Spectral similarity analysis (SSA) of resting state MEG in healthy ageing

Matthias Treder[1,2,3], Manfred Kitzbichler[2,3], Darren Price[1], Linda Geerligs[4], Cam-CAN & Ed Bullmore[2,3]

[1]Cambridge Centre for Ageing and Neuroscience (Cam-CAN); [2]BCNI, Department of Psychiatry, University of Cambridge

[3]Brain Mapping Unit, University of Cambridge; [4]MRC Cognition and Brain Sciences Unit, Cambridge, UK

Email: mst40@cam.ac.uk

Introduction

- In ageing research, alpha peak frequency has been shown to decrease with age
- Typically, no other frequency peaks can be identified from frequency spectra, possibly because their power is too low compared to the background 1/f noise
- Building on a powerful multivariate method by Nikulin et al.[1], **spatio-spectral decomposition (SSD)**, we illustrate a moving frequency window approach to identify peaks of oscillatory activity
- We combine SSD with ideas from Representational Similarity Analysis (RSA)[2] to quantify the spectral similarity across subjects. We call the method **Spectral Similarity Analysis (SSA)**.
- We show preliminary results from ongoing analyses on the Cam-CAN dataset[3]

Spatio-spectral decomposition (SSD)

SSD searches for spatial filters w that maximize the Rayleigh quotient

$$\frac{\boldsymbol{w}^\top C_s \boldsymbol{w}}{\boldsymbol{w}^\top C_n \boldsymbol{w}}$$

where C_s is the covariance matrix of the signal (target frequency band) and C_n is the covariance matrix of the noise (flanking frequency bands). The output of SSD is a **spatial filter** matrix W and a matrix of **eigenvalues** representing signal-to-noise ratios. **Spatial patterns** can be obtained from inversion of the spatial filter matrix. SSD finds narrowband oscillations. It is relatively insensitive to broadband noise sources such as muscle artifacts.

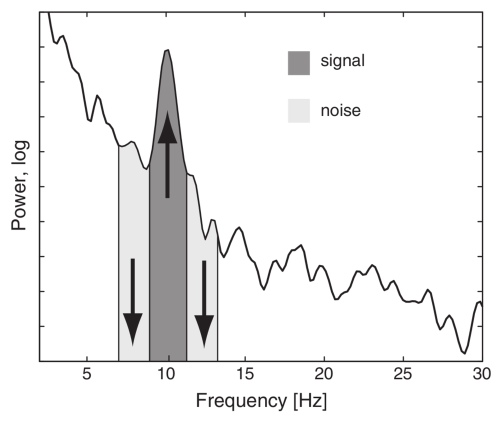


Image taken from Nikulin et al.

Spectral Similarity Analysis (SSA)

SSA combines SSD with a wavelet-filtering approach and the principles of Representational Similarity Analysis (RSA)[2]. In RSA, vectors represent cognitive representations which serve as basis for correlation matrices; in SSA, vectors represent spectral or spatial profiles of narrowband oscillations. The method operates in two steps:

1. SSD is applied separately to each target frequency in frequency space. Signal and noise frequency bands are defined using Morlet wavelets, since wavelets enable a natural increase in bandwidth with frequency (at higher frequencies, frequency bands tend to be wider). The result of this step is a **spectral profile**.
2. For the present analysis, we averaged the first 10 eigenvalues for each frequency bin. The length of the resulting vector is the number of frequency bins. The vector can be divided in sub-vectors corresponding to each frequency band. We then build a subjects $\times$ subjects **correlation matrix** based on the linear correlations of the vectors.

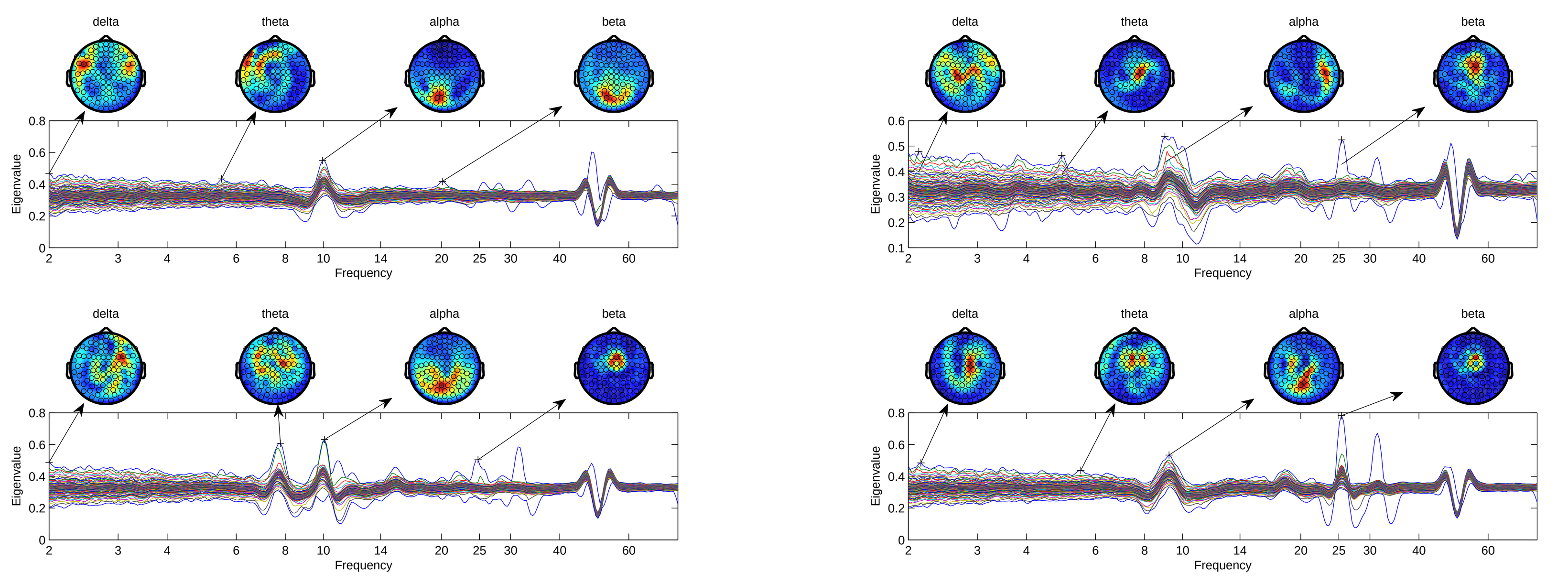
Method

- Subjects: population-representative sample of 575 subjects (about half women), aged 18-88
- Experiment: about 9-minutes resting state recording
- Hardware: Elekta Neuromag, 204 planar gradiometers, 1000 Hz sampling frequency.
- Preprocessing: Maxfilter 2.2, ICA-based denoising
- Wavelet-filtering: We selected 300 center frequencies in the range [2,80] Hz on a logarithmic scale. Since time resolution was irrelevant to our analysis, we chose a relatively "wide" wavelet with $nCycles = 30$ significant cycles, enabling a high frequency resolution. For each center frequency F, we chose left and right flanking center frequencies FL and FR as $FL = F \cdot (nCycles - 1)/(nCycles + 1)$ and $FR = F \cdot (nCycles + 1)/(nCycles - 1)$. This assured that the center and flanking wavelets were separated by 2 FWHM (full width at half maximum) in frequency space.
- All analyses were performed in MATLAB using FieldTrip.

Results

Spectral profiles and corresponding spatial patterns

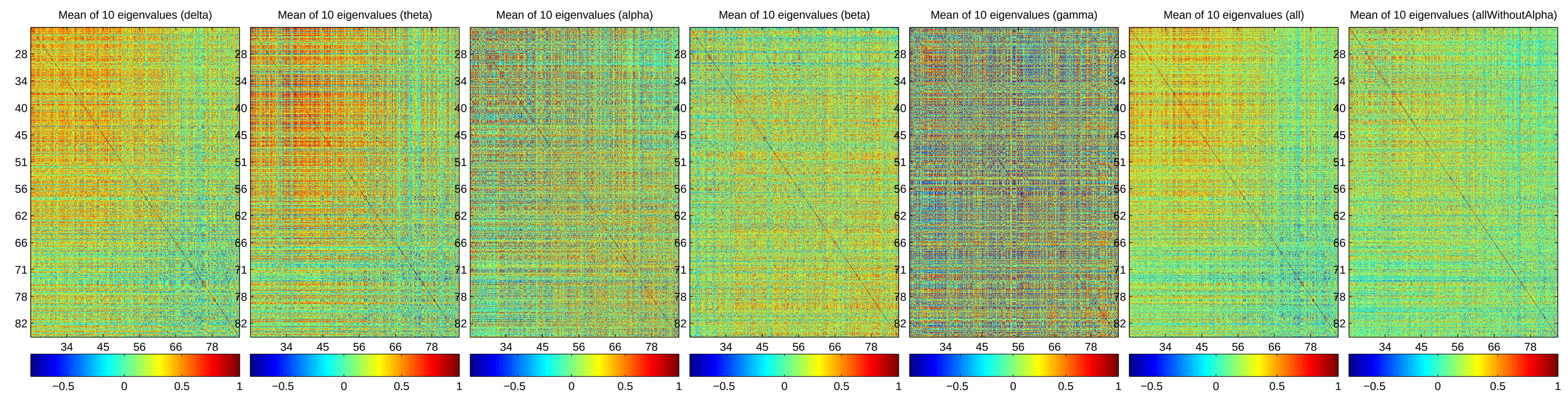
Spectral profiles for four subjects. The curves represent the eigenvalues (=signal-to-noise ratios) obtained from wavelet-based SSD with a moving frequency window. Peaks in the spectra indicate the presence of narrowband oscillations. For the highest peak in the delta/theta/alpha/beta range, the corresponding spatial pattern is shown.



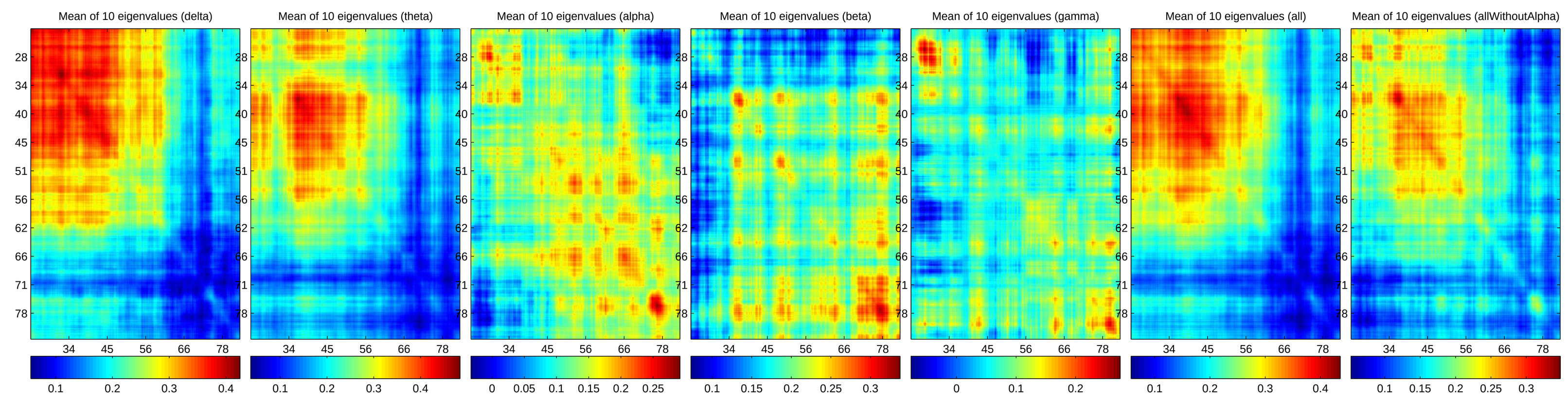
Subject x Subject similarity matrices

Using the spectral profiles, we obtained subject x subjects similarity (correlation) matrices by taking the average spectral profile across the 10 largest eigenvalues as a vector, and building a correlation matrix based on these vectors. Results are shown for different frequency bands separately, from left to right: delta, theta, alpha, beta, gamma, full spectrum, full spectrum without alpha band.

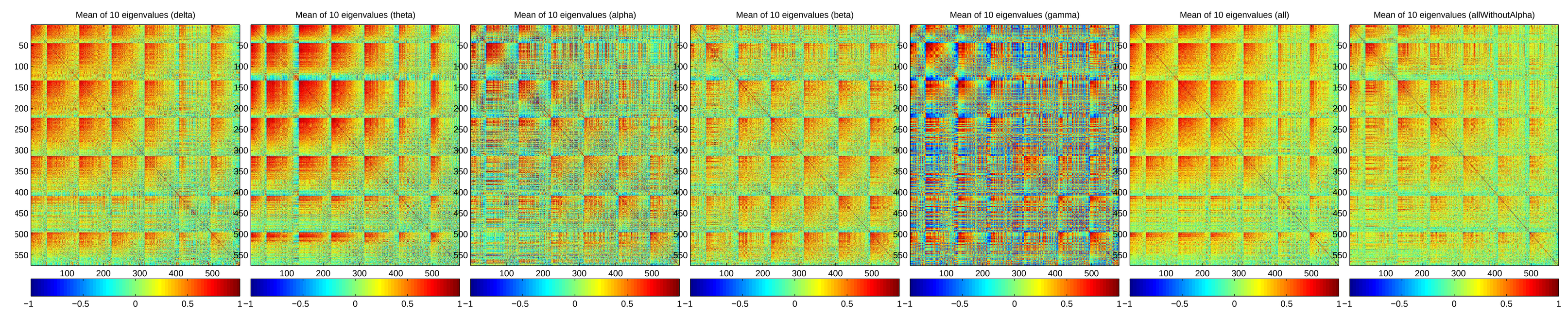
The matrix is ordered by age, from youngest (top/left) to oldest (bottom/right) subjects.



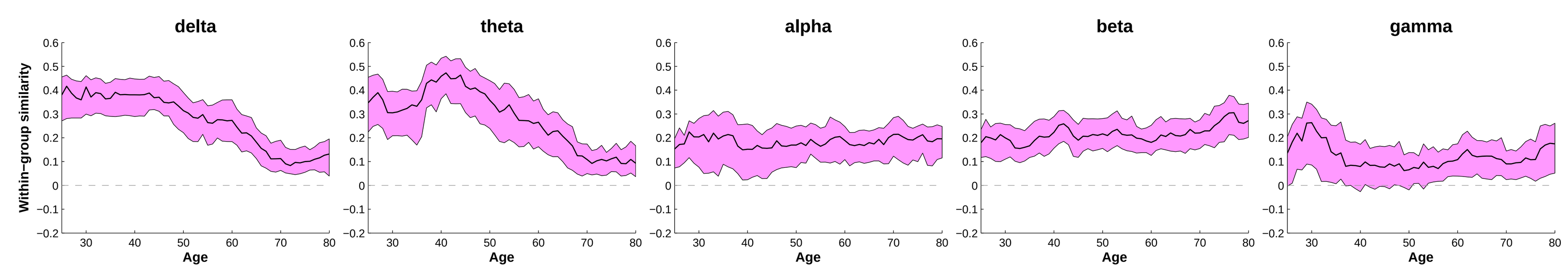
Same as above, after convolution with a 31x31 pixel averaging filter.



Same as above, after splitting subjects into deciles (18-27, 28-37, ...) and ordering subjects within deciles according to their similarity to other subjects within the decile. Following the diagonal, the plot illustrates that, for the delta/theta bands, younger subjects tend to be more similar to each other than older subjects.

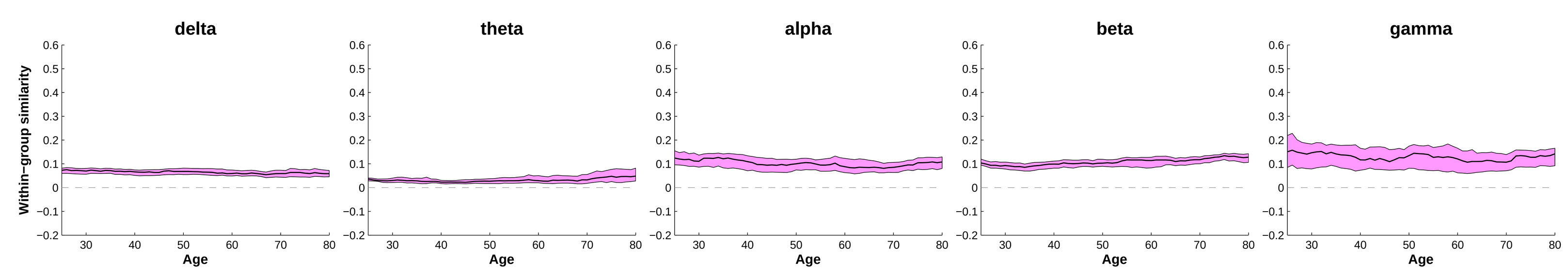


Spectral similarity within a $\pm$5 years age group for different frequency bands



We calculated distributions of mean similarities within a $\pm$5 years age range. Solid line gives the median, the borders of the shaded area correspond to the 25% and 75% percentiles. For the delta and theta band, within-group spectral similarity drops markedly (from about 0.4 to about 0.2) starting from the age of about 50 years.

Note that the effect is not visible if we simply perform the analysis on univariate power spectra:



This illustrates the power of SSA to uncover spectral similarities that are hidden with conventional analyses.

Discussion

- Our wavelet-based moving window approach using SSD successfully identified spectral profiles (and corresponding spatial patterns) of narrowband oscillations in multiple frequency bands
- Initial analyses using the Cam-CAN dataset indicate a decrease of spectral similarity within age groups ($\pm$ 5 years) with increasing age, for delta/theta frequency bands, with younger subjects being more similar to each other than older subjects.

Next steps:

- Relate the neural results to cognitive tests and demographical data (e.g., level of education) obtained in the Cam-CAN project
- Replicate analysis for other available datasets (audio-visual task, passive and active) to assure that the results are not due to peculiarities of the resting state

*

[1] Vadim V Nikulin, Guido Nolte, and Gabriel Curio. A novel method for reliable and fast extraction of neuronal eeg/meg oscillations on the basis of spatio-spectral decomposition. *NeuroImage*, 55(4):1528–1535, 2011.

[2] N Kriegeskorte, M Mur, and P Bandettini. Representational similarity analysis - connecting the branches of systems neuroscience. *Frontiers in systems neuroscience*, 2(4), 2008.

[3] MA Shafto, LK Tyler, M Dixon, JR Taylor, JB Rowe, R Cusack, AJ Calder, WD Marslen-Wilson, J Duncan, T Dalgleish, RN Henson, C Brayne, Cam-CAN, and FE Matthews. The cambridge centre for ageing and neuroscience (Cam-CAN) study protocol: a cross-sectional, lifespan, multidisciplinary examination of healthy cognitive ageing. *BMC Neurol*, 14:204, 2014.