Dynamic causal modelling (DCM)

MEG UK 2015 Workshop

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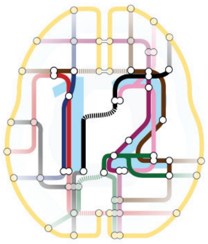
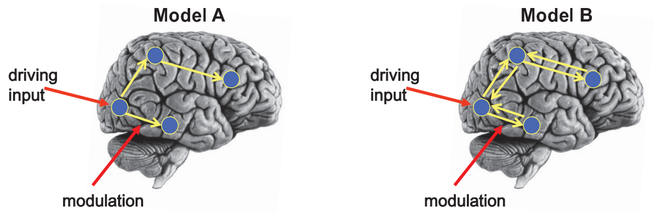


What is Dynamic Causal Modelling (DCM)?

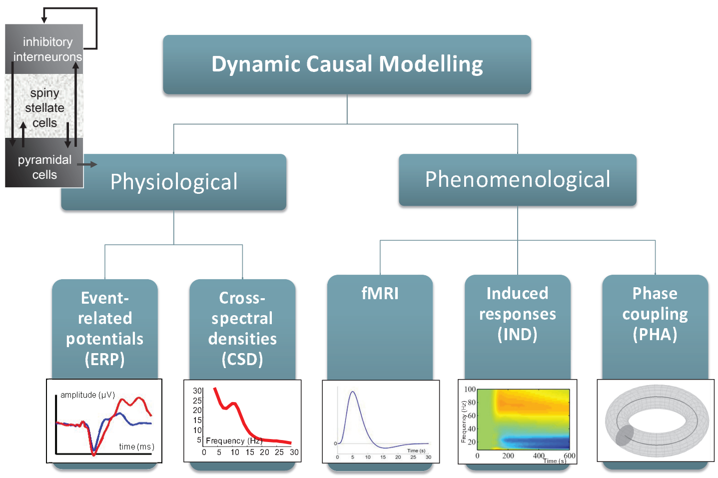
DCM is a computational modelling technique to estimate bio-physiologically relevant parameters from functional neuroimaging data

→ Based on a generative model expressed as differential equations
→ Model parameters are estimated by fitting data features of brain activity
→ **Effective connectivity** between brain regions
→ (Synaptic coupling strengths)
→ Bayesian framework (priors, posteriors, model evidence)

What can we do with DCM?



Model comparisons	*Test hypotheses* *Does model A explain the data better than model B?*
Parameter inference	*What are the connection strengths?* *How do they change between conditions?*

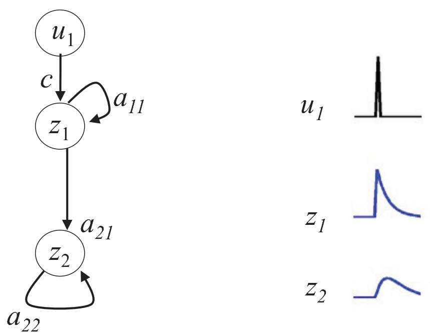


Which DCM should I use?

1) **Select data feature of interest**
   - Event-related design: event-related potentials, induced responses
   - Steady state activity: cross-spectral densities, phase coupling
2) **Select type of generative model**
   - Physiological: convolution or conductance, several options
   - Phenomenological: fixed choice
3) **Specify networks - what do you want to test?** **(A matrix)**
   - What is the hypothesis?
   - Which regions?
   - Which connections?
4) **Think about condition-specific effects** **(B matrix)**
   - Do you have more than 1 experimental condition?
   - Which connections may show a difference between conditions?

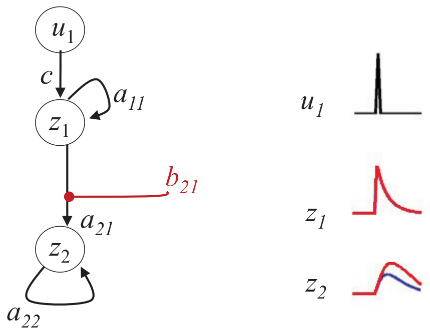
A matrix

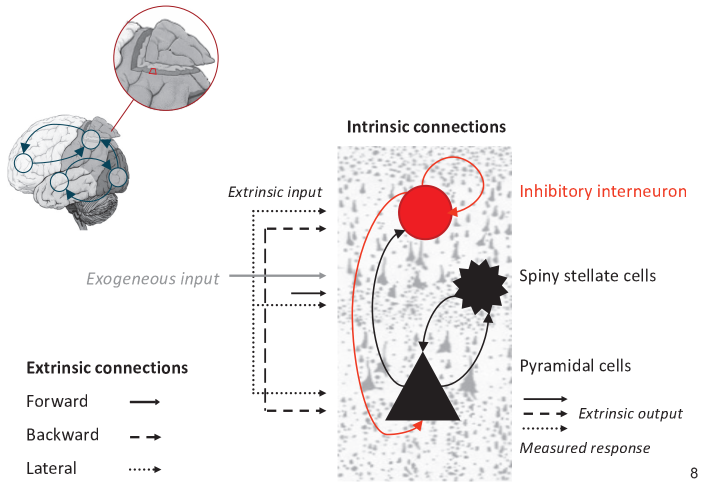
$$\begin{bmatrix}\dot{z}_1\\ \dot{z}_2\end{bmatrix} = \begin{bmatrix}a_{11} & 0\\ a_{21} & a_{22}\end{bmatrix}\begin{bmatrix}z_1\\ z_2\end{bmatrix} + \begin{bmatrix}c\\ 0\end{bmatrix}\begin{bmatrix}u_1\\ u_2\end{bmatrix}$$



A matrix **B matrix**

$$\begin{bmatrix}\dot{z}_1\\ \dot{z}_2\end{bmatrix}=\begin{bmatrix}a_{11} & 0\\ a_{21} & a_{22}\end{bmatrix}\begin{bmatrix}z_1\\ z_2\end{bmatrix}+v\begin{bmatrix}0 & 0\\ b_{21} & 0\end{bmatrix}\begin{bmatrix}z_1\\ z_2\end{bmatrix}+\begin{bmatrix}c & 0\end{bmatrix}\begin{bmatrix}u_1\\ u_2\end{bmatrix}$$

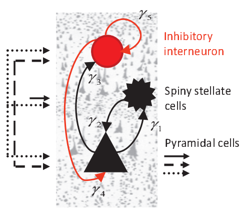


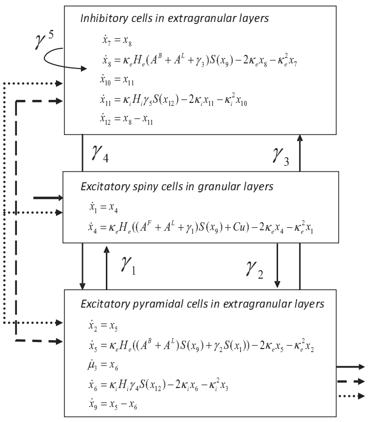


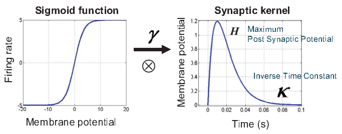
ERP & CSD

Physiological models – convolution based

LFP model



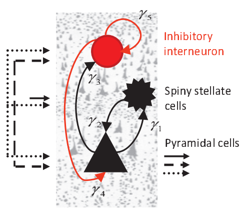


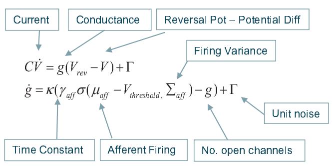


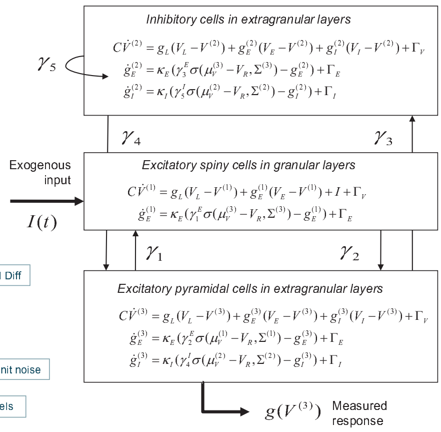
ERP & CSD

Physiological models – conductance based

NMM model







+ additional synapses for extrinsic connections

List of physiological models available for DCM

Convolution

ERP - original model for ERPs - based on Jansen & Rit (1995)

SEP - ERP model with faster dynamics to model evoked potentials

CMC - Canonical Microcircuit Model
separate superficial & deep pyramidal cells (Bastos et al. 2012)

LFP - ERP model with self-connection for inhibitory neurons (Moran et al. 2007)

NFM - ERP model as a neural field model (Pinotsis et al. 2012)

Conductance

NMM - based on Morris & Lecar (1981)

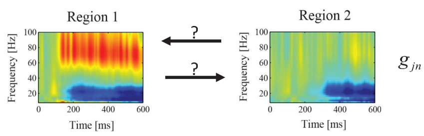
MFM - includes second order statistics (population density) (Marreiros et al. 2009)

CMM - canonical neural mass / mean field model - four populations

NMDA - includes (voltage gated) NMDA receptors (Moran et al. 2011)

See: Moran et al. (2013) Frontiers in Computational Neuroscience
"Neural masses and fields in dynamic causal modeling"

Phenomenological models – induced responses



$g_{jn}(t)$ each source j has a power time course for each frequency mode n

Within source coupling — Between source coupling — External input

$$\tau\dot{\vec{g}}(t)=\tau\begin{bmatrix}\dot{\vec{g}}_1(t)\\ \vdots\\ \dot{\vec{g}}_J(t)\end{bmatrix}=\left(\begin{bmatrix}\underline{A}_{11} & \cdots & \underline{A}_{1J}\\ \vdots & \ddots & \vdots\\ \underline{A}_{J1} & \cdots & \underline{A}_{JJ}\end{bmatrix}+\sum v\begin{bmatrix}\underline{B}_{11} & \cdots & \underline{B}_{1J}\\ \vdots & \ddots & \vdots\\ \underline{B}_{J1} & \cdots & \underline{B}_{JJ}\end{bmatrix}\right)\vec{g}(t)+\begin{bmatrix}\vec{c}_1\\ \vdots\\ \vec{c}_J\end{bmatrix}u(t)$$

Condition-specific effects term

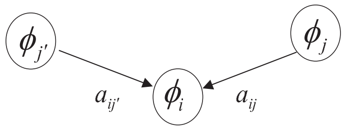
Within frequency coupling

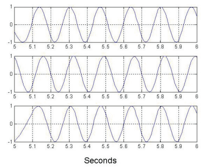
$$\underline{A}_{ij}=\begin{bmatrix}a_{ij}^{11} & \cdots & a_{ij}^{1N}\\ \vdots & \ddots & \vdots\\ a_{ij}^{N1} & \cdots & a_{ij}^{NN}\end{bmatrix}$$

Between frequency coupling

Directional cross-frequency coupling

Phenomenological models – phase coupling





ϕ_j each source *j* has a phase time course for a particular frequency

Synchronization via phase coupling

$$\dot{\phi}_i = f_i - \sum_j a_{ij} \sin(\phi_i - \phi_j)$$ In-phase coupling

$$\dot{\phi}_i = f_i - \sum_K \sum_j a_{ijK} \sin(K[\phi_i - \phi_j]) - \sum_K \sum_j b_{ijK} \cos(K[\phi_i - \phi_j])$$ All coupling

Some technical differences between DCM types

Physiological DCMs
- Model sensor level data
- Test for how many sources
- Inverse problem included
- Optimize source locations

Phenomenological DCMs
- Model source level data
- Cannot compare nr of sources
- Take specified source locations

Event-related DCMs
- External stimulus modelled with Gaussian impulse
- Require baseline interval

Steady-state DCMs
- Perturbation with white/pink noise to generate cross-spectra

Model inversion

Data feature (e.g. evoked responses)

Specify generative forward model (with prior distributions of parameters)

Expectation-Maximization algorithm

Iterative procedure:
1. Compute model response using current set of parameters
2. Compare model response with data
3. Improve parameters, if possible

1. Posterior distributions of parameters $p(\theta \mid y, m)$
2. Model evidence $p(y \mid m)$

Bayesian model comparisons

Free energy value as approximation to model evidence
→ Accuracy - complexity terms
→ Most complex model does not always win
→ Only possible to compare models describing same data
→ Only relative values between models matter

Within subjects
Significant difference: Bayes factor $\frac{p(y|m_1)}{p(y|m_2)}$ >20 = difference in log evidence >3

Between subjects
Fixed effects product individual model evidence values = sum log evidences
Random effects Estimates probability model given group data

Bayesian family comparisons for large numbers of models
Group models by common feature

Parameter inference

First select winning model

Within subjects
Look at (mean of) posterior estimates of model parameters

Between subjects
Fixed effects Bayesian parameter averaging - posterior means are averaged over subjects weighted by their precision
Random effects t-test or ANOVA

Bayesian model averaging
Useful in case of different winning models between groups
Posterior means are averaged weighted by their precision and model evidence

Further reading

Model specification and statistical inference
Stephan et al. (2010) Neuroimage. *Ten simple rules for dynamic causal modelling*
Stephan et al. (2009) Neuroimage. *Bayesian model selection for group studies*
Penny et al. (2010) PLoS One. *Comparing families of dynamic causal models*

First DCM paper & more details inversion algorithm
Friston et al. (2003) Neuroimage. *Dynamic causal modelling*

Overview of different physiological models available for DCM
Moran et al. (2013) Front Comp Neurosci. *Neural masses and fields in DCM*

Applications
ERP: David et al. (2006) Neuroimage; Garrido et al. (2007) PNAS; Boly et al. (2011) Science
CSD: Moran et al. (2009) Neuroimage, (2011) PLoS One; Friston et al. (2012) Neuroimage
IND: Chen et al. (2008, 2009) Neuroimage; Van Wijk et al. (2012) Neuroimage
PHA: Penny et al. (2009) J Neuroscience Methods

More documentation can be found in the SPM manual and online videos
http://www.fil.ion.ucl.ac.uk/spm/