



Time–Frequency Dynamics of Brain Connectivity by Stochastic Oscillator Models and Kalman Filtering

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INTRODUCTION

- **Functional connectivity** in functional magnetic resonance imaging (fMRI) is often estimated as the average pairwise similarity between the temporal dynamics of two regions of interests (ROIs) [5].
- In **time-varying functional connectivity**, where the stimulus is continuously changing, the functional connectivity is modulated in time [1–2].
- Here, we study the **dynamic functional connectivity** between pairs gray matter of voxels by considering the **time–frequency dynamics** between them.
- Each pair of time series is decomposed into oscillatory components described by a **stochastic oscillator model** [4].
- The oscillators are inferred from the data using optimal **Bayesian filtering methods**.
- The coherence between the different frequency components is converted into a **time-varying functional network**.

METHODS

- We use a stochastic oscillator model, that is described by a second order **stochastic differential equation (SDE)** for each voxel i and frequency f_j :

$$\frac{d\mathbf{x}_i(t)}{dt} = \begin{pmatrix} 0 & 2\pi f_j \\ -2\pi f_j & 0 \end{pmatrix} \mathbf{x}_i(t) + \begin{pmatrix} 0 \\ 1 \end{pmatrix} \xi_i(t),$$

where $\xi_i(t)$ is a random white noise component with spectral density q_j .

- This is a linear SDE, and it can be solved for all the observations time points $t_k, k = 1, 2, \dots$
- The discrete model can then be fitted to the fMRI data using **Kalman filtering and smoothing**.
- The model is based on **DRIFTER** — a method for removing physiological noise from fMRI data [4] — but evaluated over a set of fixed frequencies.
- Summing the **cross-coherence power surface** over frequencies defines the functional activation between the regions (see [1]).
- We compare the pairwise activation time series to **ground truth stimuli** in order to estimate **connectivity maps** describing the types of connections.

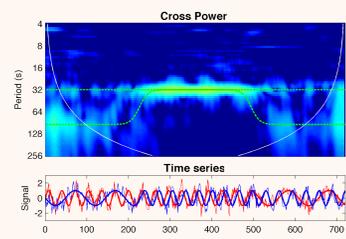


Figure 1: The time–frequency cross-power between two simulated time series.

Figure 3: The connectivity map correlated with singing in the movie. Lateralization over right temporal areas for melody/pitch processing.

Figure 4: Network for head motion in the film. Strong parietal regions, bits of fusiform face area, frontal areas and amygdala.

MATERIAL

- **Functional brain images** together with anatomical data were acquired for **14 healthy native speakers of Finnish**.
- The subjects watched 22 min 58 s of a **Finnish language film** in an MRI scanner (3 T GE Signa Excite, 8-channel head coil).
- The film was a shortened version of the feature film **“Match Factory Girl”** (dir. Aki Kaurismäki, 1990, original length 68 min).
- **16 visual and auditory features** from the film were extracted as ground truth references (see [3] for details).
- **Sequence parameters**: EPI slices: 29, TR: 2 s, TE: 32 ms, matrix size: 64×64, FA: 90°, voxel size: 3.4×3.4 mm, slice thickness: 4 mm, gap size: 1 mm. Data downsampled to 6 mm isotropic voxels, and 6235 gray matter voxels chosen for study.

RESULTS

- Figure 1 shows how the oscillator model captures the coupling of two simulated signals.
- The strongest network of **intersubject consistency** of connectivity time series is shown in Figure 2.
- Figures 3–5 show networks of linear regression between stimulus features (**singing, head motion, hand motion**) [3] and connectivity time series.
- Comparisons of intersubject consistency connections captured by the **wavelet approach by Chang and Glover [1]**: inter-hemispheric connections between the occipital lobes appear to be less consistent across subjects when using wavelets.

Figure 5: Network for hand motion in the film. Strong parietal regions and parieto–occipital connections.

CONCLUSIONS

- We have proposed a method for estimating coupling of oscillatory phenomena in fMRI data.
- The outcome can be used for estimating time-varying functional connectivity networks.
- This approach is related to that of [1], where a wavelet basis was used for modeling the cross-coherence.

ACKNOWLEDGEMENTS

We thank Max Hurme and Sirius Vuorikoski for help. We are grateful for the support provided by Fa-Hsuan Lin and Risto Ilmoniemi.

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Figure 6: The same network as in Fig. 2, but calculated by the **wavelet method** by Chang and Glover [1].

No. 1877, OHBM Conference Poster 2013, Seattle, US.

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