An Implementation Of Dynamic-Causal-Modelling

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Overview

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About

IOD (= **I**mplentation **O**f **D**ynamic-Causal-Modelling)

- Version 1.0 (2011, Diploma Thesis)
- Version 2.0 (planned for Q4/2012)
- Open Source (zlib/libpng License)
- Written in C++11
- Parallelization using OpenMP
- No required dependencies
- Optional: gnuplot, graphwiz, tcmalloc, mutt

together with:

Prof. Dr. Mario Ohlberger, Dr. Thomas Seidenbecher, Dr. Jörg Lesting

Capabilities

Scientific:

- DCM for fMRI (Linear, Bilinear, Nonlinear)
- DCM for EEG (Default, Extended, Adaption, Habituation, Linearized)
- Simulations of Systems

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Technical:

- Modular Dynamic and Forward Models
- Order 1, 2, 5 Runge-Kutta Solver (optionally adaptive)
- Remote Execution (optionally mailing results)

Extension

Major:

- EM-Algorithm Optimization
- Drift Filter

Minor:

- Positive (Definite) Temporal Correlation
- Fast Model Evidence Calculations
- Bandpass Filter
- XHTML/SVG Reporting

EM-Algorithm Optimization

Using the following linear algebra lemma:

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For more info see: `http://j.mp/himpe` (p.30-36).

Drift Filter

Drift Term $X\beta$:

- Additional set of parameters β,
- reflecting unrelated oscillations,
- modelled by a discrete cosine set X.

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- The drift matrix X can be customized to a high-pass filter.
- It is not advisable, though possible, to use as low-pass filter.

Open Issues

Major:

1. Post-Hoc Model Selection (2.0)
2. EEG Model Restructuring (2.0)
3. Model Reduction (3.0)
4. Optimal Maps (3.0)

Post-Hoc Model Selection

- An implementation of "Post-hoc selection of dynamic causal models", M.J. Rosa, K. Friston, W. Penny, Journal of Neuroscience Methods, Volume 208, Issue 1, 30 June 2012, Pages 66-78
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- and relate to the reduced models priors.

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- nonlinear

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2. prepare for model reduction.

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Model Reduction to the Rescue!
Find a surrogate model, with a low dimensional parameter space.
Two approaches are considered:

1. Projection (Complex, Precise)
2. Truncation (Simple, Coarse)

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- Replacing the EM-algorithm using optimal maps.
- Find a map that transforms the prior into the posterior distribution,
- using for example low-order polynomials,
- until the variance drops below some threshold.

Sample Report

Goto:

`http://j.mp/iodreport`

tl;dl

- Modular Implementation (`http://j.mp/himpe`)
- Replace the EM algorithm (`http://j.mp/optimalmaps`)
- Include Model Reduction

Thank You