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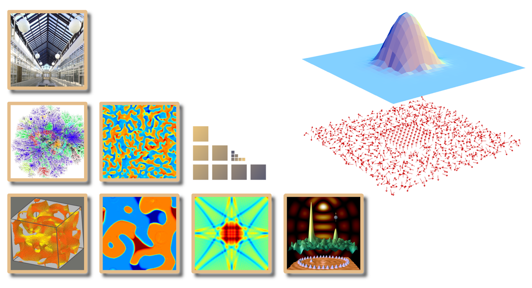

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1 Introduction

This is the introduction (let's test the labeling: 1). The material in this demo, starting from section 1.1 is from the original demo of the a0paper package.

1.1 This is a subsection

In the analysis of single-subject fMRI datasets the primary task in a voxel-based analysis is to assign a level of significance at each voxel. This will depend on the estimation of both the magnitude of the response to the stimulus and the serial dependence of the time series, and especially on the assumptions made in that estimation.

Various methods have been proposed in the literature to do this in both the time domain and frequency domain.

> Note: You should remember this! And don't ever forget to never forget about this!

The duality between these two domains implies that a given method can be computed in either domain, although this may prove easier in one domain than in the other.

> Well... Sometimes is better to forget...

By considering a periodic stimulus design in the frequency domain we found the analysis to be greatly simplified and at the same time provided insight into how non-periodic designs could be dealt with in a similar fashion.

2 Trend Removal

Many voxel time series exhibit low frequency trend components. These may may be due to aliased high frequency physiological components or

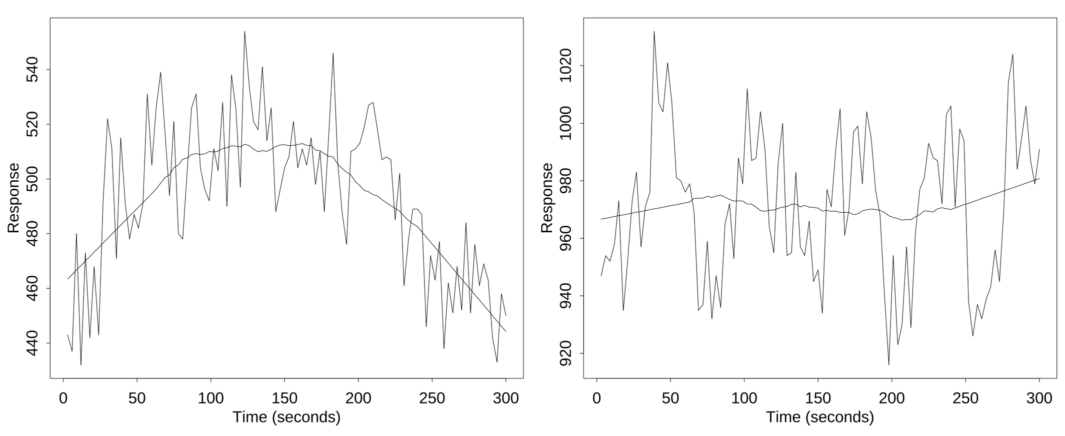

Fig. 1: Trend Removal:(left)

3 Theory

The asymptotic sampling properties of the periodogram are well-known [?]. For increasingly long series:

- $I(\omega_j)/f(\omega_j) \sim$ E where E has a standard exponential distribution.
- $I(\omega_j)$ and $I(\omega_k)$ are independent for all $k \neq j$.

where $f(\omega)$ is the spectral density of the underlying stationary stochastic process. This is a very general result, includes AR, MA and ARMA processes as special cases and is known to be accurate for series of moderate length, such as those encountered in fMRI experiments. If we assume that the underlying spectral density $f(\omega)$ is smooth then we can use a smoothed version of $I(\omega)$, which we denote $g(\omega)$, to estimate $f(\omega)$.

4 Testing for a response to the stimulus

The spectral density estimate provides us with a baseline against which to test for significant departures from the underlying process. From (I),

$$\frac{I(\omega_j)}{f(\omega_j)} \sim E \tag{1}$$

Substituting $g(\omega_j)$ for $f(\omega_j)$, we define the ratio statistic, R_j, as

$$R_j = \frac{I(\omega_j)}{g(\omega_j)}, \qquad \omega_j = j/\delta n \tag{2}$$

By calculating the statistic R_j at the fundamental frequency of activation, ω_c, we obtain a test statistic, R_c, for significant activation. Large values of R_c indicate a large effect at the fundamental frequency. All of the statistics R_j, apart from $j = 0$ and $n/2$, will have the same distribution as R_c and thus can be used as a benchmark against which to compare the theoretical distribution of R_c, at negligible computational cost. Thus the method is effectively self-calibrating.

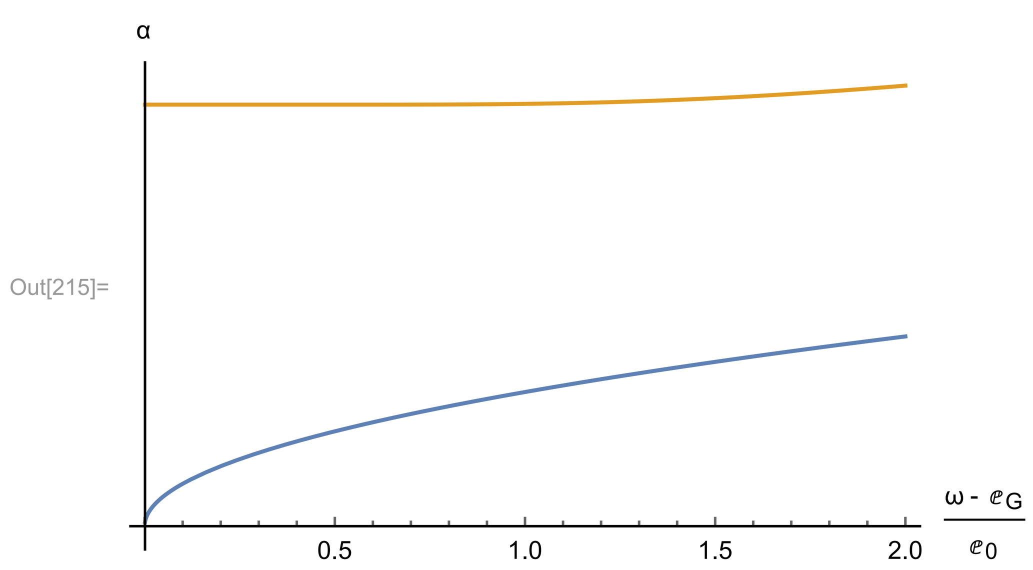

Fig. 2: p-value maps thresholded at 10^{-4} obtained using our approach (left) and an AR(1) approach (right)

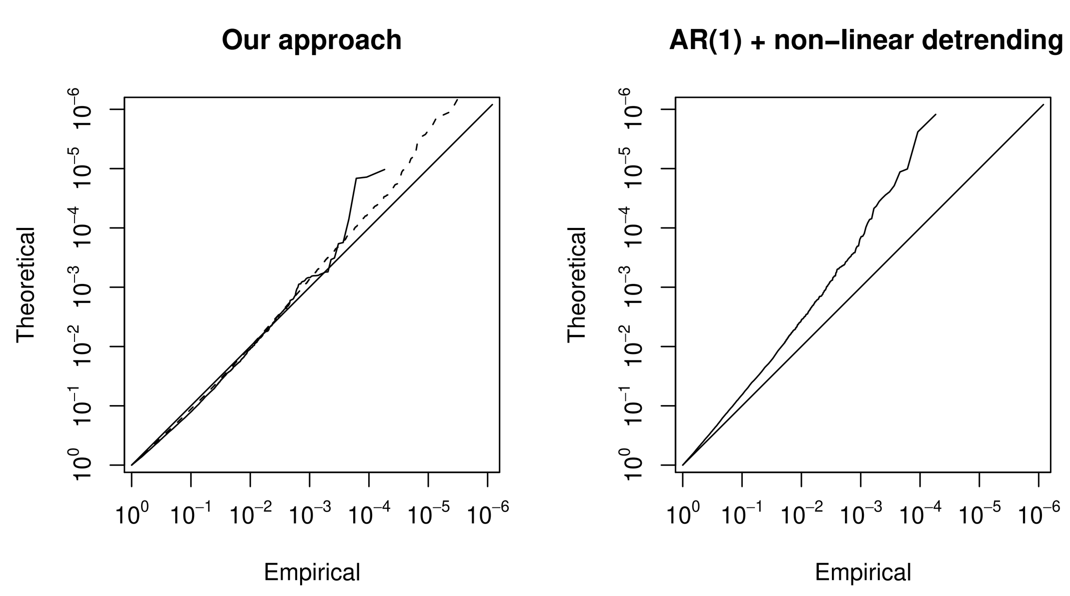

Fig. 3: PP-plots for our approach (left) and an AR(1) approach (right) applied to a null dataset

5 High frequency artefacts

In some datasets we have found high frequency artefacts that occur in narrow bands and have been attributed to Nyquist ghosting(figure 4 (right)). We have detected these artefacts using our values of R_j at high frequencies (figure 4 (left) shows a thresholded R_{88} image).

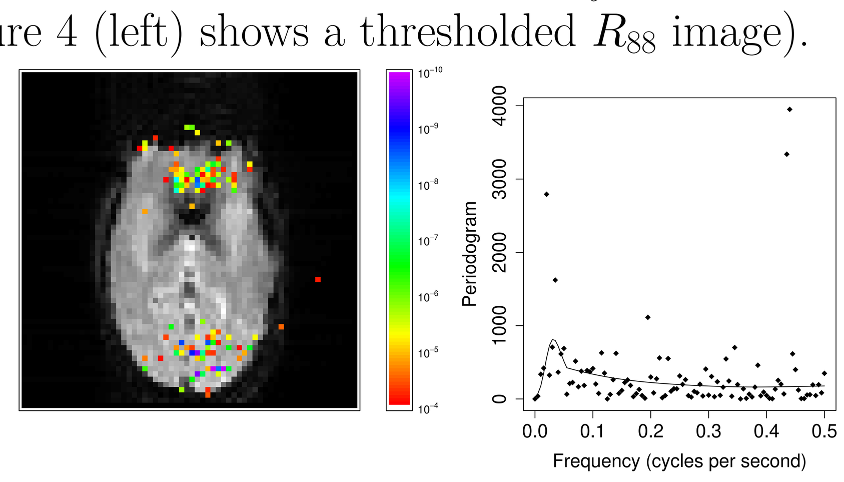

Fig. 4:

We have found that parametric-time domain models may be extremely susceptible to these artefacts whereas non-parametric spectral density estimation will be resistant. Three methods were applied to a voxel in an area exhibiting the high-frequency artefact. Method I: The AR(1) approach described above, Method II: As Method I but with high frequency artefact removed, Method III: Our approach. Comparing Method I and II, in the table below, we see that the estimated parameters are significantly different after the artefact has been removed, which results in a misleading statistic. Even after removal, there is no guarantee that the AR(1) model is flexible enough and this results in the difference between Methods II and III.

	AR(1) coefficient	$\widehat{\sigma^2}$	Numerator	Denominator	Ratio Statistic
Method I	−0.0027	15765	591.88	315.29	1.877
Method II	0.2839	11276	624.98	419.46	1.490
Method III	—	—	689.30	513.88	1.341

6 Conclusion and extensions

Non-parametric spectral estimation is shown to be an accurate and self-calibrating approach for analyzing periodic designs. The method makes few assumptions and is resistant to high-frequency artefacts whereas parametric time-domain approaches may be susceptible to these artefacts and biased by the assumptions they make on the form of the spectral density. The method can be easily extended to handle non-periodic event related designs and initial results are extremely promising. Non-parametric spectral estimation is shown to be an accurate and self-calibrating approach for analyzing periodic designs.

7 Acknowledgements

We are grateful to Dr Stephen Smith (fMRIB Centre, Oxford) for advice and datasets.