The Butterfly Effect in Primary Visual Cortex

Jizhao Liu, Jing Lian, Julien Clinton Sprott, Qidong Liu, and Yide Ma

Abstract—Exploring and establishing artificial neural networks with electrophysiological characteristics and high computational efficiency is a popular topic that has been explored for many years in the fields of pattern recognition and computer vision. Inspired by the working mechanism of the primary visual cortex, pulse-coupled neural networks (PCNNs) can exhibit the characteristics of synchronous oscillation, refractory period, and exponential decay. These characteristics empower the PCNN model to group pixels with similar spatiality and gray values and to process digital images without training. However, electrophysiological evidence shows that the neurons exhibit highly complex nonlinear dynamics when stimulated by external periodic signals. This chaos phenomenon, also known as the “butterfly effect,” cannot be explained by all PCNN models. In this work, we analyze the main obstacle preventing PCNN models from imitating a real primary visual cortex. We consider neuronal excitation as a stochastic process. We then propose a novel neural network of the primary visual cortex, called a continuous-coupled neural network (CCNN). Theoretical analysis indicates that the dynamic behavior of the CCNN is distinct from the PCNN. Numerical results show that the CCNN model exhibits periodic behavior under a DC stimulus, and exhibits chaotic behavior under an AC stimulus, which is consistent with the testing results of primary visual cortex neurons. Furthermore, the image and video processing mechanisms of the CCNN model are analyzed. For image processing tasks, this model encodes the pixel intensity as the frequency of output signals so that it can group pixels with similar gray values. For video processing tasks, the CCNN encodes changing pixels as non-periodic chaotic signals, and it encodes static pixels as periodic signals. It thus achieves the purpose of moving target object recognition by distinguishing the dynamic states corresponding to different neuron clusters in the video. Experimental results on image segmentation indicate that the CCNN model has better performance than the state-of-the-art of visual cortex neural network models.

Index Terms—Brain-like computation, continuous-coupled neural network, primary visual cortex model, pulse-coupled neural network

1 INTRODUCTION

Creating brain-like machines is a long-standing goal in computer science [1]. The development of brain-like computing includes neuron models, synapse models, network structures to chip design, memory design, and computer architecture design [2]. Research on neuron models is the basis of brain-like computing, which involves two main paths: The first path focuses on the biophysical characteristics of neurons. By constructing the mathematical model of the conductive channels, these models can simulate the electrophysiological properties of neurons. The second path focuses on the phenomenological properties of neurons. These models use simple mathematical models to describe the input-output characteristics of neurons. Therefore, they have high computational efficiency and can be applied to image and video processing algorithms [3].

In recent years, combined models have attracted extensive interest because they reduce the computational complexity while preserving the main biological characteristics of neurons [4]. Pulse-coupled neural networks (PCNNs) are a combined model which holds an important place in brain-like computation [5]. Inspired by the primary visual cortex of mammals such as cats, PCNNs can imitate synchronous oscillation and refractory periods of real neurons. These characteristics empower PCNN models to reduce the local gray level difference and make up for the small discontinuities when processing images and videos [6]. Numerous studies have proven that PCNN models achieve remarkable performances in image processing tasks, such as image segmentation [7], edge detection [8], noise reduction [9], fusion [10], enhancement [11] and quantization [12].

Most PCNN research has focused on the firing mechanism and parameter simplification. However, there is one critical aspect of the biological characteristics that have been underinvestigated. In particular, Siegel used an external periodic signal to stimulate a cat’s receptive fields and then recorded the signals of the primary visual cortex neurons [13]. The collected spiking trains revealed that neurons exhibit highly complex nonlinear dynamics when stimulated by external periodic signals. This phenomenon can be repeated by plotting the frequency spectrum of the spike train data for the primary visual cortex collected during natural image sequence stimulation.

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The closest research on nonlinear dynamics of PCNN models is the phase recurrence relation of spiking neuronal models [14]. Like other spiking neuron models, PCNN models have a basic pulse frequency. When feeding input, linking input, or reset voltage is considered as a harmonic function, the phase recurrence relation has a chaotic structure [15]. However, the spiking trains of these models are periodic. As we proved in Sec. 3.1, PCNN models exhibit periodic behavior under a periodic signal stimulus. The period of the output signal of the PCNN model is proportional to the period of the driving signal.

Therefore, chaos, also known as the butterfly effect, is difficult to observe in the output signals of PCNN models and their variations. As a consequence, the Fourier series of all PCNN models are limited, which is inconsistent with real neurons. Fig. 1 compares the experimental frequency spectrum of PCNN models with real primary visual cortex neural networks. The output signals of PCNN models have relatively simple dynamic characteristics compared to real neurons.

A major distinction between PCNNs and the standard Hodgkin–Huxley neuronal model is the choice of the pulse generator. We found the firing state may fluctuate in neuron clusters, which is not satisfied in PCNN models. In this work, we consider neuronal firing as a stochastic process and deduce a novel model, called a continuous-coupled neural network (CCNN). Numerical evidence suggests that CCNN models exhibit periodic behavior under DC stimulus and exhibit chaos with an AC stimulus, which is consistent with the testing results of primary visual cortex neurons.

On this basis, we investigate the image and video processing mechanisms of the CCNN model. For image
processing tasks, CCNN neurons encode the pixel intensity as the frequency of output signals so that the network can group pixels with similar gray values. Compared to traditional image processing methods, the PCNN and CCNN can both reduce the local gray level difference of an image and compensate for small local discontinuities in the image. Unlike PCNN and its variations, an appropriate threshold is needed to transfer the output signals to binarized results. Note that these binarized results are only used to identify the region of interest, while it is not used to update the neuron state as in the PCNN. For most image processing tasks, an adjustable threshold can enable this model to achieve better results than all PCNN models. For video signals, the CCNN neurons encode changing pixels as non-periodic chaotic signals and encode static pixels as periodic signals, thus allowing moving target object recognition by distinguishing the dynamic states corresponding to neuron clusters in the video. This unique mechanism can track changes in pixels without the need to extract features of the target, which is different from all existing video processing methods.

The main contributions of this work are summarized as follows:

- We analyze the reason that the dynamic behaviors of the PCNN and its variations are inconsistent with real neural networks.
- We propose a novel neural network, called the CCNN model. Theoretical and numerical analyses indicate that the CCNN model exhibits complex dynamic behaviors which are consistent with the observed behavior of real primary visual cortex neurons.
- We analyze the image and video processing mechanism of the CCNN model. Furthermore, we show how chaotic characteristics benefit the dynamic vision, which may provide a reasonable explanation for why chaos widely exists in the brain, and how the brain uses chaos to process information.

2 RELATED WORKS

Relevant prior work includes studies of dynamic behavior of real neurons, pulse-coupled neural networks, and moving target tracking methods.

2.1 Dynamic Behavior of Real Neurons

Experimental results from neurophysiology stated that the neurons exhibit periodic behavior under a constant stimulus. For periodic stimulus, the neurons exhibit complex chaotic behavior. In particular, when the receptive field is stimulated by a high-speed square wave signal, the neurons of the primary visual cortex of a cat (area 17) exhibit complex dynamic behaviors, and the interspike-interval (ISI) distributions have various temporal patterns as shown in Fig. 5 of ref. [13]. These characteristics can be observed by plotting the frequency spectrum of the spike train data for the primary visual cortex collected during natural image sequence stimulation,1 as shown in Fig. 1c.

1. The data used here were collected in the laboratory of Dario Ringach at UCLA and downloaded from the CRCNS website. https://crcns.org/data-sets/vc/pvc-1/conditions

2.2 Pulse-Coupled Neural Network

Neural networks can be categorized into three different generations [16]. The first generation is based on using McCulloch-Pitts neurons as computational units, which perform threshold operations and output Boolean results. Hopfield networks and Boltzmann machines are based on these neural network models. The second generation is based on computational units that output continuous values. By applying a sigmoid unit or a rectified linear unit (ReLU) as an "activation function," these networks are able to evaluate a continuous set of output values and perform complex and deep tasks. The current deep learning networks, which have multiple hidden layers between their input and output, are all based on such second-generation neurons. The third generation of networks primarily use spiking neurons of the 'integrate-and-fire' type that exchange information through the spikes. Mammals use such spikes to process information.

A pulse-coupled neural network (PCNN) is a third-generation artificial neural network proposed in the 1990s. Inspired by the primary visual cortex of mammals such as cats, a PCNN model can exhibit synchronous oscillations and process digital images without training. In the past few decades, many studies have proven that PCNN models achieve better performance than other neuron models for image processing tasks [17].

There are two main paths for studying PCNNs. The first path involves studying the parameter setting problem [18], because the PCNN model is a multiparameter iteration network, and the network's performance depends on parameter settings such as the iteration numbers, the decay factors, and linking weight coefficients. Broussard was the first to attempt setting parameters adaptively by using the gradient descent method [19]. Yin et al. used the edge gradient to determine the linking coefficient β of the PCNN, but other parameters were constant [20]. Li et al. proposed a novel autowave PCNN to solve the shortest path problem, adaptively setting the dynamic threshold according to the current network state [21]. Gao et al. proposed a modified PCNN mode by establishing a new neural threshold and a varying linking coefficient [22]. Lian et al. used a parameter-adaptive PCNN model to construct an automatic segmentation algorithm [23], [24].

The second path proposes derivative models based on a PCNN [17]. For example, Kinser simplified the PCNN model to the ICM model in 1996 and demonstrated that the ICM was useful for target recognition [25]. In 2009, Zhan et al. proposed an SCM model by modifying the internal activity and firing condition of the PCNN. They showed that the SCM has lower computational complexity and achieves very high accuracy for image retrieval tasks compared with other common methods [26]. Two years later, Chen et al. simplified the SCM model to the SPFCCN model by replacing the traditional firing condition [27]. Deng, et al. found that the firing time is not integer-based and proposed a quasi-continuous PCNN model [28]. In recent years, heterogeneous PCNN models have been proposed because researchers realized that the models should be more consistent with real biological nervous systems [29].

However, all the above research rarely focuses on the chaotic characteristics of the models. Although the phase
renewal relation is chaotic when feeding input is considered as a harmonic function, the output signal is still chaotic, as we prove in Section 3.1. Therefore, it is still unknown why chaos widely exists in the brain and how can chaos benefit the brain in processing information.

Unlike all PCNN models, our model uses sigmoid functions to replace the pulse generator. The dynamic activity, which is known as the dynamic threshold in PCNN models, is affected by the output signal at each iteration. As a consequence, our CCNN model can exhibit highly complex chaotic behavior under a periodic stimulus. For image processing tasks, this model can achieve better results than all PCNN models by setting an appropriate threshold. For video processing tasks, this model can locate changing pixels by distinguishing the dynamic states of neurons, which are different from all existing methods.

### 2.3 Moving Target Tracking Method

In recent years, mainstream visual tracking methods are mean-shift, particle filter, active contour, and scale-invariant feature transform [30], [31].

1. Mean-shift method: This algorithm first calculates the similarity between the object model and the candidate image data, and then the tracking window moves in the field of view to the search object by an applied climbing algorithm of similarity gradient direction. It reaches the target when the mean-shift algorithm converges to a local extremum [32].

2. Particle filter method: This algorithm views the tracking algorithm as a state-solving problem under Bayesian models. By solving the posterior probability of the Bayesian probability model, this method has better estimation performance than the other nonlinear filters, and it has proven to be a powerful tool in solving visual tracking problems [33].

3. Active contour method: This method first extracts the general contour of the tracking target. Then it solves the differential equations recursively to converge to a local minimum of the energy function. The energy function is usually constructed according to the smoothness of the features and contour profile of the image, such as edges and curvature. This target tracking algorithm based on contour has no restriction on the target shape and movement [34].

4. Scale-invariant feature transform method: Scale-invariant feature transform (SIFT) is a kind of machine vision algorithm. It detects and describes local features of the image. SIFT searches extreme points in the scale of space and extracts position, scale, and rotation invariant of extreme points as features [35].

5. Deep neuron network based method: DNN is a data-driven method. In recent years, many DNNs, such as recurrent neural networks (RNNs) and (long short-term memory) LSTM, are proposed for moving target tracking. These DNN based methods use training samples to adjust network connection weights. When the accuracy converges to a certain value, the training process ends. Then the unknown sample is inputted into the well trained neural network to get the prediction result [36], [37].

In summary, the above methods first extract the features of the target in the image and then locate the target in video frame by using an appropriate template matching algorithm. Unlike these methods, CCNN models encode changing pixels and static pixels as different oscillation modes. Therefore, they can locate the moving target without extracting its features. This may illustrate how chaotic characteristics benefit the moving target object recognition methods, and it may provide a reasonable explanation for why primary the visual cortex can exhibit chaotic behavior, and how the brain using chaos to process information.

### 3 Approach

The dynamic causal modeling method is used to construct a novel artificial neural network with electrophysiological characteristics and high computational efficiency. Here the dynamic behavior of the PCNN under periodic stimuli is analyzed. To obtain a better neuron model, the spiking neuron model in the mean-field neuron clusters is studied. On this basis, a continuous-coupled neural network is deduced under the assumption of a fluctuating threshold.

#### 3.1 Problem Statement and Challenges

For artificial neural networks, a model with electrophysiological characteristics can benefit the research of exploring the working mechanism of a biological neural system, while a model with high computational efficiency can be applied in real world tasks such as image and video processing, natural language processing and recommended systems. One artificial neural network with both neurophysiological characteristics and high computational efficiency could help scientists understand how the brain processes information, and inspire engineers to construct more efficient signal processing algorithms.

For ease of explanation of our approach, we list the main notation in Appendix-I.

The main obstacle in comparing PCNN models and real neural networks is the different dynamic behaviors in the presence of a periodic stimulus. In particular, real primary visual cortex neurons exhibit chaotic behavior under a periodic stimulus, while almost all PCNN models exhibit periodicity. Here a sinusoidal stimulus is used to illustrate that the output signal of the PCNN is periodic under a periodic stimulus. The detailed analysis is as follows:

The equations for the PCNN are given by:

\[
F_{ij}(n) = e^{-\alpha_f}F_{ij}(n-1) + V_I M_{ijkl} Y_{kl}(n-1) + S_{ij}
\]

\[
L_{ij}(n) = e^{-\alpha_l}L_{ij}(n-1) + V_L W_{ijkl} Y_{kl}(n-1)
\]

\[
U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n))
\]

\[
Y_{ij}(n) = \begin{cases} 
1, & \text{if} U_{ij}(n) \geq E_{ij}(n) \\
0, & \text{otherwise}
\end{cases}
\]

\[
E_{ij}(n) = e^{-\alpha_e} E_{ij}(n) + V_E Y_{ij}(n-1)
\]

where the five main parts are the couple linking \(L_{ij}(n)\), the feeding input \(F_{ij}(n)\), the modulation product \(U_{ij}(n)\), the dynamic threshold \(E_{ij}(n)\) and the spiking output \(Y_{ij}(n)\). The quantity \(S_{ij}\) is the external feeding input received by the receptive fields. The parameters \(\alpha_f\), \(\alpha_l\) and \(\alpha_e\) denote exponential decay factors that record previous input states. The functions \(V_I\) and \(V_L\) are weighting factors modulating the action potentials of the surrounding neurons. Additionally, \(M_{ijkl}\) and \(W_{ijkl}\) denote the feeding and linking synaptic weights, respectively, and \(\beta\) denotes the linking strength, which directly determines \(L_{ij}(n)\) in the modulation product \(U_{ij}(n)\).
For simplicity, the nonlinking PCNN is considered, whose mathematical model is as follows:

\[ U(n) = e^{-\alpha_f} U(n-1) + S(n) \]

\[ Y(n) = \begin{cases} 1, & \text{if } U(n) \geq E(n-1) \\ 0, & \text{otherwise} \end{cases} \]

\[ E(n) = e^{-\alpha_e} E(n-1) + V_E Y(n-1) \]  

Suppose all value of \( U, Y \) and \( E \) are initially zero, and \( S = \sin(n) \) is the sinusoidal stimulus signal.

For the first iteration \( n = 1 \), \( E(1) = 0 \), \( U(1) = S(1) \), \( Y(1) = 1 \). The neuron generates the first spike.

Since \( V_E \gg S \), the neuron cannot lead to spike bursts immediately. Thus, for the second iteration:

\[ U(2) = e^{-\alpha_f} S(1) + S(2) \]

\[ E(2) = e^{-\alpha_e} E(1) + V_E Y(1) = V_E \]

\[ Y(2) = 0 \]  

When \( n = 3 \), the PCNN state variables are:

\[ U(3) = e^{-\alpha_f} S(1) + e^{-\alpha_f} S(2) + S(3) \]

\[ E(3) = e^{-\alpha_e} E(3) + V_E Y(3) = e^{-\alpha_e} V_E \]

\[ Y(3) = 0 \]  

Suppose when \( n = n_1 \), the spiking condition \( U(n) = E(n) \) is satisfied, and the neuron generates the second spike. At this time, \( U(n) \) and \( E(n) \) are:

\[ U(n) = e^{-(n_1-1)\alpha_f} S(1) + e^{-(n_1-2)\alpha_f} S(2) + \ldots + S(n) \]

\[ E(n) = e^{-(n_1-2)\alpha_e} V_E \]  

Eq. (5) is a discrete iterative equation, which can be transformed into the integral of the function when \( n \to 0 \):

\[ U(n) = \int_0^n e^{-\alpha_f} \cos(n)dn \]  

Eq. (6) can be solved using integration by parts with the result:

\[ U(n) = \frac{e^{n_1\alpha_f} \sin(n) - \alpha_f e^{n_1\alpha_f} \cos(n)}{1 + \alpha_f^2} \]  

Since \( \sin(n) \) and \( \cos(n) \) are periodic functions, suppose their period is \( T_s \) and the period of the PCNN is \( T_r \):

\[ U(n + T_s) = e^{-nT_r\alpha_f} e^{-(n_T + T_s)\alpha_f} \sin(n + T_s) \]

\[ = e^{-nT_r\alpha_f} e^{-(n_T + T_s)\alpha_f} \cos(n) \]

\[ = e^{-T_r\alpha_f} e^{\alpha_f} \sin(n) - \alpha_f e^{\alpha_f} \cos(n) \]

\[ = e^{-T_r\alpha_f} \cdot U(n) \]  

Since \( e^{-\alpha_f} \) decays rapidly as \( n \) increases, \( U(n) \) will decay to 0 after an initial transient giving:

\[ U(n + T_r) \approx U(n + T_s) = e^{-T_r\alpha_f} \cdot U(n) \]  

At this time,

\[ E(n + T_r) = e^{-(n + T_r - 2)\alpha_e} V_E = e^{-T_r\alpha_e} \cdot E(n) \]  

Since \( T_r \) is the period of the PCNN, suppose at the \( n \)th iteration, that \( U(n) = E(n) \). Then at the \( (n + T_r) \)-th iteration,

\[ U(n + T_r) = E(n + T_r) \]

Substitute Eqs. (9) and (10) into Eq. (11) to obtain:

\[ e^{-T_r\alpha_f} \cdot U(n) = e^{-T_r\alpha_e} \cdot E(n) \Rightarrow \]

\[ e^{-T_r\alpha_f} = e^{-T_r\alpha_e} \Rightarrow \]

\[ T_e = \frac{\alpha_f}{\alpha_e} T_s \]  

From the above analysis, PCNN models exhibit periodic behavior under a periodic stimulus. This is the main obstacle for PCNNs to create a brain-like machine. Moreover, despite neurological experiments showing that chaos widely exists in the brain, its benefits remain unclear.

### 3.2 Dynamic Causal Modeling of Continuous-Coupled Neural Network

A major distinction between PCNNs and the standard Hodgkin–Huxley neuronal model is in the choice of the pulse generator. We found the firing state may fluctuate across neuron clusters. As a consequence, the firing process is stochastic, while the firing process in all PCNN models is deterministic.

The voltages during the excitation process of the neurons are shown in Fig. 2. At the resting potential, both the voltage gated sodium and potassium channels are closed. At this time, the voltages are usually ~70 mV. When neurons receive external voltage signals, the cell membrane becomes depolarized, the voltage gated sodium channels begin to open up and the neuron begins to depolarize. When the membrane potential is greater than ~55 mV, the neurons depolarize quickly, and the membrane potential reaches its peak of 40 mV. At this level, the sodium channels begin to inactivate and the voltage gated potassium channels begin to open. This combination of closed sodium channels and open potassium channels leads to the neuron re-polarizing and becoming negative again. The neuron continues to re-polarize until the cell reaches ~75 mV, which is the equilibrium potential of potassium ions. This is the point at which the neuron is hyperpolarized, between ~70 mV and ~75 mV. After hyperpolarization the potassium channels close, and the natural permeability of the neuron to sodium and...
potassium allows the neuron to return to its resting potential of \(-70\) mV. During the refractory period, which is after hyper-polarization but before the neuron has returned to its resting potential, the neuron is capable of triggering an action potential due to the sodium channels ability to be opened. However, because the neuron is more negative, it becomes more difficult to reach the action potential threshold. Therefore, using the same magnitude of stimulus signal may not make the neuron trigger the new response signal due to the hyperpolarization process. Here we assume the firing threshold is fluctuating. When the membrane potential of the neuron reaches the excitation threshold, the neuron has a 50% probability of triggering an action potential, or entering the refractory period which cannot trigger the action potential.

### 3.2.1 Spiking Neuron Networks Under Fluctuating Assumption

Due to the hyperpolarization process, the firing threshold and resting membrane potential are considered to be fluctuating following Gaussian distributions:

\[
P(X|Y_0) \sim N(X|\mu_0, \sigma^2) = \frac{1}{\sqrt{2\pi} \sigma^2} e^{-\frac{(x-\mu_0)^2}{2\sigma^2}}
\]

\[
P(X|Y_1) \sim N(X|\mu_1, \sigma^2) = \frac{1}{\sqrt{2\pi} \sigma^2} e^{-\frac{(x-\mu_1)^2}{2\sigma^2}}
\]

(13)

where \(P(X|Y_0)\) is the probability of the neuron in its resting state, \(P(X|Y_1)\) is the probability of the neuron in a firing state, \(x\) is the membrane potential, \(\mu_0\) is the average value of the resting membrane potential, \(\mu_1\) is the average value of the firing threshold, the parameter \(\sigma\) is its standard deviation (for simplicity, resting membrane potential and firing threshold are assumed to have the same standard deviation).

According to Bayesian notation, when the membrane potential of a neuron is \(x\), the firing probability is:

\[
P(Y_1|X) = \frac{P(Y_1, X)}{P(X)} = \frac{P(Y_1, X)}{P(Y_1) + P(Y_0, X)} = \frac{1}{1 + P(X|Y_0)P(Y_0) + P(X|Y_1)P(Y_1)}
\]

(14)

Substituting Eq. (13) into Eq. (14) gives the neuron firing probability:

\[
P(Y_1|X) = \frac{1}{1 + e^{-\frac{(x-\mu_0)^2}{2\sigma^2} + \ln P(Y_0) + \ln P(Y_1)}}
\]

\[
= \frac{1}{1 + e^{-\frac{(2x-\mu_0)^2}{2\sigma^2} + \ln P(Y_0) + \ln P(Y_1)}}
\]

(15)

This result shows that a spiking neural model can be transformed into a mean-field model of neuron clusters by replacing the Heaviside function with a sigmoid function. This is a useful conclusion: (1) The use of this transformation will solve the problem that spiking neural networks cannot be derived (the derivative of a Heaviside function does not exist), and thus they are unable to be directly implemented in deep neural networks. (2) This transformation will allow a simple spiking neuron model to exhibit complex dynamic behaviors that are closer to real neurons.

### 3.2.2 Construct Continuous-Coupled Neural Network

According to the previous section, when the hyperpolarization process is considered, the firing mechanism should be treated as a random fluctuating process. Replacing the firing condition with the firing probability gives the continuous-coupled neural network (CCNN) model:

\[
F_{ij}(n) = e^{-a}F_{ij}(n-1) + V_F M_{ijkl} Y_{kl}(n-1) + S_{ij}
\]

\[
L_{ij}(n) = e^{-a}L_{ij}(n-1) + V_L W_{ijkl} Y_{kl}(n-1)
\]

\[
U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n))
\]

\[
Y_{ij}(n) = \frac{1}{1 + e^{-u_{ij}(n) - E_{ij}(n)}}
\]

\[
E_{ij}(n) = e^{-a} E_{ij}(n-1) + V_E Y_{ij}(n-1)
\]

(16)

Here, for simplicity, the parameter \(a\) and \(b\) are set to 1. The five main parts are couple linking \(L_{ij}(n)\), feeding input \(F_{ij}(n)\), modulation product \(U_{ij}(n)\), dynamic activity \(E_{ij}(n)\) and continuous output \(Y_{ij}(n)\). The quantity \(S_{ij}\) is the external feeding input received by the receptive fields. The parameters \(V_F\) and \(V_L\) are weighting factors modulating the action potentials of the surrounding neurons. Additionally, \(M_{ijkl}\) and \(W_{ijkl}\) denote the feeding and linking synaptic weights, respectively, and \(\beta\) denotes the linking strength, which directly determines \(L_{ij}(n)\) in the modulation product \(U_{ij}(n)\). Fig. 3 presents an intuitive illustration of the five parts.

### 4 Dynamic Behavior Analysis

A CCNN can exhibit periodic behavior under a constant stimulus, and exhibit chaotic behavior under a periodic stimulus as shown in Fig. 4. The detailed dynamic behaviors and image and video processing mechanisms are analyzed in the rest of this section.

#### 4.1 Dynamic Behavior of CCNN Under Constant Stimulus

For simplicity, the nonlinking CCNN is considered, for which the mathematical model is as follows:

\[
U(n) = e^{-a}U(n-1) + S(n)
\]

\[
Y(n) = \frac{1}{1 + e^{-u(n) - E(n)}}
\]

\[
E(n) = e^{-a} E(n-1) + V_E Y(n-1)
\]

(17)

From Eq. (17), \(U\) is an independent variable, which is only affected by the external input \(S\). The recurrence formula for \(U\) is \(U(n) = e^{-a}U(n-1) + S\). Thus \(U\) is a geometric sequence, the general term of which is:
Variables $Y$ and $E$ are coupled and bijective. Substituting $Y$ into $E$ gives the recurrence formula:

$$E(n) = e^{-\alpha_E} E(n-1) + \frac{V_E}{1 + e^{-(U(n-1)-E(n-1))}}$$

(19)

Suppose $E$ starts from $E(0)$ where $E(n) = E(0)$. The neuron returns to the initial state:

$$\Rightarrow U(n-1) = E(0) - \ln\left(\frac{V_E}{1 - e^{-\alpha_E}} E(0) - 1\right)$$

(20)

On the other hand, from Eq. (18),

$$U(n-1) = S \cdot \frac{1 - e^{-\alpha_f} f}{1 - e^{-\alpha_f}}$$

Therefore, the period $n$ can be determined from:

$$n = 1 + \frac{1}{\alpha_f} \ln \frac{S - (1 - e^{-\alpha_f}) E(0) - \ln(V_E/(1 - e^{-\alpha_E}) E(0) - 1)}{S - (1 - e^{-\alpha_f}) (E(0) - \ln(V_E/(1 - e^{-\alpha_E}) E(0) - 1))}$$

(21)

Therefore, CCNN neurons exhibit periodicity under a constant stimulus. The frequency is determined by the intensity of the external stimulus and the initial state. For the same initial states, the greater the intensity of the stimulus, the larger the frequency of the CCNN neuron.

4.2 Dynamic Behavior of CCNN Under Periodic Stimulus

The CCNN neuron can exhibit chaotic dynamics under a periodic stimulus. Eq. (17) is the nonlinking CCNN model, where $\alpha_f = 0.1$, $\alpha_c = 1$, $V_E = 50$, $S(n) = 0.4 \sin(n)$. The phase space plot is shown in Fig. 5. The following section gives the detailed analysis of these complex dynamics.

4.2.1 Equilibrium Point

For simplicity, the nonlinking CCNN is considered, for which the mathematical model is shown in Eq. (17). Here $S = \sin(n)$ is used to analyze the dynamic behavior under a periodic stimulus. The quantity $U$ is an independent variable according to Eq. (7), given by $U(n) = e^{-\alpha_f} \sin(n) - \alpha_f e^{-\alpha_f} \cos(n)$.

According to Eq. (17), $E(n)$ is affected by $Y(n)$ at each iteration, which cannot be represented by a geometric sequence. Therefore, the CCNN model has distinct dynamic characteristics under a periodic stimulus.

In this part, nonlinear dynamic analysis methods are used to explore the dynamic characteristics of the CCNN under a periodic stimulus. The equilibrium point of the CCNN model is given by:

$$E(n+1) = E(n) \Rightarrow E(n) = e^{-\alpha_E} E(n) + \frac{V_E}{1 + e^{-(U(n)-E(n))}}$$

$$E(n) \Rightarrow E(n)(1 + e^{-(U(n)-E(n))}) = \frac{V_E}{1 - e^{-\alpha_E}}$$

(22)

Taylor expansion of $e^x$ is used to simplify Eq. (22). Here only the first two terms of the Taylor series are considered. Eq. (22) can be simplified to:

$$E(n)^2 - (U(n) - 2) E(n) - \frac{V_E}{1 - e^{-\alpha_E}} = 0$$

(23)

Fig. 4. The output signals of one CCNN neuron under different stimulus signals, the parameters are set to be $\alpha_f = 0.1$, $\alpha_c = 1$, $V_E = 50$, $E(0) = 0$, $S(n) = 0.4 \sin(n)$. (a) Input constant signal with the amplitude of $S = 0$; (b) Input constant signal with the amplitude of $S = 1$; (c) Input constant signal with the amplitude of $S = 3$; (d) Input sinusoidal signal of $S = \sin(t)$; (e) Output signal under the stimulus of $S = 0$; (f) Output signal under the stimulus of $S = 1$; (g) Output signal under the stimulus of $S = 3$; (h) Output signal under the stimulus of $S = \sin(t)$.

Fig. 5. Phase space plot of one CCNN neuron under sinusoidal stimulus: (a) Phase space plot of $U - E$ plane; (b) Phase space plot of $U - Y$ plane; (c) Phase space plot of $E - Y$ plane.
Eq. (23) is a quadratic equation with \( \Delta = (U(n) - 2)^2 + 4 \frac{V_E}{1-e^{-\alpha}} \). Since \( V_E > 0 \), \( \alpha_e > 0 \), \( 4 \frac{V_E}{1-e^{-\alpha}} > 0 \) \( \Rightarrow \Delta > 0 \), \( E(n) \) can be represented as \( E(n) = \frac{U(n)-2\pm\sqrt{((U(n)-2)^2+4\frac{V_E}{1-e^{-\alpha}})}}{2} \).

The derivative of Eq. (23) is given by:

\[
f(E(n)) = 2E(n) - U(n) + 2
\]

Therefore, for \( E(n) = \frac{U(n)-2\pm\sqrt{((U(n)-2)^2+4\frac{V_E}{1-e^{-\alpha}})}}{2} \), \( f(E(n)) > 0 \).

Since \( U(n) \) is an independent variable, Eq. (17) is a two-dimensional discrete dynamical system. According to the above analysis, it has two equilibrium points, the first of which is unstable and given by:

\[
U(n) = \frac{e^{-na}\sin(n) - a_fe^{-na}\cos(n)}{1 + a_f^2}
\]
\[
E(n) = \frac{U(n) - 2 + \sqrt{((U(n) - 2)^2 + 4\frac{V_E}{1-e^{-\alpha}})}}{2}
\]
\[
Y(n) = \frac{1}{1 + e^{-U(n)-E(n)}}
\]

The second equilibrium point is stable and is given by:

\[
U(n) = \frac{e^{-na}\sin(n) - a_fe^{-na}\cos(n)}{1 + a_f^2}
\]
\[
E(n) = \frac{U(n) - 2 - \sqrt{((U(n) - 2)^2 + 4\frac{V_E}{1-e^{-\alpha}})}}{2}
\]
\[
Y(n) = \frac{1}{1 + e^{-U(n)-E(n)}}
\]

**4.2.2 Lyapunov Exponents**

Here Lyapunov exponents are used to investigate the overall dynamic behavior. Lyapunov exponents are a measure of a system’s predictability and sensitivity to changes in its initial conditions [38]. If the largest Lyapunov exponent (LLE) is greater than zero, the system exhibits chaos. If LLE= 0, the behavior is periodic. If LLE < 0, the system will converge to a stable equilibrium point [39]. Fig. 6 shows the Lyapunov exponent spectrum of Eq. (17) under the stimulus of \( S = \sin(n) \).

From experiments, the control parameters are not equal. When \( \alpha_f \) is taken as a control parameter, the chaos exists in a small range. When \( \alpha_e \) or \( V_E \) are taken as control parameters, the chaos exist in a wide range. Note that there are some periodic windows embedded in the chaotic regions.

**4.2.3 Basin of Attraction**

The basin of attraction of a chaotic system is the set of initial conditions in the phase space whose trajectories go to the attracting set. Here we use Lyapunov exponents to explore the basin of attraction in the CCNN model. For Eq. (17), when \( \alpha_f = 0.1 \), \( \alpha_e = 0.1 \), \( V_E = 65 \) and \( S = \sin(n) \), the Lyapunov exponent spectrum is shown in Fig. 7.

**5 IMAGE AND VIDEO PROCESSING MECHANISMS**

Based on the above analysis, the image and video processing method can be obtained. The detailed mechanisms are as follows.

**5.1 Image Processing Mechanism**

Section 4.1 showed that the CCNN neurons transfer a static stimulus to a periodic signal. From Eq. (21), as the pixel-value increases, the neuron provides output signals with higher frequency. Fig. 9 illustrates the image processing mechanism. For pixels in the image, the CCNN neurons encode gray value in the frequency of the output signal and allow target object recognition by distinguishing the period corresponding to the neuron clusters.

There are several methods to calculate the frequency of the signal, such as Fourier transform, wavelet transform, s-transform and Wigne-Ville transform. Since it is shown that the CCNN model exhibits periodicity under a constant stimulus, the method used to explore the frequency of the output signal is quite simple. In this section, the time between two consecutive peaks is considered to determine the frequency of the output signal.

It is interesting to note that: (1) With larger gray values of the pixel, the output signal has higher frequency; (2) If the gray values of the pixels are close, their frequencies are also close.
5.2 Video Processing Mechanism

Section 4.2 showed that the CCNN model can transfer a dynamic stimulus to a chaotic signal. Fig. 10 illustrates the video processing mechanism. The CCNN model encodes changing pixels as non-periodic chaotic signals, and encodes static pixels as periodic signals, and allows moving target object recognition by distinguishing the dynamic states corresponding to the neuron clusters in the video frame.

From the experiments, the spike trains corresponding to the changing pixels exhibit complex dynamic behavior. The changing pixels can be located by using appropriate signal processing methods such as the Fourier transform or wavelet transform.

6 Experiments

In this section, the dynamic behaviors of the CCNN model and real neurons are compared. Nature image segmentation and breast mass segmentation are used to verify the effectiveness of the image mechanism. A designed experimental paradigm is used to verify the effectiveness of the video mechanism.

6.1 Comparative Experiment With Real Neurons

In neurophysiology experiments, nerve action potentials in response to changing stimuli are monitored and recorded by an electrode. Then, bandpass filters is used to separate the relatively high frequency components in the action potential from low frequency noise. Finally, the action potential is coded by the all-or-none law: If the voltage exceeds the threshold potential, the nerve fiber will generate a complete response; otherwise, it provides no response. A flowchart of the coding action potential is shown in Fig. 11.

Here we suppose the signals generated by the CCNN models are raw data without noise. We use a simple filter to implement the all-or-none coding process, which is described as follows:

1) Parameter setting: Set the system parameters of $\alpha_e$, $\alpha_I$ and $V_E$, the initial conditions of $U(0)$, $Y(0)$ and $E(0)$, and the length of the output sequence.
2) Pre-iteration: Iterate a few hundred times so that the orbit is on the attractor.
3) Iteration: Update $U(n)$, $Y(n)$ and $E(n)$ by Eq. (17) until $n$ reaches the desired length.
4) Evaluate the threshold for all-or-none coding: Calculate the mean value of the output sequence $Y$, and set the threshold to $th = \mu_{max}(Y)$, where $\mu$ is an adjustable coefficient. In this work, $\mu$ is set to 0.8.
5) Calculate the spike trains: Determine the value of the spike train data by $Y(n)$ and $th$. If $Y(n) \geq th$, the spike train data is $S_{out} = 1$; otherwise, it is $S_{out} = 0$.

Siegel performed detailed experiments with real neurons in the primary visual cortex and reported that “Stimuli were presented at 271.5 ms intervals. A burst of action potentials can be seen following each stimulus. By plotting the distribution of interspike intervals, it can be seen that there is a major periodicity at approximately 270 ms. There are also peaks at 175, 540, and 1080 ms. The latter two values are roughly integer multiples of the driving period” [13].

The CCNN model can reproduce this phenomenon perfectly. We use a square wave function to simulate the process of using shutters to produce high-frequency light flashes in Siegel’s experiment. The external stimulus is set to $S = A (\text{square}(\omega t, dc) + 1)$, where $A$ is the amplitude, $\omega$ is the frequency and $dc$ is the duty cycle of the stimulus signal. When $A = 0.4$, $\omega = 0.2\pi$ and $dc = 50$, the neuron exhibits chaos. Its waveform and phase space plots are shown in Fig. 12. After all-or-none coding, the spike trains, ISI...
distribution and return map are shown in Fig. 13. From these results, the output signal $Y$ and spike train data exhibit complex chaotic dynamic behavior. The resulting ISI distribution and return map are resemble those for the real neurons as seen in Fig. 3 of ref [13].

Furthermore, the CCNN neuron can exhibit various temporal patterns of activation under different periodic stimuli. This is also observed in real neurons. (see Fig. 4 and Fig. 5 in ref [13]). The detailed experiments are shown in Appendix-II.

### 6.2 Applications in Image Segmentation

As was discussed in Section 5.1, CCNN neurons encode a static image as a periodic signal perform target object recognition by distinguishing the period corresponding to neuron clusters. There are several methods to calculate the frequency of periodic signals such as the Fourier transform, the wavelet transform, the zero crossing rate, etc. Here we propose a simple method for image segmentation, which is described as follows:

1) Constructing a CCNN model: Construct a continuous-coupled neural network according to Eq. (16), with each pixel in the image corresponding to an individual neuron.

2) Parameter setting: Set the system parameters of $\alpha_i, \alpha_f, \beta, V_F, V_L$ and $V_E$ of all the neurons according to the image. Set an appropriate threshold $th$ for all-or-none coding. Set the linking weights $M_{ijkl} = W_{ijkl} = \begin{bmatrix} 0.5 & 1 & 0.5 \\ 1 & 0 & 1 \\ 0.5 & 1 & 0.5 \end{bmatrix}$.

3) Iteration: Iterate one step and calculate the values of $F_{ij}, L_{ij}, U_{ij}, Y_{ij}$ and $E_{ij}$ for the $i$th row and $j$th column of the neuron $(ij)$.

4) All-or-none coding: Using the threshold $th$ to obtain the spiking data of $S_{out}^{ij}$ of neuron $(ij)$, if $Y_{ij} \geq th$, then $S_{out}^{ij} = 1$; otherwise, $S_{out}^{ij} = 0$.

5) Constructing segmentation results: Use $S_{out}^{ij}$ to construct the resulting image.

6) Repeating: Repeat step (3), step (4) and step (5) for a few iterations, and generate multiple resulting images.

7) Select best resulting image: Select the best resulting images as the final image segmentation result.

To evaluate the effectiveness of the proposed segmentation method, we use the BSDS500 dataset, which is designed for evaluating natural edge detection that includes not only object contours but also background boundaries. The detailed experiments are shown in Appendix-III.

To compare our method with other segmentation methods, we chose ten fatty-glandular images from the Digital Database for Screening Mammography (DDSM) as test images. The detailed experiments are shown in Appendix-III. A visual comparison of one segmentation result is shown in Fig. 14.

We adopt Otsu [40], SPCNN [27], SCM [41], Dense-Unet [42], and Selective Kernel U-Net [43] as comparative algorithms to evaluate the effectiveness of our method. The Otsu method is an effective and adaptive threshold scheme that has been widely applied for image segmentation. SCM and SPCNN are two state-of-the-art networks of visual cortex neural network models, which have superior performance in applications of image segmentation. Dense-Unet and Selective Kernel U-Net are deep learning methods for biomedical image segmentation, which can provide good segmentation performance in medical images.

Compared to other image segmentation methods, the testing results of our methods and Dense-Unet are closer to segmentation results by a professional doctor. This is because when performing a single image segmentation task, the target area can be segmented in a finer-grained
manner through the adjustable threshold. Thus our method is superior to other image segmentation tasks, including state-of-the-art PCNN models.

6.3 Applications in Dynamic Vision

As discussed in Section 5.2, CCNN models encode changing pixels as non-periodic chaotic signals and encode static pixels as periodic signals, and perform moving target object recognition by distinguishing the dynamic states corresponding to the neuron clusters in the video. Fig. 15 shows this video mechanism and an application. In this video task, the CCNN is used to locate regions where blood flows in videos. Due to the heartbeat, blood periodically flows through a person's skin, causing periodic tiny changes in the color of the skin. Input the time-varying waveform of each pixel in the video into the CCNN neuron, and analyze the frequency characteristics of the corresponding signal of the CCNN neuron through wavelet transformation, and distinguish the periodically changing pixels from the constant pixels to obtain the area of interest. From Fig. 15c3, the CCNN model can accurately identify areas in the video where blood flows. Unlike all the other video processing methods described in Sec.II-C, this new video processing paradigm does not need to extract features of the target, which differ from all existing video processing methods. We implemented the above image processing mechanism in image segmentation tasks. Due to the adjustable threshold, our method is superior to other image segmentation tasks, including state-of-the-art PCNN models. Although this work has made breakthroughs in imitating the dynamic characteristics of real neurons and the mechanism of processing images and videos by primary visual cortex neural networks, a few limitations remain, which future studies should address:

- In this work, all conclusions are drawn for a nonlinking input. In the case of linking input, the analysis of the model is more complex. However, solving this problem will help explain how neurons communicate to each other and how they cooperate to accomplish cognitive tasks.
- In image processing tasks, this method can identify areas with different pixel intensities. However, real image segmentation tasks not only rely on the pixel value of the image but also on some structural information. For example, in the breast image segmentation task, the pixel intensity of the breast muscle is similar to the pixel intensity of a breast mass. In this case, the image segmentation algorithm will segment the pectoral muscle area instead of the mass area.
- In video processing tasks, it is hard to identify the dynamic state of the neurons. As we demonstrated in this manuscript, CCNN neurons exhibit chaotic behavior under periodic stimulus. The Lyapunov exponent is a strict method to distinguish dynamic states. However, the Lyapunov exponent is strictly

Fig. 15. Video processing method of CCNN model: (a) is the input video sequence, except the central, all other pixels are static; (b) is the Fourier spectrum corresponding to each neuron; (c) is an application of CCNN model: (c1) is the Pulse and blood flow video; (c2) are the corresponding signal characteristics of CCNN driven by DC signal (0 – 50 samples) and AC signal (50 – 100 samples); (c3) is the result of the video after CCNN processing.
defined on the limit where time tends to infinity. This condition cannot be satisfied in dynamic vision tasks. We initially showed that the wavelet transform can solve this problem. However, whether this is an effective method still needs further study.

- How to design algorithms for different video tasks according to the characteristics of the CCNN model is also one of the important tasks for the future.

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