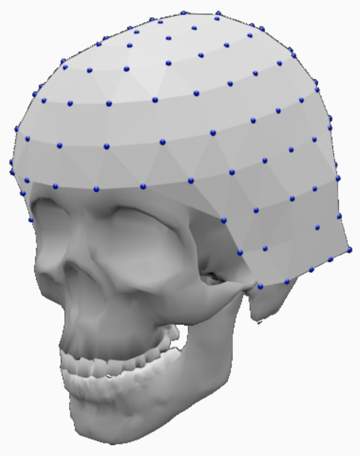
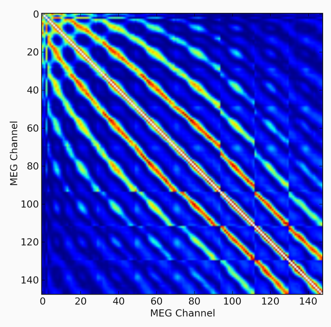
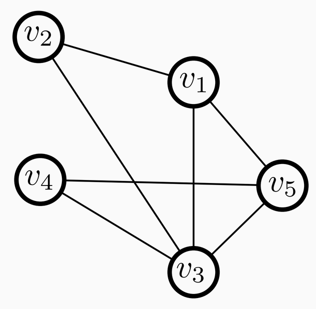
Sensor Proximity Bias in MEG Coherence

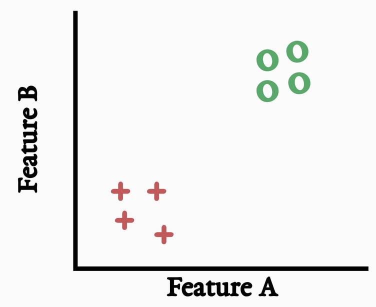
Javier Escudero[1], Athanasios Anastasiou[2], Alberto Fernández[3,4]

1: javier.escudero@ed.ac.uk -- Institute for Digital Communications; School of Engineering; The University of Edinburgh; EH9 3JL; Edinburgh; UK, 2: A.Anastasiou@swansea.ac.uk Institute of Life Science; College of Medicine, Swansea University, SA2 8PP, Swansea - Wales; UK
3: Departamento de Psiquiatría y Psicología Médica, Universidad Complutense de Madrid; Madrid; Spain, 4: Laboratorio de Neurociencia Cognitiva y Computacional, Centro de Tecnología Biomédica, Universidad Politécnica de Madrid y Universidad Complutense de Madrid; Madrid; Spain.









$$c_{m,n}(k) = f(\gamma_{m,n}(k), \delta_{m,n}(k)) + d_{m,n} + \epsilon$$

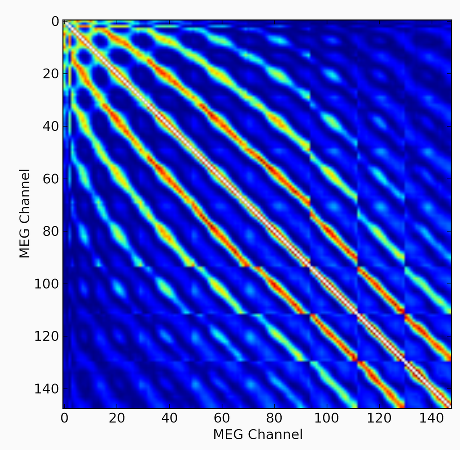
Disease / experimental effect
Default mode network effect
Close proximity effect
Other uncertainties

Acquiring MEG data to study functional connectivity networks under different conditions using graph theory is quickly becoming an established process to study key aspects of the human brain's operation

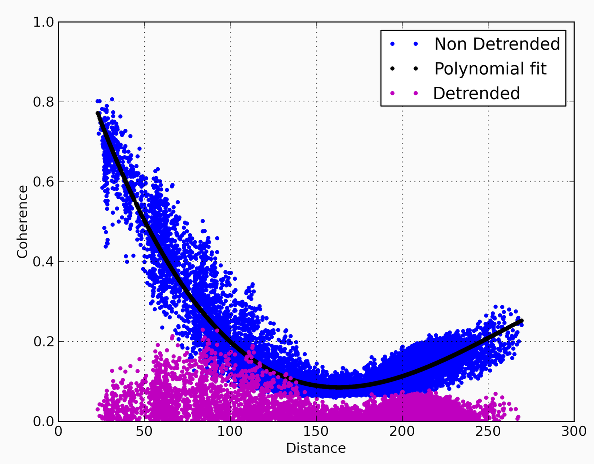
But what is the real nature of the information that is encoded in the connectivity matrix?
Could there be any systematic errors that distort the structure of the estimated functional network?

A novel detrending algorithm was developed to reduce the effect of sensor proximity on coherence values.

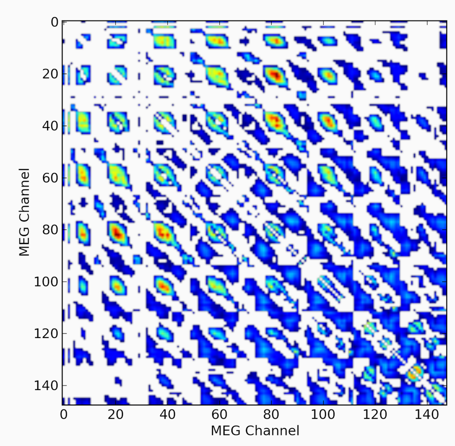
Capture the Coherence VS Distance relationship in a model and use it to detrend the coherence matrix



Before
Time series data from sensors in close proximity demonstrate increased coherence



Detrend
Plot Coherence VS Sensor-distance
Fit 3rd order polynomial through data
Remove the effect of sensor proximity

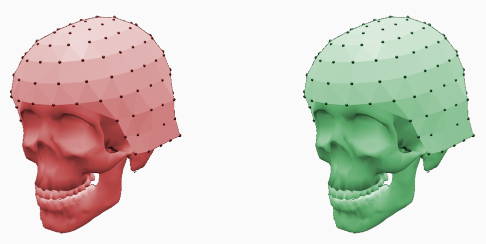


After
Characterise the coherence matrix using the weighted versions of Clustering Coefficient (C) and Average Shortest Path Length (L)

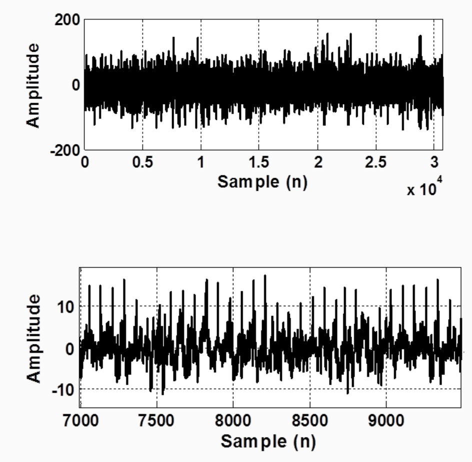
Case control study with two well defined groups of individuals (ALZheimer's and ConTroLs)

Dependent Variables: Weighted Clustering Coefficient (C) and Mean Path Length (L) using coherence as a graph's weight matrix.

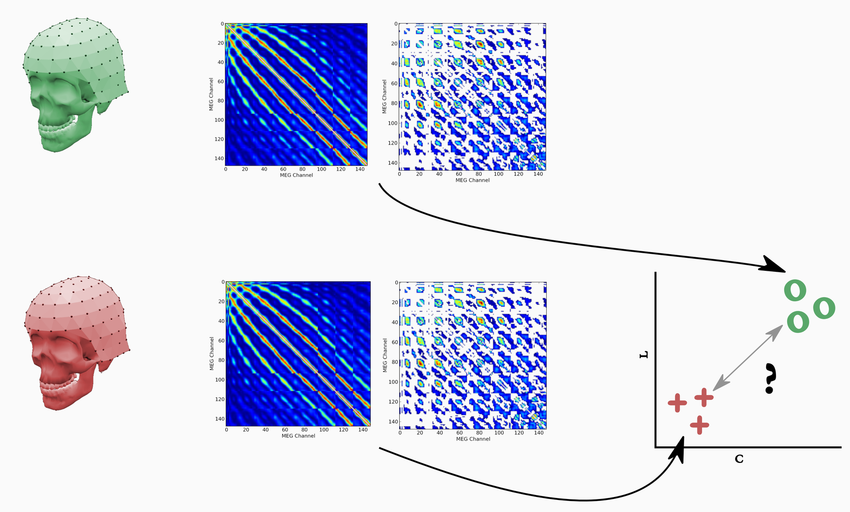
Independent Variables: Detrending treatment



Data Acquisition
MAGNES 2500 WH, 4D Neuroimaging
Sampling frequency of 169.55Hz
Physical location of sensors in space was known



Pre-processing
10 sec epochs with minimal occular activity selected
Cardiac artifact removed by constrained Blind Source Separation



Feature Extraction & Analysis
All-pairs magnitude square coherence at different spectral bands characterised using C,L

	Without Detrending		With Detrending	
	C	L	C	L
Broadband	0.628	0.669	0.17	0.298
Alpha	0.915	0.829	0.162	0.035
Delta	0.354	0.779	0.037	0.915

p-value table from unequal variance Student's t-tests showing the statistical significance of discriminating between the ALZ and CTL populations with and without detrending treatment

The coherence versus distance relationship demonstrated a convex shape consistently across the two populations with short range sensor pairs at singificantly higher levels of coherence than the mid and long range pairs.

Preliminary results show that detrending the coherence matrix improves the statistical significance of the differences between C,L across the ALZ,CTL populations for the majority of spectral bands examined.

Although encouraging, current results are limited by the reduced sample size and the fact that not all spectral bands were studied.

Detrending acts as a kind of dynamic thresholding on the coherence matrices removing a large part of data variation that depends on sensor proximity.

More work is required to confirm the effect of sensor proximity by applying the developed algorithm to larger cohorts, more spectral bands, and connectivity metrics as well as studying the impact of proximity to small-world network characteristics.

Future work will also explore short and long range pairs of connections in a data-driven way taking into account the convex coherence-distance relationship.

More details about the volume conduction effect and our motivation to study sensor proximity in MEG data in particular can be found in G. Nolte, O. Bai, L. Wheaton, Z. Mari, S. Vorbach, and M. Hallett, 'Identifying true brain interaction from EEG data using the imaginary part of coherency', Clin. Neurophysiol., vol. 115, no. 10, pp. 2292–2307, Oct. 2004.
A detailed account of the data that were used in this study can be found in J. Escudero, S. Sanei, D. Jarchi, D. Abásolo, and R. Hornero, 'Regional coherence evaluation in mild cognitive impairment and Alzheimer's disease based on adaptively extracted magnetoencephalogram rhythms', Physiol. Meas., vol. 32, no. 8, pp. 1163–1180, Aug. 2011.
For more details on our choice of the Magnitude Square Coherence to characterise functional connectivity please refer to J. Dauwels, F. Vialatte, T. Musha, and A. Cichocki, 'A comparative study of synchrony measures for the early diagnosis of Alzheimer's disease based on EEG', NeuroImage, vol. 49, no. 1, pp. 668–693, Jan. 2010.
An extensive treatment of graph theory as applied to neuroscience, including details about our choice of the Clustering Coefficient & Mean Path Length graph features can be found in E. Bullmore and O. Sporns, 'Complex brain networks: graph theoretical analysis of structural and functional systems', Nat. Rev. Neurosci., vol. 10, no. 3, pp. 186–198, Mar. 2009.
The 3D model of the skull was obtained from http://www.3dvia.com/content/8BDF778193A5B789 while the "helmet" was added in Blender (blender.org) by reconstructing a surface through the sensor physical locations.

THE UNIVERSITY OF EDINBURGH

Download a copy of this poster to your mobile device by scanning this code

Swansea University
Prifysgol Abertawe