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A data-driven framework for neural field modeling

D.R. Freestone [a,b,c,*,1], P. Aram [d,1], M. Dewar [c,e], K. Scerri [f], D.B. Grayden [a,b], V. Kadirkamanathan [d]

[a] Department of Electrical and Electronic Engineering, University of Melbourne, Melbourne, VIC, Australia
[b] The Bionic Ear Institute, East Melbourne, VIC, Australia
[c] Institute for Adaptive and Neural Computation, University of Edinburgh, Edinburgh, UK
[d] Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield, UK
[e] Department of Applied Physics and Applied Mathematics, Columbia University, New York, NY, USA
[f] Department of Systems and Control Engineering, University of Malta, Msida, MSD, Malta

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ABSTRACT

This paper presents a framework for creating neural field models from electrophysiological data. The Wilson and Cowan or Amari style neural field equations are used to form a parametric model, where the parameters are estimated from data. To illustrate the estimation framework, data is generated using the neural field equations incorporating modeled sensors enabling a comparison between the estimated and true parameters. To facilitate state and parameter estimation, we introduce a method to reduce the continuum neural field model using a basis function decomposition to form a finite-dimensional state-space model. Spatial frequency analysis methods are introduced that systematically specify the basis function configuration required to capture the dominant characteristics of the neural field. The estimation procedure consists of a two-stage iterative algorithm incorporating the unscented Rauch–Tung–Striebel smoother for state estimation and a least squares algorithm for parameter estimation. The results show that it is theoretically possible to reconstruct the neural field and estimate intracortical connectivity structure and synaptic dynamics with the proposed framework.

Introduction

Generating physiologically plausible neural field models is of great importance for studying brain dynamics at the mesoscopic and macroscopic scales. While our understanding of the function of neurons is well developed, the overall behaviour of the brain's mesoscopic and macroscopic scale dynamics remains largely theoretical. Understanding the brain at this level is extremely important since it is at this scale that pathologies such as epilepsy, Parkinson's disease and schizophrenia are manifested.

Mathematical neural field models provide insights into the underlying physics and dynamics of electroencephalography (EEG) and magnetoencephalography (MEG) (see Deco et al. (2008); David and Friston (2003) for recent reviews). These models have demonstrated possible mechanisms for the genesis of neural rhythms (such as the alpha and gamma rhythms) (Liley et al., 1999; Rennie et al., 2000), epileptic seizure generation (Lopes Da Silva et al., 2003; Suffczynski et al., 2004; Wendling et al., 2005) and insights into other pathologies (Moran et al., 2008; Schiff, 2009) that would be difficult to gain from experimental data alone.

Unfortunately, the use of these models in the clinic has been limited, since they are constructed for "general" brain dynamics whereas pathologies almost always have unique underlying patient-specific causes. Patient-specific data from electrophysiological recordings is readily available in the clinical setting, particularly from epilepsy surgery patients, suggesting an opportunity to make the patient-specific link to models of cortical dynamics. Furthermore, recent technological advances have driven an increased level of sophistication in recording techniques, with dramatic increases in spatial and temporal samplings (Brinkmann et al., 2009). However, the mesoscopic and macroscopic neural dynamic states are not directly observable in neurophysiological data, making predictions of the underlying physiology inherently difficult.

For models to be clinically viable, they must be patient-specific. A possible approach to achieve this would be to fit a general continuum neural field model, like the Wilson and Cowan (1973) (WC) or Amari (1977) models, or a neural mass model like the Jansen and Rit (1995) model, to patient-specific data. Fitting the neural models to individuals is a highly non-trivial task. Recently, however, this task has been approached from a number of standpoints. The first paper on patient-specific modeling (to the authors' best knowledge) came from Valdes et al. (1999), where they fit the neural mass model of Lopes Da

* Corresponding author at: Department of Electrical and Electronic Engineering, University of Melbourne, Melbourne, VIC, Australia.
E-mail addresses: dfreestone@bionicear.org (D.R. Freestone), p.aram@sheffield.ac.uk (P. Aram), mike.dewar@columbia.edu (M. Dewar), kenneth.scerri@um.edu.mt (K. Scerri), grayden@unimelb.edu.au (D.B. Grayden), visakan@sheffield.ac.uk (V. Kadirkamanathan).
[1] Authors contributed equally to this work.

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Silva et al. (1976) and Zetterberg et al. (1978) to EEG data using the local linearization filter (Ozaki, 1993; 1994; Ozaki et al., 2000). This paper demonstrated for the first time the feasibility of assimilating data with neural models of EEG.

Perhaps the most accepted estimation framework for neural mass models is dynamical causal modeling (DCM) (David and Friston, 2003; David et al., 2006), which has been proposed for studying evoked potential dynamics. This framework can be viewed as an extension to the work of Valdes et al. (1999) allowing for coupling of neural masses. Via a Bayesian inference scheme, DCM estimates the long range (cortico-cortical) connectivity structure between the specific isolated brain regions that best explains a given data set using the model of Jansen and Rit (1995).

Data-driven neural modeling was extended to the continuum approximation by Galka et al. (2008), where they proposed an estimation framework based on a linear damped wave equation. Using a Kalman filter maximum likelihood framework, they improved on the low resolution electromagnetic tomography (LORETA) method for solving the inverse EEG problem. Another continuum neural field model-based estimator was developed by Daunizeau et al. (2009), as an extension to the DCM framework. They argue that using a spatially extended continuum field model is superior for explaining cortical function than the neural mass DCM, since field models can explain a richer repertoire of dynamics such as traveling waves and bump solutions.

Another recent approach estimates the parameters of a modified WC neural field model using an unscented Kalman filter (Schiff and Sauer, 2008). This work takes a systems theoretic approach to the neural estimation problem, successfully demonstrating that it is possible to perform state estimation and control on spatiotemporal neural fields. This marks the first step in what has the potential to revolutionize the treatment of many neurological diseases where therapeutic electrical stimulation is viable. For other valuable contributions to data-driven neural modeling, see Nunez (2000), Jirsa et al. (2002), and Robinson et al. (2004).

We present an extension to the work of Schiff and Sauer (2008) by establishing a framework for estimating the state of the WC equations for larger scale (more space) systems via a systematic model reduction procedure. In addition, a new method is presented for estimating the connectivity structure and the synaptic dynamics. Until now, model-based estimation of local intracortical connectivity has not been reported in the literature (to the best of the authors' knowledge). Our study also extends recent work which shows that it is possible to estimate local coupling of spatiotemporal systems using techniques from control systems theory and machine learning (Dewar et al., 2009). The key development of this previous work was to represent a spatiotemporal system as a standard state-space model, with the number of states independent of the number of observations (recording electrodes in this case). In addition, the appropriate model selection tools have been developed (Scerri et al., 2009) allowing for the application of the technique to neural fields. This paper extends the linear framework of Dewar et al. (2009) and Scerri et al. (2009) to the nonlinear case required for the neural field equations.

Modeling the neural dynamics within this framework has a distinct advantage over the more standard multivariate auto-regressive (MVAR) models: the number of parameters to define the spatial connectivity is considerably smaller than the number of AR coefficients typically required to achieve the model complexity.

In this paper, we demonstrate for the first time how an intracortical connectivity kernel can be inferred from data, based on a variant of the Wilson and Cowan (1973) neural field model. This work provides a fundamental link between the theoretical advances in neural field modeling and high resolution intracranial electrophysiological data. To illustrate the estimation framework, data is generated using the neural field equations incorporating modeled sensors enabling a comparison to be made between the estimated and true parameters. The paper proceeds by first describing the continuum neural field equations that are used as the cortical model. Then a finite-dimensional neural field model is derived. The model is reduced by approximating the neural field using a set of continuous basis functions, weighted by a finite dimensional state vector. The next section establishes conditions, using spatial frequency analysis, for both sensor and basis function spacing and width, such that the dominant dynamics of the neural field can be represented by the reduced model. The state and parameter estimation procedure is described in the following section. The results for the spatial frequency analysis and parameter estimation are then presented. Finally, the implications and limitations of this framework are discussed along with planned future developments.

Methods

Neural field model

Neural field models relate mean firing rates of pre-synaptic neural populations to mean post-synaptic membrane potentials. They are popular as they are parsimonious yet have a strong link with the underlying physiology. Each neural population represents a functional cortical processing unit, such as a column. The columnar organization of the cortex is continuous, where pyramidal cells are members of many columns. In general, cortical structure can be modeled in a physiologically plausible manner as being locally homogeneous (in short range intracortical connectivity) and heterogeneous (in long range cortico-cortical and corticothalamic connectivity) (Jirsa, 2009; Qubbaj and Jirsa, 2007). In certain regions of the cortex, each column is thought to be connected locally via symmetric short range local excitation with surround inhibition (Braitenberg and Schüz, 1998). For example, this structural organization is most studied in the visual system, where the surrounding inhibition effectively tunes a cortical column to a particular receptive visual field (Sullivan and De Sa, 2006). Neural field models are descriptive of a range of neurodynamics of the cortex such as evoked potentials, visual hallucinations and epileptic behaviour (David and Friston, 2003; Bressloff et al., 2001; Breakspear et al., 2006). Field models are also capable of generating complex spatial patterns of activity such as Turing patterns, spirals and traveling oscillations (Amari, 1977; Coombes, 2005; Coombes et al., 2007).

It is an implicit assumption that the neural field model (in Eq. (12)) provides an apt description of the cortical dynamics recorded from a specific subject. Although models of this form are capable of describing a variety of cortical dynamics, there will be without doubt a mismatch between the cortex and the model. Nevertheless, there is a sufficient volume of interesting results from theoretical studies using the WC field equations that warrants the data assimilation framework. An advantage in using a lumped-parameter field model over a more detailed mathematical description is that the myriad of parameters that might influence excitability, such as specific ion concentrations, are considered to be lumped into parameters (connectivity kernel coefficients) that effectively describe the net system gain. Therefore, there are less parameters to estimate. A major challenge in model-based data analysis for the mass action of the brain is to make models sufficiently detailed, such that the parameters are meaningful, but simple enough to yield clear insights that can be related to theoretical studies (from both neuroscience and engineering perspectives).

Integro-difference equation neural field model

The combination of modeling techniques in this paper leads to a large amount of notation, so a reference of the symbols used is provided in Table 1. The model relates the average number of action potentials $g(\mathbf{r},t)$ arriving at time t and position $\mathbf{r}$ to the local post-synaptic membrane voltage $v(\mathbf{r},t)$. The post-synaptic potentials