TSDA lecture 9 - 2020

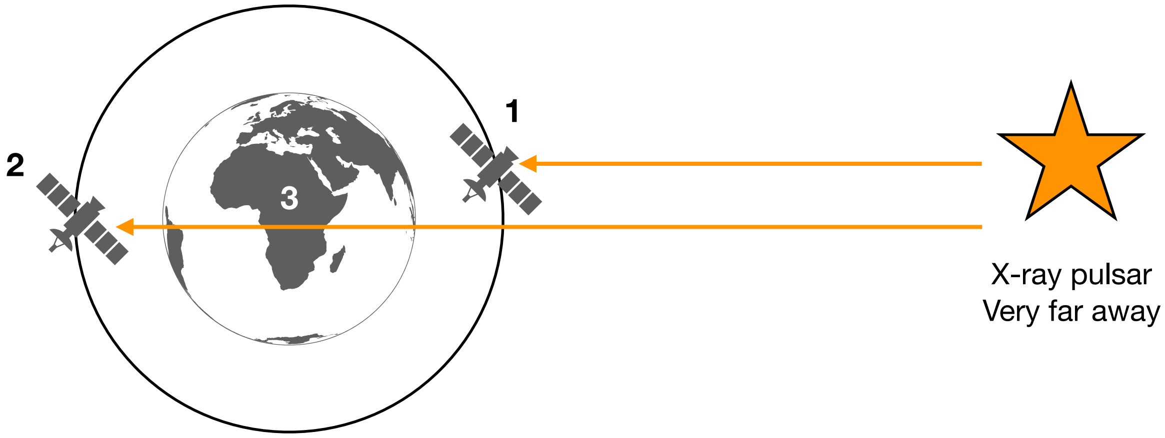
Non-Fourier methods for period detection:

- Epoch-folding — Leahy et al. (1983)
- Phase dispersion minimization (PDM) — Stellingwerf et al. (1978)
- Minimum string length — Dworetsky (1983)
- Rayleigh (Z^2) test — Leahy et al. (1983), Buccheri et al. 1983
- Analysis of Variance (AoV, ANOVA) — Schwarzenberg-Czerny (1989)
- Bayesian periodicity search — Gregory & Loredo (1992)

Event Data

- Most of the data we've looked at thus far comes as a **lightcurve**: i.e. a series of times with corresponding rate or magnitudes measurements: (t_i, y_i)
- Data may be spaced equally, randomly, or have large gaps.
- E.g. sunspot data or OGLE light curves
- In **event mode data** each photon is time-tagged and the data comprise a series of individual events
- This data format is common in X-ray and other high energy datasets

Barycentric correction



The interval between emitted pulses is Δt.

As the spacecraft moves from position **1** to position **2**, the interval between pulses gets longer due to the extra light travel time across the spacecraft orbit.

Correct all timestamps to position **3** - the barycentre.

Rayleigh (Z^2) test

- The Rayleigh power (Marda 1972) at a particular frequency measures the probability that there is a sinusoidal component present at that frequency -> equivalent to Fourier power.
- The Z^2_m test (Buccheri et al 1983) considers the sum of the Rayleigh powers in the first m harmonics.
- The Z^2_m is a generalized version of the Rayleigh test.
- More harmonics means sensitivity to signals which don't have a purely sinusoidal structure.

Rayleigh test

Consider a series of time events t_i, where $i = 1, .., n$ in which we wish to search for a sinusoidal signal of frequency f.

This signal at a frequency f will have time derivatives $\dot{f}$ and $\ddot{f}$

Set $t_1 = 0$ (arbitrary) and ascribe a phase to all events:

$$\phi_i = 2\pi \left[f t_i + \frac{1}{2}\dot{f} t_i^2 + \frac{1}{6}\ddot{f} t_i^3 + ... \right] \pmod{2\pi}$$

If data are sparse and irregularly sampled and do not contain a pulsed signal then phases ϕ_i will be distributed uniformly between 0 and 2π.

Rayleigh power:

$$nR^2 = \frac{1}{n} \left(\left[\sum_{i=1}^{n} \cos(\phi_i) \right]^2 + \left[\sum_{i=1}^{n} \sin(\phi_i) \right]^2 \right)$$

Z^2_m test

The Z_m^2 test is a **generalization** of the Rayleigh test.

The Z_m^2 statistic is:

$$Z_m^2 = \frac{2}{n} \sum_{j=1}^{m} \left(\left[\sum_{k=1}^{n} \cos(j\phi_k) \right]^2 + \left[\sum_{k=1}^{n} \sin(j\phi_k) \right]^2 \right)$$

where m is the number of harmonics you'll sum over.

While the Rayleigh test is sensitive to broad sinusoidal signals, **higher orders** of the Z^2_m test become sensitive to more **complex signal shapes**.

At high count rates, Rayleigh periodograms basically become Fourier periodograms.

Well utilized for high energy datasets, e.g. Fermi, Swift, AGILE etc.

See Brazier et al. 1994 for significances of the Rayleigh and Z^2 tests.

H test

For further reading (de Jager et al. 1989):

The *H* test is based on the $Z^2{}_m$ statistic allowing one to determine the optimum order *m* that minimizes the mean integrated square error for the given dataset:

$$H = \max(Z_m^2 - 4m - 4)$$

Working with event data

1. Download the following tools:

   1.1. SAOimage ds9 http://ds9.si.edu/site/Download.html

   1.2. FitsViewer https://heasarc.gsfc.nasa.gov/ftools/fv/

2. Download the Chandra event file from the cloudcape: acisf14329N002_evt2.fits

   2.1. Open this file with FV as a table. What columns exist?

   2.2. Use FV to try to plot an image of the file

   2.3. Now open the file with DS9

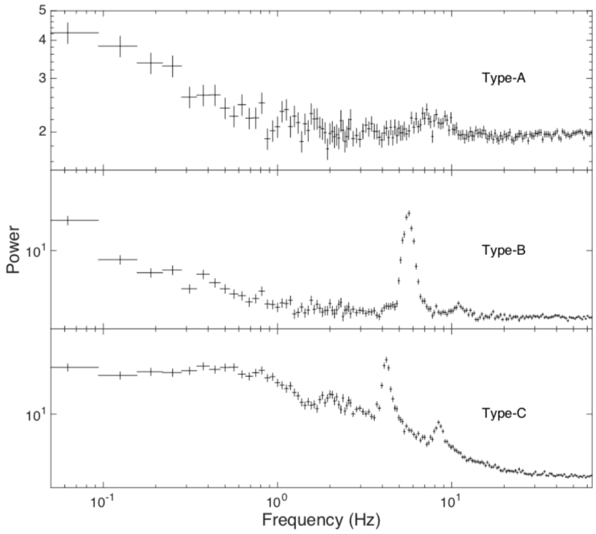
3. Filter the data spatially in FV to include only counts from the brightest point source

4. Run a Z^2 test to determine the period. Follow the method in Kargaltsev et al 2012.

A dynamical power spectrum

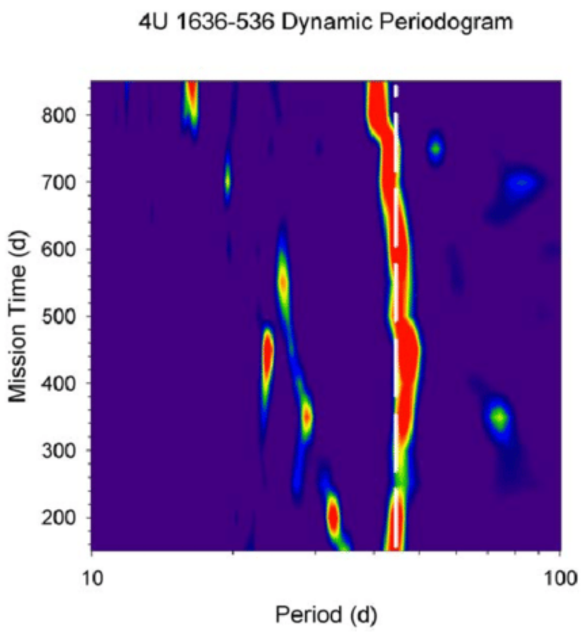
Sometimes the period/frequency of a process is not stable. Quasi-periodic observations occur in black hole binaries, in some types of cataclysmic variables.

Sometimes a period may appear for a short while. In that case, searching for it across the whole light curve may “wash it out”.



Motta 2016

A dynamical power spectrum



A dynamic power spectrum of BAT data of 4U 1636-536.

Nominal period of 42 days, with a wobble around that.

Wavelets

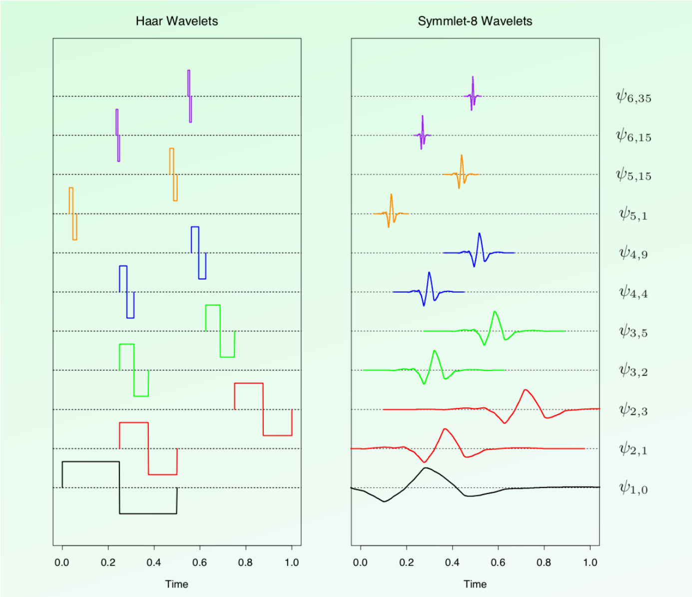


FIGURE 5.16. *Some selected wavelets at different translations and dilations for the Haar and symmlet families. The functions have been scaled to suit the display.*

Wavelets are constructed step-by-step from a scaling function (father wavelet), halving the scale at each step, and describing more details.

Hastie, Tibshirani and Friedman. *Elements of Statistical Learning*, Springer, 2009

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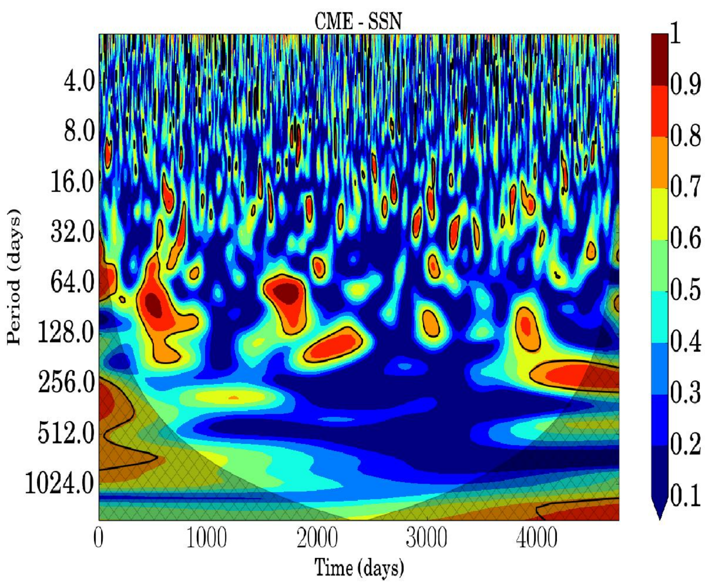
Wavelets

Another option for non-stationary time series is wavelets.

Apply a wavelet transform (amplitude, scale) to a time series.



A wavelet decomposition is a 3-D plot showing the amplitude of the signal at each scale, at each time.

Often used as a filter.

Which method to use?

- Graham et al (2013) looks at a number of period-finding algorithms applied to *optical time series*.
- *There is no "best" algorithm.*
- Dispersion-based techniques give best results, but depend on class of objects.
- Period aliasing is still an issue.

Tut 3

Question 1: PDM

1.1 Write your own implementation of the PDM algorithm

1.2 Run your implementation on the sunspot data (`zuerich-monthly-sunspot-numbers-.csv`) and plot the PDM statistic vs period.

1.3 Run the *PyAstronomy* implementation of the PDM on the sunspot data and compare results of the two implementations in terms of any periodicity in the dataset.

Question 2: Event data

2.1 Read in the event data of the magnetar *Swift J1834.9–0846* (see Kargaltsev et al. 2012 - `acisf14329N002_evt2_reg_filtered.txt`) and plot a light curve.

2.2 Calculate the Z^2_1 statistic for this time series. Can you identify the 2.48 s spin period of the neutron star?