ_{ij} the representation of the signal in the short-time Fourier basis, the test is

$$\sum_{\text{cluster}} |\theta_{ij}|^2 \Theta(|\theta_{ij}|^2 - \lambda) > \Lambda(\text{cluster size})$$

lalwrapper so

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- split time series in n overlapping segments
 - get event list for every segment
 - merge lists on master

Optimality

Problem	Optimal Test	Optimal Estimator
Binary Hypothesis $W = \{\theta\}$	Likelihood ratio	N/A
Prior on signal $p(\theta)$	Averaged likelihood ratio	Bayes estimation
Filter bank $W = \{\theta_i : i=1,2,\dots\}$	Maximum likelihood ratio	Maximum likelihood
Smooth (sparse) signal	Power after thresholding	Hard thresholding

$$y = s + n, s \in W$$

Smooth (sparse) signals

- Model the signal subspace as a L_p ball minus the (L_2) ball of signals with $\text{SNR} < \varepsilon$

$$W = U_p(C) \setminus U_2(\varepsilon)$$

for the balls

$$U_p(C) = \left\{ \theta \in R^N : \sum_i |\theta_i|^p < C^p \right\}$$

- L_p balls are made of sparse vectors if $p < 2$. Sparse vectors in the wavelet domain (or STFT) are smooth functions in the time domain.
- If $p > 2$, optimal detectors are “quadratic forms” in y .
- If $p < 2$, optimal detectors involve “coordinate-wise truncations” on y .

Remarks

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- Detectors with coordinate-wise truncations are optimal over a wide range of measures of smoothness (Besov, Triebel,...)
 - Clustering analysis is added “by hand”. No proof of optimality (yet).
 - Of course, must choose a basis where the signal is sparse. Wavelets good for that (unconditional bases of smooth functional spaces).