

Northeastern University

Research Thrust R2 Presentations

CenSSIS Research Thrust R2: Physics Based Signal Processing and Image Understanding

January 01, 2006

Controlling dimensionality in a systems approach to dynamic multimodal functional brain imaging

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Recommended Citation

Laxminarayan, Srinivas; Jonny, Manu Ben; Diamond, Solomon; Brooks, Dana; Tadmore, Gilead; Miller, Eric; and Boas, David, "Controlling dimensionality in a systems approach to dynamic multimodal functional brain imaging" (2006). *Research Thrust R2 Presentations*. Paper 14. http://hdl.handle.net/2047/d10008251

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Abstract

The complementary spatial, temporal and specificity advantages of fMRI, EEG, MEG, PET and DOT for functional brain imaging motivate interest in multimodal functional brain imaging. State-variable dynamical systems modeling of neural activity and its relation to local hemodynamics further coupled with autonomi physiology offers enhanced spatiotemporal resolution and insight into physiological signals and mechanisms. However, such a model also implies an explosion of state dimension. We discuss strategies for controlling this high dimensionality based on subspace approaches applied to the observed data and the model structure, and also describe some implications for understanding human brain function.

The Dynamic Multi-modal Integrated framework



u = observable inputs x = state variables w = process noise θ = model parameters z = physiological signal

- F = lead fields
- v = measurement nois y = measurements

State of the Art

- A biophysical model of the nuronal currents, in response to a stimulus, and its relation to the brain vasculature was proposed and developed by Riera et.al [1].
- A modified multi-compartment vascular model of blood flow in the brain was proposed by Huppert et.al [2]
- The dynamic framework [3] uses these models and combines them along with the different lead fields to get relevant information about the brain function.
- A state-space formulation of this problem leads to a exponential growth in the number of states and this dimensionality issue needs to be addressed in order to take advantage of the different modalities, in a computationally efficient manner.



Challenges and Significance Significance :

together may help.



- Challenges :
- parameters.
- The space and time scales of measurements, may be different.
- The sampling rates of the measurments may be different.
- The number of parameters involved, is huge. • Reconstruction of the parameters based on measurements, becomes a problem.

Neuronal and Windkessel model's

The neuronal model developed by Riera [1] takes in the sensory response functions and gives the voltages on the GABA and pyramidal cells, this voltage drives the vasculature and makes blood flow possible for the activated region in the brain. The neurovascular coupling is till now not clear, hence we just use a fourth order model to relate these to the windkessel model.



The multi-compartment windkessel model for vasculature developed by Huppert [2]

• A unified framework of imaging modalities will help in gaining relevant information about the brain function. The table below shows, why some of the modalities, used

| odality | Spatial Res. | Temporal Res. |
|---------|--------------|---------------|
| MRI | Good | Poor |
| TOC | Poor | Good |
| MEG | Poor | Very Good |
| EEG | Poor | Very good |
| EIT | Poor | Low |
| | | |

• Can be applied to breast imaging.

• Modalities measure different, or interrelated



The Neuronal Mass model from Riera's paper [1]

Priliminary results on the combined framework

The stimulus is a set of 8 pulses each for a duration of 40ms, at an interval of 400ms. The figures show the sensory response which drives the neuronal response and the final hemoglobin concentration changes as the vasculature is activated.



Note the time scales The hemoglobin concentration changes are measured by fMRI and DOT. This is a work in progress.

Motivation for Model reduction

- More modalities used; results in; dramatic increase in # of states.
- More accurate physiological models also increase the # of states needed if the spatial extent is taken into account.

Potential industrial applications

- Model reduction methods are useful in other biological areas of interest such as cellular transduction and regulation, which are modelled as nonlinear differential equations. Such methods are also applicable to nanophotonics.
- Brain modelling and multi-modal imaging combined with a set of efficient reduction methods and computational algorithms could help in detecting diseases like Alziemer's, schizophernia etc.

Model Reduction method: Basic Idea

• Want a $\mathbf{Z}(t)$, and $\mathbf{V}(t)$ such that

$$\dot{\hat{\mathbf{x}}}(t) = \mathbf{Z}^{T}(t)\mathbf{A}(t)\mathbf{V}(t)\hat{\mathbf{x}}(t) + \mathbf{Z}^{T}(t)\mathbf{w}(t)$$
$$\mathbf{y}(t) = \mathbf{C}(t)\mathbf{V}(t)\hat{\mathbf{x}}(t) + \boldsymbol{\nu}(t)$$

- A good constraint for getting the V(t) and $\mathbf{Z}(t)$ is that the resulting lower order system be **stable**.
- Lyapunov stability equations are

$$\mathbf{A}^{T}(t)G_{c}(t) + G_{c}(t)\mathbf{A}(t) - \mathbf{B}(t)\mathbf{B}^{T}(t) + s\mathbf{I} = 0$$

$$\mathbf{A}^{T}(t)G_{o}(t) + G_{o}(t)\mathbf{A}(t) - \mathbf{C}^{T}(t)\mathbf{C}(t) + r\mathbf{I} = 0$$

s and r are small scalar parameters so as to ensure that the matrices formed by the equations remain negative definite.

- $G_c(t)$ and $G_o(t)$ are controlability and observability grammian's.
- Balanced Truncation If we choose $\mathbf{V}(t) = \mathbf{U}_{n \times m}(t) \mathbf{\Sigma}_{m \times m}^{-1/2}(t)$. So that $G_c(t)G_o(t) = \Sigma^2(t)$. Then we get $\mathbf{Z}^T(t) = \mathbf{V}^{\dagger}(t)$ (i.e. pseudoinverse).
- Efficient algorithms for the above computation exist [6]. A thesis which gives the underlying theory and its practical application is [7].

Methods applied to Optical data

- Variable reduction by recomputing $\mathbf{V}(k)$ at every time instant using the algorithm described in [6].
- Computing the average observability grammian and using it to compute a fixed V for all time.
- Finally to select the modes to keep we used anatomical information.

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for scalp and brain.

Observations and Conclusions

From the images we can infer the following. • In this particular dataset we get around 80 times reduction in the model order. This may not actually be the case in a real dataset.

• We see that the variable order estimator's performance is bad than the averaged one, this is because we had a trivial state evolution equation. In multi-modal data we

expect the variable order estimator to perform better.

• We see that using anatomical information definitely helps while deciding which modes to keep.

Future Work

• Finish the ongoing work on the integrated framework to include EEG, MEG combined with DOT and fMRI.

• Apply model reduction techniques on it, which would also help us gain information on which models are over parametrized.