

Research article

Anti-interference ability of deep spiking neural network

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Abstract

Organisms have the advantages of self-adaptive mechanisms and an anti-interference ability. To investigate the anti-interference ability of a deep spiking neural network that simulates a biological neural system, the correlation between membrane potential and firing rate is interpreted as an anti-interference index so as to investigate the anti-interference ability of a deep spiking neural network under the regulation of synaptic plasticity in the presence of different amplitudes of an electric field. When the relative variation rate of firing rate is less than 10% or the correlation between the membrane potential is greater than half, the influence of electric field on neural network is relatively small. Otherwise, the influence is relatively large. Simulation results show that: based on the regulation of synaptic plasticity, within a certain electric field interference range, the relative rate of variation of cell firing rates is small compared with non-interference, while correlation between the membrane potential in each layer is large when compared to non-interference.

Keywords

Deep spiking neural network; synaptic plasticity; anti-interference; electric field; firing rate; correlation

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1. Introduction

Compared with other natural environments, the electromagnetic environment is invisible, untouchable, and variable. An organism under the regulation of a neural system has advantages of self-adaptive mechanisms and anti-interference abilities [1]. Organisms can resist electromagnetic interference thousand times greater than the magnitude of their own bioelectrical signals [2].

Synaptic plasticity is the structural basis of information transfer between neurons. Chen *et al.* [3] constructed a four layers feed-forward deep spiking neural network based on STDP (Spike-timing Dependent Plasticity) mechanism. Litwin-Kumar and Doiron [4] found that the STDP mechanism makes neural networks form neuronal clusters during learning and maintain cluster stability. Wei and Koulakov [5] found that the STDP mechanism is helpful for stable storage in long-term memory models of neural networks. Most of these studies are based on excitatory synaptic plasticity. However, inhibitory synaptic plasticity also plays an important role in the regulation of neural networks.

The organism adapts to an external environment with many kinds of interference factors via self-adaptive mechanism [6, 7]. Yu *et al.* [8] found that under the interference of either a DC or an AC induced electric field, a neural network can produce gamma oscillations and synchronous oscillation, respectively. Chang *et al.* [9] found that the relationship between the extent of synchronous neuronal firing and an anti-interference ability is approximately linear. Scott *et al.* [10] found that the ability of synchronous neural network firing strongly depended on the mechanisms of synaptic plasticity. Chen *et al.* [11] found that a feed-forward deep spiking neural network exhibited anti-interference ability when regulated by STDP.

A deep spiking neural network model regulated by both excitatory and inhibitory synaptic plasticity was constructed by the authors in a previous study [12]. That study focused on neural information coding by rate and temporal coding under an alternating magnetic field. In this study, the same topology of a deep spiking neural network is employed. It aims to investigate the anti-interference ability of the network under an alternating electric field by firing rate and correlation between the membrane potential which are considered as anti-interference indexes.

2. Analysis of Anti-interference Ability of Deep Spiking Neural Network

Based on Izhikevich neuron model [13], a synaptic plasticity and feed-forward deep spiking neural network model with ten layers regulated by both excitatory and inhibitory synaptic plasticity was constructed as in a previous study [12].

2.1. Izhikevich neuron model subject to an electric field

An alternating electric field can influence the membrane potential of neurons [14]. The relationship between the external alternating electric field E and the cell membrane depolarization voltage ΔV can be described as [15]:

$$\frac{d\Delta V}{dt} + \frac{\Delta V}{\tau} = \frac{\lambda}{\tau} E \quad (1)$$

where λ represents the polarization length and τ represents Maxwell-Wagner time constant [16].

The alternating electric field E can be described as:

$$E(t) = \frac{A}{\omega} \sin(\omega t) \quad (2)$$

where A represents amplitude and ω represents angular frequency [17]. According to equation (1) and equation (2), the cell membrane depolarization voltage ΔV due to an alternating electric field E can be described as:

$$\Delta V(t) = \lambda \frac{A \sin(\omega t) - 2\pi f \tau \cos(\omega t)}{1 + (\omega \tau)^2}. \quad (3)$$

In the model, the order of magnitude τ is generally 10^{-10} ms; the frequency f is located in the range of extremely low frequencies [18]. Therefore, the cell membrane depolarization voltage ΔV can be approximated described as follows:

$$\Delta V(t) = \lambda \frac{A}{\omega} \sin(\omega t) \quad (4)$$

where polarization length $\lambda = 1\text{mm}$; angular frequency $\omega = 0.1\pi$ rad/s [19]. Cell membrane depolarization voltage ΔV can be seen as an external disturbance of the cell membrane voltage $v(t)$. The cell membrane voltage $v(t)$ under the electric field can be described as [20]:

$$v(t) \rightarrow v(t) + \Delta V(t) \quad (5)$$

The Izhikevich neuron model under the alternating electric field can be obtained by introducing equation (5) into the mathematical model of the Izhikevich neuron described in [12].

2.2. Firing rate

The pulse time sequence $S(t)$ of neurons with regard to each action potential generated by a neuron has a time function similar to δ . It can be described as:

$$S(t) = \sum_m \delta(t - t(m)) \quad (6)$$

where $t(m)$ is the firing moment of neurons. The value of $S(t)$ in the firing moment is one, and at other times is set to zero. The pulse time sequence clearly shows both the firing moments and firing rate.

The inter-spike interval (ISI) is the difference between two adjacent firing moments of a neuron. It is described as:

$$ISI_n = t_n - t_{n-1} \quad (7)$$

The firing rate of a single neuron is evaluated by dividing the average value of the ISIs (ms) by 1000. The firing rate of the neural network is evaluated by the average firing rate values of all neurons. The smaller the relative variation rate of firing rate, the better the anti-interference ability of the deep spiking neural network. When the relative variation rate of firing rate is less than 10%, the influence of electric field on the neural network is relatively small.

To investigate the influence of different electric field amplitudes on pulse time sequence of a deep spiking neural network, an electric field interference with amplitudes of 2 mV, 10 mV, or 20 mV are added to the deep spiking neural network. The pulse time sequence diagrams of the output layer neuron under different electric field amplitudes are shown in Fig. 1.

From the Fig. 1, the abscissa gives simulation time; the ordinate gives the time of the action potential. The firing rate is 11.1 Hz under non-interference, the firing rates are 11.2 Hz, 11.4 Hz, and 12.0 Hz under the electric field amplitudes of 2 mV, 10 mV, and

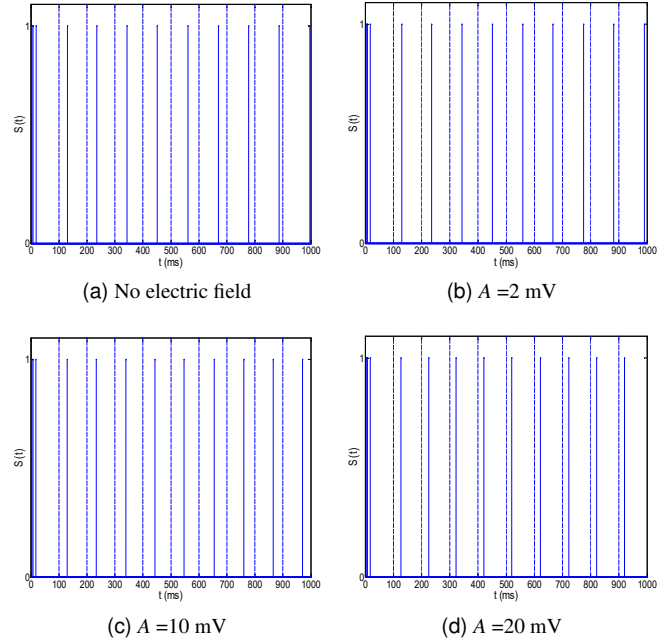


Fig. 1. Pulse time sequence diagrams.

20 mV, respectively. The fluctuations generated by electric field interference are 0.61%, 2.69% and 8.30%, respectively. Simulation results show that with the increased of electric field amplitude, the fluctuations are getting larger. This proved that with the increased electric field amplitude, the influence on firing moment and firing rate of the output layer neuron are all increased.

To further investigate the influence of electric field interference on the firing rate, an electric field interference with different amplitudes was added to the deep spiking neural network. The range of the electric field amplitude A was set to [1, 20] mV, and the step length was set to 1 mV. Simulation results showed that the firing rate of each layer in the deep spiking neural network was within the range of 6.7 Hz to 12.0 Hz. Normalized firing rate of each layer in the deep spiking neural network for different electric field amplitudes A is shown in Fig. 2.

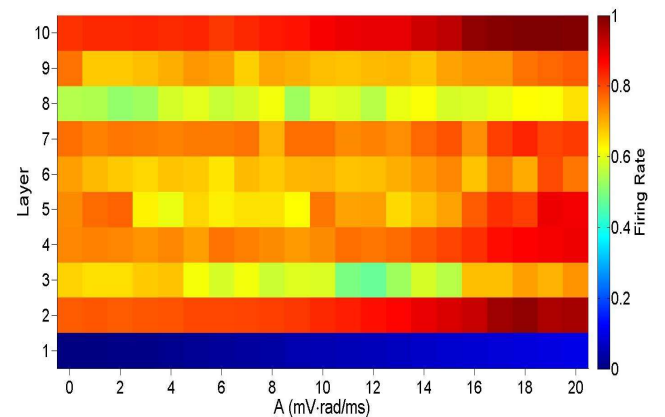


Fig. 2. The firing rate of each layer.

From Fig. 2, the abscissa gives the electric field amplitude, the ordinate gives the number of layers, and the color-map gives the firing rate after normalization. Red indicates a higher neuron firing rate. Blue indicates a lower neuron firing rate. The figure shows that the firing rate of each layer increases with increased electric field amplitude. When the electric field amplitude is constant, the firing rate shows a trend of fluctuation with an increased number of layers.

Trend of firing rates in output the layer neuron under different electric field amplitudes A is shown in Fig. 3.

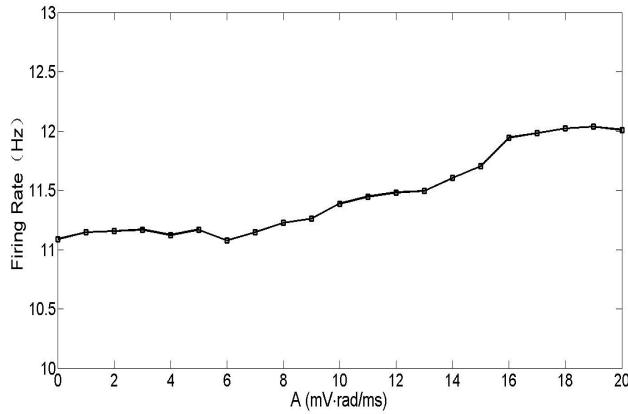


Fig. 3. Firing rate of output layer neuron.

In Fig. 3, the abscissa gives the electric field amplitude; the ordinate gives the firing rate of the output neuron. When the electric field amplitude is in the range 0 mV to 6 mV, the firing rate is in the range of 11.1 Hz to 11.2 Hz. The firing rate is typically stable. When the electric field amplitude is in the range of 6 mV to 16 mV, the firing rate is in the range of 11.1 Hz to 11.9 Hz. The firing rate shows a marginally increasing trend. When the electric field amplitude is in the range 16 mV to 20 mV, the firing rate is in the range of 11.9 Hz to 12.0 Hz and the firing rate is effectively stable.

The relative variation rate of firing rate in the output layer neuron under different electric field amplitudes A is shown in Fig. 4.

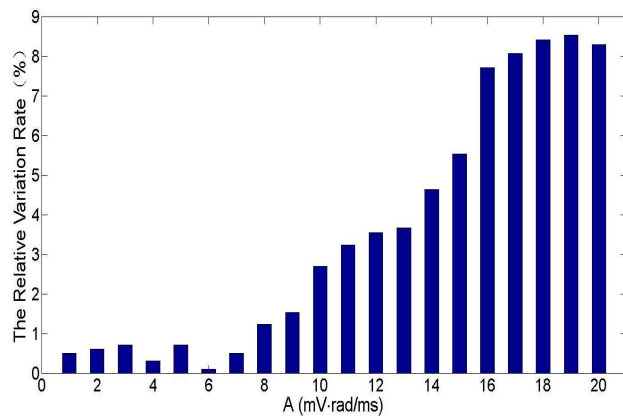


Fig. 4. The relative variation rate of firing rate.

In Fig. 4, the abscissa gives the electric field amplitude and the ordinate gives the firing rate of the output neuron. When the electric

field amplitude is in the range of 1 mV to 20 mV, the relative variation rate of firing rate is less than 8.53%. An electric field amplitude in the range of 1 mV to 20 mV has little influence on the firing rate of the deep spiking neural network.

2.3. Correlation between the membrane potential

Correlation between the membrane potential can reflect the similarity degree of neuron membrane potential before and after electric field interference. The greater the correlation value is, the higher the similarity degree is before and after interference. Correlation coefficient can describe the correlation between the membrane potential quantitatively. The correlation coefficient can be described as follows:

$$\rho_{ij}(\tau) = \frac{\sum_{t=t_1}^{t_2-\tau+1} x_i(t)x_j(t+\tau)}{\sqrt{\sum_{t=t_1}^{t_2-\tau+1} x_i^2(t) \sum_{t=t_1}^{t_2-\tau+1} x_j^2(t+\tau)}} \quad (8)$$

where $\rho_{ij}(\tau)$ is correlation coefficient; $[t_1, t_2]$ is simulation duration; x_i is neuron membrane potential before electric field interference; x_j is neuron membrane potential after electric field interference. The larger the value of $\rho_{ij}(\tau)$ is, the better the anti-interference ability of the deep spiking neural network is. When the correlation between the membrane potential is greater than half, the influence of electric field on neural network is relatively small.

In order to investigate the influence of electric field interference on correlation between the membrane potential, the electric field interference with different amplitudes is added to deep spiking neural network. The range of the electric field amplitude A is set to be [1, 20] mV, the step length is set to be 1 mV. The correlation of the membrane potential of each layer in deep spiking neural network under different electric field amplitudes is shown in Fig. 5.

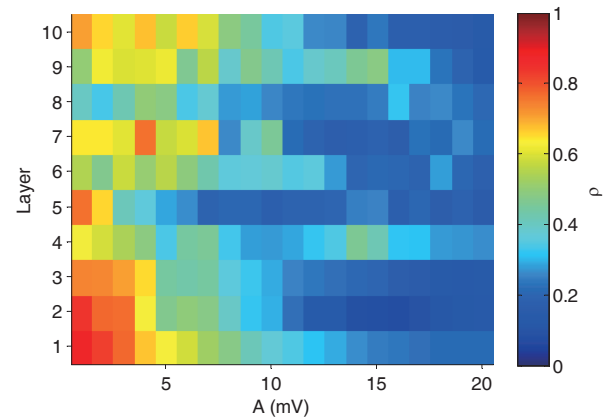


Fig. 5. Correlation between membrane potential of each layer.

From the Fig. 5, the abscissa gives the electric field amplitude; the ordinate gives the number of layers; the color-map represents the correlation between the membrane potential of each layer. Red indicates a higher correlation between the membrane potential in each layer. Blue indicates lower correlation between the membrane potential in each layer. The figure shows that the correlation between the membrane potential in each layer decreases with increased elec-

tric field amplitude. When the electric field amplitude is in the range of 0 mV to 7 mV, the correlation between the membrane potential of each layer is relatively large. When the electric field amplitude is in the range of 7 mV to 20 mV, the correlation between the membrane potential of each layer is relatively small.

The correlation trend between the membrane potential in output layer and other layers for different electric field amplitudes A is shown in Fig. 6.

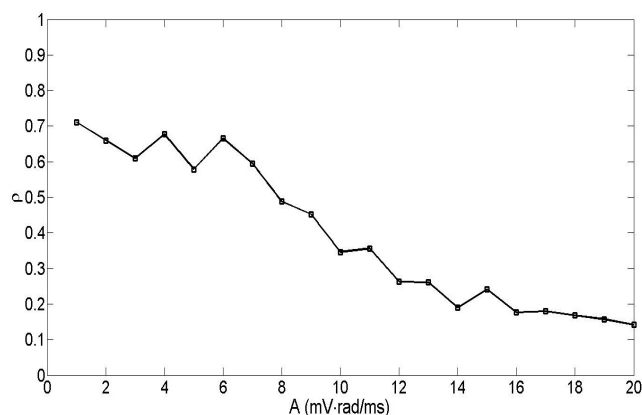


Fig. 6. Correlation between the membrane potential of the output layer neuron and other layers.

From the Fig. 6, the abscissa gives electric field amplitude; the ordinate gives the correlation between the membrane potential of the output layer neuron and other layers. With increased electric field amplitude, the correlation between the membrane potential shows a decreasing trend of fluctuations. When the electric field amplitude is 1 mV, the correlation between the membrane potential and membrane potential in other layers attains a maximum value of 0.71. When the electric field amplitude was 20 mV, the correlation between the membrane potential between layers attained the minimum value of 0.14.

According to Fig. 6, the correspondence between membrane potential correlations and electric field amplitude A are shown in Table.1. From Table.1, with an increase in the range of electric field amplitude, the range of correlations between the membrane potential of the output layer neuron and other layers is decreased. When the electric field amplitude is in the range of 1 mV to 9 mV, the correlation between membrane potential of the different layers is relatively large, whereas, the influence of the electric field on the correlation between the membrane potential of different layers is relatively small; when the electric field amplitude is in the range of 10 mV to 20 mV, the value of correlation is relatively small, the influence of electric field on the correlation between the membrane potential is relatively large.

Table 1. Correspondences between membrane potential correlations and electric field amplitude

range of electric field amplitude	1 ~ 4	5 ~ 9	10 ~ 13	14 ~ 20
range of correlation	0.61 ~ 0.71	0.45 ~ 0.67	0.26 ~ 0.36	0.14 ~ 0.24

3. Conclusion

We conclude from the simulation results that with increased electric field amplitude, neuron firing rate is increased and the correlation between the membrane potential of different layers in the neural network is decreased. When the relative variation rate of firing rate is less than 10% or the correlation between the membrane potential is greater than half, the influence of electric field on neural network is relatively small. Otherwise, the influence is relatively large. Based on the regulation of synaptic plasticity, under a certain electric field interference range, the variation of firing rate is relatively small compared with non-interference; the correlation between the membrane potential of neurons in different network levels is relatively large compared with non-interference. A certain range of electric field interference has little influence on activity in the deep spiking neural network. The deep spiking neural network has ability to resist electric field interference.

Acknowledgments

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Conflict of Interest

All authors declare no conflict of interest.

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