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► To cite this version:

Nikolaos Vardalakis, Amélie Aussel, Nicolas P. Rougier, Fabien B Wagner. A dynamical computational model of theta generation in hippocampal circuits to study theta-gamma oscillations during neurostimulation. eLife, inPress. hal-04383365

HAL Id: hal-04383365

<https://inria.hal.science/hal-04383365>

Submitted on 9 Jan 2024

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A dynamical computational model of theta generation in hippocampal circuits to study theta-gamma oscillations during neurostimulation

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Abstract

Neurostimulation of the hippocampal formation has shown promising results for modulating memory but the underlying mechanisms remain unclear. In particular, the effects on hippocampal theta-nested gamma oscillations and theta phase reset, which are both crucial for memory processes, are unknown. Moreover, these effects cannot be investigated using current computational models, which consider theta oscillations with a fixed amplitude and phase velocity. Here, we developed a novel computational model that includes the medial septum, represented as a set of abstract Kuramoto oscillators producing a dynamical theta rhythm with phase reset, and the hippocampal formation, composed of biophysically-realistic neurons and able to generate theta-nested gamma oscillations under theta drive. We showed that, for theta inputs just below the threshold to induce self-sustained theta-nested gamma oscillations, a single stimulation pulse could switch the network behavior from non-oscillatory to a state producing sustained oscillations. Next, we demonstrated that, for a weaker theta input, pulse train stimulation at the theta frequency could transiently restore seemingly physiological oscillations. Importantly, the presence of phase reset influenced whether these two effects depended on the phase at which stimulation onset was delivered, which has practical implications for designing neurostimulation protocols that are triggered by the phase of ongoing theta oscillations. This novel model opens new avenues for studying the effects of neurostimulation on the hippocampal formation. Furthermore, our hybrid approach that combines different levels of abstraction could be extended in future work to other neural circuits that produce dynamical brain rhythms.

Introduction

Neurostimulation methods have emerged as promising therapeutic modalities to restore neurological functions in a broad range of motor and cognitive disorders (*Gupta et al., 2023*). In the context of learning and memory, deep brain stimulation (DBS) of the entorhinal area or hippocampus has been shown to either enhance (*Suthana et al., 2012; Suthana and Fried, 2014; Titiz et al., 2017; Jun et al., 2019*) or disrupt (*Jacobs et al., 2016; Goyal et al., 2018; Lozano et al., 2016*) memory encoding. These conflicting results may originate from differences in experimental protocols and from a poor understanding of their biophysical underpinnings. Among such mechanisms, the in-

40 involvement of hippocampal theta oscillations (4-12 Hz) and their interactions with higher-frequency
41 gamma oscillations (30-120 Hz) in memory-related processes has been reported in multiple studies
42 (*Lisman et al., 2005; de Almeida et al., 2007; Lega et al., 2012; Lin et al., 2017; Malkov et al., 2022;*
43 *Abbaspoor et al., 2023*). Moreover, the modulation of gamma oscillations by the phase of theta os-
44 cillations in hippocampal circuits, a phenomenon termed theta-gamma phase-amplitude coupling
45 (PAC), correlates with the efficacy of memory encoding and retrieval (*Jensen and Colgin, 2007; Tort*
46 *et al., 2009; Canolty and Knight, 2010; Axmacher et al., 2010; Fell and Axmacher, 2011; Lisman and*
47 *Jensen, 2013; Lega et al., 2016*). Experimental and computational work on the coupling between
48 oscillatory rhythms has indicated that it originates from different neural architectures and corre-
49 lates with a range of behavioral and cognitive functions, enabling the long-range synchronization
50 of cortical areas and facilitating multi-item encoding in the context of memory (*Hyafil et al., 2015*).

51 Neurostimulation protocols that affect these rhythms, such as theta burst stimulation (*Titiz*
52 *et al., 2017*), have also been shown to optimally induce long-term potentiation (LTP) (*Larson and*
53 *Munkácsy, 2015*). Another potential mechanism underlying the effect of hippocampal neurostim-
54 ulation might be the reset of the phase of theta oscillations in response to exogenous inputs, such
55 as a novel sensory input or a pulse of electrical stimulation applied to the fornix or perforant path
56 (*Buño et al., 1978; Williams and Givens, 2003*). Theta phase reset is known to facilitate LTP (*McCart-*
57 *ney et al., 2004*) and naturally occurs during both encoding and retrieval of associative memories
58 (*Kota et al., 2020*). In this context, the design of a computational model that replicates memory-
59 related theta-gamma oscillations and theta phase reset is of uttermost importance to investigate
60 the effects of electrical stimulation on the hippocampal formation and possibly optimize neurostim-
61 ulation protocols for memory improvement.

62 Models of memory-related theta-gamma oscillations in the hippocampal formation have been
63 developed across different resolution levels, ranging from abstract mean-field approaches (*Traub*
64 *et al., 1997; Onslow et al., 2014; Segneri et al., 2020*) to biophysically-realistic conductance-based
65 models (*Lundqvist et al., 2006; Herman et al., 2013; Aussen et al., 2018*). Neural masses, which
66 represent the mean activity of a neuronal population, can generate gamma oscillations through
67 reciprocal interactions between an excitatory and inhibitory population (*Traub et al., 1997; Onslow*
68 *et al., 2014*), or even using a self-projecting inhibitory population (*Segneri et al., 2020*). Under exci-
69 tatory oscillatory input at theta frequencies, these models are capable of generating theta-nested
70 gamma oscillations. Similarly, these oscillations can be observed in more complex models of the
71 hippocampal formation composed of single-compartment excitatory and inhibitory neurons con-
72 nected through conductance-based synapses following the Hodgkin-Huxley formalism (*Hodgkin*
73 *and Huxley, 1952*), and driven by a fixed oscillatory theta input (*Aussen et al., 2018*). Theta-nested
74 gamma oscillations also appear in multi-compartment models of prefrontal cortex activity during
75 memory retrieval (*Lundqvist et al., 2006; Herman et al., 2013*). Finally, several models have inves-
76 tigated the functional link between the hippocampal theta rhythm and memory processes, show-
77 ing that encoding and retrieval occur at different phases within each theta cycle through phasic
78 changes in neuronal activity and LTP (e.g., *Hasselmo et al. (2002); Cutsuridis et al. (2010)*).

79 In terms of neurostimulation, most computational work has focused on the mechanisms under-
80 lying DBS of the basal ganglia for motor disorders such as Parkinson's disease (*Rubin and Terman,*
81 *2004; Pirini et al., 2009; Mina et al., 2013; Ebert et al., 2014*), peripheral nerve stimulation (*Rattay*
82 *et al., 2003; Kipping and Nogueira, 2022*), spinal cord stimulation (*Rattay et al., 2000; Capogrosso*
83 *et al., 2013*), or has remained generic (*Basu et al., 2018*). However, models investigating neurostim-
84 ulation of hippocampal circuits are scarce (*Hendrickson et al., 2016; Bingham et al., 2018*), and do
85 not take into account the effects on theta-gamma oscillations. For example, a detailed multicom-
86 partment model of the rat dentate gyrus was able to replicate experimentally recorded local field
87 potentials induced by different electrode placements and pulse amplitudes during stimulation of
88 the perforant path (*Bingham et al., 2018*). To model the impact of neurostimulation on neuronal
89 oscillations, a more abstract formalism based on Kuramoto phase oscillators (*Kuramoto, 1984*) has
90 been introduced in the context of Parkinson's disease and essential tremor, which enabled the de-

91 sign of novel neurostimulation paradigms that enhance or disrupt neuronal synchrony in basal
92 ganglia circuits (*Tass, 2003; Ebert et al., 2014; Asllani et al., 2018; Weerasinghe et al., 2019*).

93 To our knowledge, there is currently no model of the hippocampal formation that is able to
94 replicate both theta-gamma PAC and theta phase reset during neurostimulation. To investigate
95 the effects of neurostimulation on hippocampal circuits while taking into account these two mech-
96 anisms, we modified an existing biophysical model of the hippocampal formation (*Aussel et al.,*
97 *2018*). In this original model, however, the theta rhythm was considered as an oscillatory input of
98 fixed amplitude and phase velocity, which is inconsistent with theta phase reset. To circumvent this
99 limitation, we combined this biophysical model with abstract Kuramoto oscillators that acted as a
100 dynamical source of theta rhythm, thereby modeling medial septum inputs to the hippocampal for-
101 mation. This new hybrid dynamical model could generate both theta-nested gamma oscillations
102 and theta phase reset, following a particular phase response curve (PRC) inspired by experimental
103 literature (*Lengyel et al., 2005; Akam et al., 2012; Torben-Nielsen et al., 2010*).

104 We then leveraged this model to explore the effect of single-pulse and pulse-train stimulation
105 on theta-gamma oscillations. In the absence of theta input from the medial septum, single-pulse
106 stimulation produced a transient effect consisting of one or several bursts of activity, depending
107 on stimulation amplitude. The presence of multiple bursts depended on the single-cell calcium dy-
108 namics and M-type potassium adaptation current. In the presence of weak theta input, designed
109 to mimic a pathological state that impairs theta-gamma oscillations, single-pulse stimulation could
110 produce long-lasting or even persistent activity by switching the network to a highly synchronized
111 state characterized by theta-nested gamma oscillations. When phase reset was not included in the
112 model, this effect was more pronounced when the stimulation pulse was delivered at the peak of
113 the theta rhythm. However, when strong theta reset was considered, the phase at which stimula-
114 tion was delivered did not influence the outcome. In the presence of an even weaker theta input,
115 mimicking a pathological state that completely abolishes theta-gamma oscillations, only pulse train
116 stimulation could restore physiological theta-gamma oscillations during the stimulation period. As
117 for the previous results, this effect was phase-dependent only when theta reset was not included.

118 These results provide a new framework to interpret neurostimulation interventions that inter-
119 fere with hippocampal oscillations and aim at improving memory function. It can be further ex-
120 tended to investigate the effects of more complex neurostimulation protocols, and the impact of
121 stimulation location and amplitude on the observed network dynamics.

122 Results

123 A computational model of the hippocampal formation with dynamical theta input

124 We first developed a computational model of hippocampal circuits, able to generate both theta-
125 nested gamma oscillations and theta phase reset. To achieve this, we combined an existing con-
126 ductance-based model of the hippocampal formation (*Aussel et al., 2018*) with a set of Kuramoto
127 phase oscillators (*Kuramoto, 1984*) that were used to model the dynamical theta input originating
128 from pacemaker neurons in the medial septum (*Wang, 2002*) (*Figure 1A*). Such ensembles of os-
129 cillators are designed to exhibit a strong phase reset of their collective rhythm in response to a
130 perturbation (*Levnajić and Pikovsky, 2010*). The hippocampal model contained excitatory and in-
131 hibitory neuronal populations in the entorhinal cortex (EC), dentate gyrus (DG), CA3 and CA1 fields
132 within a coronal slice of the human hippocampus (*Figure 1B-C*). The output of the hippocampal
133 formation (i.e., the activity of CA1 pyramidal neurons) was provided as an input to the Kuramoto
134 oscillators, simulating the hippocampal-septal projections through the fornix (*Williams and Givens,*
135 *2003; Nuñez and Buño, 2021; Takeuchi et al., 2021*). The oscillations produced by the collective be-
136 havior of Kuramoto oscillators represented a population average of their activity: highly synchron-
137 ized and desynchronized states generated respectively high and low amplitude theta oscillations
138 (*Figure 1D*). The number of oscillators was chosen so that their synchronization level (i.e., their or-
139 der parameter) and their frequency distribution were sufficiently close to their asymptotic behavior

140 for a large number of oscillators (*Figure S1*).

141 Biologically, GABAergic neurons from the medial septum project to the EC, CA3, and CA1 fields
142 of the hippocampus (*Toth et al., 1993; Hajós et al., 2004; Manseau et al., 2008; Hangya et al., 2009;*
143 *Unal et al., 2015; Müller and Remy, 2018*). Although the respective roles of these different pro-
144 jections are not fully understood, previous computational studies have suggested that the direct
145 projection from the medial septum to CA1 is not essential for the production of theta in CA1 micro-
146 circuits (*Mysin et al., 2019*). Since our modeling of the medial septum is only used to generate a
147 dynamic theta rhythm, we opted for a simplified representation where the medial septum projects
148 only to the EC, which in turn drives the different subfields of the hippocampus. In our model, Ku-
149 ramoto oscillators are therefore connected to the EC neurons and they receive projections from
150 CA1 neurons (see methods for more details).

151 From a conceptual point of view, our model is thus composed of excitatory-inhibitory (E-I) cir-
152 cuits connected in series, with a feedback loop going through a population of coupled phase oscil-
153 lators. In the next sections, we first describe the generation of gamma oscillations by individual E-I
154 circuits (*Figure 2*), and illustrate their behavior when driven by an oscillatory input such as theta
155 oscillations (*Figure 3*). We then present a thorough characterization of the effects of theta input
156 and stimulation amplitude on theta-nested gamma oscillations (*Figure 4* and *Figure 5*). Finally,
157 we present some results on the effects of neurostimulation protocols for restoring theta-nested
158 gamma oscillations in pathological states (*Figure 6* and *Figure 7*).

159 **Generation of gamma oscillations by E-I circuits**

160 It is well-established that a network of interconnected pyramidal neurons and interneurons can
161 give rise to oscillations in the gamma range, a mechanism termed pyramidal-interneuronal net-
162 work gamma (PING) (*Traub et al., 2004; Onslow et al., 2014; Segneri et al., 2020*). This mechanism
163 has been observed in several optogenetic studies with gradually increasing light intensity (i.e., un-
164 der a ramp input) affecting multiple different circuits, such as layer 2-3 pyramidal neurons of the
165 mouse somatosensory cortex (*Adesnik and Scanziani, 2010*), the CA3 field of the hippocampus in
166 rat in vitro slices (*Akam et al., 2012*), and in the non-human primate motor cortex (*Lu et al., 2015*).
167 In all cases, gamma oscillations emerged above a certain threshold in terms of photostimulation
168 intensity, and the frequency of these oscillations was either stable or slightly increased when in-
169 creasing the intensity further. We sought to replicate these findings with our elementary E-I circuits
170 composed of single-compartment conductance-based neurons driven by a ramping input current
171 (*Figure 2* and *Figure S2*). As an example, all the results in this section will be shown for an E-I cir-
172 cuit that has similar connectivity parameters as the CA1 field of the hippocampus in our complete
173 model (see section "Hippocampal formation: inputs and connectivity" in the methods).

174 For low input currents provided to both neuronal populations, only the highly-excitable in-
175 terneurons were activated (*Figure 2A*). For a sufficiently high input current (i.e., a strong input that
176 could overcome the inhibition from the fast-spiking interneurons), the pyramidal neurons started
177 spiking as well. As the amplitude of the input increased, the activity of the both neuronal popu-
178 lations became synchronized in the gamma range, asymptotically reaching a frequency of about
179 60 Hz (*Figure 2A* bottom panel). Decoupling the populations led to the abolition of gamma oscil-
180 lations (*Figure 2B*), as neuronal activity was determined solely by the intrinsic properties of each
181 cell. Interestingly, when the ramp input was provided solely to the excitatory population, we ob-
182 served that the activity of the pyramidal neurons preceded the activity of the inhibitory neurons,
183 while still preserving the emergence of gamma oscillations (*Figure S2A*). As expected, decoupling
184 the populations also abolished gamma oscillations, with the excitatory neurons spiking a frequency
185 determined by their intrinsic properties and the inhibitory population remaining silent (*Figure S2B*).

186 To further characterize the intrinsic properties of individual inhibitory and excitatory neurons,
187 we derived their input-frequency (I-F) curves, which represent the firing rate of individual neurons
188 in response to a tonic input (*Figure S3A*). We observed that for certain input amplitudes, the fir-
189 ing rates of both types of neurons was within the gamma range. Interestingly, in the absence of

190 noise, each population could generate by itself gamma oscillations that were purely driven by the
191 input and determined by the intrinsic properties of the neurons (*Figure S3B*). Adding stochastic
192 Gaussian noise in the membrane potential disrupted these artificial oscillations in decoupled pop-
193 ulations (*Figure S3C*). All subsequent simulations were run with similar noise levels to prevent the
194 emergence of artificial gamma oscillations.

195 Another potent way to induce gamma oscillations is to drive fast-spiking inhibitory neurons
196 using pulsed optogenetic stimulation at gamma frequencies, a strategy that has been used both in
197 the neocortex (*Cardin et al., 2009*) and hippocampal CA1 (*Iaccarino et al., 2016*). In particular,
198 Cardin and colleagues systematically investigated the effect of driving either excitatory or fast-
199 spiking inhibitory neocortical neurons at frequencies between 10 and 200 Hz (*Cardin et al., 2009*).
200 They showed that fast-spiking interneurons are preferentially entrained around 40-50 Hz, while ex-
201 citatory neurons respond better to lower frequencies. To verify the behavior of our model against
202 these experimental data, we simulated pulsed optogenetic stimulation as an intracellular current
203 provided to our reduced model of a single E-I circuit. Stimulation was applied at frequencies be-
204 tween 10 and 200 Hz to excitatory cells only, to inhibitory cells only, or to both at the same time
205 (*Figure S4*). The population firing rates were used as a proxy for the local field potentials (LFP), and
206 we computed the relative power in a 10-Hz band centered around the stimulation frequency, simi-
207 larly to the method proposed in (*Cardin et al., 2009*). When presented with continuous stimulation
208 across a range of frequencies in the gamma range, interneurons showed the greatest degree of
209 gamma power modulation (*Figure S4*). Furthermore, when the stimulation was delivered to the ex-
210 citatory population, the relative power around the stimulation frequency dropped significantly in
211 frequencies above 10 Hz, similar to the reported experimental data (*Cardin et al., 2009*). The main
212 difference between our simulation results and these experimental data is the specific frequencies
213 at which fast-spiking interneurons showed resonance, which was around 40 Hz in the mouse barrel
214 cortex and around 90 Hz in our model, a fast gamma rhythm. This could be attributed to several fac-
215 tors, such as differences in the cellular properties between cortical and hippocampal fast-spiking
216 interneurons, or the differences between the size of the populations and their relevant connectivity
217 in the cortex and the hippocampus.

218 **Theta-gamma oscillations and theta phase reset under dynamical theta input**

219 Once we validated that our elementary E-I circuits were able to generate gamma oscillations under
220 an input of sufficiently high amplitude, we studied the behavior of the whole model when the theta
221 input was dynamically provided by the Kuramoto oscillators as described above (*Figure 1*). As in the
222 original model (*Aussel et al., 2018*), the input theta rhythm drove the network to produce spiking
223 activity in the gamma range preferentially around the peak of theta in all excitatory and inhibitory
224 populations (*Figure 3A* and *Figure S5*). Spectrograms of the CA1 population firing rates revealed
225 that these bursts of activity around each theta peak were characterized by oscillations around 60
226 Hz (*Figure 3A*). This was confirmed by power spectral densities, which showed a clear peak at 4
227 Hz (corresponding to the theta drive) and increases in gamma band activity between 40 and 80
228 Hz (*Figure 3B*). To quantify PAC between theta and gamma oscillations, we used the modulation
229 index (MI) (*Tort et al., 2008, 2010*), which has been shown to outperform other similar measures
230 (*Hülsemann et al., 2019*). However, we discovered that this metric would give erroneous results
231 in our simulated datasets due to the absence of certain frequency components. To overcome
232 this limitation and avoid artifacts, uniform noise was added to the firing rates prior to computing
233 the MI (*Figure S6*). We first visualized the quantification of PAC using the comodulogram, which
234 indicates the MI as a function of two frequencies corresponding to the modulating phase signal
235 and the modulated amplitude signal. This analysis confirmed that gamma-band signals between
236 45 and 75 Hz were modulated by lower theta frequencies between 3 and 6 Hz, which we quantified
237 by computing a global MI in frequency ranges encompassing theta (3-9 Hz) and gamma (40-80
238 Hz) (*Figure S5B*). To refine this analysis, we also computed a similar MI between the amplitude of
239 various gamma frequencies and the phase of theta, which indicated that oscillations between 40

240 and 80 Hz occur preferentially around the peak of theta (*Figure 3C* and *Figure S5B*).

241 Next, we verified that our model was able to display theta phase reset during single-pulse stim-
242 ulation (depolarizing pulse, 1-ms duration). This mechanism is tightly linked with the concept of
243 PRC, which characterizes the phase delay or advancement that follows a single pulse delivered to
244 an oscillatory system, as a function of the phase at which this input is delivered. Although there
245 is no direct measurement of the PRC of septal neurons, such characterizations have been per-
246 formed for individual pyramidal cells in the CA3 and CA1 fields of the hippocampus (*Lengyel et al.,*
247 *2005; Kwag and Paulsen, 2009; Akam et al., 2012*). These PRCs appear biphasic and show a phase
248 advancement (respectively delay) for stimuli delivered in the ascending (respectively descending)
249 slope of theta. We modeled this behavior by a specific term (which we called the phase response
250 function) in the general equation of the Kuramoto oscillators (see methods, *Equation 1*). Impor-
251 tantly, introducing a phase offset in the phase response function disrupted theta-nested gamma
252 oscillations (*Figure S7*), which suggests that the septohippocampal circuitry must be critically tuned
253 to be able to generate such oscillations. The strength of phase reset could also be adjusted by a
254 gain that was manually tuned. In the presence of the physiological phase response function and
255 of a sufficiently high reset gain, a single stimulation pulse delivered to all excitatory and inhibitory
256 CA1 neurons could reset the phase of theta to a value close to its peaks (*Figure 3A*). We computed
257 the PRC of our simulated data for different stimulation amplitudes and validated that our neuronal
258 network behaved according to the phase response function set in our Kuramoto oscillators (*Fig-*
259 *ure 3D*). It should be noted that including this phase reset mechanism affected the generated theta
260 rhythm even in the absence of stimulation, extending the duration of the theta peak and thereby
261 slowing down the frequency of the generated theta rhythm.

262 Importantly, our approach is generalizable and can be applied to other models producing theta-
263 nested gamma oscillations. For instance, we adapted the neural mass model by Onslow and col-
264 leagues (*Onslow et al., 2014*), replaced the fixed theta input by a set of Kuramoto oscillators, and
265 demonstrated that it could also generate theta phase reset in response to single-pulse stimulation
266 (*Figure S8*). These results illustrate that the general behavior of our model is not specific to the
267 tuning of individual parameters in the conductance-based neurons, but follows general rules that
268 are captured by the level of abstraction of the Kuramoto formalism.

269 Overall, we successfully developed a new model of the hippocampal formation able to exhibit
270 both theta-nested gamma oscillations and theta phase reset in response to stimulation. We then
271 decided to explore further the effects of various stimulation protocols on its dynamics.

272 **Effects of theta input and stimulation amplitudes on theta-gamma oscillations**

273 We investigated the behavior of the model across multiple states of varying septal theta input am-
274 plitude in response to single-pulse stimulation delivered to CA1. In the absence of theta drive, a
275 single stimulation pulse elicited either zero or two bursts of spiking activity (depending on stimula-
276 tion amplitude) separated by about 200 ms (*Figure 4A, C*). We first sought to understand the origin
277 of this second burst, as it showed that even a single pulse could induce transient periodic activity
278 around 5 Hz in our model, a frequency within the theta range. A previous model has shown that the
279 presence of Calcium-Activated Non-specific cationic (CAN) currents can lead to self-sustained theta
280 oscillations in the hippocampus (*Giovannini et al., 2017*). Moreover, this study showed a direct link
281 between the increased excitation provided by the CAN current and the spike-frequency adaptation
282 properties of the M-current, directly affecting transitions from an asynchronous low-firing regime
283 to synchronous bursting. We tested the role of the CAN current in the response to single-pulse
284 stimulation by completely removing it from our simulations, which abolished the second burst of
285 activity (*Figure 4B*). Moreover, the time interval separating the two bursts likely resulted from the
286 interplay between the depolarizing CAN current and hyperpolarizing M current (*Figure 4A*).

287 In the presence of dynamic theta input, the effects of single-pulse stimulation depended both
288 on theta input amplitude and stimulation amplitude, highlighting different regimes of network ac-
289 tivity (*Figure 5* and *Figure S9, Figure S10, Figure S11*). For low theta input, theta-nested gamma oscil-

290 lations were initially absent and could not be induced by stimulation (**Figure 5A**). At most, the stim-
291 ulation could only elicit a few bursts of spiking activity that faded away after approximately 250 ms,
292 similar to the rebound of activity seen in the absence of theta drive. For increasing theta input, the
293 network switched to an intermediate regime: upon initialization at a state with no spiking activity, it
294 could be kicked to a state with self-sustained theta-nested gamma oscillations by a single stimula-
295 tion pulse of sufficiently high amplitude (**Figure 5B**). This regime existed for a range of septal theta
296 inputs located just below the threshold to induce self-sustained theta-gamma oscillations without
297 additional stimulation, as characterized by the post-stimulation theta power, gamma power, and
298 theta-gamma PAC (**Figure 5D**). Removing CAN currents from all areas of the model abolished this
299 behavior **Figure S12**, which is interesting given the role of this current in the multistability of EC
300 neurons (**Egorov et al., 2002; Fransén et al., 2006**) and in the intrinsic ability of the hippocampus
301 to generate theta-nested gamma oscillations (**Giovannini et al., 2017**). For the highest theta input,
302 the network became able to spontaneously generate theta-nested gamma oscillations, even when
303 initialized at a state with no spiking activity and without additional neurostimulation **Figure 5C**.

304 **Neurostimulation for restoring theta-gamma oscillations in pathological states**

305 Based on the above analyses, we considered two pathological states: one with a moderate theta in-
306 put (i.e., moderately weak projections from the medial septum to the EC) that allowed the initiation
307 of self-sustained oscillations by single stimulation pulses (**Figure 5**, point B), and one with a weaker
308 theta input characterized by the complete absence of self-sustained oscillations even following
309 transient stimulation (**Figure 5**, point A). In each case, we sought to assess whether single-pulse
310 or pulse train stimulation could induce or restore theta-nested gamma oscillations and whether
311 this effect depended on the phase at which stimulation was delivered (i.e., at the peak or trough of
312 the theta cycle). We hypothesized that any possible phase relationship would also depend on the
313 phase reset mechanism. To test this hypothesis, we ran a series of simulations using two different
314 models: one without phase reset and one with strong phase reset (i.e., the reset gain was set at
315 the value used in **Figure 3**).

316 In the case of a moderate theta input and in the presence of phase reset, delivering a pulse at
317 either the peak or trough of theta could induce theta-nested gamma oscillations (**Figure 6A** and **6C**).
318 By contrast, in the absence of phase reset, only stimulation delivered at the peak of theta was able
319 to induce such oscillations, after some time delay (**Figure 6B**, D). Quantification of these results in
320 terms of theta power, gamma power, and theta-gamma PAC showed strongly similar responses
321 between stimulation delivered at the peak or trough of theta with phase reset enabled, similar but
322 weaker responses with stimulation delivered at the peak of theta with phase reset disabled, and
323 no response in the case of trough stimulation with phase reset disabled (**Figure 6E**).

324 In the case of a weak theta input that completely abolished neuronal oscillations, we delivered
325 stimulation pulses continuously at a frequency matching that of the underlying theta rhythm for a
326 duration of 2 s, in order to restore physiological oscillations (**Figure 7**). The stimulation onset was
327 timed to either the peak or trough of the ongoing theta cycle. The continuous delivery of pulses
328 produced similar results as single-pulse stimulation. With phase reset, pulse train stimulation re-
329 stored theta-nested gamma oscillations within the whole network, irrespective of the phase of
330 stimulation onset (**Figure 7A**, C). Notably, stimulation delivered at the trough forced a reset of the
331 phase of theta rhythm and led to the subsequent delivery of pulses at the peak of theta. Interest-
332 ingly, in the absence of phase reset, peak-targeted stimulation induced theta-gamma oscillations
333 in all network areas easily, while trough-targeted stimulation created artificial bursts that propa-
334 gated in other areas with difficulty, requiring multiple pulses to achieve a fraction of the results
335 of peak-targeted stimulation (**Figure 6B**, D). Comparing these simulations based on theta power,
336 gamma power, and theta-gamma PAC within CA1 (**Figure 7E**) showed similar albeit less striking dif-
337 ferences as single-pulse stimulation, possibly because CA1 was driven directly by the stimulation.
338 Notably, gamma power in the absence of theta phase reset, was higher when utilizing pulse trains.
339 These differences were even more pronounced in areas other than CA1, as can be seen by the

340 gradual emergence of oscillations for trough stimulation without phase reset (*Figure 7D*).

341 Discussion

342 Highlights

343 In summary, we have developed a novel computational model to investigate the effects of elec-
344 trical stimulation on a slice of the hippocampal formation, incorporating two important features
345 related to memory: theta-nested gamma oscillations and theta phase reset. The key innovation
346 compared to previous models (e.g., *Aussel et al. (2018)*) is the introduction of a set of abstract Ku-
347 ramoto oscillators, which represent pacemaker neurons in the medial septum and are interfaced
348 with biophysically realistic neuronal models in the hippocampus. From a methodological point of
349 view, this hybrid interfacing between two levels of abstraction represents an innovation in itself
350 and could be applied to other systems or brain structures that are driven by dynamical rhythms.
351 The main outcomes reported here relate to the importance of the theta reset mechanism when
352 examining the effects of neurostimulation on hippocampal oscillations.

353 A very interesting finding concerns the behavior of the model in response to single-pulse stim-
354 ulation for certain values of the theta amplitude (*Figure 5*). For low theta amplitudes, a single stim-
355 ulation pulse was capable of switching the network behavior from a state with no spiking activity
356 to one with prominent theta-nested gamma oscillations. Whether such an effect can be induced
357 in vivo in the context of memory processes remains an open question. Nevertheless, delivering a
358 single stimulation pulse bilaterally to the human hippocampus during a memory task is sufficient
359 to impair memory encoding (*Lacruz et al., 2010*), suggesting that even single-pulse stimulation can
360 indeed have wide network effects that are behaviorally relevant.

361 The second main finding is that the timing of individual stimulation pulses with respect to the
362 phase of the ongoing theta rhythm matters differently depending on the presence or absence
363 of phase reset (*Figure 6* and *Figure 7*). Human intracranial stimulation data indicate that the re-
364 ceptivity of hippocampal circuits to single-pulse stimulation is modulated by the phase of theta
365 (*Lurie et al., 2022*). A number of studies have also reported conflicting results in terms of memory
366 outcomes, which could potentially be attributed to the induction of phase reset through stimula-
367 tion (*Suthana et al., 2012; Jacobs et al., 2016*). To our knowledge, however, the degree of phase
368 reset that follows each stimulation pulse remains unknown and should be investigated in future
369 experimental studies. From a technological point of view, the two regimes with and without phase
370 reset have opposite predictions concerning the need for closed-loop stimulation protocols that
371 would trigger stimulation in real-time based on the phase of ongoing theta oscillations. Such phase-
372 triggered stimulation would be most useful if the phase reset mechanism remains relatively limited.
373 When this mechanism becomes too strong, regular continuous stimulation appears sufficient to
374 restore physiological theta-gamma oscillations (*Figure 7*).

375 It should also be noted that the reset gain in our simulations (*Equation 1*, gain G_{reset}) was either
376 completely turned off or set at a high value, producing a strong effect that always reset the phase
377 of theta to its peak. In reality, the degree of theta phase reset is dynamic, depending on the en-
378 vironment and associated task requirements (*Rizzuto et al., 2003; Mormann et al., 2005; Jackson*
379 *et al., 2008*), and may be affected by neurodegenerative disorders that affect the connections be-
380 tween the hippocampal formation and the medial septum. Importantly, our proposed framework
381 can simulate intermediate values of the reset gain, which should ideally be fitted to experimental
382 data in future applications.

383 Finally, we modeled pathological states by reducing the maximum amplitude of the theta in-
384 put (*Equation 2*, gain G_θ) until theta-nested gamma oscillations were impaired or even abolished
385 (*Figure 5*). This choice was meant to simulate neurodegeneration in the medial septum, which is
386 known to be affected in Alzheimer's disease, leading to oscillatory disruptions (*Nelson et al., 2014;*
387 *Hampel et al., 2018; Takeuchi et al., 2021*). Another possibility would be that neurodegeneration
388 limits the ability of the septal pacemaker neurons to synchronize, thus producing a weaker col-

389 lective theta rhythm without affecting the maximum amplitude of individual oscillators. Although
390 we simulated this change in our model by reducing the synchronization parameter, the effects
391 on hippocampal oscillations were less pronounced (*Figure S12*). Linking these different modeling
392 parameters to experimental biomarkers will be important in future work.

393 **Limitations**

394 Even though we took great care in developing a precise representation of the hippocampal forma-
395 tion, the resulting model remains a simplification that could be further enriched. In particular, we
396 deliberately modeled only a single theta generator, while multiple intra- and extra-hippocampal
397 generators are known to co-exist (*Kocsis et al., 1999; Hummos and Nair, 2017*). We decided to
398 model septal pacemaker neurons projecting to the EC as the main source of hippocampal theta as
399 reported in multiple experimental studies (*Buzsáki, 2002; Buzsáki et al., 2003; Hangya et al., 2009;*
400 *Colgin, 2013*). However, experimental findings and previous models have also proposed that direct
401 septal inputs are not essential for theta generation (*Wang, 2002; Colgin, 2013; Mysin et al., 2019*),
402 but play an important role in phase synchronization of hippocampal neurons. Furthermore, the
403 model does not account for the connections between the lateral and medial septum and the hip-
404 pocampus (*Takeuchi et al., 2021*). These connections include the inhibitory projections from the
405 lateral to the medial septum and the monosynaptic projections from the hippocampal CA3 field to
406 the lateral septum. An experimental study has highlighted the importance of the lateral septum in
407 regulating the hippocampal theta rhythm *Bender et al. (2015)*, an area that has not been included
408 in the model. Specifically, theta-rhythmic optogenetic stimulation of the axonal projections from
409 the lateral septum to the hippocampus was shown to entrain theta oscillations and lead to behav-
410 ioral changes during exploration in transgenic mice. To account for these discrepancies, our model
411 could be extended by considering more realistic connectivity patterns between the medial / lateral
412 septum and the hippocampal formation, including glutamatergic, cholinergic, and GABAergic re-
413 ciprocal connections (*Müller and Remy, 2018*), or by considering multiple sets of oscillators each
414 representing one theta generator.

415 In terms of neuronal cell types, we also made an important simplification by considering only
416 basket cells as the main class of inhibitory interneuron in the whole hippocampal formation. How-
417 ever, it should be noted that many other types of interneurons exist in the hippocampus and have
418 been modeled in various works with higher computational complexity (e.g., *Bezaire et al. (2016);*
419 *Chatzikalymniou et al. (2021)*). Among these various interneurons, oriens-lacunosum moleculare
420 (OLM) neurons in the CA1 field have been shown to play a crucial role in synchronizing the activity
421 of pyramidal neurons at gamma frequencies (*Tort et al., 2007*), and in generating theta-gamma
422 PAC (e.g., *Neymotin et al. (2011); Ponzi et al. (2023)*). Additionally, these cells may contribute to
423 the formation of specific phase relationships within CA1 neuronal populations, through the inte-
424 gration between inputs from the medial septum, the EC, and CA3 (*Mysin et al., 2019*). Future work
425 is needed to include more diverse cell types and detailed morphologies modeled through multiple
426 compartments.

427 Another limitation of our model concerns synaptic transmission delays, which have been largely
428 neglected and could affect the phase relationships between the medial septum and different hip-
429 pocampal subfields. Experimental studies have indeed reported time delays in the population
430 activities of connected anatomical structures (i.e., from EC to DG) (*Mizuseki et al., 2009*), with pyra-
431 midal cells in downstream areas like CA3 and CA1 preferentially firing at different phases of theta
432 (*Dragoi and Buzsáki, 2006*). Propagation effects could also depend on the spatial scale of the model.
433 We also decided to represent only a thin coronal slice of the hippocampal formation, and it re-
434 mains unclear how an anatomically-accurate model of the whole structure would behave in terms
435 of propagation of spontaneous and electrically-induced neuronal activity.

436 Importantly, we did not consider learning through synaptic plasticity, even though such mech-
437 anisms could drastically modify synaptic conduction for the whole network (*Borges et al., 2017*).
438 Even more interestingly, the inclusion of spike-timing-dependent plasticity would enable the inves-

439 tigation of stimulation protocols aimed at promoting LTP, such as theta-burst stimulation (*Larson*
440 *and Munkácsy, 2015*). This aspect would be of uttermost importance to make a link with memory
441 encoding and retrieval processes (*Axmacher et al., 2006; Tsanov and Manahan-Vaughan, 2009; Ju-*
442 *tras et al., 2013*) and with neurostimulation studies for memory improvement (*Titiz et al., 2017;*
443 *Solomon et al., 2021*).

444 From the point of view of neurostimulation, future work is needed to extend the current model
445 to a multi-compartment representation of neurites, since axons are known to be preferentially ac-
446 tivated by extracellular electrical stimulation (*Rattay et al., 2003*). Specifically, multi-compartment
447 cable models have been developed to investigate spike initiation and propagation by modeling
448 the axon as a series of resistance-capacitance circuits following its trajectory (*Rattay et al., 2003;*
449 *Joucla and Yvert, 2012; Ashida and Nogueira, 2018*). These models are particularly suited to study
450 the effects of extracellular stimulation, which are non-intuitive and depend as a first approxima-
451 tion on the second spatial derivative of the electrical potential along the cell membrane (*Rattay,*
452 *1986; Rattay et al., 2003; McIntyre et al., 2004; Rattay et al., 2018*). Here, we have modeled electri-
453 cal stimulation as an intracellular current applied equally across all neurons in the targeted area,
454 which is extremely simplified but enables computational tractability. Future developments will fo-
455 cus on developing an equivalent multicompartment model with realistic axonal trajectories while
456 making sufficient simplifications to allow for realistic computation times.

457 Finally, we likened conditions of low theta input to pathological states characteristic of oscil-
458 lopathies such as Alzheimer's disease, as these conditions disrupted all aspects of theta-gamma
459 oscillations in our model: theta power, gamma power, and theta-gamma PAC *Figure 5*. However,
460 it should be noted that changes in theta or gamma power in these pathologies are often unclear,
461 and that the most consistent alteration that has been reported in Alzheimer's disease is a reduction
462 of theta-gamma PAC (for review, see *Kitchigina (2018)*). Future work should explore the effects of
463 cellular alterations intrinsic to the hippocampal formation and their impact on theta-gamma oscil-
464 lations.

465 **Outlook**

466 Overall, this new model of the hippocampal formation represents a methodologically innovative
467 basis to further explore multiple neurostimulation strategies that target hippocampal oscillations.
468 Moreover, the limitations discussed above represent important avenues for future refinements,
469 which will require significant work to overcome the costs in terms of computational tractability (e.g.,
470 modeling the whole hippocampus, or using multicompartment models of axonal trajectories and
471 dendritic trees). Ultimately, such model refinements should allow the investigation of the effects
472 of extracellular stimulation using charge-balanced biphasic pulses and multipolar electrode con-
473 figurations with realistic electrode geometries. Most importantly, we believe that our current work
474 may also serve as an inspiration for future computational models of oscillopathies (not necessarily
475 limited to the hippocampus), which could benefit from interfacing abstract sets of synchronizing
476 oscillators and investigating their interactions with biophysically-realistic neurons.

477 **Materials and Methods**

478 **Computational Model**

479 Overall Architecture

480 We aimed to develop a computational model of the hippocampal formation that is able to generate
481 theta-nested gamma oscillations and takes into account the dynamic nature of the theta input
482 from the medial septum, i.e., the reset of the theta phase following strong activity in the perforant
483 path or fornix (*Buño et al., 1978; Williams and Givens, 2003*). To this end, we adapted a previous
484 biophysical model of the human hippocampal formation under fixed sinusoidal input (*Aussel et al.,*
485 *2018*) and interconnected it with an abstract representation of the medial septum, modeled as an
486 assembly of Kuramoto oscillators (*Kuramoto, 1984*) (*Figure 1*).

487 More precisely, we modeled a 15-mm thick coronal slice of the hippocampal formation which
 488 comprises the DG, the CA3 and CA1 subfields of the hippocampus, and the EC, all populated with
 489 excitatory and inhibitory Hodgkin-Huxley neurons. For the medial septum, we opted for a sim-
 490 plified representation where the medial septum projects only to the EC, which in turn drives the
 491 different subfields of the hippocampus (see also L142-151). In our model, Kuramoto oscillators
 492 are therefore connected to the EC neurons and they receive projections from CA1 neurons (see
 493 sections below for more details).

494 Medial septum: Kuramoto Oscillators

495 The medial septum contains pacemaker neurons (*Varga et al., 2008; Hangya et al., 2009*) that syn-
 496 chronize with one another and generate a global theta rhythm. In turn, these pacemaker neurons
 497 drive downstream areas that receive projections from the medial septum. Here, we modeled the
 498 entire medial septum neuronal assembly as a set of coupled phase oscillators following the Ku-
 499 ramoto model (*Kuramoto, 1984*), which generated the driving theta rhythm that was provided to
 500 the hippocampal formation through the EC (*Breakspear et al., 2010*).

501 Kuramoto oscillators have also been used to investigate the effects of neurostimulation on
 502 synchronized brain rhythms in the context of Parkinson's disease or essential tremor (*Tass, 2003;*
 503 *Weerasinghe et al., 2019*). Here, each Kuramoto oscillator was described by its phase θ_i , which
 504 evolves over time according to the following equation:

$$\frac{d\theta_i}{dt} = \omega_i + \frac{k}{N} \sum_{j=1}^N \sin(\theta_j - \theta_i) + G_{reset} X(t) Z(\theta_i) \quad (1)$$

505 The term ω_i denotes the natural frequency of oscillator i , and is normally distributed around the
 506 center frequency f_0 and with standard deviation σ . The synchronization parameter k represents
 507 the coupling strength of the group of oscillators, and N is the number of oscillators. Higher values
 508 for the synchronization parameter indicate stronger coupling between pairs of oscillators, thus af-
 509 fecting how fast or slow their phases tend to synchronize. The final product $G_{reset} X(t) Z(\theta_i)$ is used
 510 to describe the effects of external inputs on the phase of the oscillators. Here, the only external
 511 input originates in the projections from CA1 to the medial septum. It is described by the instanta-
 512 neous firing rate $X(t)$ of the CA1 excitatory population. G_{reset} is an arbitrary gain that determines
 513 the strength of the CA1 input to the oscillators. Finally, the function $Z(\theta_i)$ describes how the effects
 514 of CA1 inputs on the oscillators depend on the phase of the ongoing theta rhythm.

515 The coherence and phase of the driving theta rhythm I_θ were computed using the order pa-
 516 rameter r to extract the mean amplitude A and the mean phase ϕ of the ensemble of Kuramoto
 517 oscillators as follows:

$$\begin{cases} r(t) &= \frac{1}{N} \sum_{i=1}^N e^{j\theta_i(t)} \\ A(t) &= \text{Re}(r) \\ \phi(t) &= \text{Im}(r) \\ I_\theta(t) &= G_\theta A(t) \frac{\cos(\phi(t))+1}{2} \end{cases} \quad (2)$$

518 where the mean amplitude $A(t)$ and the mean phase $\phi(t)$ are derived by taking the real and imagi-
 519 nary part of the order parameter respectively, and the output theta rhythm $I_\theta(t)$ is a rectified cosine,
 520 multiplied by a gain G_θ that controls the maximum output amplitude (in nA).

521 To simulate the effect of the projections from CA1 to the medial septum on the phase of the
 522 oscillators, an approximation of the instantaneous firing rate of the CA1 excitatory population was
 523 used as the term $X(t)$. To obtain the instantaneous firing rate, we convolved the CA1 population
 524 spike train with an exponential kernel using the following equations:

$$\begin{cases} \frac{dX}{dt} &= -\frac{X}{\tau_{FR}} \\ X_{t+1} &= X_t + \frac{1}{N \tau_{FR}}, \forall t \in t^S \end{cases} \quad (3)$$

Table 1. Full list of the default parameter values for the Kuramoto oscillators.

Parameter	Value
Number of oscillators (N)	250
Center frequency (f_0)	6 Hz
Standard deviation (σ)	0.5 Hz
Synchronization ratio ($\frac{k}{N}$)	15
Phase reset gain (G_{reset})	4
Peak phase (θ_{peak})	0 rad
Firing rate time constant (τ_{FR})	10 ms

where t^S denotes the ordered set of the spike timings, and τ_{FR} determines the exponential decay of the kernel, which was set to 10 ms to compute population activity (for single neurons, a typical value is 100 ms) (Gerstner et al., 2014).

Hereafter, we call the term $Z(\theta)$ the phase response function, to distinguish it from the PRC obtained from experimental data or simulations (see section below "Data Analysis", "Phase Response Curve"). Briefly, the PRC of an oscillatory system indicates the phase delay or advancement that follows a single pulse, as a function of the phase at which this input is delivered. The phase response function $Z(\theta)$ was chosen to mimic as well as possible experimental PRCs reported in the literature (Lengyel et al., 2005; Kwag and Paulsen, 2009; Akam et al., 2012). These PRCs appear biphasic and show a phase advancement (respectively delay) for stimuli delivered in the ascending (respectively descending) slope of theta. To accurately model this behavior, we used the following equation for the phase response function, where θ_{peak} represents the phase at which the theta rhythm reaches its maximum and the parameter ϕ_{offset} controls the desired phase offset from the peak:

$$Z(\theta_i) = -\sin(\theta_i - (\theta_{peak} + \phi_{offset})) \quad (4)$$

An overview of the default parameters for the Kuramoto oscillators and the bidirectional connections between medial septum-hippocampal formation can be found in Table 1.

Hippocampal formation: Hodgkin-Huxley Neurons

The following sections describe in detail how individual neurons and synapses were modeled, and are adapted from the original work by Aussenel and colleagues (Aussenel et al., 2018). Neurons were modeled as conductance-based single compartments, following the Hodgkin-Huxley formalism (Hodgkin and Huxley, 1952), in line with previous work (Aussenel et al., 2022, 2018). The temporal evolution of the membrane potential of each neuron is described by a differential equation whose general form reads:

$$C_m \frac{dV_m}{dt} = -I_L - \sum_{channel} I_{channel} - \sum_{j \in [E, I]} I_{syn_j} + I_\theta + I_{stim} + \eta \quad (5)$$

I_L denotes the leakage current. $I_{channel}$ are currents associated with specific ion channels, namely potassium (I_K), fast sodium (I_{Na}), and low-threshold calcium (I_{Ca}) currents, the CAN current (I_{CAN}) (Giovannini et al., 2017), and the M-type potassium channel current (I_M) responsible for spike adaptation (Kosenko et al., 2012; Sun and Kapur, 2012; Kwag et al., 2014). I_{syn} represents the currents originating from synaptic inputs to the cell and can be either depolarizing (negative sign) or hyperpolarizing (positive sign). η is a Gaussian random noise term accounting for other external inputs and synaptic fluctuations. Theta input from the medial septum is modeled as a depolarizing current and is denoted by I_θ , while electrical stimulation is denoted by I_{stim} . Excitatory neurons represent pyramidal cells in EC, CA3, and CA1, and granule cells in DG. They were modeled with I_{Na} , I_K , and I_{Ca} , and I_M currents, with the addition of I_{CAN} for pyramidal cells. Fast-spiking interneurons in all areas were modeled with I_{Na} and I_K currents. The complete description for all of the above

558 ionic channels and their corresponding currents can be found in (Giovannini et al., 2017). Leakage
 559 currents followed the following equation:

$$I_L = (g_L \times A) \times (V_m - E_L) \quad (6)$$

560 where g_L is the maximum leakage conductance, A is the area of the single compartment corre-
 561 sponding to the membrane of a neuron, and E_L is the reversal potential of the leakage channel.
 562 Channel currents I_K , I_M , I_{CAN} obey the following set of equations:

$$\begin{aligned} I_K &= g_K \times A \times n^4 \times (V_m - E_K) \\ I_M &= g_M \times A \times p \times (V_m - E_M) \\ I_{CAN} &= g_{CAN} \times A \times m_{CAN}^2 \times (V_m - E_{CAN}) \end{aligned} \quad (7)$$

563 where g_K , g_M , g_{CAN} are the maximum conductances for the respective channel, and n , p , m_{CAN} are
 564 the respective gating variables defined by the following differential equations:

$$\begin{aligned} \frac{dn}{dt} &= \frac{n_\infty - n}{\tau_n} \\ \frac{dp}{dt} &= \frac{p_\infty - p}{\tau_p} \\ \frac{dm_{CAN}}{dt} &= \frac{m_{CAN,\infty} - m_{CAN}}{\tau_{m_{CAN}}} \end{aligned} \quad (8)$$

565 For the potassium and CAN currents, the steady-state values for their corresponding gating vari-
 566 ables n_∞ and $m_{CAN,\infty}$ and their corresponding time constants τ_K and τ_{CAN} depend on the following
 567 functions of the transition rate constants:

$$\begin{aligned} n_\infty &= \frac{\alpha_n}{\alpha_n + \beta_n} & m_{CAN,\infty} &= \frac{\alpha_{m_{CAN}}}{\alpha_{m_{CAN}} + \beta_{m_{CAN}}} \\ \tau_n &= \frac{0.2}{\alpha_n + \beta_n} & \tau_{m_{CAN}} &= \frac{0.2}{\alpha_{m_{CAN}} + \beta_{m_{CAN}}} \end{aligned} \quad (9)$$

568 The sodium current (I_{Na}) and calcium current (I_{Ca}) follow a similar set of equations:

$$\begin{aligned} I_{Na} &= g_{Na} \times A \times m^3 \times h \times (V_m - E_{Na}) \\ I_{Ca} &= g_{Ca} \times A \times m^2 \times h \times (V_m - E_{Ca}) \end{aligned} \quad (10)$$

569 with two gating variables m and h defined by the following differential equations:

$$\begin{aligned} \frac{dm}{dt} &= \frac{m_\infty - m}{\tau_m} & \frac{dn}{dt} &= \frac{n_\infty - n}{\tau_n} \\ m_\infty &= \frac{\alpha_m}{\alpha_m + \beta_m} & h_\infty &= \frac{\alpha_h}{\alpha_h + \beta_h} \\ \tau_m &= \frac{0.2}{\alpha_m + \beta_m} & \tau_h &= \frac{0.2}{\alpha_h + \beta_h} \end{aligned} \quad (11)$$

570 The gating variable of I_{CAN} depends on the calcium concentration within the neuron ($[Ca]_i^{2+}$), given
 571 by:

$$\begin{aligned} \frac{d[Ca]_i^{2+}}{dt} &= \gamma(I_{Ca}) + \frac{([Ca]_\infty^{2+} - [Ca]_i^{2+})}{\tau_{[Ca]^{2+}}} \\ \gamma(I_{Ca}) &= \frac{-k_u \times I_{Ca}}{2 \times F \times d \times A} \end{aligned} \quad (12)$$

572 where $\tau_{[Ca]^{2+}} = 1s$ represents the rate of calcium removal from the cell, $[Ca]_\infty^{2+} = 0.24 \text{ mol/L}$ is the
 573 calcium concentration if the calcium channel remains open for a duration of $\Delta T \rightarrow \infty$, $k_u = 10^4$ is a
 574 unit conversion constant, F is the Faraday constant, and $d = 1 \mu m$ is the depth at which the calcium
 575 is stored inside the cell.

Table 2. Full list of parameter values and expressions for pyramidal neurons

Parameter	Expression
A	$29.10^3 cm^2$
C_m	$1. \mu F/cm^2$
g_L	$0.01 mS/cm^2$
E_L	$-70 mV$
g_K	$5 mS/cm^2$
E_K	$-100 mV$
$\alpha_{n,K}$	$-0.032 \frac{V_m+40 mV}{-1+e^{-0.02(V_m+40 mV)}}$
$\beta_{n,K}$	$0.5 e^{-\frac{V_m+43 mV}{40 mV}}$
g_{Na}	$50 mS/cm^2$
E_{Na}	$50 mV$
$\alpha_{m,Na}$	$-0.32 \frac{V_m+42 mV}{-1+e^{-\frac{4 mV}{V_m+42 mV}}}$
$\beta_{m,Na}$	$0.28 \frac{V_m+15 mV}{e^{-\frac{3 mV}{V_m+15 mV}}-1}$
$\alpha_{h,Na}$	$0.128 e^{-\frac{3 mV}{V_m+38 mV}}$
$\beta_{h,Na}$	$\frac{4}{1+e^{-\frac{V_m+15 mV}{5 mV}}}$
g_M	$90 \mu S/cm^2$
E_M	$-100 mV$
p_∞	$\frac{1}{1+e^{-0.01(V_m+35 mV)}}$
τ_p	$\frac{1}{3.3 e^{-\frac{(V_m+35 mV)}{20 mV}} + e^{-\frac{(V_m+35 mV)}{20 mV}}}$
g_{Ca}	$0.1 mS/cm^2$
E_{Ca}	$120 mV$
$\alpha_{m,Ca}$	$-0.055 \frac{V_m+27 mV}{-1+e^{-\frac{17 mV}{V_m+27 mV}}}$
$\beta_{m,Ca}$	$-0.94 e^{-\frac{V_m+75 mV}{17 mV}}$
$\alpha_{h,Ca}$	$-0.000457 e^{-\frac{V_m+13 mV}{50 mV}}$
$\beta_{h,Ca}$	$\frac{0.0065}{e^{-\frac{V_m+15 mV}{28 mV}}}$
g_{CAN}	$25 \mu S/cm^2$
E_{CAN}	$-20 mV$
$\alpha_{m,CAN}$	$0.0002 e^{1.4 \frac{[Ca]_i^{2+}}{0.5 mol/L}}$
$\beta_{m,CAN}$	$0.0002 e^{1.4}$

576 Noise (η), accounting for random inputs to the network, was simulated as intracellular current
577 acting on the membrane voltage and following the properties of a Gaussian random variable with
578 a mean of $0 \mu V$ and a standard deviation of $1000 \mu V$ ($\eta_E \sim N(0, 1000) \mu V$) for excitatory neurons and
579 a mean of $0 \mu V$ and standard deviation of $100 \mu V$ ($\eta_I \sim N(0, 100) \mu V$) for inhibitory neurons. The
580 ratio of 1:10 between the noise terms was adapted from the original work and it accounts for the
581 higher excitability of the inhibitory neurons as well as the E-I population size ratios.

582 The original model introduced some parameters representing the vigilance state (i.e., active
583 wakefulness vs slow-wave sleep). However, the present model only focused on the state of active
584 wakefulness, since this is when memory-related theta-nested gamma oscillations occur. For all
585 simulations, the parameters were set so that the network operated in the wakefulness regime in
586 a healthy hippocampus (Aussel et al., 2018). The full expressions for all the parameters defined
587 above can be found in **Table 2** for pyramidal cells and in **Table 3** for interneurons.

Table 3. Full list of parameter values and expressions for interneurons

Parameter	Expression
A	$14 \cdot 10^3 \text{ cm}^2$
C_m	$1 \mu\text{F/cm}^2$
g_L	0.1 mS/cm^2
E_L	-65 mV
g_K	9 mS/cm^2
E_K	-90 mV
$\alpha_{n,K}$	$0.01 \frac{V_m + 34 \text{ mV}}{1 - e^{-0.1(V_m + 34 \text{ mV})}}$
$\beta_{n,K}$	$0.125 e^{-\frac{V_m + 44 \text{ mV}}{80 \text{ mV}}}$
g_{Na}	35 mS/cm^2
E_{Na}	55 mV
$\alpha_{m,Na}$	$0.1 \frac{V_m + 35 \text{ mV}}{1 - e^{-0.1(V_m + 35 \text{ mV})}}$
$\beta_{m,Na}$	$4 e^{-\frac{V_m + 60 \text{ mV}}{18 \text{ mV}}}$
$\alpha_{h,Na}$	$0.07 e^{-\frac{V_m + 58 \text{ mV}}{20 \text{ mV}}}$
$\beta_{h,Na}$	$\frac{1}{1 + e^{-0.1(V_m + 28 \text{ mV})}}$

588 Synaptic Models

589 Inter-neuronal interactions were modeled as instantaneous AMPA and GABA-A synapses using the
 590 synaptic currents I_{synE} and I_{synI} respectively. Synaptic currents were described by the following bi-
 591 exponential differential equations:

$$\begin{aligned}
 I_{synI,E} &= g_{I,E}(V_m - E_{I,E}) \\
 \frac{dg_{I,E}}{dt} &= \frac{1}{\tau_{g_{I,E}}}(-g_{I,E} + h_{I,E}) \\
 \frac{dh_{I,E}}{dt} &= -h_{I,E} \frac{1}{\tau_{h_{I,E}}}
 \end{aligned} \tag{13}$$

592 where $E_{I,E}$ are the synaptic resting potentials, and $\tau_{g_{I,E}}$ and $\tau_{h_{I,E}}$ are the synaptic time constants of
 593 rise and decay for inhibitory and excitatory neurons respectively. The occurrence of a pre-synaptic
 594 spike leads to an increase of the values h_I or h_E in the post-synaptic neuron by a fixed amount,
 595 which depends on the type of synapse and the region (due to the presence of cholinergic effects
 596 described in the initial model). Specific values for the intra-area and inter-area synaptic connec-
 597 tions are given in **Table 4** and **Table 5** respectively.

Table 4. A pre-synaptic spike causes an increase in the conductances h_e and h_i in the post-synaptic neuron. The values for the intra-area connections are given here. Empty cells indicate no connection between the populations.

	E → E	E → I	I → E	I → I
EC		20 pS	600 pS	
DG		180 pS	1800 pS	
CA3	20 pS	20 pS	600 pS	
CA1		60 pS	1800 pS	1800 pS

598 Hippocampal formation: neuron types and numbers

599 Each area of the network is comprised of two populations, one excitatory and one inhibitory. Excita-
 600 tory cells in the DG represent granule cells and pyramidal neurons in all other areas. Interneurons
 601 represent basket cells across all areas. The ratio between pyramidal neurons and interneurons

Table 5. A pre-synaptic spike causes an increase in the conductances h_e and h_i in the post-synaptic neuron. The values for the inter-area connections are given here. Empty cells indicate no connection between the areas. Recurrent projections are not allowed and are marked with dashes.

Source \ Target	EC	DG	CA3	CA1
EC	-	20 pS	20 pS	20 pS
DG		-	180 pS	
CA3			-	20 pS
CA1	60 pS			-

602 was directly adapted from *Aussel et al. (2018)*. The ratio between pyramidal neurons and interneurons was kept as a ratio of 10:1 for all areas except the dentate gyrus, where the ratio was 100:1.
 603
 604 The number of neurons per subfield of the hippocampal formation is summarized in *Table 6*.

Table 6. Number of neurons per subfield of the hippocampal formation, divided by neuron type.

Area	N_{Exc}	N_{Inh}
EC	10,000	1,000
DG	10,000	100
CA3	10,000	100
CA1	10,000	1,000

605 A two-dimensional simplified image depicting a coronal slice of the hippocampal formation
 606 (*Aussel et al., 2018*) was used as a basis for a two-dimensional manifold that was uniformly popu-
 607 lated by neurons following a density-driven approach (*Rougier, 2018*). Pyramidal neurons were
 608 uniformly distributed within the stratum pyramidale (or within the stratum granulosum for the den-
 609 tate gyrus) and interneurons were uniformly distributed within the stratum oriens. Initial neuron
 610 positions were drawn from a blue noise distribution and a Voronoi diagram was computed. To ad-
 611 just the positions of the neurons over a centroidal Voronoi diagram, the Lloyd relaxation algorithm
 612 was applied for 1000 iterations. Transitioning from a two-dimensional manifold to a 3D reconstruc-
 613 tion of the hippocampal formation was achieved through the addition of the third coordinate with
 614 values uniformly distributed between 0 and 15 mm.

615 Hippocampal formation: inputs and connectivity

616 The hippocampal formation receives most of its external inputs from the EC. Activity from the EC
 617 is projected to all hippocampal subfields, starting with the DG. DG granule cells project onto the
 618 CA3 pyramidal cells via mossy cell fibers. CA3 projects in turn to CA1 via Schaffer collaterals. These
 619 connections form the tri-synaptic pathway. Direct connections from the EC towards the CA3 and
 620 CA1 subfields through the monosynaptic pathway are also considered. Pyramidal neurons from
 621 CA1 project to pyramidal neurons and interneurons in the EC, closing the hippocampal-entorhinal
 622 loop. CA1 pyramidal neurons also project to the medial septum through the fornix. An overview
 623 of the connections between areas is presented in panel B of *Figure 1*.

624 In the current model, EC pyramidal neurons and interneurons receive oscillatory theta input
 625 from the medial septum in the form of an excitatory intracellular current as described in *Equa-*
 626 *tion 2* and *Equation 5*. Projections from CA1 towards the medial septum were modeled as a signal
 627 representing the collective firing rate of the CA1 pyramidal neurons. All connections towards and
 628 from the medial septum are summarized in panels A and B of *Figure 1*.

629 Synaptic connectivity between neurons within a region is characterized using a probability p
 630 and is distance-based, following a Gaussian-like distribution (*Equation 14*) with a width σ of $2500\mu\text{m}$
 631 (excitatory synapses) and $350\mu\text{m}$ (inhibitory synapses). The value of A_{intra} defines the maximum

632 probability of connection between two neurons separated by an infinitesimal distance (i.e., for
 633 $D \rightarrow 0$). The maximum values for A_{intra} are given in **Table 7**.

$$p = A_{intra} \exp\left(-\frac{D^2}{2\sigma^2}\right) \quad (14)$$

634 Inter-area connectivity followed a similar Gaussian-like distribution (**Equation 15**), however,
 635 only excitatory projections were considered and the distance D_z was computed only across the
 636 z-coordinate. Pyramidal neurons from the source area projected to pyramidal neurons and in-
 637 terneurons in the target area, with connectivity probabilities drawn from the said distribution with
 638 a width σ of 1000 μm .

$$p = \min(1, A_{inter} \exp\left(-\frac{D_z^2}{2\sigma^2}\right)) \quad (15)$$

Table 7. Maximum probability of connection (A_{intra} , **Equation 14**) between neurons within each region.

	Py-Py	Py-Inh	Inh-Py	Inh-Inh
EC	0	0.37	0.54	0
DG	0	0.06	0.14	0
CA3	0.56	0.75	0.75	0
CA1	0	0.28	0.3	0.7

639 Tuning input gain and connection strengths: targeted firing rates

640 We adjusted the input gain (G_θ) and inter-area connection strengths (A_{inter}) to target an overall os-
 641 cillatory rhythm $f_{osc,targ}$ at the driving frequency of the input, i.e., 6 Hz, and a mean firing rate of
 642 each excitatory population $f_{exc,targ}$ also at 6 Hz (meaning that each excitatory cell should spike on
 643 average once per theta cycle). Because of the ratio between excitatory and inhibitory neurons in
 644 the model, this resulted in firing rates of about 60 Hz in inhibitory neurons. These targeted val-
 645 ues were inspired by literature in behaving rodents showing that hippocampal pyramidal neurons
 646 typically fire at rates below 10 Hz, usually between 1 and 2 Hz, and that interneurons fire at rates
 647 between 20 and 80 Hz (**Hirase et al., 2001**). In practice, the obtained firing rates were constrained
 648 by the simplifications made in the model.

649 The mean population firing rate f_{exc} was computed by counting the number of spikes in the
 650 last second of a 3-s simulation run, to avoid edge effects due to the non-physiological initial con-
 651 ditions, and by averaging this number over time and across neurons. The oscillatory frequency
 652 f_{osc} was computed as the mean of the inverse of the timing between all pairs of consecutive peaks
 653 in the theta rhythm. Finally, the metric used to adjust parameters (input strength and connection
 654 strengths) was calculated as the Euclidean distance between the targeted and obtained firing rate
 655 and oscillatory rate:

$$J = \sqrt{(f_{exc} - f_{exc,targ})^2 + (f_{osc} - f_{osc,targ})^2} \quad (16)$$

656 Tuning input and connection strengths: detailed procedure

657 The input gain (G_θ , **Equation 2**) and inter-area connection strengths (A_{inter} , **Equation 15**) were se-
 658 quentially adjusted using the following heuristics. All simulations were performed for a duration
 659 of 3 s, and the first 2 s were excluded from the analysis to avoid edge effects. The network was
 660 initialized with membrane voltages uniformly distributed in the range $[-70, -60]$ mV. Our initial
 661 point was a fully uncoupled model in which all the connection strengths were set to 0. The tuning
 662 procedure was performed in the absence of noise.

Table 8. Inter-area connection strengths (A_{inter}). The source is always the excitatory population of the subfield. The same values are used when targeting excitatory and inhibitory populations. Empty cells indicate no connections. EC: Entorhinal Cortex, DG: Dentate Gyrus.

Source \ Target	Target			
	EC	DG	CA3	CA1
EC	-	13.0	0.14	1.1
DG		-	0.14	
CA3			-	1.1
CA1	0.2			-

- 663 1. First, we adjusted the amplitude of the theta input to a value that would produce a mean
664 firing rate of 6 Hz in the excitatory population of the EC. To this end, the input strength was
665 progressively increased from 0 to 0.5 nA in steps of 0.01 nA, and the value that maximized
666 our metric was selected.
- 667 2. We then adjusted similarly the connection strength from the EC to the DG, increasing it from
668 0 to 20 in steps of 0.1.
- 669 3. We repeated the procedure to jointly tune the connection strengths from EC and DG to CA3,
670 assuming an equal contribution from these two areas. These two connection strengths were
671 set to the same value and were increased from 0 to 5 in steps of 0.1.
- 672 4. We followed the same procedure to jointly tune the connection strengths from CA3 and EC
673 to CA1, assuming again an equal contribution from these two areas.
- 674 5. The last connection from CA1 to EC was more difficult to tune because it closes the feedback
675 loop and induces complex dynamics when too strong. To tune it, we temporarily uncoupled
676 CA1 from all other structures and temporarily added a fixed sinusoidal input at the target
677 frequency of 6 Hz to both excitatory and inhibitory CA1 neurons. We first adjusted this input
678 amplitude to generate a mean firing rate of about 6 Hz in CA1 excitatory neurons. Next, the
679 connection strength from CA1 to EC was adjusted to also achieve a mean firing rate of 6 Hz
680 in EC excitatory neurons.
- 681 6. Because EC receives both an external input and feedback from CA1, we assumed that both
682 these contributions should be decreased for the system to behave in a physiological range
683 in the presence of the feedback loop. We, therefore, decided to divide by two the connection
684 strength from CA1 to EC obtained in step 5. All other connection strengths were then set
685 again to the values tuned in the previous steps, and the temporary external input to CA1 was
686 removed. The external theta input to the EC was reinstated and tuned again as in step 1.

687 Following the above procedure, the inter-area synaptic connectivity parameters were set for all
688 subsequent simulations. The values are summarized in **Table 8**. Empty cells denote no effective
689 connectivity.

690 Numerical Implementation

691 The model was implemented with the Brian2 libraries for Python (*Stimberg et al., 2019*) (see Data
692 availability section for access to the code). Simulations were performed using a timestep of 0.1 ms
693 and a total simulation duration ranging between 3-10 seconds (depending on the experiment, see
694 results section). The average time for simulating 1 second for the complete model locally was 10
695 minutes.

696 Neural mass model interfaced with Kuramoto oscillators

697 The neural masses represented in **Figure S8** were modeled using the Wilson-Cowan formalism,
698 with parameters adapted from *Onslow et al. (2014)*. Specifically, the firing rates of the excitatory
699 and inhibitory populations were determined by the following equations:

$$\begin{cases} \tau_E \frac{dE}{dt} = -E + f(g_E \theta_E + W_{EE} E - W_{IE} I + stim_E(t)) \\ \tau_I \frac{dI}{dt} = -I + f(g_I \theta_I + W_{EI} E) \end{cases} \quad (17)$$

700 with the following parameters: $\tau_E = \tau_I = 3.2ms$, $g_E = 0.7$, $g_I = 0$, $W_{EE} = 4.8$, $W_{EI} = W_{IE} = 4$, and
 701 $W_{II} = 0$. The sigmoid response function was not modified from the original work, and was defined
 702 as:

$$f(x) = \frac{1}{1 + e^{-\beta(x-x_m)}} \quad (18)$$

703 with parameters β and x_m set to 4 and 1 respectively, according to the original model. The Kuramoto
 704 oscillators were modeled according to **Equation 1**. For these simulations we used a set of $N = 100$
 705 oscillators with a center frequency f_0 of 4 Hz, a synchronization ratio $\frac{k}{N}$ of 25, and a strong phase
 706 reset gain G_{reset} of 90. Other parameters were kept as previously shown in **Table 1**. The neural
 707 masses were coupled to the Kuramoto oscillators by linking the variable $X(t)$ in **Equation 1** with
 708 the variable $E(t)$ in **Equation 17**.

709 We increased the phase reset gain significantly compared to the Hodgkin-Huxley model, as the
 710 Onslow model utilized a sigmoid function with values between 0 and 1, whereas the instantaneous
 711 firing rate of the populations of single-compartment neurons was much higher and therefore had
 712 a stronger phase resetting effect.

713 Data Analysis

714 During each simulation, we monitored and exported the following data for subsequent analysis: (i)
 715 spike timings per neuron, (ii) time series of ionic currents, (iii) septal input theta rhythm and phase,
 716 and (iv) time series of electrical stimulation. Theta phase was wrapped between $[-\pi, \pi]$ with a
 717 phase of 0 radians corresponding to the peak of theta rhythm. All PAC analyses were performed
 718 using the *TensorPAC* toolbox for Python (**Combrisson et al., 2020**).

719 Firing rates

720 To obtain instantaneous firing rates, the corresponding spike trains were binned in 5-ms rectan-
 721 gular windows with a 90% overlap (i.e., consecutive windows were spaced by 0.5 ms). The number
 722 of spikes within each bin was normalized by the bin size and the number of neurons in the group,
 723 yielding instantaneous population firing rates. Where reported (i.e., values μ_I and μ_E in **Figure 3A**),
 724 the mean population firing rates within a given time window (typically lasting several seconds) were
 725 computed by binning all spikes in that time window and normalizing by the window width and the
 726 number of neurons in the population.

727 Spectral analyses

728 Power spectral density (PSD) estimates were calculated based on Welch's method. The periodo-
 729 gram was computed using 1-s windows with a 90% overlap, yielding a frequency resolution of 1
 730 Hz. The average spectral power within a specific frequency band was calculated using Simpson's
 731 rule within the desired frequency band $[f_l, f_h]$. Spectrograms were computed using the short-time
 732 Fourier transform with a sliding Hann window of 100-ms width and 99% overlap, yielding a fre-
 733 quency resolution of 10 Hz.

734 Modulation Index

735 The MI (**Tort et al., 2008**) was used to estimate the degree of PAC between theta and gamma oscil-
 736 lations in the model. To compute the MI, the normalized firing rate traces were band-pass filtered
 737 in the frequency ranges of interest: 3-9 Hz for theta (referred to as the "phase signal") and 40-80
 738 Hz for gamma (referred to as the "amplitude signal"). Then, the phase and amplitude time series
 739 were extracted from the filtered signals using the Hilbert transform. A histogram of the mean am-
 740 plitude of gamma over the phase of theta was then extracted, using phase bins of 5 degrees. The MI

741 was finally calculated as the Kullback-Leibler divergence between the mean amplitude distribution
742 and the uniform distribution. A higher MI indicates stronger PAC. For a schematic representation
743 regarding the computation of the MI, refer to Figure 1 in *Tort et al. (2010)*. These computations
744 were performed using the provided *PreferredPhase* and *Pac* methods from the *TensorPAC* library
745 for Python (*Combrisson et al., 2020*).

746 Comodulograms

747 Comodulograms represent the amount of PAC between two ranges of frequencies, used to ex-
748 tract respectively a phase and an amplitude signal. Specifically, we computed the MI between 80%
749 overlapping 1-Hz frequency bands used to compute the phase of the signal (in the theta range),
750 and 90% overlapping 10-Hz frequency bands used to compute the amplitude of the signal (in the
751 gamma range). The resulting distribution of MI values was subsequently plotted as heat maps. An
752 inherent problem with the computation of the MI using simulated data was the lack of frequency
753 components in some frequency bands. Filtering the data within 1-Hz frequency bands thus created
754 a flat signal, resulting in high values of the MI despite the absence of modulation. To overcome
755 this limitation, we added uniform noise to the firing rate signals prior to computing the MI, with an
756 amplitude of approximately 20% of the maximum instantaneous firing rates. The results with and
757 without added noise are presented in *Figure S6*.

758 Phase dependency of PAC

759 For a given theta frequency, PAC depends on the phase of the underlying theta oscillation. To
760 identify this relationship and the theta phase that maximizes coupling, we used the *PreferredPhase*
761 function of the *TensorPAC* toolbox. More precisely, we applied a Hilbert transform to extract the
762 phase of the theta signal (firing rate band-pass filtered between 3 and 9 Hz) and the amplitude of
763 the gamma signal band-pass filtered within narrow (10-Hz wide) frequency ranges between 20 and
764 100 Hz with a 90% overlap. For each narrow gamma range, we binned the amplitude with respect
765 to the phase in a similar way as in the calculation of the MI. We obtained a vector of the binned
766 high-frequency amplitudes with respect to the phase of the low-frequency phase, represented as
767 a polar plot as in *Figure 3C*.

768 Phase Response Curves

769 The PRC of an oscillatory system indicates the phase delay or advancement that follows a single
770 pulse, as a function of the phase at which this input is delivered. To characterize the PRC of our
771 computational model, we applied a single stimulation pulse to CA1 across different phases of the
772 theta rhythm and calculated the resulting change in the theta phase. We split a single theta cycle
773 into intervals of width $\pi/8$ radians and applied a single stimulation pulse of a given amplitude.
774 For each case, we ran two simulations: one with a stimulation pulse and one without. Finally, we
775 compared the theta phase 2.5 ms post-stimulation and at the same time but in the absence of
776 stimulation. The resulting values for the phase difference $\Delta\phi$ were plotted against the stimulation
777 phase and are presented in *Figure 3D* for varying stimulation amplitudes.

778 Acknowledgments

779 Simulations presented in this paper were carried out using the PlaFRIM experimental testbed, sup-
780 ported by Inria, CNRS (LABRI and IMB), Université de Bordeaux, Bordeaux INP and Conseil Régional
781 d'Aquitaine (see <https://www.plafrim.fr>).

782 Additional information

783 Funding

784 This work was supported by the Bordeaux Neurocampus junior chair program co-funded by the
785 Région Nouvelle-Aquitaine and the University of Bordeaux Initiative of Excellence (IdEx) (F.B.W.,
786 Neurocampus junior chair), and the European Union's Horizon Europe research and innovation

787 program under European Research Council (ERC) Starting Grant agreement N° 101040391 (F.B.W.,
788 MEMOPROSTHETICS).

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794 **Conflicts of interest**

795 The authors declare no conflicts of interest.

796 **Data availability**

797 All model files and analysis scripts are available at the following repositories under the GNU Gen-
798 eral Public License v3.0 license:

799 ZENODO: <https://www.doi.org/10.5281/zenodo.8354987>

800 GITHUB: <https://github.com/NikVard/memstim-hh>

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Figures

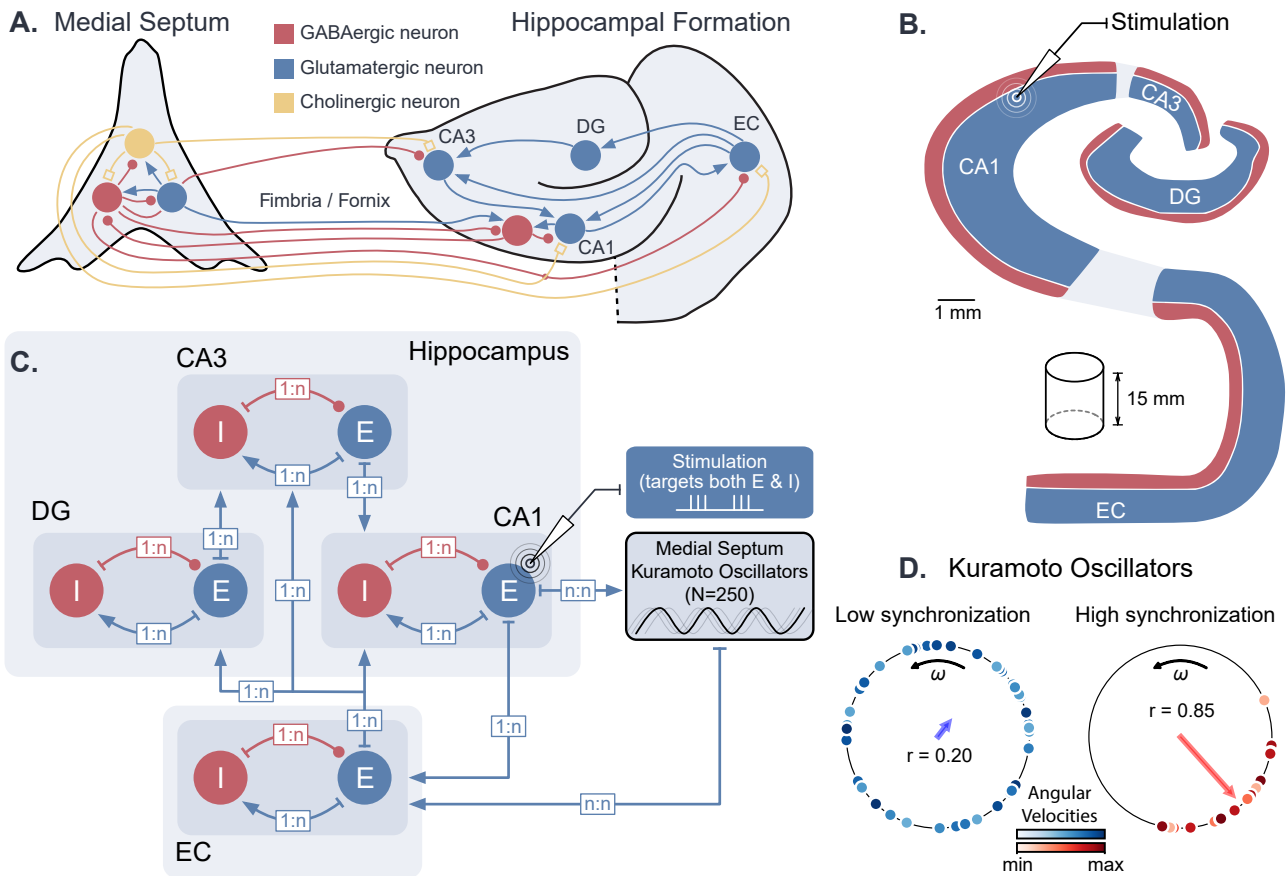


Figure 1. Dynamical computational model of the hippocampal formation and medial septum oscillatory drive. **A.** Anatomical representation of the neuronal types and interconnections within and between the medial septum and the hippocampal formation (EC: entorhinal cortex, DG: dentate gyrus, CA3 and CA1 fields of the hippocampus) **B.** Simplified anatomy of the hippocampal formation, modeled as a 15-mm thick cylindrical slice, with spatially segregated excitatory and inhibitory neurons (blue: excitatory neurons, consisting of granule cells in DG and pyramidal cells in other areas; red: inhibitory basket cells). **C.** Model architecture and connectivity. Each area is comprised of one excitatory and one inhibitory neuronal population. Theta drive is provided through input from the medial septum, which is modeled as a set of 250 Kuramoto oscillators and receives feedback connections from CA1. Electrical stimulation is modeled as an intracellular current affecting both excitatory and inhibitory populations in the targeted area (shown here for CA1). **D.** Illustration of Kuramoto oscillators with two different levels of synchronization. Each dot represents one oscillator, its position on the circle indicates its phase and its color its angular velocity. Higher synchronization corresponds to a clustering of the dots around a similar phase. “ r ” indicates the order parameter, which is a measure of synchronization.

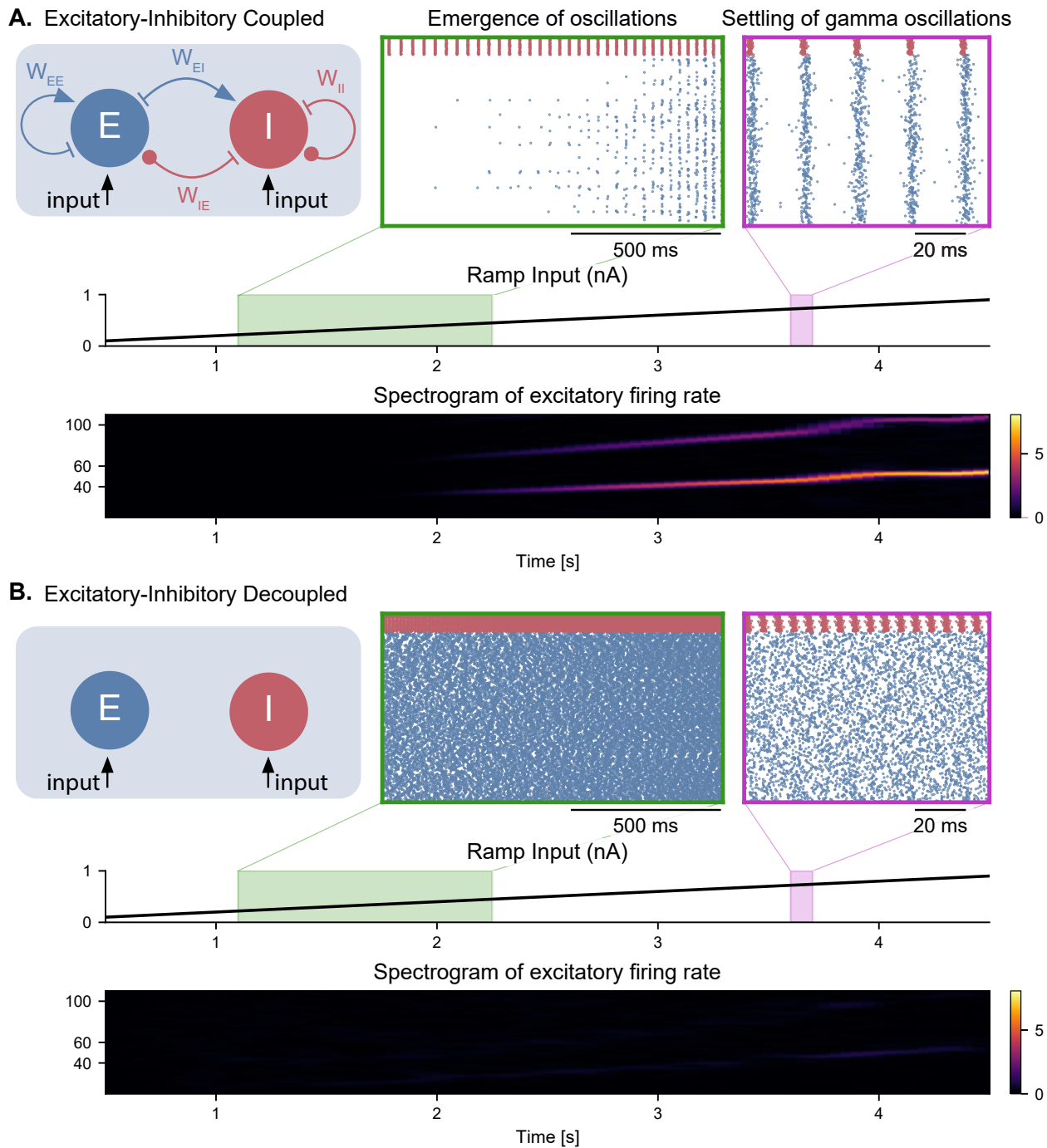


Figure 2. Emergence of gamma oscillations in coupled excitatory-inhibitory populations under ramping input to both populations. A. Two coupled populations of excitatory pyramidal neurons ($N_E = 1000$) and inhibitory interneurons ($N_I = 100$) are driven by a ramping current input (0 nA to 1 nA) for 5 s. As the input becomes stronger, oscillations start to emerge (shaded green area), driven by the interactions between excitatory and inhibitory populations. The green inset shows the raster plot (neuronal spikes across time) of the two populations during the green shaded period (red for inhibitory; blue for excitatory). When the input becomes sufficiently strong (shaded magenta area), the populations become highly synchronized and produce oscillations in the gamma range (at approximately 50 Hz). The spectrogram (bottom panel) shows the power of the instantaneous firing rate of the pyramidal population as a function of time and frequency. It reveals the presence of gamma oscillations that emerge around 2s and increase in frequency until 4 s, when they settle at approximately 60 Hz. **B.** Similar depiction as in panel A, with the pyramidal-interneuronal populations decoupled. The absence of coupling leads to the abolition of gamma oscillations, each cell spiking activity being driven by its own inputs and intrinsic properties.

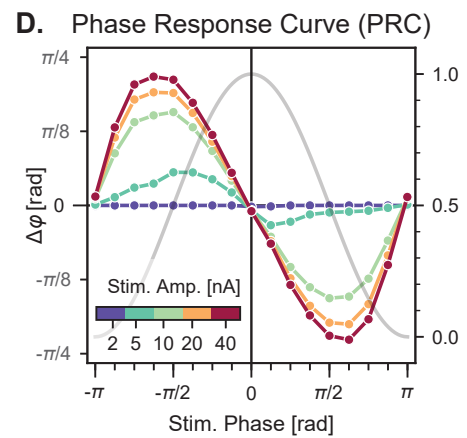
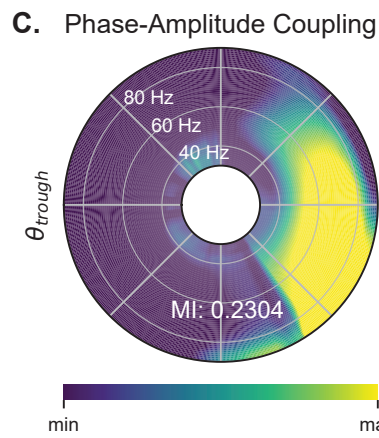
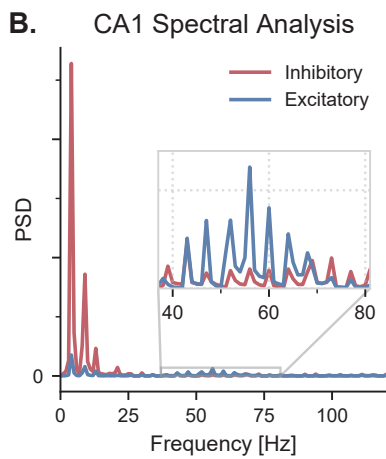
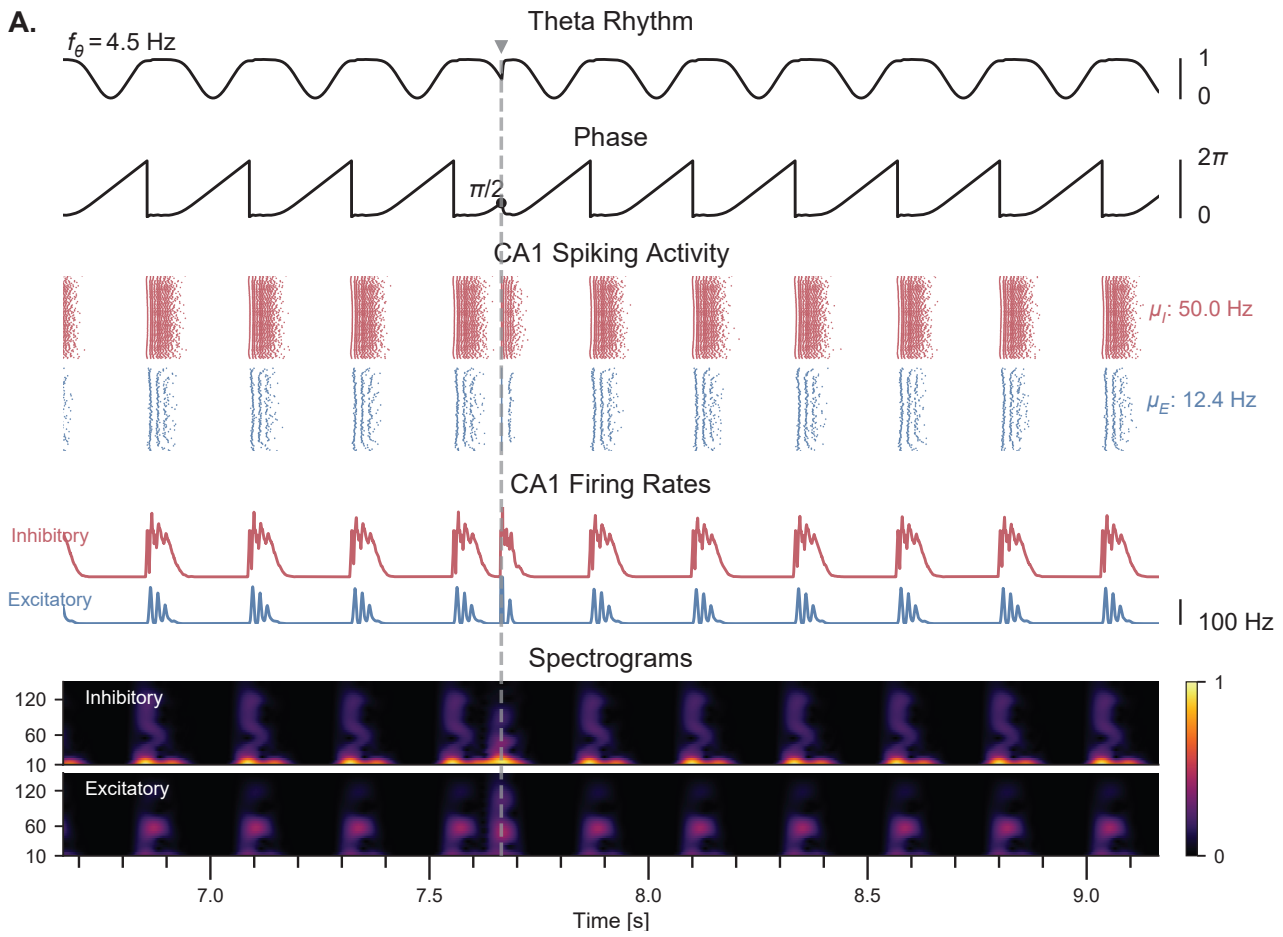


Figure 3. Theta-nested gamma oscillations and theta phase reset in response to a single stimulation pulse. **A.** Representative example of the network behavior, spontaneously producing theta-nested gamma oscillations and characterized by a reset of the theta phase following a single stimulation pulse (vertical grey line, applied here in CA1 at a theta phase of $\pi/2$, i.e., in the middle of the descending slope). Top to bottom: theta rhythm originating from the medial septum and provided as an input to the EC (f_θ : mean oscillation frequency), instantaneous phase of the theta rhythm, raster plots indicating the spiking activity of CA1 excitatory (blue) and inhibitory (red) neurons (μ_E and μ_I : mean firing rates within the shaded area), average population firing rates in CA1 (computed as a windowed moving average with a sliding window of 100 ms with 99% overlap), spectrograms for each CA1 population (windowed short-time fast Fourier transform using a Hann sliding window: 100 ms with 99% overlap). Spectrograms show gamma oscillations (around 60 Hz) modulated by the underlying theta rhythm (~ 4 Hz), indicating theta-gamma PAC. Theta phase reset after stimulation is associated with a rebound of spiking activity and theta-nested gamma oscillations. **B.** Power spectral densities of the CA1 firing rates. Theta peaks are found at 4 Hz for excitatory and inhibitory cells. Gamma activity is located between 40 and 80 Hz. **C.** PAC as a function of theta phase and gamma frequency. The polar plot represents the amplitude of gamma oscillations (averaged across all theta cycles, see methods) at each phase of theta (theta range: 3-9 Hz, phase indicated as angular coordinate) and for different gamma frequencies (radial coordinate, binned in 10-Hz ranges), indicating that gamma oscillations between 40 and 80 Hz occur preferentially around the peak of theta. The MI gives an overall quantification of how the phase of low-frequency oscillations (3-9 Hz) modulates the amplitude of higher-frequency oscillations (40-80 Hz) (see *Methods* and *Figure supplement 2*). **D.** PRC in response to a single stimulation pulse applied in CA1 at various phases of the ongoing theta rhythm and for various stimulation amplitudes (color-coded). The phase difference (left y-axis) shows the theta phase induced by the stimulation pulse (computed 2.5 ms after the pulse), compared to the phase computed at the same time in a scenario without stimulation. Positive and negative phase differences respectively indicate phase advances and delays. The grey trace shows the normalized amplitude of theta (right y axis) for different phases, used to indicate the peak and trough of the rhythm. Stimulation applied in the ascending slope of theta ($[-\pi, 0]$) produced a phase advance and accelerated the rhythm towards its peak (0 radians). Conversely, stimulation during the descending slope ($[0, \pi]$) produced a phase delay that slowed down the rhythm. Higher stimulation amplitudes yielded a stronger effect.

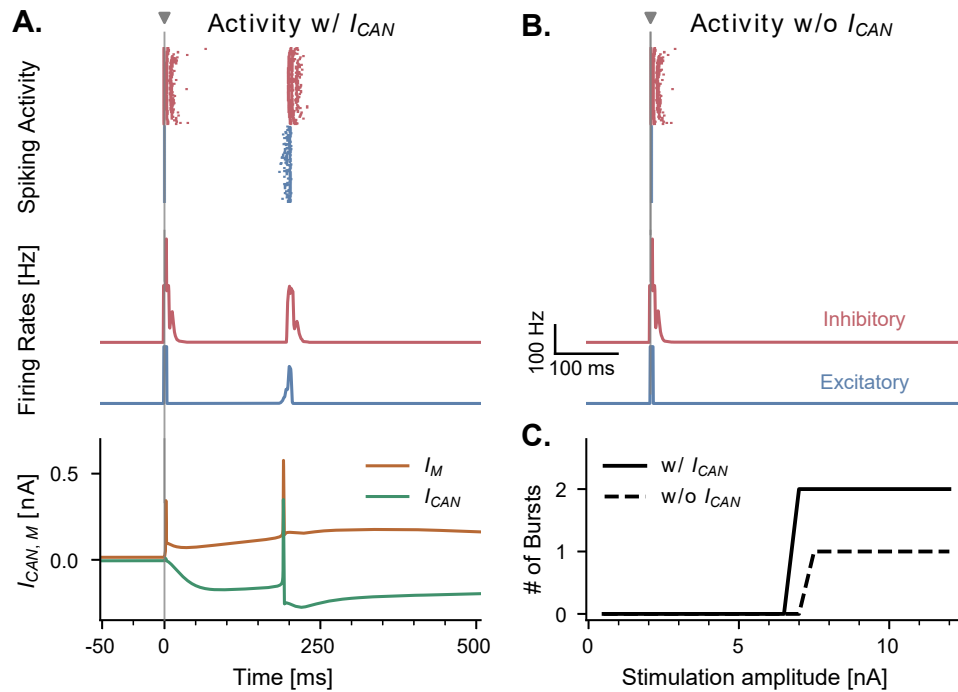


Figure 4. CAN and adaptation (M) currents modulate neuronal responses to single-pulse stimulation in the absence of theta input. A. Network response to single-pulse stimulation in the absence of medial septum input. Stimulation (grey vertical line, 10 nA, applied in CA1) induced an instantaneous burst of activity lasting about 20 ms in both excitatory and inhibitory CA1 neurons, followed by a secondary burst approximately 200 ms later (raster plot and firing rate traces), associated with specific CAN- and M- currents dynamics (bottom traces, illustrated for a representative CA1 excitatory neuron). Positive (I_M) and negative (I_{CAN}) currents indicate respectively a hyperpolarizing and depolarizing effect on the cell membrane potential. **B.** Similar representation as in A., but in the absence of CAN channel. Stimulation induced only a single burst of activity, indicating that CAN channels are necessary to observe a rebound of activity. **C.** Number of bursts in CA1 spiking activity following a single stimulation pulse at various amplitudes (x-axis), shown both in the presence and absence of CAN channels in excitatory neurons. The absence of the CAN current leads to the abolition of the second burst, irrespective of stimulation amplitude.

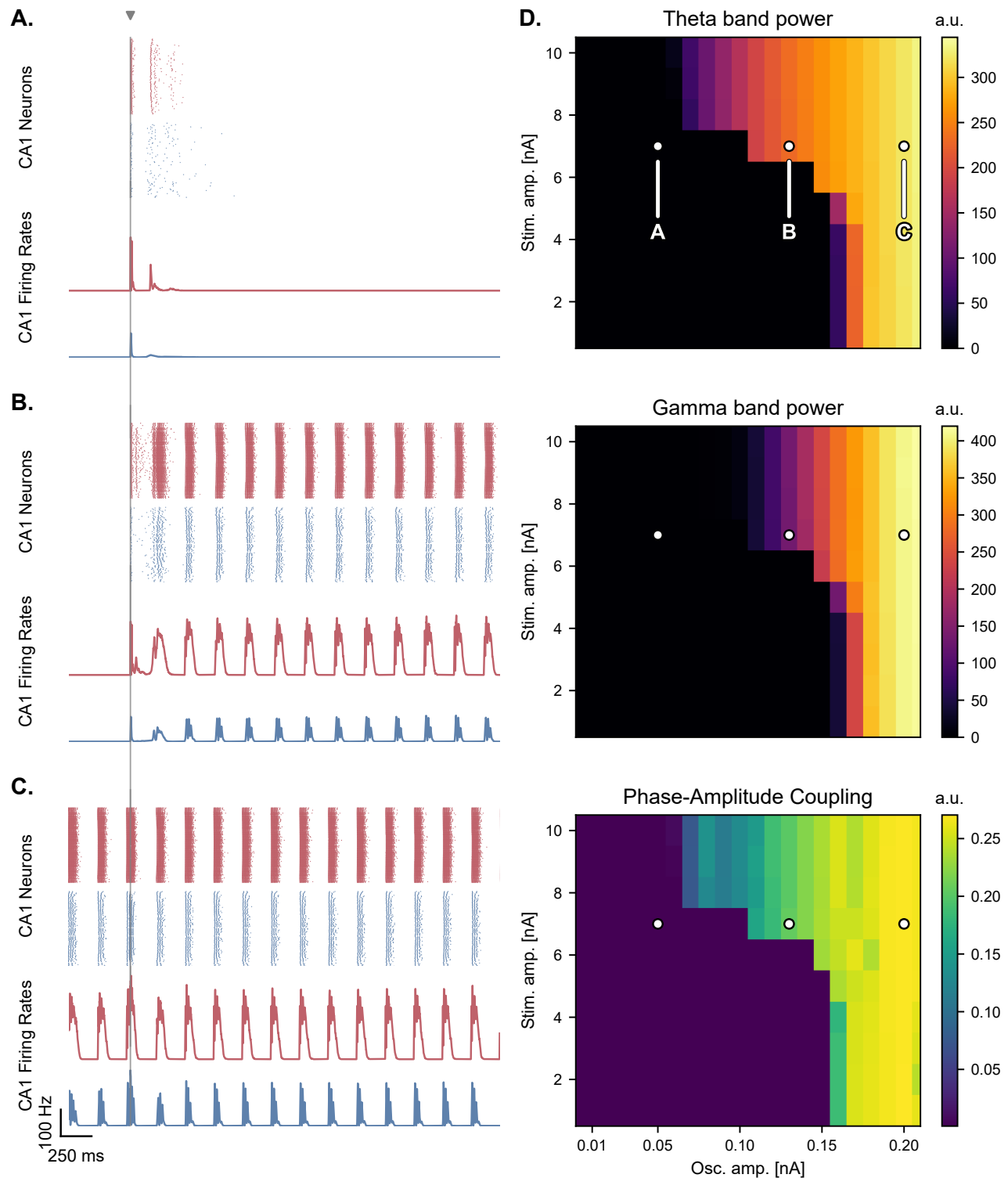


Figure 5. Medial septum oscillatory drive and stimulation amplitude govern the steady-state response to single-pulse stimulation. A-C. Network responses to single-pulse stimulation (vertical line) under medial septum input (with phase reset), shown for different amplitudes of the medial septum oscillatory drive (A-C: increasing oscillator amplitudes). **A.** Low oscillatory input: stimulation induces only two bursts of spiking activity as in **Figure 4**. **B.** Medium oscillatory input: a single stimulation pulse switches network behavior from no activity to sustained oscillations driven by the medial septum. **C.** Higher oscillatory input: theta drive is capable of inducing self-sustained theta-nested gamma oscillations. In this case, stimulation is delivered at the peak of theta oscillations and does not show a pronounced effect on theta-gamma oscillations. **D.** Steady-state response to single-pulse stimulation as a function of medial septum oscillatory input (x-axis) and stimulation amplitude (y-axis), characterized by three metrics: theta power (3-9 Hz), gamma power (40-80 Hz), and PAC (quantified using the MI). White dots: parameter combinations corresponding to panels A-C.

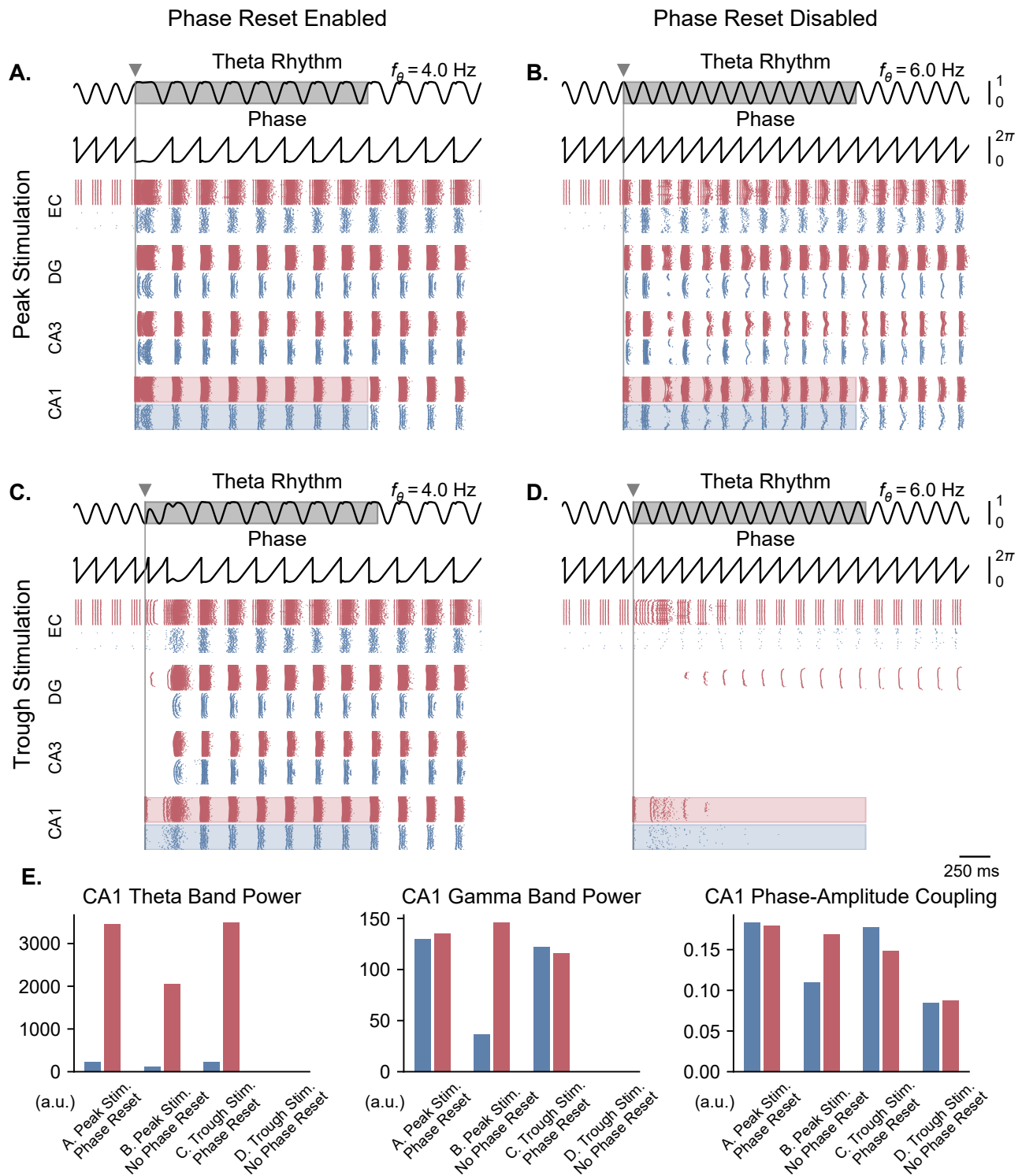


Figure 6. Single-pulse stimulation phase differentially affects network responses depending on the presence of theta phase reset. All results shown here were obtained for parameters from **Figure 5B** (theta oscillation amplitude: 0.13 nA, stimulation amplitude: 7.0 nA). A single stimulation pulse was delivered at the peak (**A, B**) or trough (**C, D**) of the underlying theta rhythm, either in the presence (**A, C**) or absence (**B, D**) of theta phase reset. With phase reset, both peak and trough stimulation switch network behavior from no activity to sustained oscillations. Without phase reset, only peak stimulation can induce sustained oscillations. **E.** Quantification of theta power, gamma power, and PAC (measured using the MI) in CA1 excitatory (blue) and inhibitory (red) populations in all 4 cases (metrics are computed in the shaded areas of panels A-D).

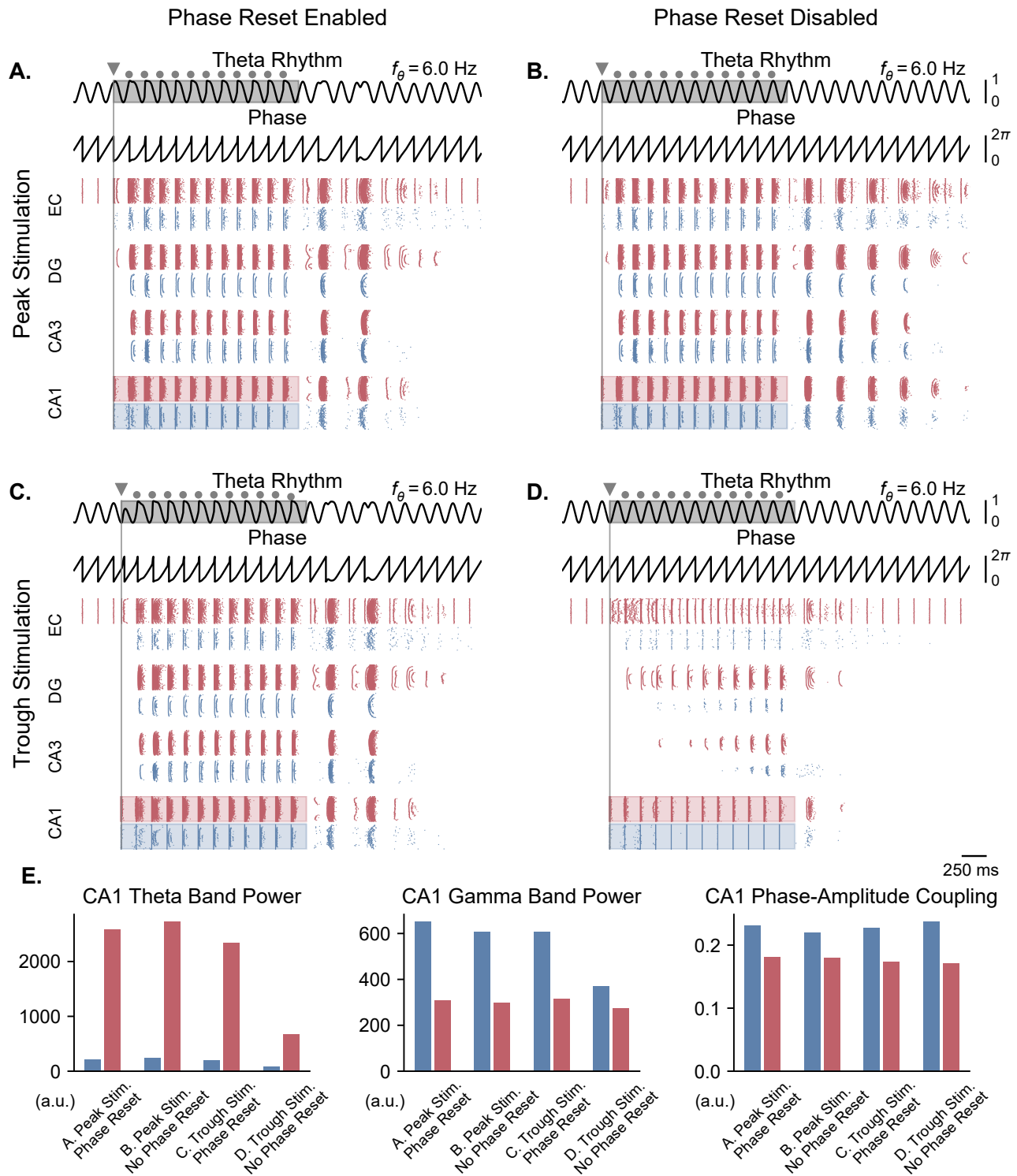


Figure 7. Pulse train stimulation restores theta-nested gamma oscillations depending on stimulation timing and theta phase reset. All results shown here were obtained for parameters from **Figure 5A** (theta oscillation amplitude: 0.05 nA; stimulation amplitude: 7.0 nA). Representations are similar to **Figure 6**, with the difference that stimulation consisted of a pulse train delivered at 6 Hz for a duration of 2 s (individual pulses indicated by grey dots, first pulse by a triangle). The pulse train was delivered at the peak (A, B) or trough (C, D) of the underlying theta rhythm, either in the presence (A, C) or absence (B, D) of theta phase reset. With phase reset, both peak and trough stimulation switch network behavior from no activity to sustained oscillations. Without phase reset, only peak stimulation can induce sustained oscillations. **E.** Quantification of theta power, gamma power, and PAC (measured using the MI) in CA1 excitatory (blue) and inhibitory (red) populations in all 4 cases (metrics are computed during the pulse train, within the shaded areas of panels A-D).

Appendix
Supplementary Figures

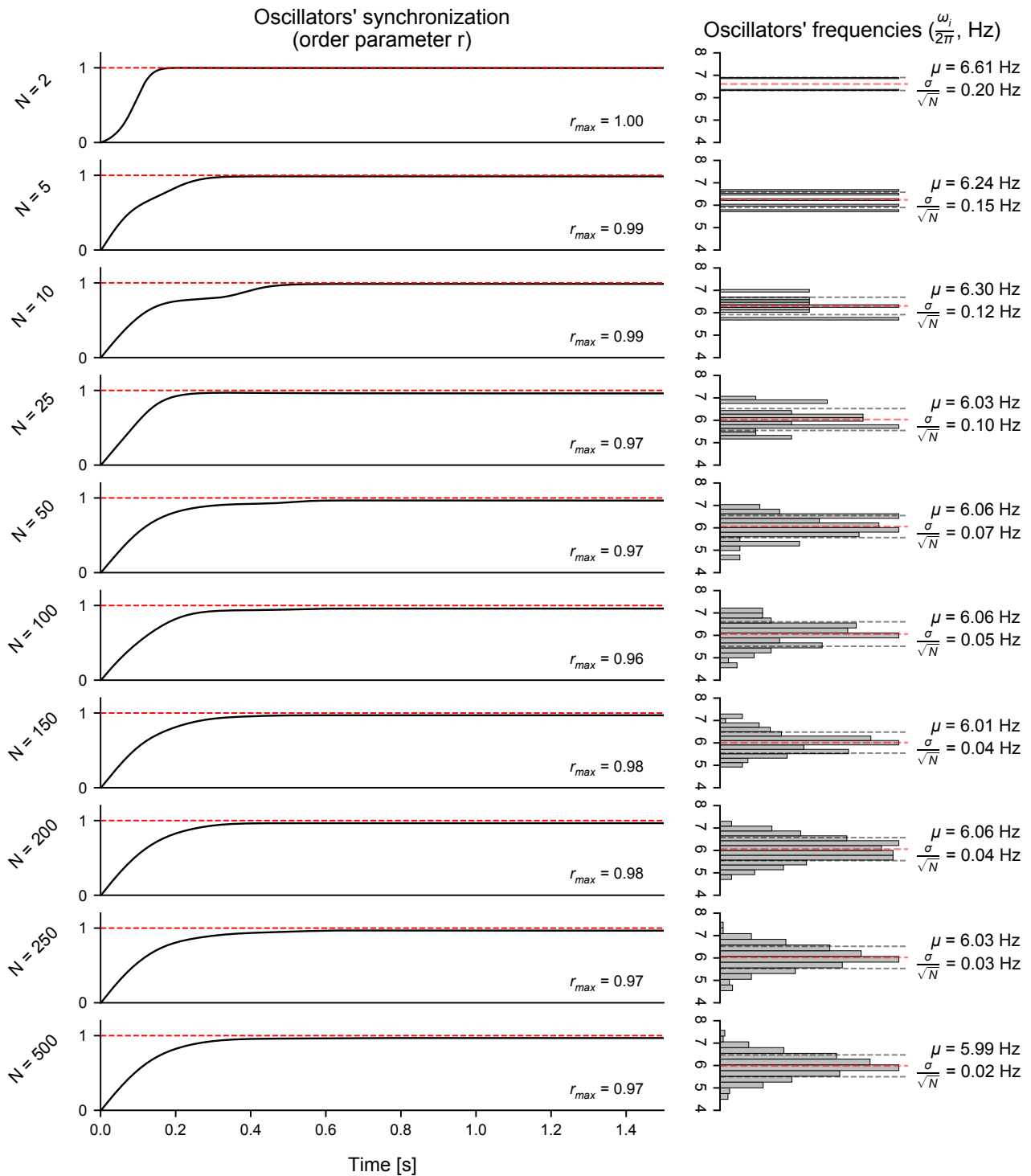
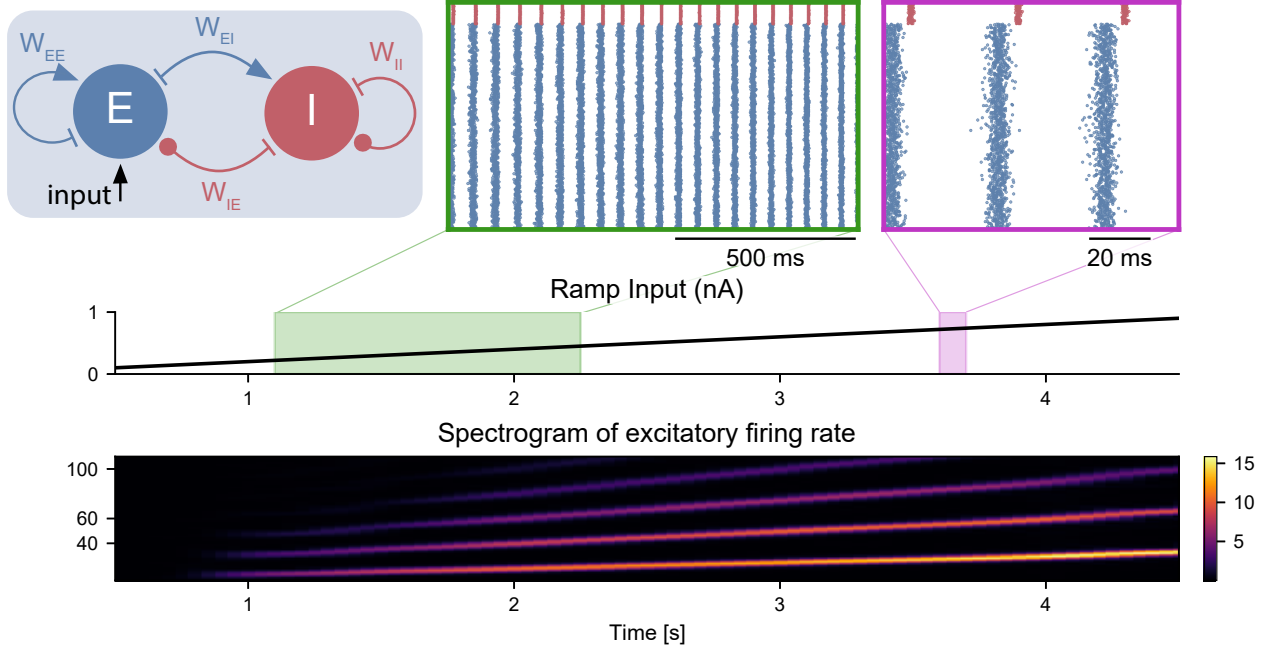


Figure S1. (Figure 1 – Figure Supplement 1) Influence of the number of Kuramoto oscillators on their collective dynamics. **Left:** influence of the number of Kuramoto oscillators (N) on the convergence over time of the order parameter (r), which is a measure of synchronization of the set of oscillators. The above results were obtained using a synchronization ratio k/N of 25. Upon initialization, the oscillators' natural frequencies (ω_i) were normally distributed with a center frequency ($f_0 = 6$ Hz). Initial phases were uniformly distributed around the unit circle ($U \sim [0, 2\pi]$). **Right:** histograms of the natural frequencies (ω_i), together with the distribution mean (μ) and standard error of the mean (σ/\sqrt{N}). As the number of oscillators increases, the mean frequency appears closer to the desired center frequency of 6 Hz, and the standard error of the mean is reduced. Overall, increasing the number of oscillators past 250 did not yield any substantial change in the convergence of the order parameter or the distribution of natural frequencies. This number of oscillators was therefore chosen for all subsequent analyses.

A. Excitatory-Inhibitory Coupled



B. Excitatory-Inhibitory Decoupled

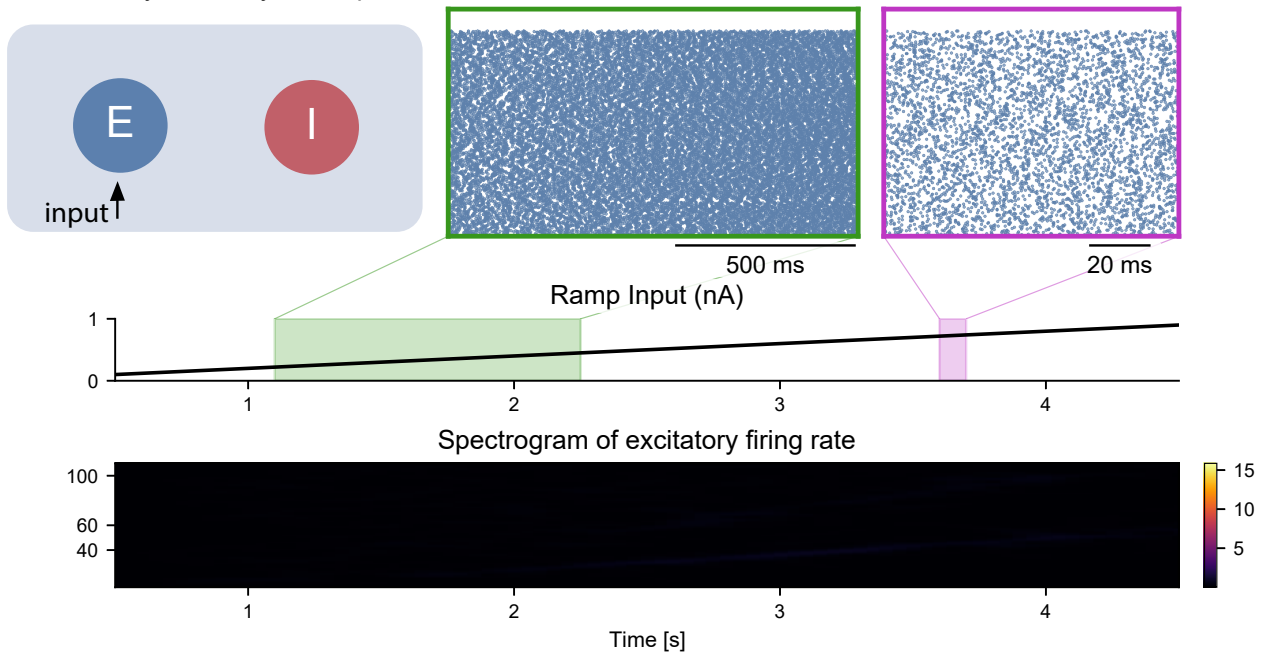


Figure S2. (Figure 2 – Figure Supplement 1) Emergence of gamma oscillations in coupled excitatory-inhibitory populations under ramping input to the excitatory population. Similar representation as in Figure 2, but with the input provided only to the excitatory population. All conclusions remain the same. In addition, the inhibitory population does not show any spiking activity in the decoupled case.

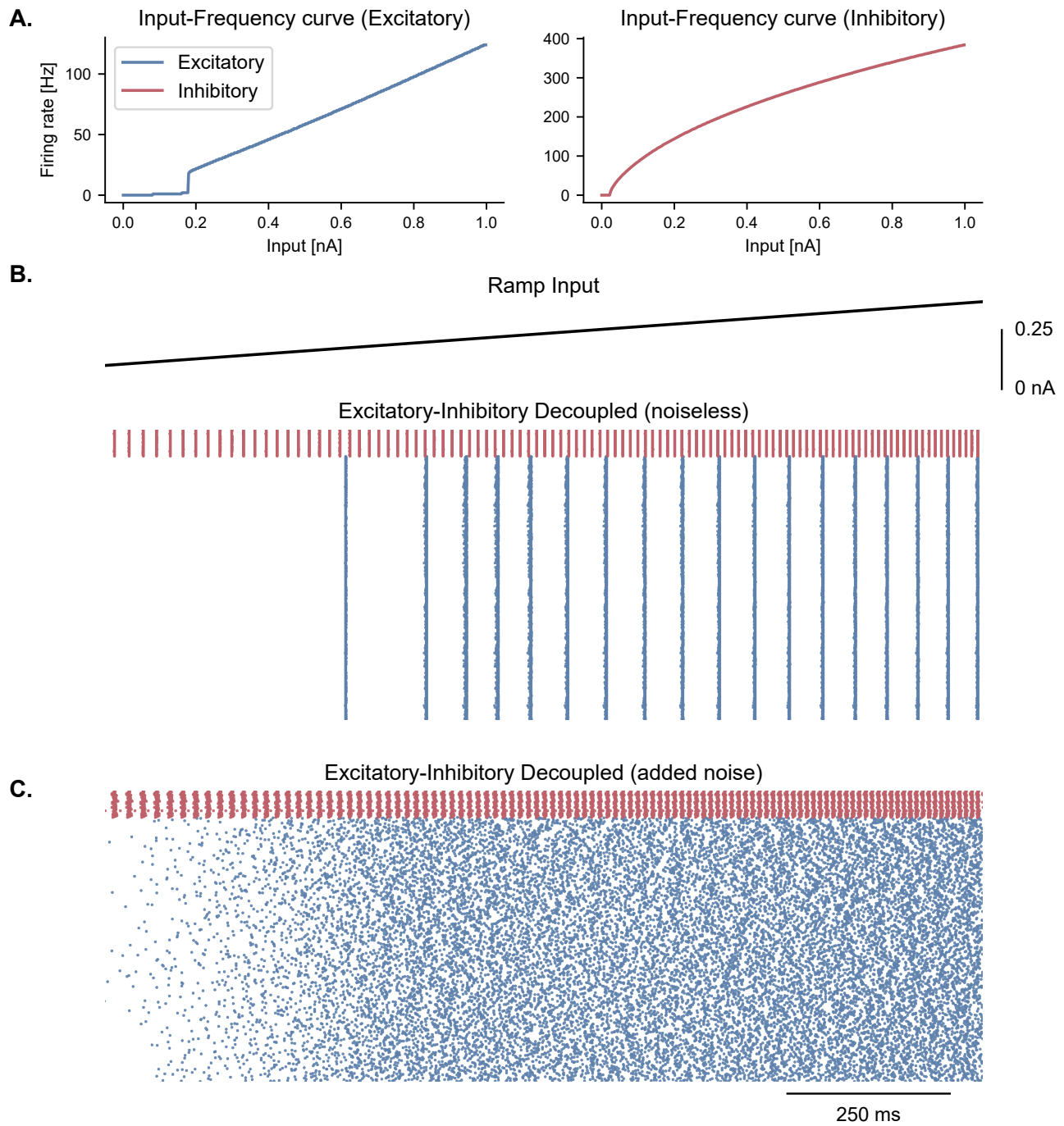


Figure S3. (Figure 2 – Figure Supplement 2) Cell-intrinsic spiking activity in decoupled excitatory and inhibitory populations under ramping input. A. Input-Frequency (I-F) curves for excitatory cells (left panel; pyramidal neurons with I_{CAN}) and inhibitory cells (right panel; interneurons, fast-spiking) used in the model. Above a certain tonic input (around 0.35 nA for excitatory and 0.1 nA for inhibitory neurons), neurons can spike in the gamma range. **B.** Raster plot showing the spiking activity of excitatory (blue, $N_E = 1000$) and inhibitory (red, $N_I = 100$) neurons in decoupled populations under ramping input (top trace) and in the absence of noise in the membrane potential. Despite random initial conditions across neurons, oscillations emerge in both populations due to the intrinsic properties of the cells, with a frequency that is predicted by the respective I-F curves (panel **A.**). **C.** Similar representation as panel **B.** but with the addition of stochastic noise in the membrane potential of each neuron. The presence of noise disrupts the emergence of oscillations in these decoupled populations.

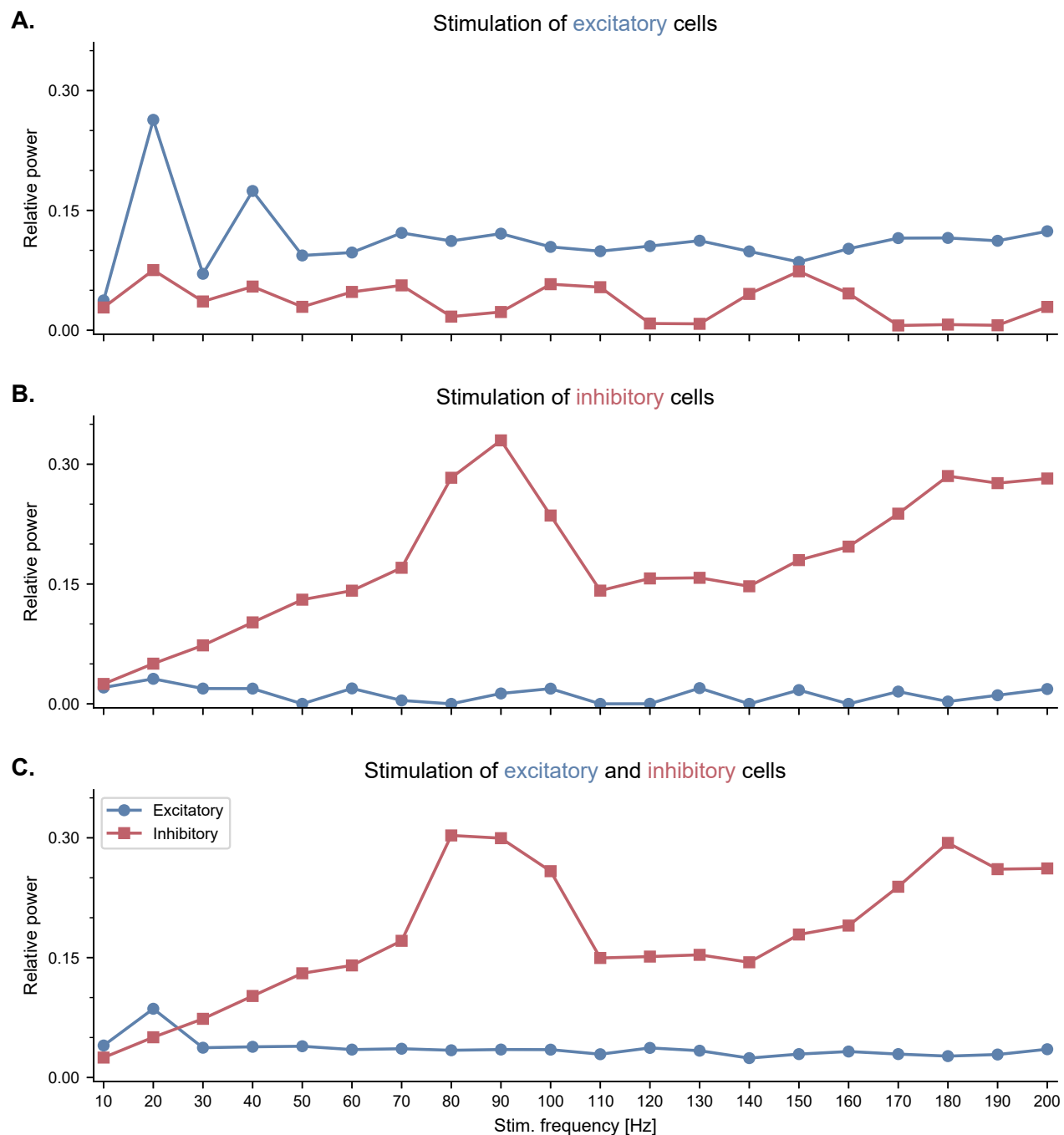


Figure S4. (Figure 2 – Figure Supplement 3) Neuronal entrainment of fast-spiking interneurons by pulsed optogenetic stimulation in the high gamma range. All panels show the effects of pulsed optogenetic stimulation of specific cell types (**A.** excitatory only, **B.** inhibitory only, **C.** both excitatory and inhibitory cells) at different frequencies, similar to the experiments reported by Cardin and colleagues (*Cardin et al., 2009*). Pulsed stimulation was delivered continuously with a frequency ranging from 10 to 200 Hz. The relative power was calculated similarly to *Cardin et al. (2009)*. Specifically, for each stimulation frequency, we computed first the power spectral density of the population firing rates using Welch’s method, and then the ratio between the power within a 10-Hz band centered around the stimulation frequency and the total power across all frequencies. **A.** Pulsed stimulation of excitatory cells shows a higher relative power in the stimulated neurons at low frequencies (20 and 40 Hz). **B.** Pulsed stimulation of inhibitory cells reveals neuronal entrainment, i.e., a peak in their relative power, in the high gamma range (80-100 Hz). **C.** Simultaneous pulsed stimulation of both populations reveals a strong entrainment of inhibitory cells in the high gamma range, and a more modest entrainment of excitatory cells at low frequencies.

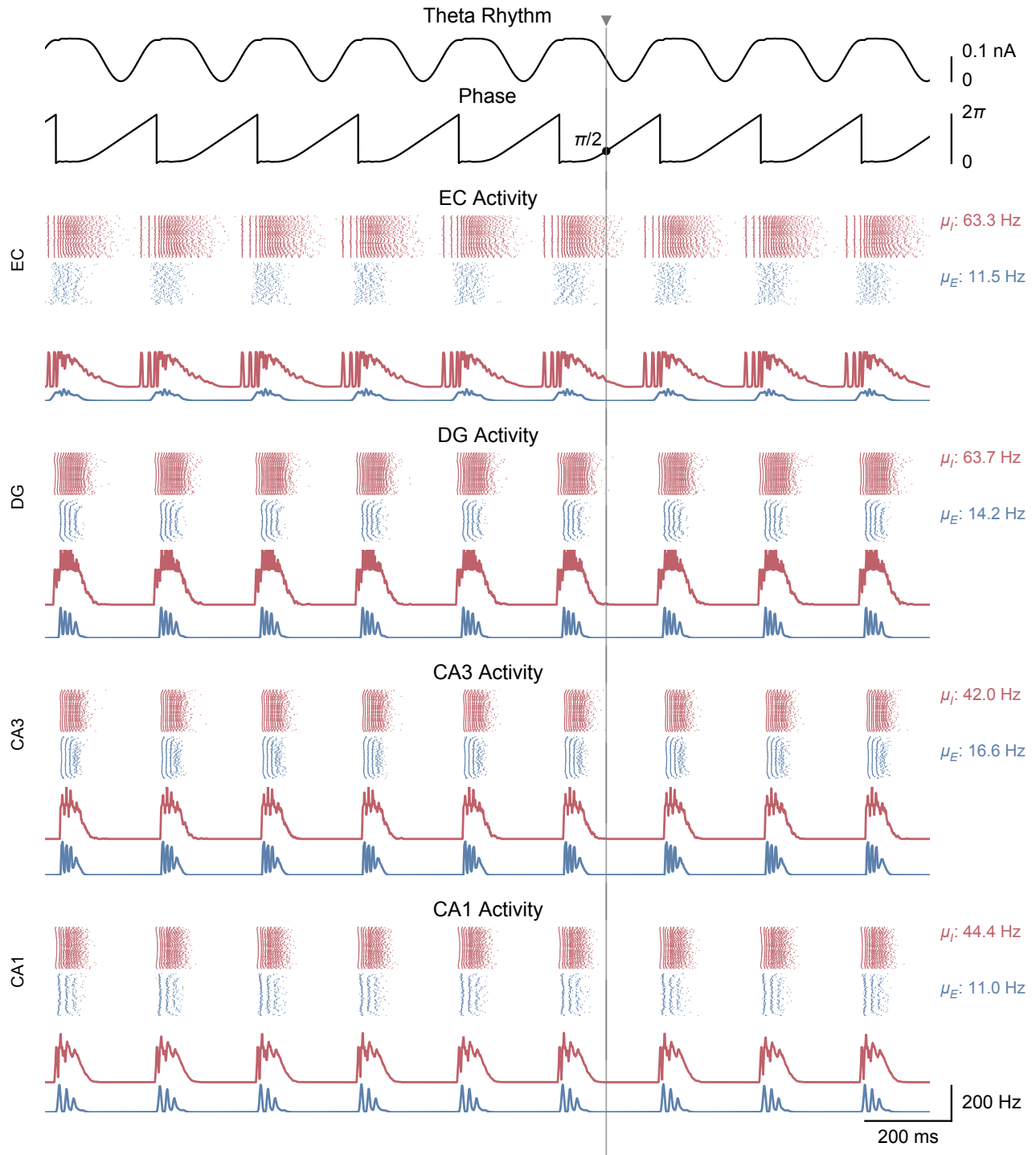


Figure S5. (Figure 3 – Figure Supplement 1) Whole-network behavior producing theta-nested gamma oscillations and theta phase reset in response to a single stimulation pulse. This figure shows the behavior of all areas of the hippocampal formation during the simulation illustrated in Figure 3A. All areas display bursts of gamma activity that occur almost synchronously at the peak of each theta cycle in both excitatory and inhibitory neuronal populations (μ_E and μ_I : mean firing rates within the shaded area). The CA1 excitatory population firing rate is supplied back to the medial septum. A single stimulation pulse (vertical line and grey triangle) delivered to both CA1 populations at a phase of $\pi/2$ (i.e., halfway through the descending slope) resets the phase of the theta rhythm according to the PRC shown in Figure 3D.

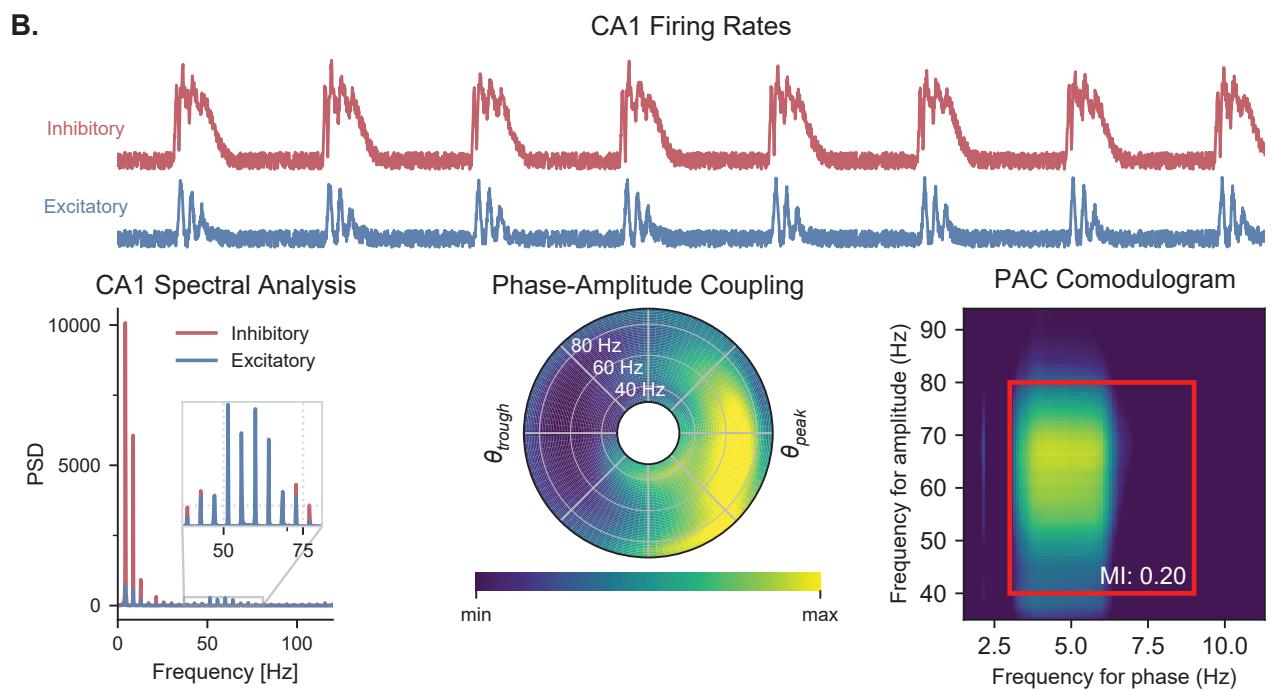
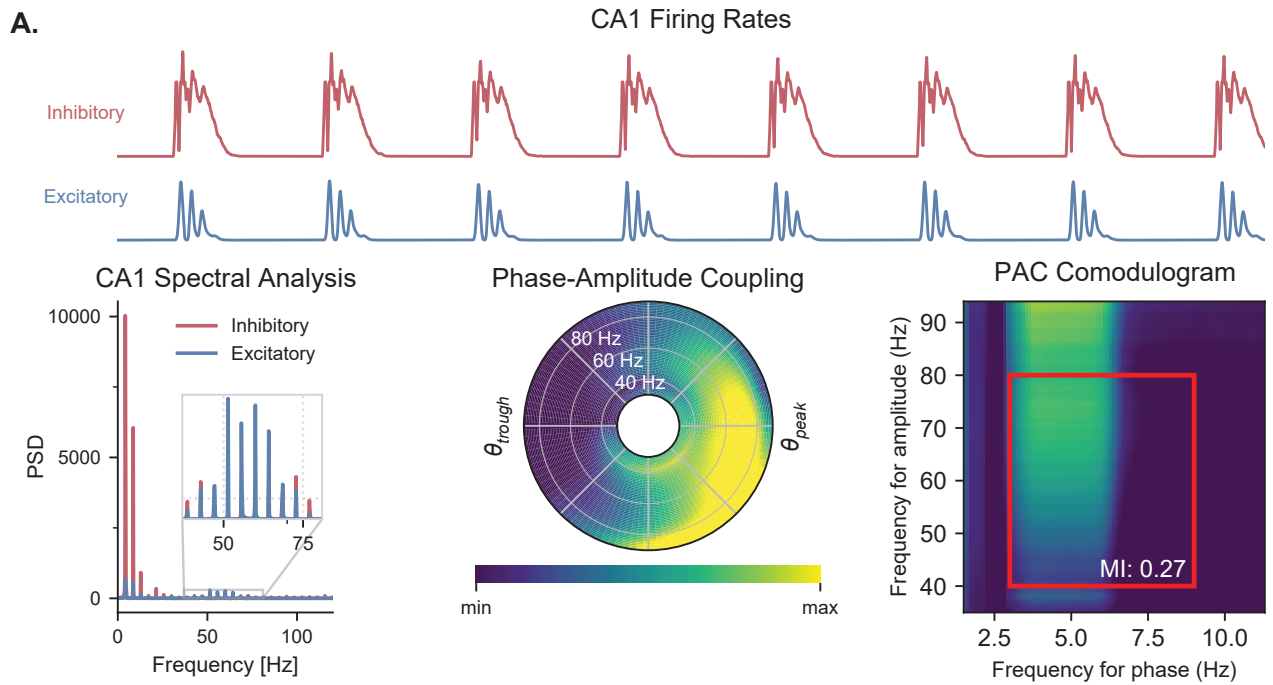


Figure S6. (Figure 3 – Figure Supplement 2) Quantification of PAC with and without noise. A. Quantifying PAC in the absence of noise produced inaccurate identification of the coupled frequency bands, due to the complete absence of oscillations at some frequencies. All analyses are based on the CA1 firing rates (top traces) during a representative simulation. Power spectral densities of these firing rates (**left**) indicate that some frequencies have a power of 0. PAC of the excitatory population was assessed using two graphical representations, the polar plot (**middle**) and comodulogram (**right**), and quantified using the MI. The comodulogram was calculated by computing the MI across 80% overlapping 1-Hz frequency bands in the theta range and across 90% overlapping 10-Hz frequency bands in the gamma range and subsequently plotted as a heat map. In the absence of noise, a slow theta frequency centered around 5 Hz is found to modulate a broad range of gamma frequencies between 40 and 100 Hz. The value indicated on the comodulogram indicates the average MI in the 3-9 Hz theta range and 40-80 Hz gamma range. As in **Figure 3**, the polar plot represents the amplitude of gamma oscillations (averaged across all theta cycles) at each phase of theta (theta range: 3-9 Hz, phase indicated as angular coordinate) and for different gamma frequencies (radial coordinate, binned in 1-Hz ranges). **B.** Adding uniform noise to the firing rate (with an amplitude ranging between 15 and 25% of the maximum firing rate) improved the identification of the coupled frequency bands. In this case, the slower theta frequency centered around 5 Hz modulates a gamma band located between 45 and 75 Hz.

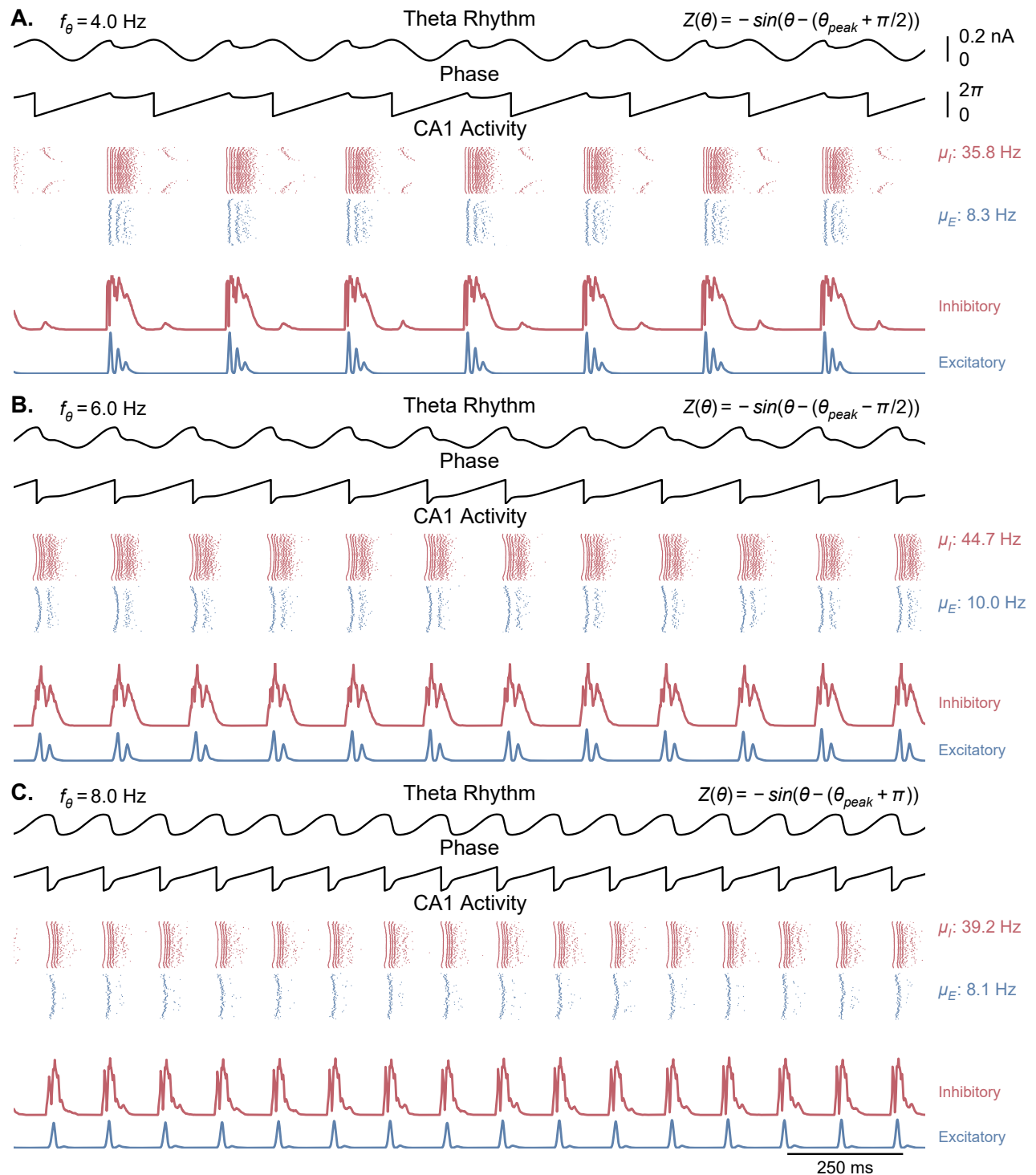
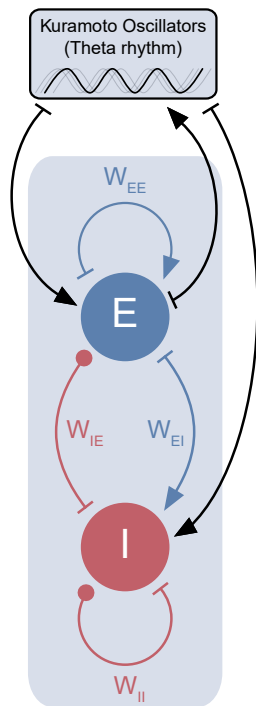


Figure S7. (Figure 3 – Figure Supplement 3) Network behavior generated by Kuramoto oscillators with non-physiological phase response functions. Each panel is similar to *Figure 3A*, but with a different offset added to the phase response function of the Kuramoto oscillators (see methods, *Equation 4*). The center frequency was set to 6 Hz in all of these simulations. Overall, theta oscillations in these cases are less sinusoidal and show more abrupt phase changes than in the physiological case. **A.** A phase offset of $-\pi/2$ leads to an overall theta oscillation of 4 Hz, with a second peak following the main theta peak. **B.** A phase offset of $+\pi/2$ reduces the peak of theta, resetting the rhythm to the middle of the ascending phase. **C.** A phase offset of π or $-\pi$ leads to the CA1 output resetting the theta rhythm to the trough of theta.

A. Neural Mass Model



B.

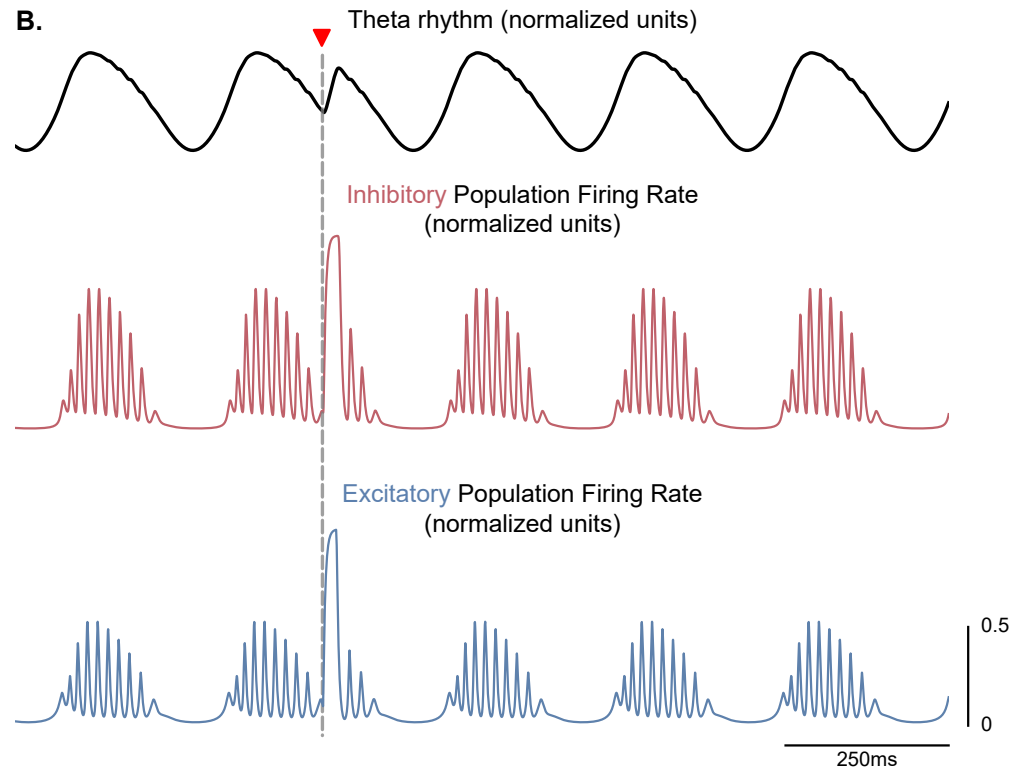


Figure S8. (Figure 3 – Figure Supplement 4) A neural mass model of coupled excitatory and inhibitory neurons driven by Kuramoto oscillators generates theta-nested gamma oscillations and theta phase reset. **A.** Two coupled neural masses (one excitatory and one inhibitory) driven by Kuramoto oscillators, which represent a dynamical oscillatory drive in the theta range, were used to implement a neural mass equivalent to our conductance-based model represented in **Figure 1**. Neural masses were modeled using the Wilson-Cowan formalism, with parameters adapted from *Onslow et al. (2014)* ($W_{EE} = 4.8$, $W_{EI} = W_{IE} = 4$, $W_{II} = 0$). **B.** The normalized population firing rates exhibit theta-nested gamma oscillations (middle and bottom panels) in response to the dynamic theta rhythm (top panel). A stimulation pulse delivered at the descending phase of the rhythm to both populations (marked by the inverted red triangle) produces a robust theta phase reset, similarly to **Figure 3A**.

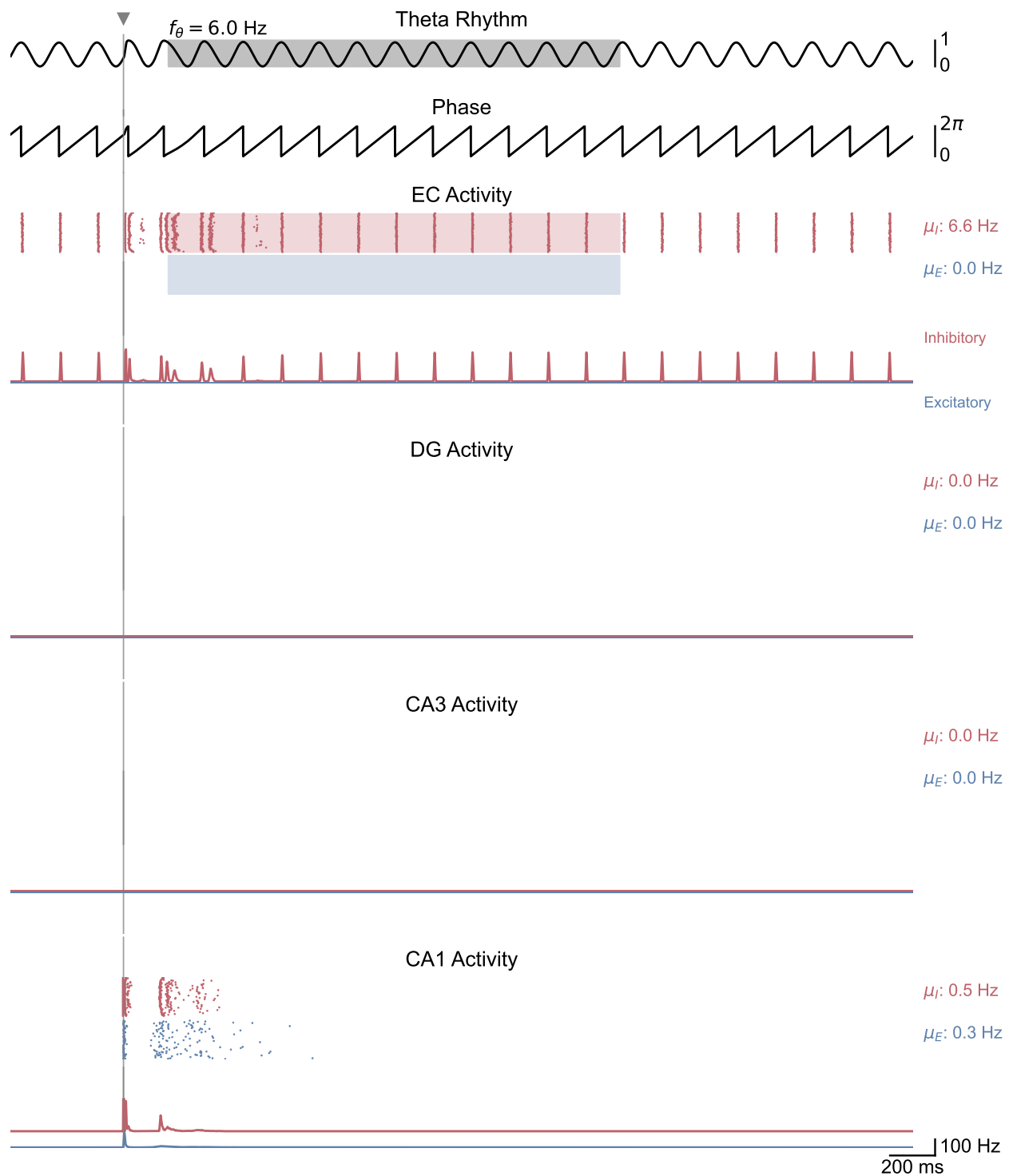


Figure S9. (Figure 5 – Figure Supplement 1) Whole-network behavior in response to single-pulse stimulation under low theta oscillatory drive. This figure shows the behavior of all areas of the hippocampal formation during the simulation illustrated in Figure 5A. A single stimulation pulse delivered to both CA1 populations induces two bursts of spiking activity that propagate only from CA1 to EC.

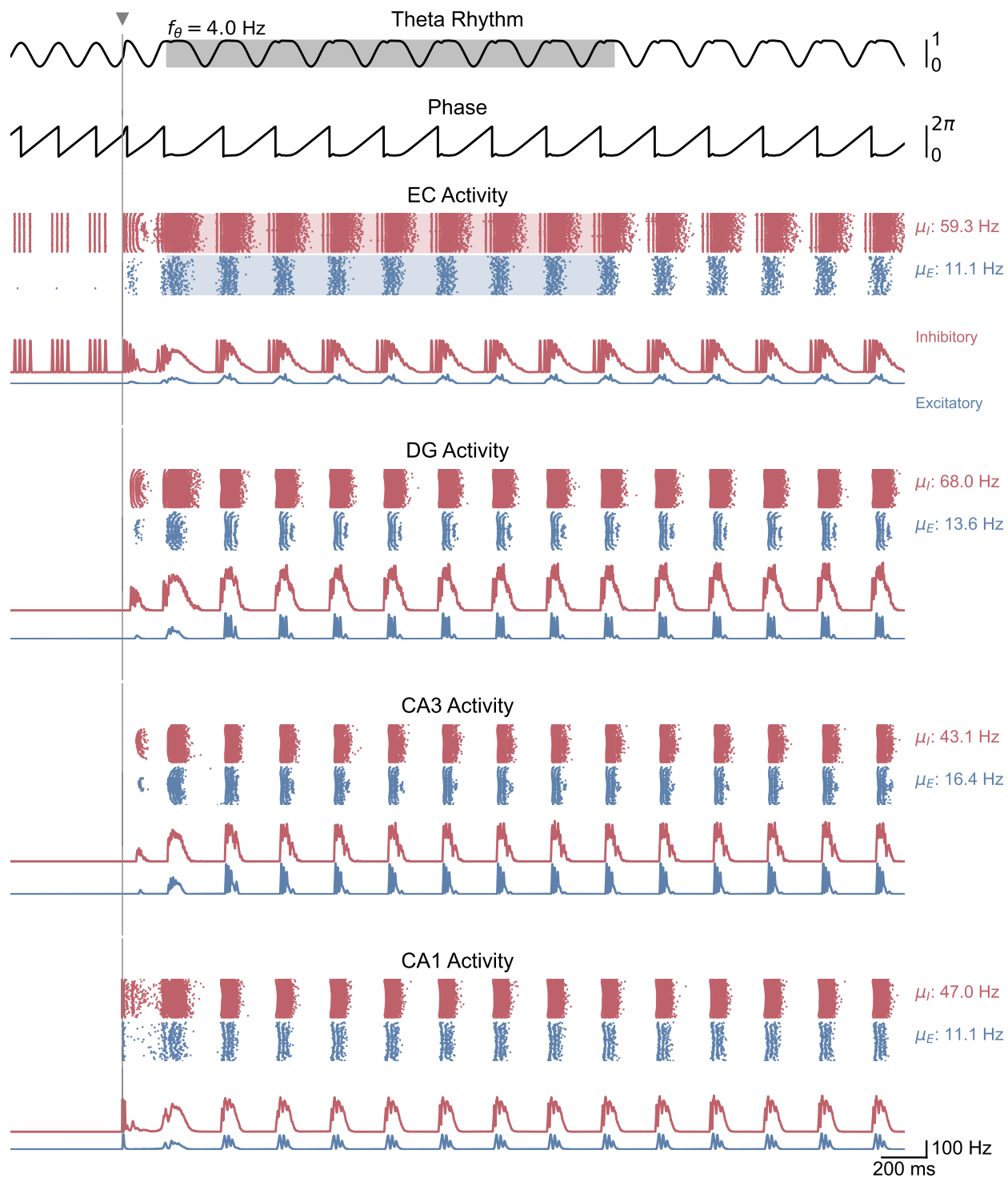


Figure S10. (Figure 5 – Figure Supplement 2) Whole-network behavior in response to single-pulse stimulation under medium theta oscillatory drive. This figure shows the behavior of all areas of the hippocampal formation during the simulation illustrated in Figure 5B. A single stimulation pulse switches network behavior from no activity to sustained oscillations driven by the medial septum.

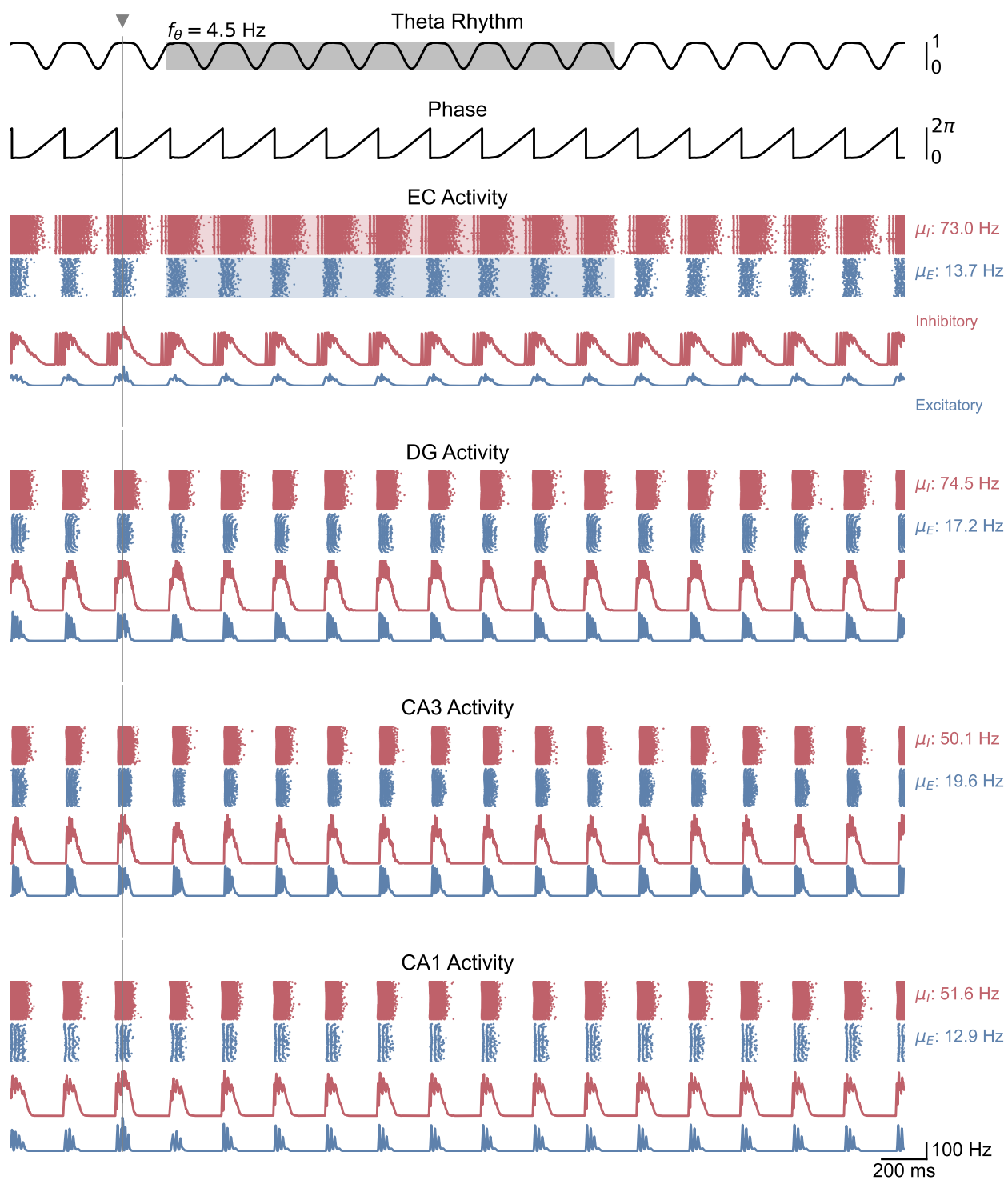


Figure S11. (Figure 5 – Figure Supplement 3) Whole-network behavior in response to single-pulse stimulation under higher theta oscillatory drive. This figure shows the behavior of all areas of the hippocampal formation during the simulation illustrated in Figure 5C. Theta oscillatory drive is enough to induce self-sustained theta-nested gamma oscillations. In this case, stimulation is delivered at the peak of theta and does not induce a pronounced effect on theta-gamma oscillations.

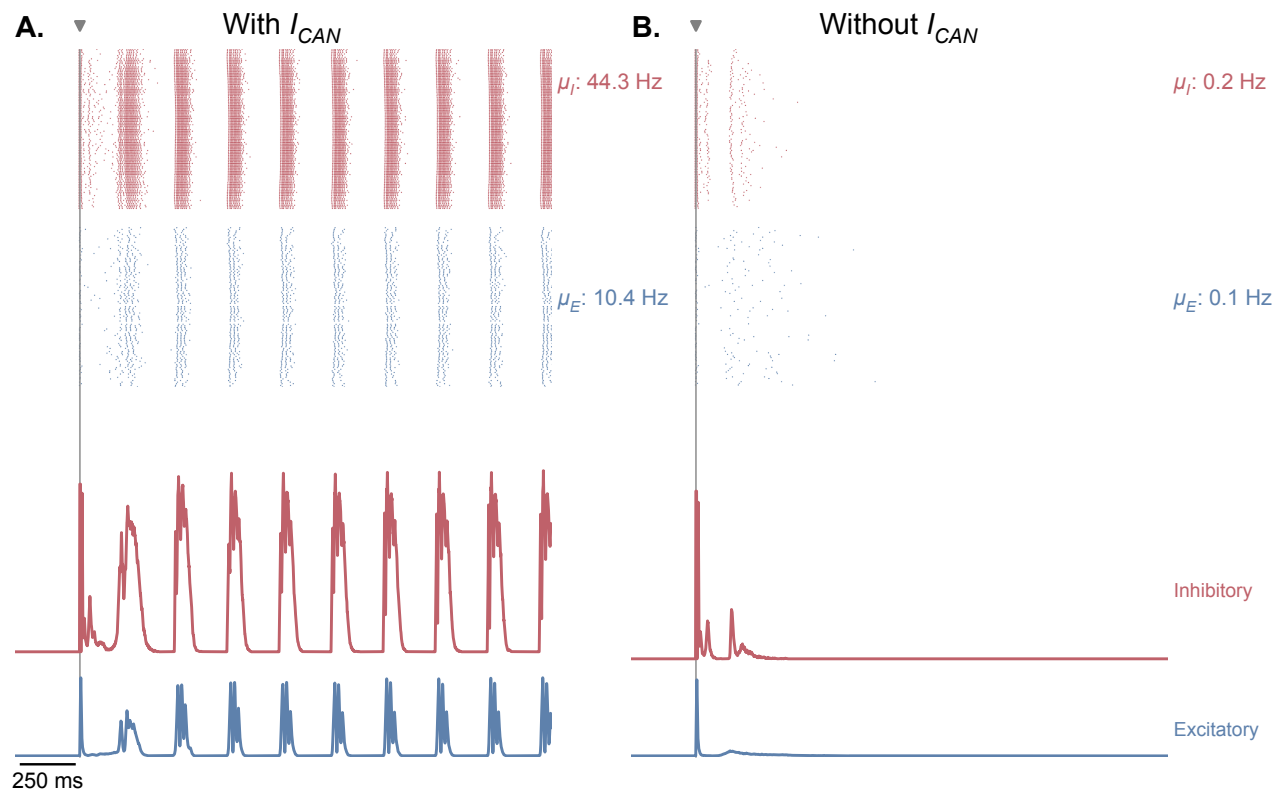


Figure S12. (Figure 5 – Figure Supplement 4) CAN currents are necessary for the production of self-sustained theta-gamma oscillations in response to single-pulse stimulation. A. Same as Figure 5B. **B.** Similar simulation as panel A., but without the presence of CAN currents in the EC, CA3 and CA1 fields of the hippocampus. Removing CAN currents from the model abolishes self-sustained theta-nested gamma oscillations in response to a single stimulation pulse (for the parameters represented in Figure 5, point B).

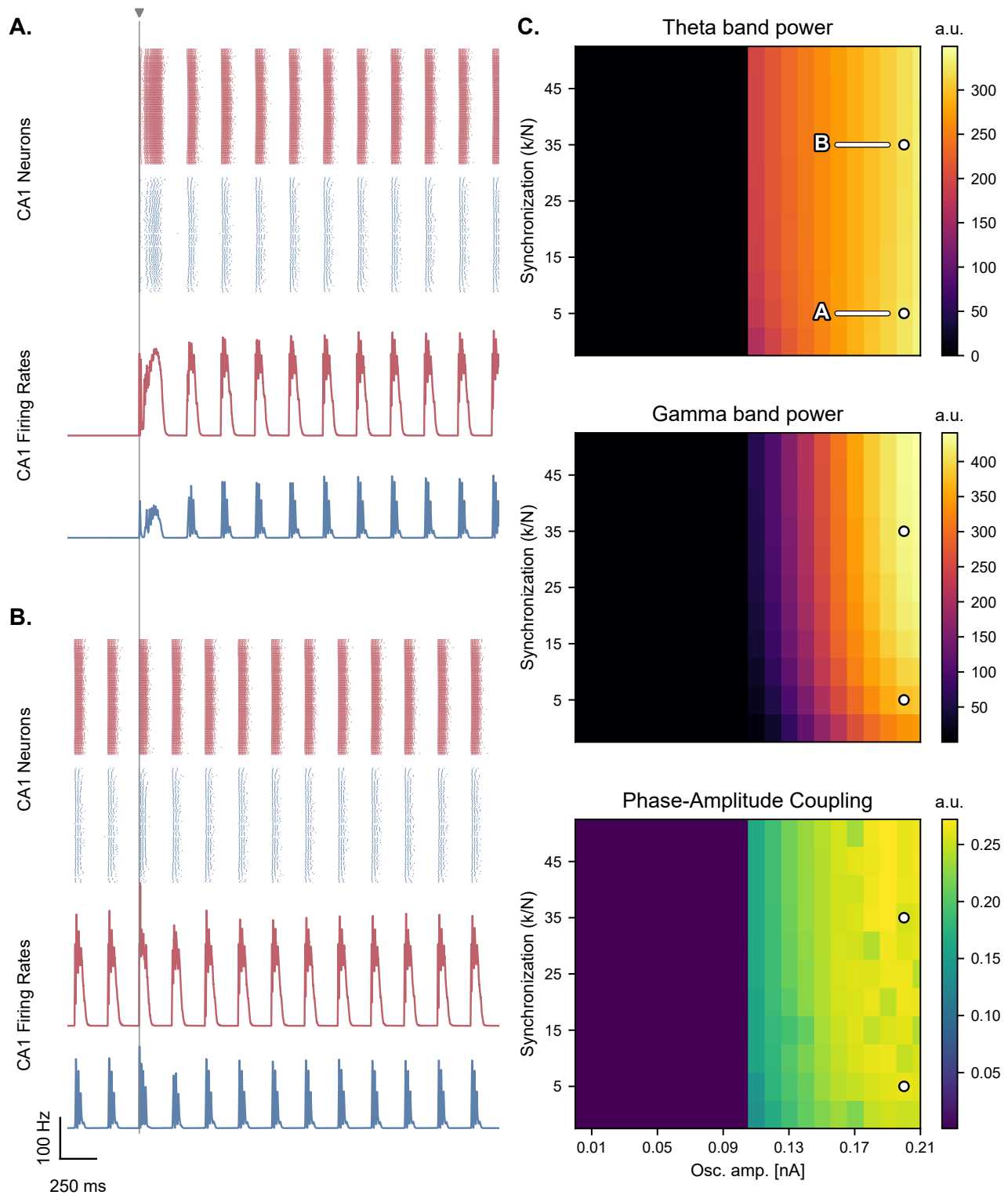


Figure S13. (Figure 5 – Figure Supplement 5) Synchronization level of the oscillators minimally affects the production of theta-nested gamma oscillations. A., B. Network responses to single-pulse stimulation (vertical line) under medial septum input (with phase reset), shown for different synchronization parameter ratios of the Kuramoto oscillators (A,B: $\frac{k}{N}$ of 5 and 35 respectively; stimulation amplitude: 7.0 nA). **Panel B.** indicates that the model can produce oscillations without external stimulation when the synchronization level is higher. **C.** Steady-state response to single-pulse stimulation as a function of medial septum oscillatory input (x-axis) and synchronization parameter ratio ($\frac{k}{N}$, y-axis), characterized by three metrics: theta power (3-9 Hz), gamma power (40-80 Hz), and PAC (quantified using the MI). White dots: parameter combinations corresponding to panels A and B.