

Signal propagation of a feedforward neural network under electromagnetic stimulation

Huilan Yang(杨惠兰), Wei Zhang(张伟), and Junjie Bao(包俊杰)

Citation: Chin. Phys. B, 2026, 35 (**6**): 068301. DOI: 10.1088/1674-1056/ae5218
http://cpb.iphy.ac.cn; http://iopscience.iop.org/cpb

What follows is a list of articles you may be interested in

Orientation and alignment during materials processing under high magnetic fields

Zhong-Ming Ren(任忠鸣), Jiang Wang(王江), Rui-Xin Zhao(赵睿鑫)
Chin. Phys. B, 2019, 28 (**4**): 048301. DOI: 10.1088/1674-1056/28/4/048301

The electric field and frequency responses of giant electrorheological fluids

Hanqing Zhao(赵汉青), Rong Shen(沈容), Kunquan Lu(陆坤权)
Chin. Phys. B, 2018, 27 (**7**): 078301. DOI: 10.1088/1674-1056/27/7/078301

Electrical field-driven ripening profiles of colloidal suspensions

Zi-Rui Wang(王子瑞), Wei-Jia Wen(温维佳), Li-Yu Liu(刘雳宇)
Chin. Phys. B, 2018, 27 (**6**): 068301. DOI: 10.1088/1674-1056/27/6/068301

SPECIAL TOPIC — Biophysical circuits: Modeling & applications in neuroscience

Signal propagation of a feedforward neural network under electromagnetic stimulation

Huilan Yang(杨惠兰)[1,2,†], Wei Zhang(张伟)[1], and Junjie Bao(包俊杰)[1]

[1] *Tianjin University of Commerce, Tianjin* 300134, *China*
[2] *Hebei University of Technology, Tianjin* 300130, *China*

(Received 6 January 2026; revised manuscript received 13 March 2026; accepted manuscript online 16 March 2026)

Cortical networks exhibit distinct layered characteristics, with neurons in each layer collectively responsible for the transmission and processing of external signals. Information transfer between different regions and layers of the cerebral cortex is crucial for information processing in the nervous system. Investigating signal propagation among neural networks helps us understand the top-down or bottom-up information transmission mechanisms of the nervous system. In this study, a five-layer feedforward neural network with time delay was constructed. By calculating the discharge timing, signal-to-noise ratio, and population Fano factor of the multi-layer neural network, the characteristics of signal propagation between different levels of the nervous system under electromagnetic stimulation were investigated. The results show that the delay time has a significant impact on signal propagation; under appropriate delay time conditions, the neural network can achieve effective signal propagation. Electromagnetic stimulation can significantly improve the signal-to-noise ratio of neural network signal propagation, shorten the signal propagation time, and enhance the stability of signal propagation. This study not only provides an important theoretical basis for revealing the regulatory mechanisms of signal transmission between different levels of the nervous system but also offers useful references for the future development of electromagnetic neural modulation technologies and the treatment of diseases related to impaired signal transmission in the nervous system.

Keywords: neural networks, signal propagation, electromagnetic stimulation, time delay

PACS: 83.60.Np, 87.19.lj, 87.19.lq

DOI: 10.1088/1674-1056/ae5218 **CSTR:** 32038.14.CPB.ae5218

1. Introduction

Neurons are excitable cells in the nervous system that process and transmit information. Neuronal signals and communication support almost all aspects of brain activity and function.[1,2] In biological experiments, it has been found that the prefrontal cortex on both sides of the brain encodes short-term memory information in parallel, and this encoding can be realized through the interaction of different brain regions. The modular mode of action enhances the robustness of the brain and thus promotes the behavior of experimental animals.[3] In the field of computational neurodynamics, Zhou and colleagues[4] found that network modularization enables the brain to process information "with low energy consumption" and "efficiently respond," and they found that a scale-free avalanche in the dynamic mode enables the network to respond more effectively to external stimuli.

In recent years, the direction of information transmission in neural networks has become a research hotspot, and the "top-down" or "bottom-up" information transmission mechanisms of the nervous system have been explored.[5–7] The intrinsic discharge rate of a neuron population can determine the path of signal transmission. In a nearest-neighbor network, nodes with higher discharge frequencies promote reliable signal transmission and establish priority directions for information flow. By increasing the discharge frequency, lower-order nodes can serve as functional centers, spreading their activity patterns through multiple synapses in the network.[8] The communication between different regions of the brain also relies on stable phase relationships: in a symmetrical dynamic state, signal transmission is undirected, and in a symmetrical interrupt state, signal transmission exhibits significant directionality.[9] In oscillatory excitation–suppression neural networks, resonance can overcome the drawback of sparse connections between layers and promote synchronous propagation.[10] Guo and colleagues[11] studied the induction and propagation of transient synchronous activities in neural networks with short-term plasticity; they proved that synaptic facilitation significantly enhanced synchronous propagation in a feedforward neural network and synaptic enhancement of intralayer or interlayer coupling enhanced synchronous propagation.

Previous works have discussed the effects of external factors on information propagation in feedforward networks, such as the probability of interlayer connectivity,[12] noise intensity,[13,14] synaptic weight,[15] temperature[16] and electromagnetic radiation.[17–21] Research has shown that bidirectional connections between brain regions have a new function of shaping faster and more reliable communication between

[†]Corresponding author. E-mail: hlyang@tjcu.edu.cn

© 2026 Chinese Physical Society and IOP Publishing Ltd. All rights, including for text and data mining, AI training, and similar technologies, are reserved.

brain regions. By adding feedback, information transmission between neural module networks can be effectively enhanced, overcoming the fragility and sparsity of brain connections.[22] Under small delays, information transmission between two bidirectional excitatory coupled neural networks is from the high-frequency sender to the low-frequency receiver. In addition, in the case of bidirectional coupling asymmetry, as the delay changes, feedback can enhance or reduce information transmission.[23] Moderate temperature and morphology allow the stable propagation of synchronous spikes in feedforward networks and maximize the energy efficiency of information transmission.[24]

Electromagnetic neural regulation technology is a unique non-invasive neural regulation method that can specifically stimulate the cerebral cortex, cause depolarization of neurons, alter neuronal membrane potential, and affect cortical excitability.[25–27] At the same time, it can also be used to detect the causal relationship between brain activity and sensorimotor processing and to regulate complex cognitive functions such as memory performance.[28] Transcranial magnetic stimulation (TMS) of different functional brain regions causes spontaneous electroencephalography (EEG) oscillations in different frequency bands.[29] Borich *et al.* used TMS combined with EEG to evaluate brain connectivity in the primary motor cortex of patients with chronic stroke[30] and found that the phase coherence of the beta frequency band was significantly increased in stroke patients, indicating that TMS-induced EEG responses can be used to predict abnormal connectivity in the cerebral hemispheres of stroke patients. Hoy *et al.*[31] used intermittent theta burst stimulation to stimulate the dorsolateral prefrontal cortex of the brain and analyzed the changes in EEG signals before and after N-back working memory tasks. Their results showed that electromagnetic stimulation enhanced the connectivity of theta waves in the frontal and parietal lobes, as well as the energy of gamma waves in the parietal lobe. Kito *et al.*[32] studied the changes in resting-state EEG functional connectivity in patients with depression before and after high-frequency repetitive transcranial magnetic stimulation (rTMS), and showed that rTMS can regulate the synchronous activity of beta frequency bands between the left prefrontal cortex and the marginal region, improving the functional connectivity between the left prefrontal cortex and the marginal region. Chung *et al.*[33] studied the effect of TMS stimulation on cortical response in the prefrontal cortex and found that the amplitude of N100 and P200 evoked by the prefrontal cortex significantly increased after stimulation.

It has been demonstrated that the methods of network science for modeling and analyzing network communication dynamics are very useful for simulating functional brain connections and predicting emergent network states.[34,35] The anatomical and functional differences between various brain regions indicate that the brain is a highly modular system. Selective communication between brain regions is crucial for brain function. Understanding the mechanisms of information transmission will have a profound impact on multiple disciplines, spanning biology, medicine, information technology, and engineering. At present, the research on information dissemination in neural networks is not comprehensive, and there is a lack of research on information dissemination in modular neural networks under electromagnetic effects. Whether electromagnetic effects have a positive effect on signal propagation and how to improve signal propagation ability are urgent issues that need to be explored.

In this study, we constructed a multilayer feedforward neural network and focused on investigating the effects of electromagnetic stimulation parameters and network parameters on signal propagation within the neural network. Our results demonstrate that the inter-layer delay time exerts a significant influence on signal propagation, which is consistent with previous findings. In addition, by analyzing the signal-to-noise ratio (SNR) of signal transmission and the population Fano factor (pFF) under electromagnetic stimulation, we obtained several novel conclusions: electromagnetic stimulation has a distinct positive effect on improving the SNR, shortening signal transmission time, and enhancing the stability of signal propagation. We hope that our findings can deepen our understanding of the brain's signal processing mechanisms and provide theoretical guidance for the development of electromagnetic modulation techniques.

2. Materials and methods

A feedforward neural network has the main characteristics of the modular architecture of brain neurons. In a feedforward network, sparse and weak interlayer connections easily lead to the failure of signal transmission. Research has shown that adding feedback between multi-layer networks can make the process of signal processing more efficient.[22] We have constructed a feedforward neural network with feedback and delay; the connections between neurons are shown in Fig. 1 (feedback connections have been added between the first and second layers of the network).

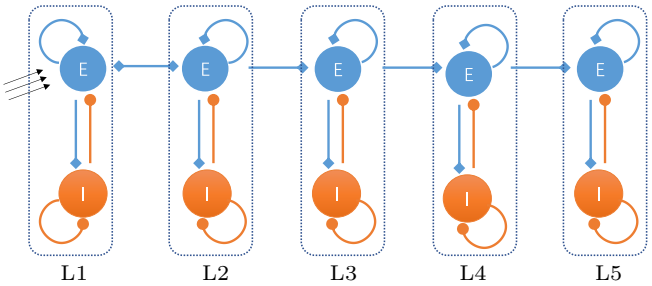


Fig. 1. Schematic diagram of the structure of a complex neural network. E represents excitatory neurons, I represents inhibitory neurons, diamond-headed arrows represent excitatory synaptic connections, circular-headed arrows represent inhibitory synaptic connections. There is a feedback connection between layer 1 and layer 2.

Each layer is composed of 100 Hodgkin–Huxley model[36] type neurons connected by excitatory or inhibitory synapses with a certain probability. According to previous experimental physiological studies, the ratio of excitatory and inhibitory neurons in the mammalian neocortex is usually very close to 4:1. Therefore, we constructed the network according to this ratio:[37] 80% of excitatory neurons and 20% of inhibitory neurons form an excitation–inhibition balance network. The dynamics of the multilayer feedforward network composed of improved neurons are described by

$$\begin{cases} C_{\rm m}\dfrac{{\rm d}V_i}{{\rm d}t} = I_i^{\rm syn} + I_i^{\rm noise} - I_i^{\rm Na} - I_i^{\rm K} - I_i^{\rm L}, \\ I_i^{\rm Na} = G_{\rm Na} m_i^3 h_i (V_i - E_{\rm Na}), \\ I_i^{\rm K} = G_{\rm K} n_i^4 (V_i - E_{\rm K}), \\ I_i^{\rm L} = G_{\rm L}(V_i - E_{\rm L}), \\ \dfrac{{\rm d}x_i}{{\rm d}t} = \phi(\alpha_{x_i}(1-x_i) - \beta_{x_i} x_i), \quad (x_i = m_i, n_i, h_i). \end{cases} \tag{1}$$

Here V_i is the membrane potential and $I_i^{\rm Na}$, $I_i^{\rm K}$, $I_i^{\rm L}$, $I_i^{\rm syn}$ and $I_i^{\rm noise}$ are the sodium, potassium, leakage, synaptic and noise currents, respectively. The symbols $G_{\rm Na}$, $G_{\rm K}$ and $G_{\rm L}$ denote the maximum sodium, potassium and leakage conductances, respectively, $E_{\rm Na}$, $E_{\rm K}$ and $E_{\rm L}$ denote the reversal potentials of those channels and m_i, h_i and n_i denote the channel gating variables.

The membrane potential function is defined in the excitatory neuron model as

$$\alpha_{m_i} = \frac{0.1(V_i+33)}{1-\exp[-(V_i+33)/10]}, \tag{2}$$

$$\beta_{m_i} = 4\exp[-(V_i+53.7)/12], \tag{2}$$

$$\alpha_{n_i} = \frac{0.01(V_i+34)}{1-\exp[-(V_i+34)/10]}, \tag{3}$$

$$\beta_{n_i} = 0.125\exp[-(V_i+44)/25], \tag{3}$$

$$\alpha_{h_i} = 0.07\exp[-(V_i+50)/10], \tag{4}$$

$$\beta_{h_i} = \frac{1}{1+\exp(-(V_i+20)/10)}. \tag{4}$$

The membrane potential function is defined in the inhibitory neuron model as

$$\alpha_{m_i} = \frac{-0.1(V_i+35)}{-1+\exp[-(V_i+35)/10]}, \tag{5}$$

$$\beta_{m_i} = 4\exp[-(V_i+60)/18], \tag{5}$$

$$\alpha_{n_i} = \frac{-0.01(V_i+34)}{-1+\exp[-(V_i+34)/10]}, \tag{6}$$

$$\beta_{n_i} = 0.125\exp[-(V_i+44)/80], \tag{6}$$

$$\alpha_{h_i} = 0.07\exp[-(V_i+58)/20], \tag{7}$$

$$\beta_{h_i} = \frac{1}{1+\exp(-(V_i+28)/10)}. \tag{7}$$

The parameters of the excitatory and inhibitory neuron models were selected as shown in Table 1.[38,39]

Table 1. Parameters of excitatory and inhibitory neurons.

Parameter	Value (inhibitory)	Value (excitatory)	Description
$C_{\rm m}$ (μF/cm^2)	1	1	membrane capacitance
$G_{\rm K}$ (mS/cm^2)	9	10.5	potassium channel membrane conductance
$G_{\rm Na}$ (mS/cm^2)	35	50	sodium channel membrane conductance
$G_{\rm L}$ (mS/cm^2)	0.1	0.1	leak channel membrane conductance
$E_{\rm K}$ (mV)	–90	–100	potassium channel reversal potential
$E_{\rm Na}$ (mV)	55	55	sodium channel reversal potential
$E_{\rm L}$ (mV)	65	–61	leak channel reversal potential
ϕ	5	1	temperature coefficient

Synaptic delay refers to the time lag in chemical synapses from the onset of depolarization at the presynaptic nerve terminal to the generation of postsynaptic potential in the postsynaptic cell. Synaptic time delay is an indispensable condition for signal transmission in neural networks. With a certain delay time, signals can be smoothly transmitted to the destination in a multi-layer network. We used chemical synapses with time delays, and the kinetic equation is

$$I_i^{\rm syn} = g_{\rm syn} s_i (V_i(t-\tau_{\rm d}) - V_{\rm syn}), \tag{8}$$

$$\frac{{\rm d}s_i}{{\rm d}t} = \alpha/[1+\exp(-(V_i-20)/2)] - \frac{s_i}{\tau}, \tag{9}$$

where $g_{\rm syn}$ denotes the synaptic coupling strength, s_i is the gating variable, $\tau_{\rm d} = t_{\rm d}$ is the within-layer delay time, $\tau_{\rm d} = T_{\rm d}$ is the inter-layer delay time, and $V_{\rm syn}$ is the threshold voltage. The excitatory synaptic transmission parameters mediated by AMPA are $\alpha = 3.48$, $\tau = 2$ ms and $V_{\rm syn} = 0$ mV. The inhibitory synaptic transmission parameters mediated by GABA are $\alpha = 1$, $\tau = 10$ ms and $V_{\rm syn} = -70$ mV.

The neurons are randomly connected with a probability P. In each layer, P denotes the connection probability between excitatory and inhibitory neurons; $P_{\rm ee}$, $P_{\rm ii}$, $P_{\rm ie}$, and $P_{\rm ei}$ are the four types of connection probabilities adopted. $P_{\rm ee}^{\rm A}$ denotes the inter-layer connection probability. The connection strength between neurons is denoted by g. For intralayer connection strengths, we use $g_{\rm ee}$, $g_{\rm ei}$, $g_{\rm ii}$, and $g_{\rm ie}$; for interlayer connection strength, we use $g_{\rm e-e}$ to denote the feedforward coupling and $g_{\rm e-e}^{\rm B}$ for feedback coupling.

Each neuron is stimulated by background noise that follows a Poisson distribution. Under this background noise, the

neural network exhibits a state of random firing.

The specific connection parameters of the neural network are shown in Table 2.

Table 2. Parameters in the neural network (E, excitatory; I, inhibitory).

Name	Value	Description
P_{ee}	0.2	E–E connection probability
P_{ii}	0.2	I–I connection probability
P_{ie}	0.2	I–E connection probability
P_{ei}	0.2	E–I connection probability
P_{ee}^{A}	0.2	inter-layer E–E connection probability
g_{ee} (μS/cm^2)	0.5	E–E coupling strength
g_{ei} (μS/cm^2)	1.0	E–I coupling strength
g_{ii} (μS/cm^2)	3	I–I coupling strength
g_{ie} (μS/cm^2)	6	I–E coupling strength
g_{e-e}^{F} (μS/cm^2)	0.22	feedforward coupling strength
g_{e-e}^{B} (μS/cm^2)	0.22	feedback coupling strength
g_P (nS)	0.1	Poisson input intensity
λ_P^E	1	excitatory Poisson input variance
λ_P^I	4	inhibitory Poisson input variance
t_d (ms)	0.5	within-layer delay time
T_d (ms)	0–18	range of inter-layer delay time

Equilibrium potentials for various ions in the neuronal model are derived from the Nernst–Planck equation. Based on this equation, and in the absence of a magnetic field, the currents for individual ion channels can be expressed as follows:[40,41]

$$J_{Na} = -R_g T \mu_{Na} \nabla C_{Na} + F \mu_{Na} C_{Na} E, \tag{10}$$

where J_{Na} is the current intensity (A/m^2), C_{Na} is the ion concentration (with a typical value of 1.25×10^{-3} mol/m^3), ∇C_{Na} is the respective concentration gradient vector (mol/m^4), E is the transmembrane electric field (V/m), R_g is the gas constant (8.31 J$\cdot$K$^{-1}\cdot$mol^{-1}), μ_{Na} is the ionic mobility for Na^+ ions (m^2/(V$\cdot$s)), T is the absolute temperature (300 K) and F is the Faraday number (0.965×10^5 C$\cdot$mol^{-1}). The potassium and leakage ions are described analogously, with concentrations $C_K = 1.15\times10^{-3}$ mol/m^3, $C_L = 2\times10^{-3}$ mol/m^3, and corresponding gradient vectors ∇C_K and ∇C_L.

The two components of Eq. (1) have distinct physical origins. The first term, representing diffusion flux, is derived from Fick's law using the Nernst–Einstein relation between the diffusion coefficient and ionic mobility. The second term applies Ohm's law to describe the drift component of ion motion.

According to electromigration theory, the electric drift velocity v of an ion in solution is given by[39]

$$v = \mu_{Na} E. \tag{11}$$

The ionic current density is given by the product of the ion flux velocity as

$$J_{Na} = N_A z e C_{Na} v = N_A z e C_{Na} \mu_{Na} E = z F C_{Na} \mu_{Na} E, \tag{12}$$

where N_A represents the Avogadro constant, e denotes the charge on the electron, and z stands for valence electrons.

Under the influence of an external magnetic field, Eq. (11) takes the following form:

$$v_{Na} = \mu_{Na}(E + v_{Na} B_{ext}). \tag{13}$$

The external magnetic field B_{ext} is modeled as a sinusoidal function, with B representing the magnetic field intensity and f standing for the magnetic field frequency. Taking TMS as a representative example of an electromagnetic modulation technique, the stimulation frequency commonly used in clinical and research settings is typically below 20 Hz, with the intensity generally set between 80% and 120% of the motor threshold. Based on the findings of our previous studies,[40,41] B was varied within the range -25 mT, and f was set in the range -25 Hz. The angle between the direction of ion flux and the magnetic field vector was $\pi/2$. In our study, unless otherwise specified, the stimulation parameters were set to $B = 5$ mT and $f = 10$ Hz.

Following Eqs. (10), (12), and (13), the sodium channel current under magnetic field stimulation is calculated as follows:[39,40]

$$J_{Na} = -R_g T \mu_{Na} \nabla C_{Na} + F \mu_{Na} C_{Na} E + \mu_{Na} J_{Na} B_{ext}. \tag{14}$$

Therefore, the effect of the magnetic field is modeled by introducing an additive current term $\Delta I_{Na} = \mu_{Na} J_{Na} B_{ext}$ for I_{Na}. The formulation extends analogously to potassium and leakage ions, resulting in the additional terms $\Delta I_K = \mu_K J_K B_{ext}$ and $\Delta I_L = -\mu_L J_L B_{ext}$. The following necessary parameters $\mu_{Na} = 3$ m^2/(V$\cdot$s), $\mu_K = 3.8$ m^2/(V$\cdot$s), and $\mu_L = 1$ m^2/(V$\cdot$s) are adopted from Refs. [42–45].

The dynamics of the neuronal network are driven by the superposition of intrinsic ionic currents and electromagnetic stimulation. The temporal evolution of the system can therefore be formulated as follows:

$$\begin{cases} C_m \dfrac{dV_i}{dt} = -I_i^{syn} - I_i^{Na} - I_i^{K} - I_i^{L} + I_i^{noise} \\ \qquad\qquad + \Delta I_i^{Na} + \Delta I_i^{K} + \Delta I_i^{L}, \\ I_i^{Na} = G_{Na} m_{\infty,i}^3 h_i (V_i - E_{Na}), \\ I_i^{K} = G_K n_i^4 (V_i - E_K), \\ I_i^{L} = G_L (V_i - E_L). \end{cases} \tag{15}$$

To determine whether the signal has successfully propagated to the last layer of the neural network, we use the average membrane potential to define the signal propagation SNR in the network:[10]

$$\mathrm{SNR} = \frac{\mathrm{VAR}\left[Y_{stim}(t)\right]}{\mathrm{VAR}\left[Y_{ongoing}(t)\right]}, \tag{16}$$

where VAR denotes variance, $Y_{stim}(t)$ represents the normalized average membrane potential of the fifth-layer network under pulse stimulation and $Y_{ongoing}(t)$ represents the normalized average membrane potential of the fifth-layer network without stimulation: the larger the SNR, the better the signal propagation.

The stability of signal propagation is closely related to the intrinsic activity synchronization of neural networks. To stabilize the propagation of peak network activity, the network needs to remain stable and not exhibit strong synchronized oscillations of group activity. When the synchronization of the electrical activity of neural networks is too strong, signal propagation will be adversely affected. By calculating the overall pFF and analyzing the synchronization of background activity in neural networks, pFF is defined as

$$\mathrm{pFF} = \frac{\mathrm{VAR}\,[X(t)]}{\mathrm{MEAN}\,[X(t)]}, \tag{17}$$

where $X(t)$ is the peak count vector of all excitatory neurons in each layer of the network. To convert the spike sequence into a spike discharge count, a time window of $\Delta t = 0.0002$ s is used, and the number of spike discharges is calculated in each time window to convert the discharge sequence into a spike count sequence. The normalized variance of group activities is related to the synchronization of group activities, as the group variance is the sum of the individual variance and covariance of neurons. The larger the value of pFF, the stronger the synchronization of neural network group activity.

In order to study the propagation of signals in multi-layer neural networks, an external pulse packet is injected into the excitatory neurons of the first layer. The formula for a single pulse packet is as follows:

$$P(t) = \sum_{k=1}^{a} g(t - t_k), \quad t_k \sim N(0, \sigma^2), \tag{18}$$

$$g(t) = \begin{cases} A, & |t| \le t_{\mathrm{w}}/2, \\ 0, & \text{otherwise}. \end{cases} \tag{19}$$

The parameters of a single pulse packet are a and σ; $a = 10$ represents the number of pulses in the pulse packet and $\sigma = 3$ ms represents the Gaussian distribution with variance at the time of pulse occurrence. The amplitude of a single pulse packet is $A = 0.15$ μA/cm^2 and the pulse width is $t_{\mathrm{w}} = 2$ ms.

The Euler method is employed to solve the neural network equations for computing the neuronal membrane potential. The time step is set to 0.01 ms, the total simulation duration to 3000 ms, and the transient period to 500 ms.

3. Results

3.1. SNR of neural network signal propagation under electromagnetic stimulation

The delay time between layers of a multilayer neural network has a strong regulatory effect on signal propagation. To explore how electromagnetic stimulation affects signal transmission in multi-layer neural networks, we examined signal propagation under various inter-layer delay times and calculated the SNR during transmission. At 1000 ms, 10 pulse packets with an interval of 50 ms were injected into the excitatory neurons in the first layer of the neural network. We investigated the effect of electromagnetic stimulation on the signal propagation process in neural networks under different inter-layer delay times, as illustrated in Fig. 2. The blue curve indicates the average membrane potential of the neural network without electromagnetic stimulation, and the red curve corresponds to that with electromagnetic stimulation.

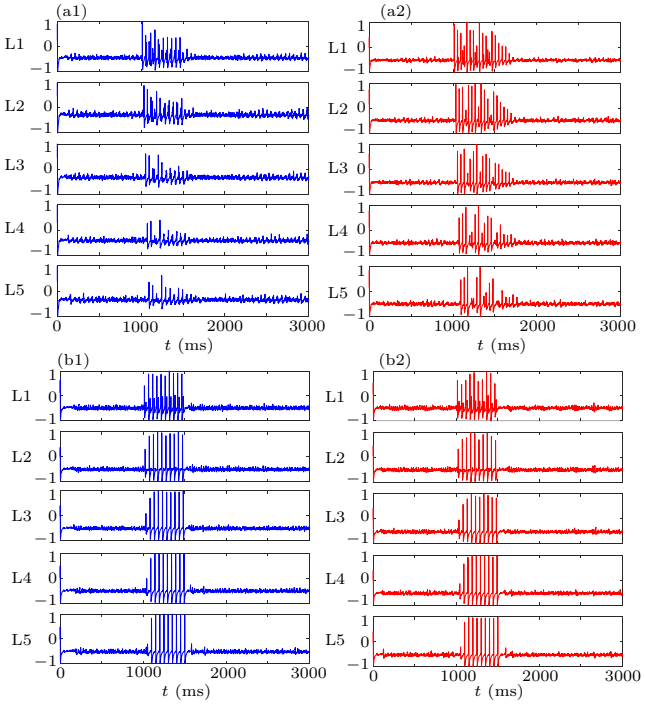


Fig. 2. The propagation process of a periodic signal: (a1) without electromagnetic stimulation, $T_{\mathrm{d}} = 18$ ms; (a2) with electromagnetic stimulation, $T_{\mathrm{d}} = 18$ ms; (b1) without electromagnetic stimulation, $T_{\mathrm{d}} = 7.5$ ms; (b2) with electromagnetic stimulation, $T_{\mathrm{d}} = 7.5$ ms.

In the absence of electromagnetic stimulation, and with $T_{\mathrm{d}} = 18$ ms, signal propagation can be clearly observed from the first to the fourth layer. By the time the signal reaches the fifth layer, the changes in the neural firing sequence caused by the signal have become very weak. Through calculation of the SNR of the neural network at the fifth layer (SNR = 1.5), it is evident that signal transmission has failed. In the presence of electromagnetic stimulation, and with $T_{\mathrm{d}} = 18$ ms, the average membrane potential induced by signal propagation from the first to the fifth layer is significantly larger compared with the scenario without electromagnetic stimulation. By calculating the SNR of the neural network at the fifth layer (SNR = 2.4), it is found that the SNR has improved by approximately 60

In the case where $T_{\mathrm{d}} = 7.5$ ms, the neural network at the fifth layer can also effectively transmit the signal received by the neural network at the first layer, with minimal change in the normalized membrane potential. By calculating the SNR at the fifth layer (SNR = 4.18), it is evident that the signal has been successfully transmitted, indicating that the neurons at the fifth layer have successfully conveyed the input signal from the first layer. Under electromagnetic stimulation, the neural network at the fifth layer can still effectively transmit the signal received by the neural network at the first layer, with

minimal change in the normalized membrane potential. By calculating the SNR at the fifth layer (SNR = 4.32), it is found that the SNR has increased by approximately 3.8 % compared with the scenario without electromagnetic stimulation.

These results indicate that without electromagnetic stimulation, the signal propagation ability of neural networks varies with different interlayer delays, and an appropriate interlayer delay time can achieve a relatively high SNR for signal propagation between multilayer networks. When electromagnetic stimulation is added, it can significantly improve the transmission capacity of neural networks, especially for cases where the network signal transmission strength is relatively weak.

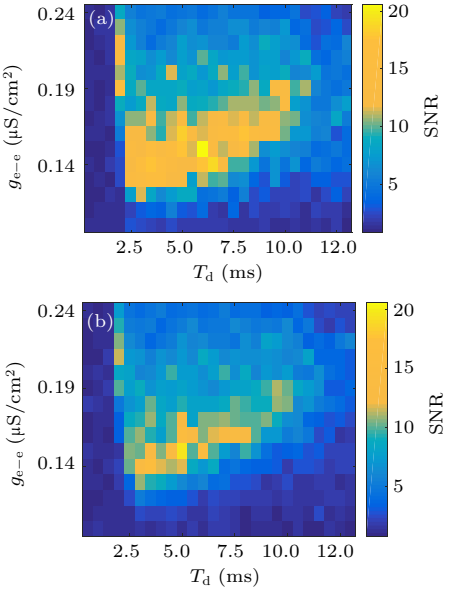


Fig. 3. Effects of inter-layer delay time and inter-layer coupling strength on SNR: (a) SNR of neural network signal transmission without electromagnetic stimulation; (b) SNR of neural network signal transmission with electromagnetic stimulation.

By traversing the inter-layer delay time and coupling strength within a certain range, we obtained the SNR variation diagrams of neural networks under both electromagnetic stimulation and with no electromagnetic stimulation. When the inter-layer delay time is small, the signal propagation SNR of the neural network is the lowest and the influence of interlayer coupling strength on the SNR is not significant. When the interlayer delay time is constant, the SNR of signal transmission increases first and then decreases with the increase of interlayer coupling strength, reaching its maximum value at an appropriate coupling strength. Similarly, when the interlayer coupling strength is constant, the SNR of signal transmission increases first and then decreases with an increase in the delay time. At an appropriate delay time, the SNR reaches its extreme value. These results indicate that selecting an appropriate interlayer delay time and interlayer coupling strength can effectively regulate the signal transmission of neural networks. By comparing Figs. 3(a) and 3(b), it can be seen that when the delay time is very small, electromagnetic stimulation has almost no effect on the SNR of signal transmission in the neural network. Under electromagnetic stimulation, the parameter range that can adjust the SNR does not change much compared with the case without electromagnetic stimulation, but there is a significant increase in amplitude. These results indicate that electromagnetic stimulation combined with interlayer coupling strength and interlayer delay time can regulate the SNR of signal propagation and effectively improve the interlayer signal propagation capability of neural networks.

We set the interlayer delay time to 7.5 ms. With this delay, the intrinsic oscillation frequency of the neural network is 11 Hz. We then analyzed the influence of electromagnetic stimulation strength and frequency on the SNR of the neural network. The results are shown in Fig. 4. A higher intensity of electromagnetic stimulation results in a higher SNR, indicating enhanced signal transmission capability of the neural network. Optimal signal transmission in the neural network is achieved when the electromagnetic stimulation frequency matches the intrinsic oscillation frequency of the network (11 Hz). The results shown in Fig. 4 exhibit a clear "Arnold tongue" structure, indicating that when the electromagnetic stimulation frequency is consistent with the neural oscillation frequency, it causes entrainment activity, thereby improving the SNR of neural network signal propagation. The optimal modulation frequency of electromagnetic stimulation depends on the natural oscillation frequency of the neural network.

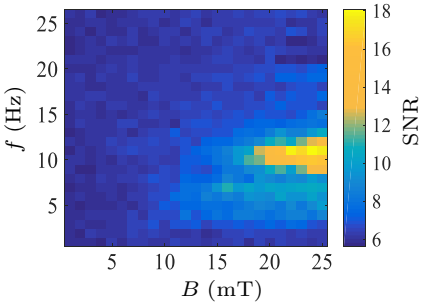


Fig. 4. SNR under different electromagnetic stimulation frequencies and intensities.

3.2. Propagation time of neural network signals under electromagnetic stimulation

In order to investigate the effect of electromagnetic stimulation on signal transmission speed, the SNR at the last layer of the neural network was calculated for varying numbers of signal input pulse packets. An inappropriate delay time can prevent signals from reaching the last layer of the neural network; therefore, an inter-layer delay time of $T_d = 7.5$ ms was chosen. The relationship between the number of pulse packets and SNR was then calculated both in the presence and the absence of electromagnetic stimulation; the results are shown in Fig. 5. Figure 5(a) illustrates the relationship between SNR and the number of pulse packets, revealing that SNR values are generally higher under electromagnetic stimulation than without. When SNR = 4, approximately six pulse packets are

required for the signal to propagate to the last layer of the neural network under electromagnetic stimulation, whereas about seven pulse packets are needed in the absence of electromagnetic stimulation. As shown in Fig. 5(b), for the same amount of signal transmission, the signal propagation time in the neural network under electromagnetic stimulation is nearly 50 ms shorter than that without electromagnetic stimulation, indicating a significant increase in propagation speed. These results demonstrate that electromagnetic stimulation can markedly reduce signal propagation time in feedforward neural networks, thereby enhancing signal transmission efficiency.

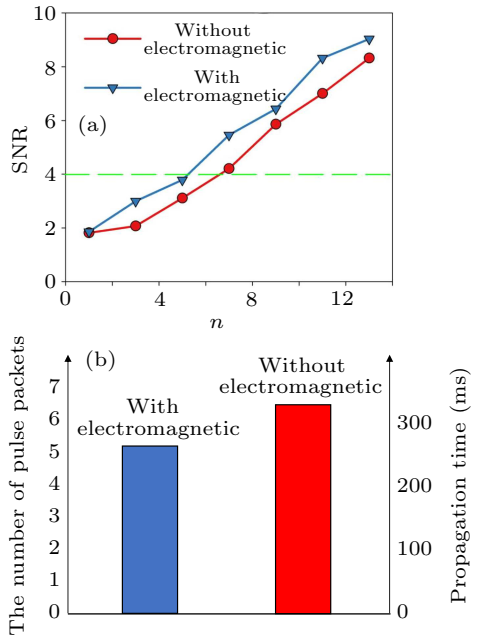


Fig. 5. Propagation speed of a signal in a neural network with or without electromagnetic stimulation: (a) relationship between SNR and the number of pulse packets; (b) diagram comparing propagation time.

3.3. Stability of neural network signal propagation under electromagnetic stimulation

The interlayer coupling strength and delay time in neural networks are of great significance for signal propagation. When these two parameters are appropriately set, the neural network exhibits excellent propagation capabilities for external input signals. However, when these parameters are misaligned, the neural network may experience abnormal synchronization, which disrupts normal signal propagation. By calculating the pFF of the spike frequency sequence of the neural network in the absence of signal input, we compared the thresholds of coupling strength and delay time that lead to abnormal synchronization in the neural network under both the presence and absence of electromagnetic stimulation, thereby investigating the impact of electromagnetic stimulation on the stability of neural network signal propagation.

To study the effect of electromagnetic stimulation on the stability of neural network signal transmission, we calculated the pFF of the neural network under different intensities of electromagnetic stimulation. The results are shown in Fig. 6.

As shown in Fig. 6, the neural network exhibits a wide range of moderate synchronicity with and without electromagnetic stimulation. When the interlayer coupling strength and interlayer delay time increase, the group synchronization of the neural network increases and its signal propagation ability weakens. Figure 6(b) shows that when the electromagnetic stimulation strength is $B = 5$ mT, the neural network has a wider range of moderate synchronization in the g_{e-e}–T_d parameter space, indicating that the signal propagation parameter range of the neural network is significantly larger than that without electromagnetic stimulation, and the signal propagation stability is improved. As shown in Fig. 6(c), when the electromagnetic stimulation strength is $B = 10$ mT, the excessive synchronization interval of the neural network in the g_{e-e}–T_d parameter space increases, and the range of neural network signal propagation parameters becomes smaller, resulting in a decrease in the stability of neural network signal propagation. Our results indicate that an appropriate intensity of electromagnetic stimulation keeps neural networks in a moderately synchronized state, reduces excessive synchronization of neural networks, increases the parameter range for smooth propagation of neural network signals, and improves the signal propagation stability of neural networks.

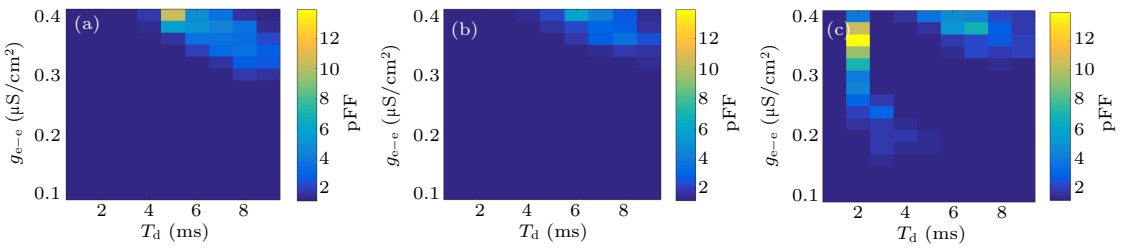


Fig. 6. Effects of inter-layer delay time and inter-layer coupling strength on SNR under electromagnetic stimulation: (a) population Fano factor (pFF) of the neural network without electromagnetic stimulation; (b) pFF of the neural network under electromagnetic stimulation ($B = 5$ mT, $f = 10$ Hz); (c) pFF of the neural network under electromagnetic stimulation ($B = 10$ mT, $f = 10$ Hz).

4. Conclusion and perspectives

Communication between neural networks is currently a major focus of research. Biological research has demonstrated that electromagnetic stimulation can modulate neural activity, enhancing the propagation of brain signals, the functional connectivity between brain regions, and the spectral power of rhythmic oscillations.[46,47] When feedback connections are introduced to feedforward neural networks, their capacity for

signal propagation is significantly enhanced. The theoretical findings of our study align with these biological experiments, revealing the mechanisms by which electromagnetic stimulation enhances brain signal propagation from a neurodynamic perspective. The signal propagation process in multilayer neural networks is notably influenced by interlayer coupling strength and delay time. With appropriate coupling strength and delay time, neural network signal propagation proceeds smoothly with a high SNR. Electromagnetic stimulation can markedly improve the SNR of neural network signal transmission. Our in-depth research reveals that the enhancement of SNR in neural network signal propagation by electromagnetic stimulation is closely tied to the intrinsic oscillatory state of the neural network. When the frequency of electromagnetic stimulation matches the oscillation frequency of the neural network, the SNR achieves optimal improvement. Furthermore, we investigated changes in neural network signal propagation time under electromagnetic stimulation. Our results indicate that even fewer pulse packets can propagate smoothly to the next layer of the neural network under electromagnetic stimulation, with a significant reduction in propagation time. Signal propagation in neural networks is closely linked to the collective activity of neural populations. Electromagnetic stimulation alters the overall oscillatory activity of neural networks to some extent, potentially leading to changes in signal propagation within the network. By analyzing neural population activity, we observed that the bidirectionality of electromagnetic stimulation modulates the parameter space of population activity dynamics. Moderate electromagnetic stimulation expands this parameter space, thereby enhancing the stability of signal propagation.

The findings of this study underscore the significant impact of electromagnetic stimulation on neural network signal propagation. They provide a theoretical foundation for further exploring how the brain nervous system processes external signal stimuli and offer insights into the mechanisms underlying electromagnetic neural regulation technology. Feedback plays a crucial role in the nervous system, yet the various feedback connection patterns in feedforward networks remain underexplored. This study focuses solely on signal propagation in multilayer neural networks with single-layer feedback. Future research could delve into the effects of multiple feedback modes on neural network signal propagation.

Acknowledgement

This project was supported by the Tianjin Municipal Education Commission Scientific Research Program Project (Grant No. 2025KJ149).

References

[1] Shibata T, Hattori N, Nishijo H, Takahashi T, Higuchi Y, Kuroda S and Takakusaki K 2025 *Front. Cell. Neurosci.* **18** 1525816
[2] Seguin C, Sporns O and Zalesky A 2023 *Nat. Rev. Neurosci.* **24** 557
[3] Chen G, Kang B, Lindsey J, Druckmann S and Li N 2021 *Cell* **184** 3717
[4] Liang J H, Wang S J and Zhou C S 2022 *Natl. Sci. Rev.* **9** nwab102
[5] Lyu X, Liu T and Ma Y 2025 *Schizophrenia* **11** 36
[6] Zhang Y and Reynolds J N J 2024 *Curr. Neuropharmacol.* **22** 1566
[7] Trajkovic J, Veniero D, Hanslmayr S, Palva S, Cruz G, Romei V and Thut G 2025 *PLoS Biol.* **23** e3002688
[8] Pariz A, Esfahani Z G, Parsi S S, Valizadeh A, Canals S and Mirasso C R 2018 *NeuroImage* **172** 349
[9] Dumont G and Gutkin B 2019 *PLoS Comput. Biol.* **15** e1007019
[10] Hahn G, Bujan A F, Frégnac Y, Aertsen A and Kumar A 2014 *PLoS Comput. Biol.* **10** e1003811
[11] Wu S, Zhou K, Ai Y, Zhou G, Yao D and Guo D 2021 *Cogn. Neurodyn.* **15** 53
[12] Yi M and Yang L 2010 *Phys Rev E* **81** 061924
[13] Ge M, Jia Y, Lu L, Xu Y, Wang H and Zhao Y 2020 *Nonlinear Dyn.* **99** 2355
[14] Yu D, Wang G, Li T, Ding Q and Jia Y 2023 *Commun. Nonlinear Sci.* **117** 106894
[15] Lu L, Jia Y, Kirunda J B, Xu Y, Ge M, Pei Q and Yang L 2019 *Nonlinear Dyn.* **95** 1673
[16] Dai S, Lu L, Wei Z, Zhu Y and Yi M 2022 *Chaos Solitons Fractals* **164** 112762
[17] Wang G W, Ge M Q, Lu L L, Jia Y and Zhao Y J 2021 *Nonlinear Dyn.* **103** 2627
[18] Lu L L, Jia Y, Liu W H and Yang L J 2017 *Complexity* **2017** 7628537
[19] Ge M, Lu L and Xu Y 2020 *Chaos Solitons Fractals* **133** 109645
[20] Wang G, Wu Y, Xiao F, Ye Z and Jia Y 2022 *Physica A* **598** 127274
[21] Liu Y, Ma J, Xu Y and Jia Y 2019 *Int. J. Bifurcat. Chaos* **29** 1950156
[22] Rezaei H, Aertsen A, Kumar A and Valizadeh A 2020 *PLoS Comput. Biol.* **16** e1008033
[23] Pariz A, Fischer I, Valizadeh A and Mirasso C 2021 *PLoS Comput. Biol.* **17** e1008129
[24] Ding Q, Wu Y, Li T, Yu D and Jia Y 2023 *Chaos Solitons Fractals* **171** 113464
[25] Jiao D, Xu L and Gu Z 2024 *Neural Regen. Res.* **20** 917
[26] Taylor J L, Bhatt P, Hernandez B, Iv M, Adamson M M, Heath A, Yesavage J A and McNerney M W 2025 *NeuroImage: Clin.***47** 103819
[27] Odermatt I A, Schulthess-Lutz M, Mihelj E, Howell P, Heimhofer C, McMackin R, Ruddy K, Freund P, Kikkert S and Wenderoth N 2025 *J. Neurosci.* **45** e2189242025
[28] Georgiev C, Author C, Mongold S J, Cabaraux P, Naeije G, Duque J and Bourguignon M 2025 *Imaging Neurosci.* **3** imag_a_00570
[29] Li R Z, Xu G Z and Yang S 2020 *Life Sci. Instrum.* **18** 3
[30] Borich M R, Wheaton L A, Brodie S M, Lakhani B and Boyd L A 2016 *Neurosci. Lett.* **618** 25
[31] Hoy K E, Bailey N, Michael M, Fitzgibbon B, Rogasch N C, Saeki T and Fitzgerald P B 2016 *Cereb. Cortex* **26** 4563
[32] Kito S, Hasegawa T, Takamiya A, Noda T, Nakagome K, Higuchi T and Koga Y 2017 *J. Neuropsychiatry Clin. Neurosci.* **29** 155
[33] Chung S W, Rogasch N C, Hoy K E and Fitzgerald P B 2018 *Brain Stimul.* **11** 566
[34] Yu F, Wang X Q, Guo R Y, Ying Z J, He Y and Zou Q 2025 *Chin. Phys. B* **34** 120501
[35] Wang X J, Hu H, Huang C, Kennedy H, Li C, Logothetis N, Lu Z L, Luo Q, Poo M M, Tsao D, Wu S, Wu Z, Zhang X and Zhou D 2020 *Natl. Sci. Rev.* **7** 1418
[36] Hodgkin A, Huxley A and Katz B 1952 *J. Physiol.* **116** 424
[37] Gelman D M and Marín O 2010 *Eur. J. Neurosci.* **31** 2136
[38] Wang X J and Buzsáki G 1996 *J. Neurosci.* **16** 6402
[39] Compte A, Sanchez-Vives M V, McCormick D A and Wang X J 2003 *J. Neurophysiol.* **89** 2707
[40] Yang H L, Wang H B, Guo L and Xu G Z 2022 *J. Comput. Neurosci.* **50** 109
[41] Yang H L, Xu G Z and Wang H B 2022 *Cogn. Neurodyn.* **16** 707
[42] Hodgkin A L and Keynes R D 1953 *J. Physiol.* **119** 513
[43] Harris E J 1954 *J. Physiol.* **124** 248
[44] Socorro A and Garcia F 2012 *Int. Agrophys.* **26** 167
[45] Gao Y, Zheng Y, Chen R, Wang H, Dong L and Dou J 2016 *IEEE Trans. Magn.* **52** 5001008
[46] Riedel P, Heil M, Bender S, Dippel G, Korb F M, Smolka M and Marxen M 2019 *Hum. Brain Mapp.* **40** 4301
[47] Esposito R, Bortoletto M and Miniussi C 2020 *Neuroscientist* **26** 471