On self-feedback connectivity in neural mass models applied to event-related potentials

Vahab Youssofzadeh, Girijesh Prasad, KongFatt Wong-Lin *

Intelligent Systems Research Centre, School of Computing and Intelligent Systems, University of Ulster, Magee Campus, Northland Road, L'Derry BT48 7JL, UK

A B S T R A C T

Neural mass models (NMMs) applied to neuroimaging data often do not emphasise intrinsic self-feedback within a neural population. However, based on mean-field theory, any population of coupled neurons is intrinsically endowed with effective self-coupling. In this work, we examine the effectiveness of three cortical NMMs with different self-feedbacks using a dynamic causal modelling approach. Specifically, we compare the classic Jansen and Rit (1995) model (no self-feedback), a modified model by Moran et al. (2007) (only inhibitory self-feedback), and our proposed model with inhibitory and excitatory self-feedbacks. Using bifurcation analysis, we show that single-unit Jansen–Rit model is less robust in generating oscillatory behaviour than the other two models. Next, under Bayesian inversion, we simulate single-channel event-related potentials (ERPs) within a mismatch negativity auditory oddball paradigm. We found fully self-feedback model (FSM) to provide the best fit to single-channel data. By analysing the posterior covariances of model parameters, we show that self-feedback connections are less sensitive to the generated evoked responses than the other model parameters, and hence can be treated analogously to "higher-order" parameter corrections of the original Jansen–Rit model. This is further supported in the more realistic multi-area case where FSM can replicate data better than JRM and MoM in the majority of subjects by capturing the finer features of the ERP data more accurately. Our work informs how NMMs with full self-feedback connectivity are not only more consistent with the underlying neurophysiology, but can also account for more complex features in ERP data.

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Introduction

Mesoscale neurocomputational models can account for the dynamics of brain activities by using mean-field approaches to reduce, simulate and analyse models of neuronal populations (or 'lumped') contingent on the level of realism sought (Amit and Brunel, 1997; Deco et al., 2008; Grimbert, 2008; Moran et al., 2013; Wilson and Cowan, 1973; Wong and Wang, 2006). One such model type, the neural mass models (NMMs), can account for the collective behaviour of neuronal and synaptic activities (Beurle, 1956). Such models can mimic experimental results from data with sources as diverse as local field potentials, magneto/electroencephalography (M/EEG), and functional magnetic resonance imaging (fMRI) (Friston and Dolan, 2010; Moran et al., 2013). NMMs also have the added advantages of being computationally efficient (as compared e.g. to spiking neuronal network models), capacity to incorporate sufficiently biologically realistic features (e.g. intrinsic neuronal/synaptic timescales and mechanisms), and allow mathematical tractability (i.e. rigour theoretical analysis of the model's behaviour) (David et al., 2007; Deco et al., 2008).

NMM was first used by Wilson and Cowan (1972, 1973) to describe the temporal evolution of subpopulations in excitatory and inhibitory cells in a simplified "cortical microcircuit column" of Mountcastle (1957). Subsequently, many other NMMs have been proposed to account for various neuroimaging data, especially EEG activities (David et al., 2005; Freeman, 1987; Jansen and Rit, 1995; Nunez, 1974; Da Silva et al., 1974; Valdes-Sosa et al., 2009; van Rotterdam et al., 1982; Wendling et al., 2000, 2005; Zetterberg et al., 1978). A particular seminal work by Jansen and Rit (1995) described an NMM that consists of three neuronal subpopulations of excitatory (e.g. spiny stellate and excitatory deep pyramidal), and inhibitory interneuron cells (e.g. basket cells). A simplified representation of the model is shown in Fig. 1a. Subsequent work by David and Friston (2003) used this Jansen–Rit model (JRM) to study the effects of connectivity strength and propagation of synaptic delays on EEG rhythms using two coupled neural populations. They reproduced the power spectra of EEG signals by fitting the model parameters. Moreover, they extended the JRM into a larger range of interconnected cortical sources, allowing the study of brain-wide interactions and is now used in the popular hypothesis-driven framework dynamic causal modelling (DCM) for event-related potentials (ERPs) (David et al., 2005; Friston et al., 2003). Moran et al. (2007) augmented the model's formulation by including two additional effects: spike-frequency adaptation (Benda
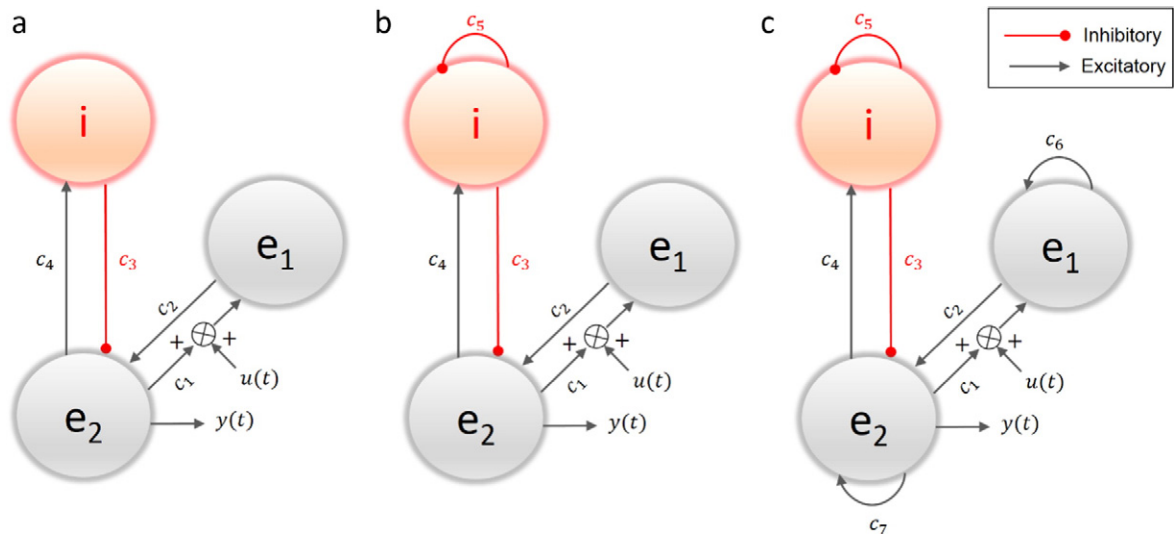
Fig. 1. The schematic representation of three NMMs of a cortical unit with two excitatory ('e_1' and 'e_2') and one inhibitory ('i') subpopulations. a). NMM described by Jansen and Rit (1995). The coupling parameters are specified by c_i, $i = 1, ..., 4$. b). NMM described by Moran et al. (2007). The model has an extra inhibitory self-feedback connection (c_5) within the inhibitory neural population ('i'). Note that we have ignored the propagation delay from 'e_2' to 'e_1' neurons. c). The fully self-feedback model (FSM) has three self-feedback connections (c_5, c_6, c_7). The exogenous input and endogenous output: $u(t)$ and $y(t)$.

and Herz, 2003) and backpropagation intrinsic inhibitory connections (Waters et al., 2005) to model steady-state responses (Moran et al., 2009). Those effects play a key role in slow- and high-frequency oscillations, respectively (Buzsáki and Wang, 2012; Moran et al., 2007). The architecture of the Moran et al. model (MoM), as shown in Fig. 1b, has an added self-inhibitory feedback connection to the inhibitory neural population ('i') and an embedded delay to the excitatory spiny neural population ('e_1'). The rationale in MoM is that the spectral profile can better represent the behaviour of time series of longer time recordings (e.g., local field potentials, or spontaneous EEGs).

Most NMMs from the literature have involved a simplified neural circuit architecture (David and Friston, 2003; David et al., 2005, 2006a; Jansen and Rit, 1995; Moran et al., 2013). However, the local cortical neuronal circuits based on neuroanatomical findings are more complex (Bastos et al., 2012; Douglas and Martin, 2004, 2010; Mountcastle, 1957; Reimann et al., 2013; Thomson and Bannister, 2003). Moreover, some important connectivities have been ignored in many NMMs. These include the local reciprocal interactions in a variety of neuronal types or feedback influence of action potentials on dendritic membrane potentials (Haeusler and Maass, 2007; Vetter et al., 2001; Waters et al., 2005). In particular, based on mean-field theory, any population of coupled neurons is intrinsically endowed with effective self-coupling, and these intra-population self-feedbacks can be crucial for generating certain brain activities (Wilson and Cowan, 1973; Wilson and Cowan, 1972). Functionally, they can act as a self-controlling mechanism among inhibitory cells that are important for generating gamma rhythm EEG activities (40–70 Hz) (Buzsáki and Wang, 2012; Vida et al., 2006) or self-excitation among excitatory neurons for learning, memory, decision-making and other related cognitive processes (Deco et al., 2008; Douglas et al., 1995; Durstewitz et al., 2000; Hopfield, 1982, 1984; Wong and Wang, 2006).

In mismatch negativity auditory oddball (MMN-AOD) paradigm, the occasional deviant ("oddball") stimuli violate the expectations due to regular ("standard") stimuli and is indicated by an increased response in ERP components (Alho, 1995; Garrido et al., 2009) and gamma band activities (Todorovic et al., 2011). They mostly appear in the vicinity of fronto-central and temporal (auditory cortex) brain areas between 100 and 250 ms post-stimulus (Giard et al., 1990; Näätänen et al., 2007). In terms of the generation of mismatch responses, it has been hypothesised that the inability of higher cortical areas to predict

sensory information, resulting in a prediction error, can lead to enhanced activities relative to predictable responses (Garrido et al., 2007a; Lieder et al., 2013; Summerfield et al., 2008; Wacongne et al., 2012). Moreover, they can be caused by involuntary (top–down) attention and automatic reactions to change in stimuli (Escera and Corral, 2008; Prinzmetal et al., 2010). Such behaviours can be interpreted as interneuronal feedback effects (Bastos et al., 2012).

In the present work, we seek to further understand the computational roles of similar interneuronal feedback in MMN-AOD using ERP data. Specifically, we introduce an extension of previous NMMs (David and Friston, 2003; David et al., 2005, 2006a; Jansen and Rit, 1995; Moran et al., 2007) that comprises self-feedback connections within each of the three ('e_1', 'e_2', and 'i') neural subpopulations in line with the known biology (Haeusler and Maass, 2007). Hereafter, we name it as the fully self-feedback model (FSM) (Fig. 1c). This model will be compared to the classic JRM and the modified version (without spike-frequency adaptation) of the MoM. For simplicity, we shall henceforth study and term this modified model MoM. Initially, we make use of bifurcation analysis (i.e., sudden changes in dynamic behaviour) to examine the oscillatory behaviours of the three models. Next, under a forward modelling approach, we simulate the ERPs obtained from five subjects. The Bayesian inversion is employed to optimise the free parameters and fit the outputs to the observed data. To further understand the underlying neural dynamics of MMN process, an inference is made on the intrinsic parameters. A goodness-of-fit assessment, based on free energy (or log-model evidence) criterion is employed to address the face validity of the models (Penny, 2012). Finally, we extend our simulations to the multi-area modelling by coupling multiple single-area models. Using five interconnected units and under a forward–backward functional hypothesis, we compare the outcome from 3 NMMs. The results and implications are further discussed in the sections below.

Materials and methods

Generative models

The basic structure of our proposed single cortical source is presented in Fig. 2. Compared with the JRM, our FSM has three extra self-feedback connections, each assigned to 3 subpopulations consisting of