

Noise-induced maximization of integrated information in FitzHugh-Nagumo networks

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Increasing evidence suggests that consciousness is linked to a system's ability to integrate information. Integrated information measures how much information a system holds beyond the sum of its independent parts. In this study, we explore how noise can maximize integrated information in small-scale FitzHugh-Nagumo neural networks. This noise-driven optimization occurs in both oscillatory and excitable regimes, as well as at the bifurcation point. Furthermore, we observe a noise-induced correlation between integrated information and coherence, and notably, the maximization of integrated information is accompanied by disparate coherence patterns in different regimes. Our findings provide insights into how noise can enhance information processing and potentially consciousness in neural systems and reveal a connection between information integration and the regularity of neural activity.

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Introduction. Consciousness is the state of being aware of and able to experience one's surroundings, thoughts, and sensations [1–3]. Despite being a central feature of human existence, it remains elusive, tied to the first-person perspective, and difficult to observe and measure. Integrated information theory (IIT), despite the inevitable limitations, has become a popular theory of consciousness, offering a theoretical framework to explain and quantify consciousness, proposing that consciousness arises from a system's capacity to integrate information [4–8]. Neurons play a critical role in processing and integrating information within the nervous system and numerous studies have been dedicated to modeling the properties arising from the neural networks [9–13]. While several studies have focused on understanding and measuring integrated information within neural networks, the relationship between integrated information and the underlying biophysical properties remains largely unexplored [14–16].

While noise is often viewed as a source of disorder, it can, paradoxically, induce coherent and structured responses, and sometimes even intelligence, in nonlinear systems [17–21]. It encompasses a wide range of behaviors where stochastic fluctuations fundamentally alter or even create dynamical patterns, from triggering phase transitions to enhancing signal detections. A typical example is the celebrated coherence resonance [22–24]. It occurs when the addition of random noise to a nonlinear system leads to the emergence of more regular oscillations even in the absence of periodic forcing. The

behavior has been observed in a variety of systems, including neural networks, chemical reactions, and climate models.

In this work, we demonstrate that noise can induce the maximization of integrated information in coupled small-scale neural networks. The neuronal dynamics are described by the FitzHugh-Nagumo model [25]. The FitzHugh-Nagumo model has two regimes depending on the parameter a , which will be introduced in the *Methods* section. We shed light on the correlation between integrated information and coherence, and most importantly, the integrated information is accompanied by different coherence patterns in different regimes. In the oscillatory regime ($a < 1$), integrated information has negative correlation with coherence before its maximum and flips afterward. This is as expected and can be interpreted with the definition of integrated information and coherence. In the excitable regime ($a > 1$), the maximum of integrated information exists until a certain level of a , exhibiting an unprecedented phase transition. At bifurcation point, $a = 1$ shows consistently positive correlation between integrated information and coherence, as well as the coincidence of the maxima. Moreover, the maximized integrated information decreases with the parameter a . We also report the phase transition of the coherence near the bifurcation point. Apart from these observations, our system also provides a testbed to investigate the impact of noise on integrated information, as opposed to the models (e.g., autoregressive process) used in previous studies [26,27].

The remainder of the paper is organized as follows. The next section provides the mathematical details of modeling the coupled neurons, as well as the tools to compute integrated information and coherence. The third section presents the essential results that demonstrate the noise-induced maximization of integrated information and the accompanying coherence in different regimes. The fourth section concludes the paper and discusses future directions.

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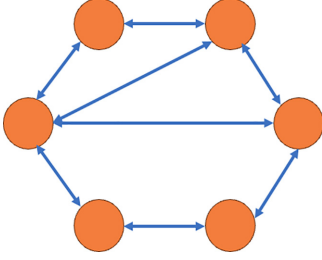


FIG. 1. The asymmetric topology.

Methods. In the current study, we investigate small-scale coupled neural networks using the FitzHugh-Nagumo model, for its balance between computational efficiency and biological relevance. We limit the number of neurons to 6 ($N = 6$) since the computational cost of integrated information is substantial (even with some simplification in place). This will become clear later when integrated information is introduced. We focus on neural networks because the brain is widely considered the primary source of consciousness that the IIT seeks to explain, and neurons are the brain's fundamental units for processing information. In this work, we consider bidirectional networks with three different topologies:

(1) A fully connected network such that all neurons are connected to each other except for the self-loop.

(2) A ring topology network where each neuron is only connected to its neighbors.

(3) A ring topology network with two additional randomly created edges (asymmetric topology for illustrative purposes) as shown in Fig. 1.

These configurations will span network topologies with different degrees of connectivity, as well as symmetry/asymmetry. The dynamics of the coupled neurons are described as

$$\begin{aligned} \frac{du_i}{dt} &= u_i - \frac{u_i^3}{3} - v_i + P \sum_{j=1}^N W_{ij}(u_j(t) - u_i(t)), \\ \varepsilon \frac{dv_i}{dt} &= u_i + a + \sqrt{2D}\zeta_i(t). \end{aligned} \quad (1)$$

In the above equations, i denotes the index of neurons. The dimensionless variable u is the voltagelike variable and v resembles the recovery variable. W denotes the connection matrix and the connections between neurons in the present study are bidirectional. For example, for a fully connected network, all off-diagonal elements of the matrix are 1, while the diagonal elements are 0. P is the coupling strength and we choose $P = 0.1$ for this study. In this relatively simplistic model, the afferent current to a neuron is described as a scaling of the voltage difference between the presynaptic and the postsynaptic neurons and choosing $P = 0.1$ can prevent the occurrence of nonphysiologically plausible spikes. ε is the timescale parameter and the value is typically between 10 and 100 to reflect the slow timescale of the recovery variable. We choose $\varepsilon = 20$ for this study. ζ stands for the Gaussian white noise with $\langle \zeta_i(t) \rangle = 0$ and $\langle \zeta_i(t)\zeta_j(t') \rangle = \delta_{ij}\delta(t - t')$, where t and t' are any time points. D represents the noise intensity, and in this work, we will limit D to less than 20 to avoid the prevalence of nonphysiologically plausible spikes caused

by large D in numerical simulation. One may also explore larger noise intensity but needs to be more careful with the step size and simulation protocols. Moreover, small intensities are often more informative given the nature of the noise. A single FitzHugh-Nagumo neuron in the absence of noise ($D = 0$) undergoes a supercritical Hopf bifurcation at $|a| = 1$. The system is in the excitable regime when $|a| > 1$ and the oscillatory regime when $|a| < 1$. In this work, we focus on the case when a is positive. The dynamics of the fast variable u were simulated using the fourth-order Runge-Kutta method and the dynamics of the slow variable v were simulated using the Euler-Maruyama rule to account for the stochasticity in the slow variable v with time step $\Delta t = 0.1$. The total simulation time T is fixed at $T = 100\,000$ to ensure enough samples for the calculation of integrated information that is due to be introduced later. Time will remain dimensionless throughout this work and the first 5000 time steps will be burned out for the analysis. Additionally, in practice, the neuronal activities are often represented in the form of spike trains. Therefore, the simulated dynamics were binarized with threshold $u_{\text{thr}} = 1$ to facilitate the downstream analysis. In other words, upon transformation, the activities of each neuron will be represented as a sequence of 0 and 1. Choosing a relatively high threshold will avoid (too many) consecutive spikes in the simulation, as the spikes produced by biological neurons are usually very sparse.

Time coherence characterizes the spike regularity of a neuron, measuring the variation in the interspike interval. It is well known in the context of coherence resonance. The time coherence (Fano-factor) can be described by the coefficient of variation

$$C = \frac{\sqrt{\langle t_{\text{ISI}}^2 \rangle - \langle t_{\text{ISI}} \rangle^2}}{\langle t_{\text{ISI}} \rangle}, \quad (2)$$

where t_{ISI} is the time interval between subsequent spikes. The bracket stands for the mean of the variable and it is estimated from the simulated spike trains mentioned above. To avoid any ambiguity in the future, we reiterate that a higher value of the coefficient of variation (C) indicates a lower level of coherence. Note that in the case of two or more consecutive spikes, the spike time of this particular episode is chosen to be the time at which the first spike is observed. The time intervals t_{ISI} from individual neurons are thereafter flattened in a single vector, and the mean and standard deviation are calculated accordingly.

Integrated information is defined as the amount of information a system generates as a whole, beyond the independent contribution of its parts. To this end, several measures have been proposed thus far, and in this work, we adopted the measure Φ^* as introduced in Ref. [28]. First, it provides the means to compute the integrated information of time series from a decoding perspective. This mismatched decoding framework was proposed in Ref. [29] for investigating to what extent the decoding process in the brain can be simplified and was applied to spike data for vertebrate retina. Second, it satisfies the theoretical requirements for IIT, such as the lower and upper bounds. One can refer to Ref. [28] for a comprehensive treatment of the derivation of the measure. Φ^* investigates the relationship between two variables x and y such that $y(t) =$

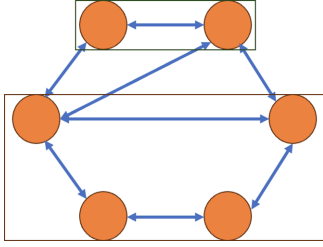


FIG. 2. Partition example.

$x(t + \tau)$. Namely, x and y belong to the same sequence with y being the state τ time steps after $x(t)$. They are sourced from the simulated spike trains mentioned above. In this work, we choose $\tau = 10$ to investigate the decoding with short delay. In the above context, x is the collective state of six neurons with binary output at time t in the network. Intuitively, Φ^* quantifies the loss of information as a consequence of mismatched decoding when the network is hypothesized to be partitioned into k individual parts and the correlation between them is nonexistent. Therefore, Φ^* with respect to a specific partition π can be described mathematically as

$$\Phi_{\pi}^* = I(x, y) - I_{\pi}^*(x, y). \quad (3)$$

Here, π can be defined as $\pi = [M_1, M_2, \dots, M_k]$ and M_j denotes the part j whose correlation with the other parts is ignored. In the present context, M_j is a subset of neurons in the network. For instance, in our six-neuron setting, a bipartition example ($k = 2$) could be as shown in Fig. 2 such that one part has two neurons and the other has four neurons. The state variables that stand for these two parts are M_1 and M_2 . Note that the partitioning of the network does not remove the edges between neurons from different parts and the simulated dynamics of each neuron will not be altered. It only restricts the computation of the mismatched decoding probability, which will be introduced later, to the respective subsets (parts). $I(x, y)$ defines the mutual information between x and y for the whole network:

$$I(x, y) = H_x + H_y - H_{xy}, \quad (4)$$

in which H_x denotes the entropy with respect to the variable x such that

$$H_x = - \sum_x p(x) \log_2(p(x)). \quad (5)$$

I_{π}^* defines the amount of information obtained from mismatched decoding with a particular partition π and can be expressed as

$$\begin{aligned} I_{\pi}^*(x, y) = & - \sum_y p(y) \log_2 \sum_x p(x) (q(y|x))^{\beta} \\ & + \sum_{x,y} p(x, y) \log_2 (q(y|x))^{\beta}, \end{aligned} \quad (6)$$

where β is the value that maximizes I_{π}^* . $q(y|x)$ measures the mismatched decoding probability, which is the product of the conditional probability distribution in each part:

$$q(y|x) = \prod_{j=1}^k p(M_j^t | M_j^{t-\tau}). \quad (7)$$

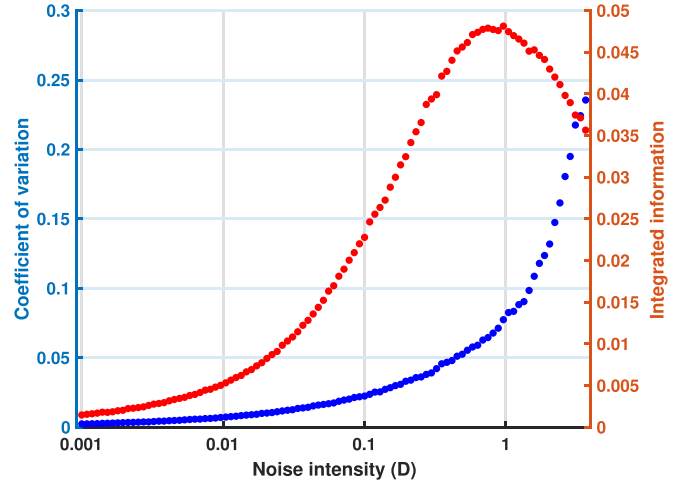


FIG. 3. Noise-induced coherence and integrated information in the oscillatory regime ($a = 0.6$) in a fully connected network. The noise intensity D is evenly sampled on the log scale.

The final estimate of the integrated information Φ^* is the partition π at which the value is minimized. Note that Φ^* carries an enormous computational cost as the exploration of all possible partitions is required. Hence, the Queyranne's algorithm only exploring the bipartition was applied to accelerate the simulation and this simplification has been shown to be valid by previous studies [26,30].

Finally, it is worth noting that, regardless of any potential connection to consciousness, Φ^* in itself contains meaningful implications for dynamical systems that may not be otherwise quantified. In a way, it provides a measure that balances the information richness of individual components in the system, as well as the correlation across space and time.

Results. Figure 3 shows that the integrated information is maximized at a certain noise intensity in the fully connected network in the oscillatory regime. Note that D is evenly sampled on the log scale to visualize the trend at very low noise. Besides, the coherence and integrated information are negatively correlated before the integrated information reaches the maximum and become positively correlated afterward. Recall again that the coefficient of variation is negatively correlated with coherence. In order to profoundly understand the observed phenomena, we delve into the neuronal dynamics when $a = 0.6$ that underpin different sections of the integrated information curve as shown in Fig. 4. Here, we only include a few spikes so that the frequency can be better interpreted. The integrated information is peaked near $D = 0.8$. At low noise level ($D = 0.1$), the spikes are highly regular and the neurons are fully synchronized. In the oscillatory regime, small noise sustains the oscillatory behaviors and the neurons can be synchronized when coupled. $D = 0.8$ witnesses a slight increase in spiking frequency and the regularity slightly declines. Therefore, it gives rise to lower coherence. The increased integrated information agrees with the definition of entropy. The entropy is maximized when both outcomes have an equal chance to occur, and hence, the increased frequency of spikes will move the probability of spike occurrence closer to 0.5. Simultaneously, the synchronization among neurons is still largely preserved and the mutual

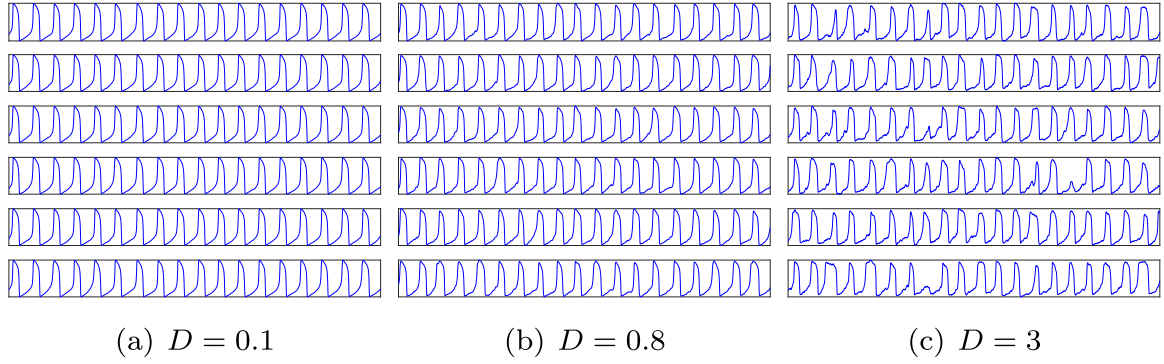


FIG. 4. Snippets of dynamics with various D when $a = 0.6$ (oscillatory regime) of a fully connected network. Here, we only include a few spikes to observe the fine details.

information essentially remains unchanged (see *Methods* section for the definition of integrated information). When D keeps increasing (e.g., $D = 3$), the spiking pattern becomes more irregular and we notice that both integrated information and coherence decrease. The decreased integrated information may be explained by the decreased correlation between different parts of the system as a consequence of the increased chaos intrinsic to the components. One may note that the partition of the system as introduced in the *Methods* section when calculating integrated information does not considerably con-

tribute to the pattern of integrated information with respect to noise, as the neurons are largely synchronized. However, it will become nontrivial and Φ^* will play its role in the excitable regime when the system becomes more chaotic, as the patterns in integrated information and coherence may not be easily deduced.

Figure 5 displays the results near the bifurcation point. Notably, the maximum of integrated information approximately coincides with the minimum of the coefficient of variation (maximum of coherence) at the bifurcation point $a = 1$.

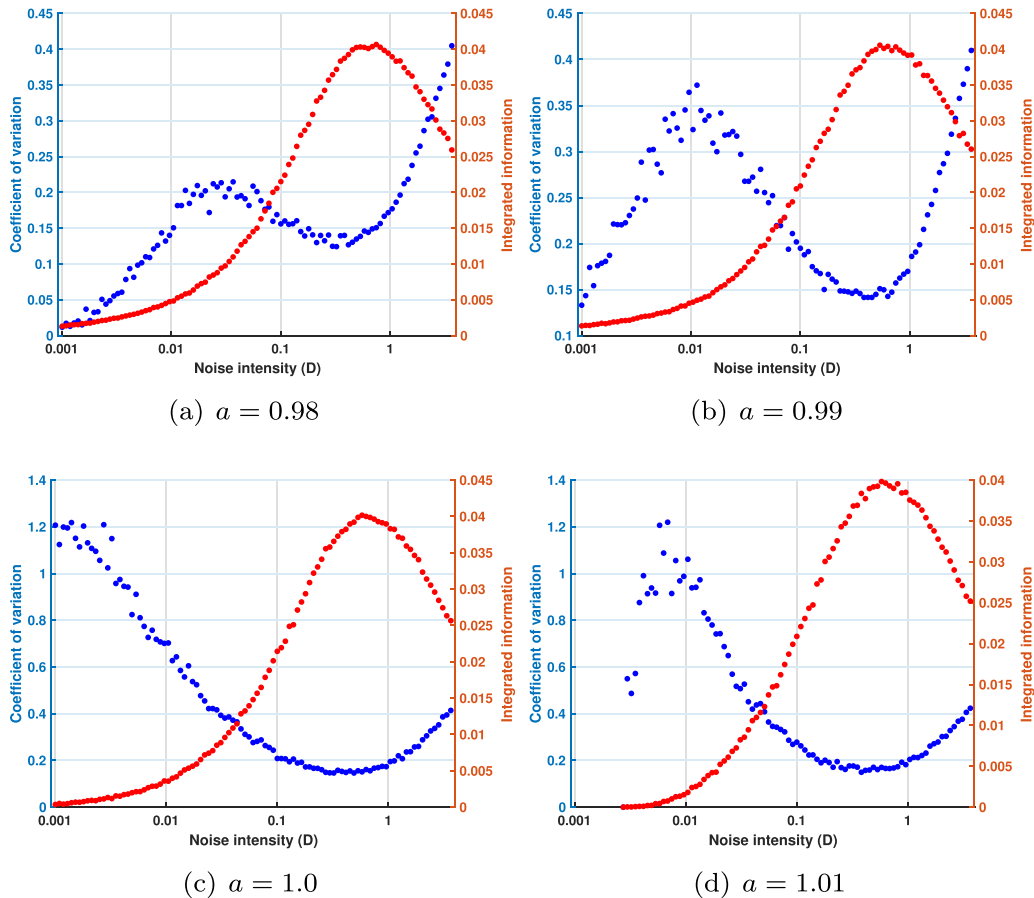


FIG. 5. Noise-induced coherence and integrated information near the bifurcation point $a = 1$ in a fully connected network. The noise intensity D is evenly sampled on the log scale.

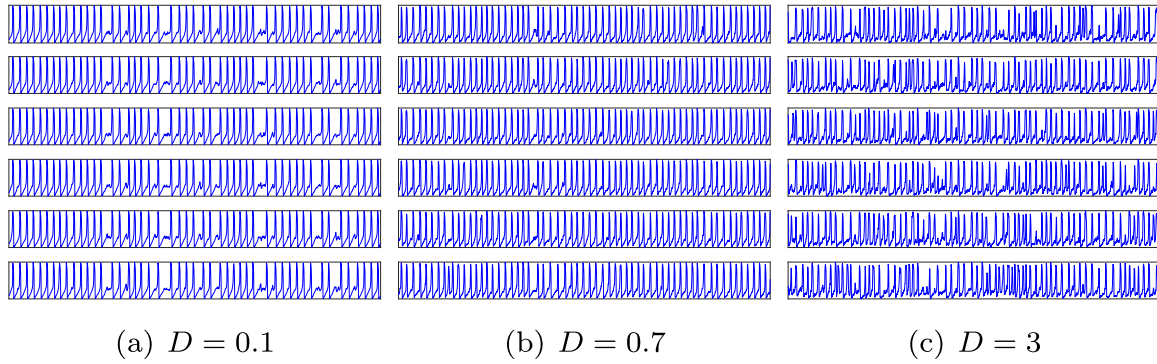


FIG. 6. Snippets of dynamics with various D when $a = 1$ (bifurcation point) of a fully connected network. Here, we include longer time series than Fig. 4 to demonstrate the chaos.

In other words, the maximization of integrated information approximately coincides with the coherence resonance. Moreover, in contrast to the oscillatory regime, the coherence and integrated information are always positively correlated beyond a certain noise intensity. Figure 6 exhibits the dynamics of the coupled neurons that correspond to different sections of the integrated information at the bifurcation point ($a = 1$). Here, we include longer time series in order to better demonstrate the chaos intrinsic to the dynamics. The integrated information pattern largely resembles that in the oscillatory regime. However, unlike in the oscillatory regime, the increase in integrated information is accompanied by increased spiking frequency as well as increased coherence. At a large noise level, the regularity is disrupted and we observe that both integrated information and coherence decline. The maximum of the integrated information is achieved when the spiking frequency is relatively large, while the regularity is well preserved. We also notice that the coherence pattern undergoes a phase transition when entering the bifurcation point. The coherence at low noise intensity massively decreases when transitioning from $a = 0.98$ to $a = 1.0$. The scatteredness when D is low at $a = 1.01$ arises from the insufficient number of spikes generated in the excitable regime under low noise intensity, which will also be seen in the next paragraph.

In the excitable regime (Fig. 7), the noise needs to attain a certain intensity in order to excite individual neurons. The noise-optimized integrated information is largely preserved until certain values of a , which will be discussed later. The correlation between integrated information and coherence is effective beyond a certain noise intensity and the coherence resonance is observed. To better study the disappearance of the maximum of integrated information in the excitable regime, Fig. 8 shows a close-up of the high-noise area of the integrated information curve with $a = 1.6$ and 1.8 . As can be seen, the maximum has more or less vanished when $a = 1.6$ and the integrated information shows no sign of the maximum appearance even when D reaches 20 when $a = 1.8$. This reveals an unprecedented phase-transition phenomenon for integrated information in the excitable regime with respect to the parameter a . As before, we present the neuronal dynamics for the fully connected network in various sections of the integrated information curve in Fig. 9. When $a = 1.3$, namely, when the maximum still exists, the integrated information is peaked when the spikes become more frequent while a certain

degree of local regularity is formed (around $D = 1.2$), though less obvious than in the oscillatory regime [Figs. 9(a)–9(c)]. However, when the maximum becomes nonexistent ($a = 1.8$), there is essentially no emerging pattern intrinsic to the neuronal dynamics other than a slight increase in frequency [Figs. 9(d)–9(f)]. A salient difference between the excitable and the oscillatory regimes is the level of chaos inherent in the neuronal dynamics and consequently the interpretability of the integrated information pattern. However, this is why the present study is valuable. The integrated information pattern can be largely deduced from the neuronal models and theoretical definitions in the oscillatory regime, whereas it can be conceived without the calculation of integrated information (which searches through different partitions of the system) in the excitable regime.

Finally, by inspection of the integrated information curves from Figs. 3, 5, and 7, the maximum of integrated information decreases with a , showing that the excitable level of the system is negatively correlated with the integrated information.

With respect to the other two network topologies (ring and asymmetric), Figs. 10 and 11 show identical qualitative patterns in the oscillatory and excitable regimes, respectively. It is noticeable that for the same set of parameters, the maximum

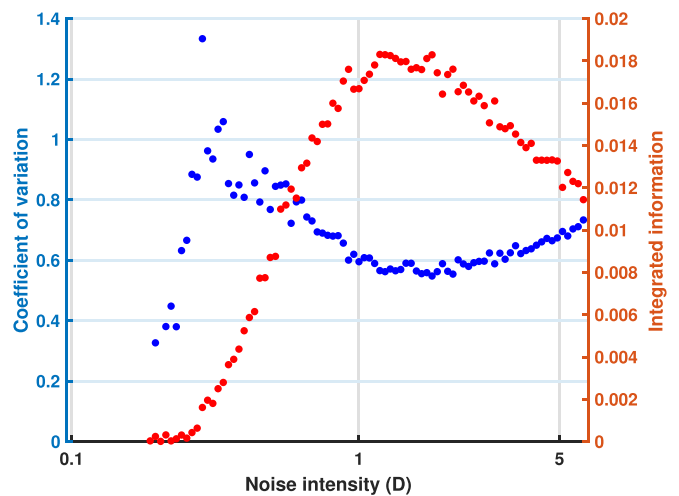


FIG. 7. Noise-induced coherence and integrated information in the excitable regime ($a = 1.3$) in a fully connected network. The noise intensity D is evenly sampled on the log scale.

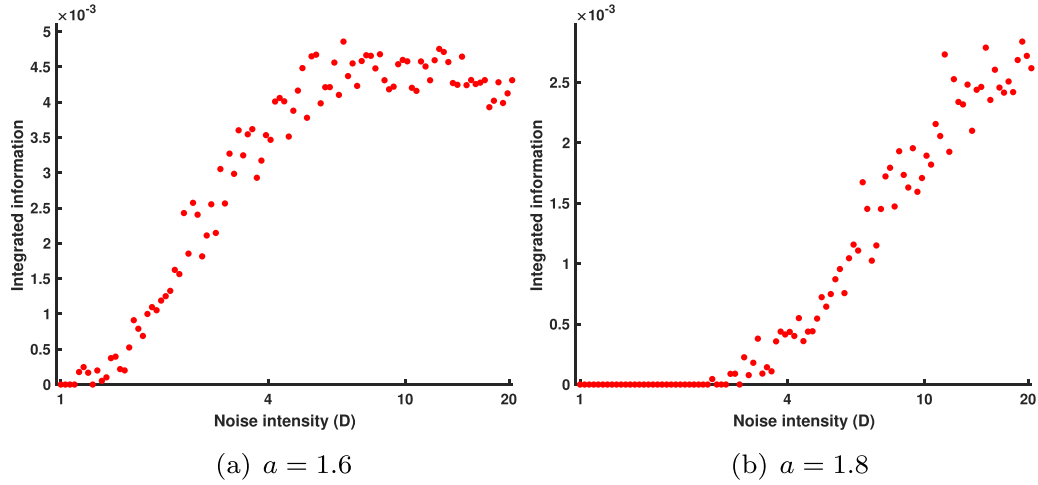


FIG. 8. Disappearance of the maximum of integrated information in the excitable regime in a fully connected network. The noise intensity D is evenly sampled on the log scale.

of integrated information of the fully connected network is higher than the other two topologies. This can be attributed to the fact that higher connectivity tends to increase synchronization, which in turn raises integrated information. Regarding the disappearance of the maximum of integrated information in the excitable regime, we observe that the fully connected network retains its peak over a wider range of increasing a values than the other two topologies (Fig. 12), suggesting that higher connectivity enhances the robustness of peak persistence.

Conclusions and discussions. In this study, we have shown that noise can play a constructive role in enhancing integrated information in small-scale neural networks governed by the FitzHugh-Nagumo model. Our results reveal that noise not only promotes the maximization of integrated information but also gives rise to distinct coherence patterns across different dynamical regimes. Specifically, in the oscillatory regime ($a < 1$), we observed a sign change in the correlation between coherence and integrated information around its maximum. In contrast, the excitable regime ($a > 1$)

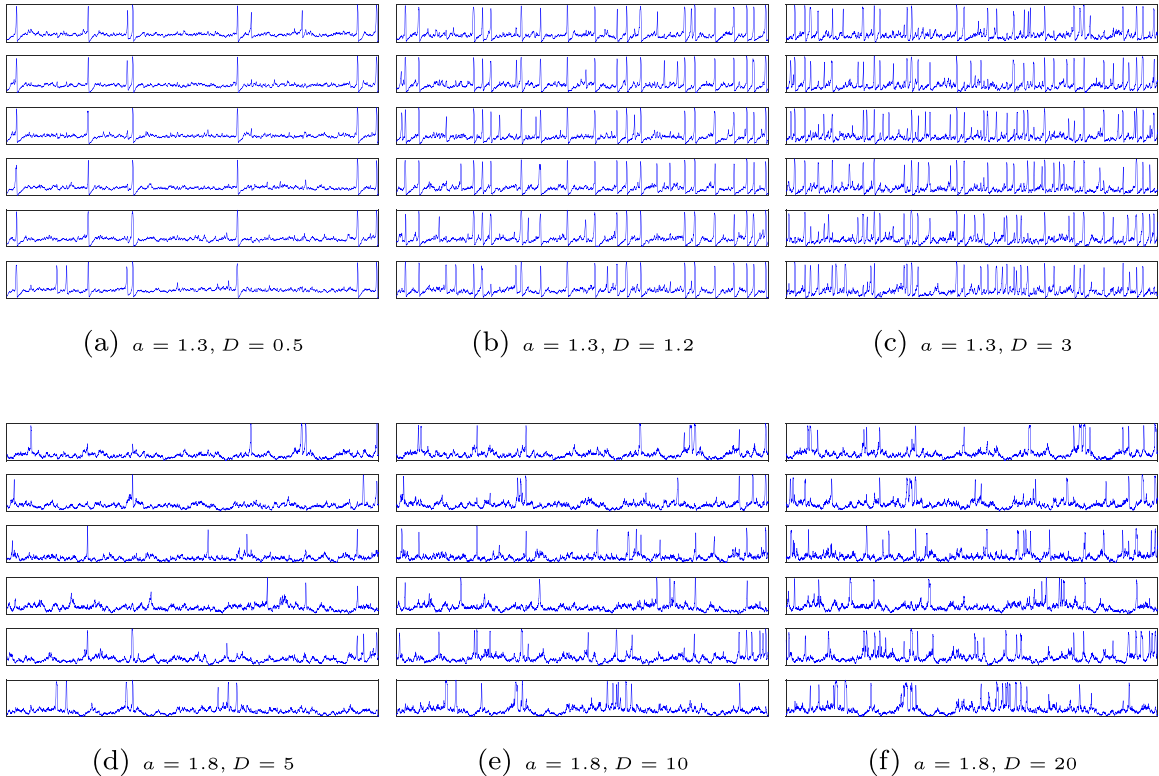


FIG. 9. Snippets of dynamics with various D when $a = 1.3$ and $a = 1.8$ (excitable regime) of a fully connected network. Here, we include longer time series than Fig. 4 to demonstrate the chaos.

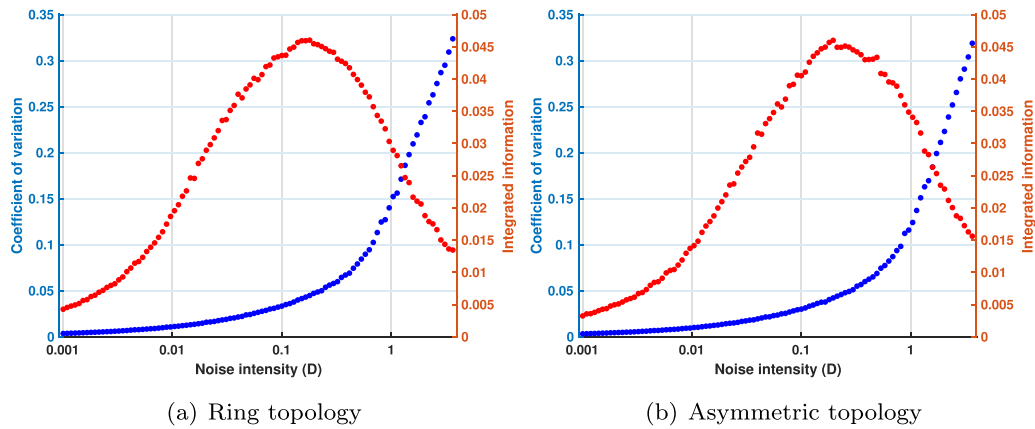


FIG. 10. Noise-induced coherence and integrated information in the oscillatory regime for the ring and the asymmetric topologies when $a = 0.6$.

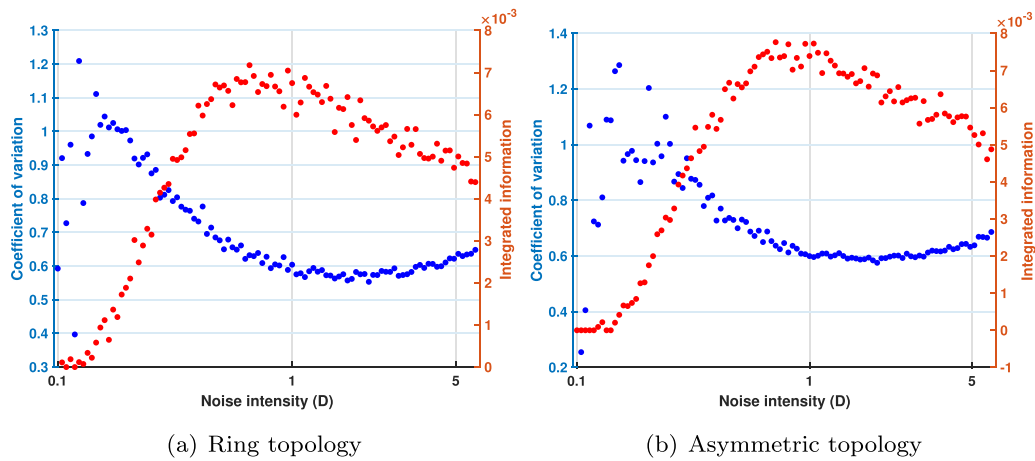


FIG. 11. Noise-induced coherence and integrated information in the excitable regime for the ring and the asymmetric topologies when $a = 1.3$.

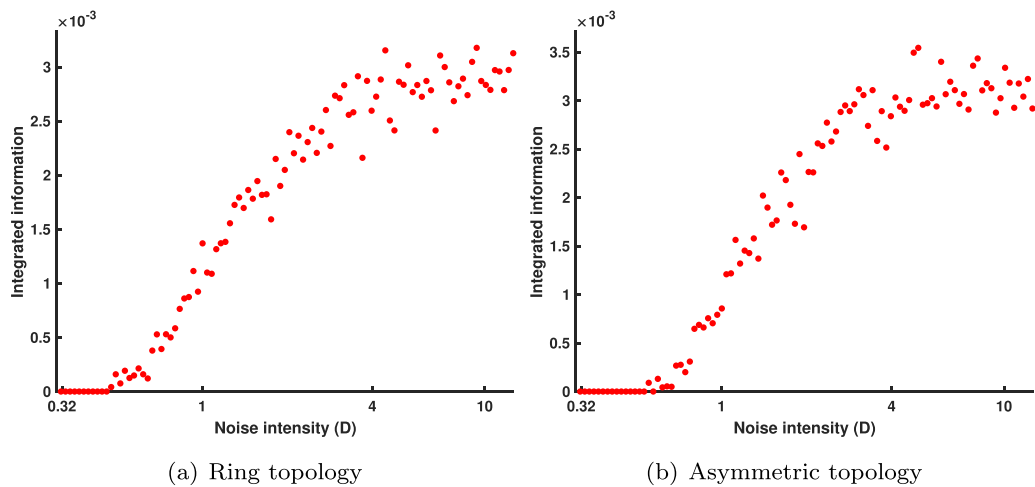


FIG. 12. Disappearance of the maximum of integrated information in the excitable regime for the ring and the asymmetric topologies when $a = 1.5$.

presented a unique phase transition beyond which integrated information could no longer be maximized. At the bifurcation point ($a = 1$), coherence and integrated information exhibited a consistently positive correlation and coincided in their maxima. These observations can also be perceived across the continuous parameter space of a , regardless of the dynamical regimes. Namely, the noise-induced maximization of integrated information exists until a certain value of a . Furthermore, the maximized integrated information falls against the increase of a . However, the coherence pattern varies across different regimes, reflecting distinct underlying neuronal dynamics. A transition in coherence patterns was observed as the system moved from the oscillatory to the excitable regime. These findings underscore the nontrivial role of stochasticity in shaping the information processing of neuronal systems, which cannot be easily inferred from the spiking patterns. They open avenues for understanding how noise can mediate transitions in consciousness-related measures, suggesting that randomness may not merely be a source of disorder, but also a mechanism for enhancing and regulating consciousness-related behaviors.

Additionally, as compared to previous works [26,27], our study provides a simulation platform to investigate the effect of noise on integrated information that possesses several distinctive properties. In Ref. [26], the authors calculated the integrated information measures (including Φ^*) of the dynamics produced by a network of nodes governed by an autoregressive process:

$$\mathbf{x}_{t+1} = \mathbf{A}\mathbf{x}_t + \boldsymbol{\epsilon}_t, \quad (8)$$

where $\mathbf{x}_t$ denotes the state of nodes at time step t , $\mathbf{A}$ denotes the transition matrix, and $\boldsymbol{\epsilon}_t$ denotes the noise term, following a zero-mean Gaussian distribution with a covariance matrix. Our system differs in multiple ways. First, the FitzHugh-Nagumo model is a classic neuronal model and is arguably better suited for studying integrated information, which has implications for consciousness. Since neurons communicate via spikes, it also enables the study of binary variables rather than continuous variables. Second, the autoregressive process is linear, whereas our system is nonlinear, and it is believed that most dynamical systems in nature are inherently nonlinear. Third, as the FitzHugh-Nagumo model involves a fast variable u and a slow variable v , our system allows us to examine how noise influences interactions across different timescales, something the autoregressive process cannot enable. In a more recent study [27], the Hodgkin-Huxley model was employed to compute Φ^* that arises from a six-neuron neural network. The work was focused on the impact of the bidirectional communication between neurons and astrocytes and a thorough assessment of noise effect is lacking. In this

work, the noise was introduced to the fast variable (voltage variable) in the form of a Poisson spike train and a similar maximization of Φ^* was not reported. Conversely, the noise is introduced to the slow variable (summary of the combined gating effects) in our work, reflecting our current understanding that the opening/closing of ion channel gates is the primary source of electrical noise. Also mathematically, the slow variable integrates the noise over time and better imitates real neural spiking behavior, whereas adding to the fast variable may generate nonphysiologically plausible spikes. The FitzHugh-Nagumo model also provides a neat framework to explore the behaviors in different regimes (controlled by a) and is more computationally efficient than the Hodgkin-Huxley model.

Furthermore, we would like to reiterate that the correspondence between integrated information and consciousness should not be overinterpreted, as the validity of integrated information as a representation of consciousness remains a topic of active debate [31–33]. Nonetheless, as explained earlier, Φ^* itself provides, to some extent, a balanced measure that characterizes the information richness of individual components and the correlation across space and time, which is meaningful from the dynamical system perspective and may not be otherwise quantified.

In recent years, increasing attention has been given to the interaction between neurons and astrocytes, which plays a vital role in maintaining central nervous system homeostasis and supporting neural function. Once thought to be merely passive support cells, astrocytes are now recognized as active contributors to synaptic transmission. Through bidirectional communication with neurons, they modulate synaptic strength, regulate extracellular ion and neurotransmitter levels, and influence plasticity and information processing. In response, various mathematical models have been developed to describe these processes at the network level [34–36]. Exploring the impact of double noise—separately introduced to neurons and astrocytes—on neuronal dynamics and integrated information would therefore be of particular interest. Notably, astrocytic calcium signaling occurs on a much slower timescale than neuronal spiking, offering a valuable opportunity to investigate the synergistic effects of noise operating at different temporal scales.

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Data availability. The data that support the findings of this Letter are openly available [37].

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