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Q1 Spike phase synchronization in multiplex cortical neural networks

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HIGHLIGHTS

- Chemical synapses and gap junctions in *C. elegance* networks have different synchronizability.
- The cortical networks have better synchronizability than the random networks.
- Modularity of the networks is one of the main driving effects for their synchronizability.

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ABSTRACT

In this paper we study synchronizability of two multiplex cortical networks: whole-cortex of hermaphrodite *C. elegans* and posterior cortex in male *C. elegans*. These networks are composed of two connection layers: network of chemical synapses and the one formed by gap junctions. This work studies the contribution of each layer on the phase synchronization of non-identical spiking Hindmarsh–Rose neurons. The network of male *C. elegans* shows higher phase synchronization than its randomized version, while it is not the case for hermaphrodite type. The random networks in each layer are constructed such that the nodes have the same degree as the original network, thus providing an unbiased comparison. In male *C. elegans*, although the gap junction network is sparser than the chemical network, it shows higher contribution in the synchronization phenomenon. This is not the case in hermaphrodite type, which is mainly due to significant less density of gap junction layer (0.013) as compared to chemical layer (0.028). Also, the gap junction network in this type has stronger community structure than the chemical network, and this is another driving factor for its weaker synchronizability.

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1. Introduction

Many real systems can be modeled as networks; a collection of individual nodes interacting through (directed or undirected, weighted or unweighted) edges [1–3]. The last two decades have witnessed tremendous progress on understanding statistical and dynamical properties of complex networked systems. It has been shown that many real networks share some common properties such as small-worldness [4], scale-free degree distribution [5] and community structure [6]. Such properties significantly influence how dynamical processes evolve on networks and the way collective actions emerge [7]. Synchronization is the most widely studied collective behavior in networked systems [8]. It happens when two (or more) dynamical systems meet and interact; if the interactions between the individual dynamical units are strong enough, their behavior shows a time-correlated activity, i.e., they get into synchrony. There are different types of synchronization phenomenon such as complete, bubbling and lag synchronization. The synchronization type observed in

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many real systems is phase synchronization that is due to (often) weak coupling between the dynamical units [9]. Two (or more) dynamical systems are phase synchronized if their phases get into coherency.

Recently, there has been much effort in the community of network science on moving from single-layer modeling of network systems to multi-layer modeling, which is mainly due to enhanced resolution of network datasets [10]. In single-layer modeling of a networked system, all node-to-node interactions are treated the same and the only difference between them is characterized by their weight (in some applications the links can have positive or negative weights). However, in a multi-layer framework, the connection links are organized in different layers, which allows considering temporal- or context-related properties of the interactions. Indeed, multi-layer networks include a set of nodes and several layers of connections, accurately describing the node-to-node interactions, and/or the whole system's parallel functioning. Examples of such multi-layer networks include road and rail traffic networks [11], air transportation networks [12], online social networks with several types of relations such as friendship, vicinity, membership and partnership [13], and international trade networks [14]. Although there are many research studies addressing the problem of synchronization (or consensus) in single-layer networked systems, there are few works investigating the problem in multi-layer networks [15,16]. In this work we study the role of layers on the synchronization phenomenon in two real multi-layer cortical neural networks.

Temporal synchronization of neuronal activities plays an important role in neural binding and information processing mechanisms [17,18]. Various brain disorders such as schizophrenia and Alzheimer's disease are linked to abnormality in the synchronization level of the brain [19–22]. Often, a specific mathematical neuron model is employed, and real or synthetic networks are used to study the synchronization phenomenon in neural networks [23–26]. There are two types of connections in neuronal networks: uni-directional chemical synapses and bi-directional electrical couplings through gap junctions. Various studies reported that these two modalities of synaptic transmission closely interact in brain's functioning, see a review in Ref. [27]. For example, studying the role of these two types of synaptic connections on the central respiratory rhythm-generating system showed that the chemical couplings are mainly responsible for the production of respiratory cycle timing, while both electrical and chemical connections are involved in short-time-scale synchronization [28].

Both chemical synapses and gap junctions have been shown to be important in synchronizing the neural activity [28–31]. It has been shown that combined electrical and chemical couplings entrain synchronized gamma oscillations, which is required to many cognitive functions of the brain [32,33]. These two types of connections orchestrate action potential timings in oscillatory interneuronal networks. Electrical coupling through gap junctions have been frequently reported to enhance synchronization in the gamma frequencies [29]. A computational study suggests that electrical coupling have the main role in providing synchrony among neuronal networks, while chemical connections have the complementary role [25]. Jhou et al. introduced multistate synchronization in combined chemically and electrically coupled neural networks [34]. They identified the regions for coupling strength to achieve the synchronization. Baptista et al. studied the combined action of chemical and gap junction connections in model small-world networks [35]. They provided numerical simulations on Hindmarsh–Rose neurons coupled through excitatory/inhibitory chemical synapses and gap junctions. Previous works studied the role of chemical and electrical coupling on model networks (e.g., random, small-world and scale-free network topologies). In this work, we consider two real multiplex networks: whole-cortex connectivity network in hermaphrodite *C. elegans* [36] and that of posterior cortex in male *C. elegans* [37], and study the phase synchronization of spike trains. Each of these networks has two distinct connection layers, chemical synapses and gap junctions, each with its own functionality in the system. We study the role of each layer in the synchronization. We also compare the synchronizability of each layer with corresponding randomized networks, allowing to study the role of network synchronization in its evolution process.

2. Dynamical equations

In this work we consider multiplex networks as the connection structure. In these networks, the connections exist in different layers, and the nodes are identical across the layers. We study phase synchronization among N neurons with the same dynamics. On each node of the connection graph a dynamical system sits and the equations of the motion of the dynamical network read as

$$\dot{\boldsymbol{x}}_i(t) = F(\boldsymbol{x}_i(t)) + \sum_{l=1}^{M} \sigma_l \sum_{j=1}^{N} a_{l,ij} H_l\left(\boldsymbol{x}_j(t), \boldsymbol{x}_i(t)\right); \quad i = 1, 2, \ldots, N, \tag{1}$$

where $\boldsymbol{x}_i \in \mathbb{R}^d$ are the state vectors and $F : \mathbb{R}^d \to \mathbb{R}^d$ defines the individual system's dynamical equation. M is the number of layers, and the individual dynamical systems are coupled via a unified coupling strength σ_l and coupling matrix $A_l = (a_{l,ij})$ in each layer. Here we consider binary connections that is $a_{l,ij} = 1$, if there is a link from node i to j in layer l, and zero otherwise. There are no self-loops that means the diagonal entries of A_l equal to zero. $H_l(.)$ is a projection function showing the coupling function between the individual units in layer l. Considering linear coupling between the dynamical systems in all layers, Eq. (1) can be rewritten as

$$\dot{\boldsymbol{x}}_i(t) = F(\boldsymbol{x}_i(t)) + \sum_{l=1}^{M} \sigma_l \sum_{j=1}^{N} a_{l,ij} H\left(\boldsymbol{x}_j(t) - \boldsymbol{x}_i(t)\right); \quad i = 1, 2, \ldots, N. \tag{2}$$

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