It may be time to improve the neuron of artificial neural network

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Abstract

Artificial neural networks (ANNs) have won numerous contests in pattern recognition, machine learning, or artificial intelligence in recent years. The neuron of ANNs was designed by the stereotypical knowledge of biological neurons 70 years ago. Artificial Neuron is expressed as $f(wx + b)$ or $f(WX)$. This design does not consider dendrites' information processing capacity. However, some recent studies show that biological dendrites participate in the pre-calculation of input data. Concretely, biological dendrites play a role in extracting the interaction information among inputs (features). Therefore, it may be time to improve the neuron of ANNs. According to our previous studies (DD), this paper adds the dendrites' function to artificial Neuron. The dendrite function can be expressed as $W^{i,i-1}A^{i-1} \circ A^{0|1|2|\dots|i-1}$. The generalized new neuron can be expressed as $f(W(W^{i,i-1}A^{i-1} \circ A^{0|1|2|\dots|i-1}))$. The simplified new neuron can be expressed as $f(\sum(WA \circ X))$. After improving the neuron, there are so many networks to try. This paper shows some basic architecture for reference in the future.

Interesting things: (1) The computational complexity of dendrite modules ($W^{i,i-1}A^{i-1} \circ A^{i-1}$) connected in series is far lower than Horner's method. Will this speed up the calculation of basic functions in computers? (2) The range of sight of animals has a gradient, but the convolution layer does not have this characteristic. This paper proposes receptive fields with a gradient. (3) The networks using Gang neurons can delete traditional networks' Fully-connected Layer. In other words, the Fully-connected Layers' parameters are assigned to a single neuron, which reduces the parameters of a network for the same mapping capacity.

One important thing: ResDD can replace the current all ANNs' Neurons (ResDD modules+ One Linear module)! ResDD has controllable precision for better generalization capability!

Index Terms

Neural network, neuron, DD, Gang transform, Gang neuron, Receptive fields with gradient, Acceleration algorithm

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I. INTRODUCTION

AN artificial neural network is an algorithmic architecture that imitates the biological brain [1], [2]. Today, neural networks are gradually changing our lives and making the world better [3]. First of all, I want to thank those who contribute to the present state of the art, e.g., Geoffrey Hinton, YannLeCun, Yoshua Bengio, and so on.

Recently, artificial neural networks, particularly “deep learning” [4], have made some impressive advances in many fields, such as machine vision, speech recognition, autonomous vehicles, and machine translation. Thus, in the tech world today, optimism is high. Some people think ANNs are approaching human intelligence gradually, even it is still far away [2], [3].

Neurons are the fundamental units of the biological brain. Accordingly, the fundamental units of ANNs are artificial neurons. With the development of technology, people have a deeper understanding of the biological brain and neurons. However, the artificial neuron has maintained its original architecture. It may be time to improve the neuron of the artificial neural network.

A brief introduction about the necessary knowledge and latest developments in artificial neural networks and biological neural networks is the following.

A. Artificial neural networks

An ANN consists of many interconnected functional units or neurons and can learn the relationship of input space and output space. Thus, they are usually used to solve classification and regression problems [5]. Over the years, based on the application and data’s characteristics, different ANN architectures have been developed, such as Convolutional Neural Networks (CNN) [6], [7] in computer vision, Recurrent Neural Networks (RNN) [8] or Long Short Term Memory Network (LSTM) [9] in sequence and time series modeling, and Generative Adversarial Network (GANs) [10].

In the last decade, some newer architectures are developed to endure the need to develop human-like efficient machines in different application areas. From the perspective of information, they can be divided into a network focusing on spatial information [CNN, the representative field is computer vision (CV).] and a network focusing on temporal information [RNN, the representative field is natural language processing (NLP).]. There are several newer CNN architectures and efficient mechanisms: Alexnet [7], VGG [11], Googlenet [12], Inception-V3 [13], ResNet [14], ResNeXt [15], Convolutional Block Attention Module (CBAM) introduced by Woo et al. [16], and competitive squeeze-excitation (SE) mechanism introduced by Hu et al. [17]. There are several newer RNN architectures and efficient mechanisms: Deep Recurrent Attentive Writer (DRAW) [18], Grid Long Short-Term Memory [19], gating mechanism introduced by Jing et al. [20], and factorized recurrent network architecture introduced by Belletti et al. [21].

Besides, the learning of ANNs—by changing the distribution of weights to approximate the relationship between input and output space— has been studied. Lately, success was achieved in many techniques, such as L1 and L2 regularization [22], batch normalization [23], a good collection of weight initialization techniques [24], [25], and a good set of activation functions [5].

Fig. 1. Traditional neuron. (a) Traditional artificial neuron. (b) Traditional imitation to biological neuron.

B. Biological neural network

The human brain has approximately 100 billion biological neurons, and neurons are connected via specialized structures known as synapses to sense stimulations and pass signals to other neurons [26]. A neuron is the fundamental structural and functional unit of the neural information network and comprises a cell body (soma), dendritic trees, and an axon [27], [28]. The most extended parts of many neurons are dendrites [29], and the active electrical properties of dendrites shape neuronal input.

In the field of biology, researchers have been studying the mechanism of the element of neurons over the years [27], [30]–[32]. Recently, a study discovered a class of calcium-mediated dendritic action potentials (dCaAPs) [32], [33]. Here, we quote the original words in the literature: “These dCaAPs enabled the dendrites of individual human neocortical pyramidal neurons to classify linearly nonseparable inputs—a computation conventionally thought to require multilayered networks.” [32] ***Computing exists in the intersection of dendrites. This means that biological dendrites participate in pre-calculation in a biological neural network.***

Reviewing the previous ANNs, I found few studies highlight improving the neuron of ANNs. Fortunately, it happens that Gang et al. [34] propose a module with low computational complexity named DD or Gang transform. The module can solve linearly inseparable problems by Hadamard product. Therefore, it can simulate the dendrites and improve the neuron of ANNs.

II. ARTIFICIAL NEURON

A. Traditional artificial neuron

In 1943, McCulloch and Pitts proposed ANN models with adjustable weights [35]. More than a decade later, Rosenblatt put forward the Perceptron Learning Algorithm [36]. In 1986, Rumelhart et al. proposed learning representations by back-propagating errors [37]. By then, a typical artificial neuron was established.

Figure 1 shows the traditional artificial neuron. This architecture ignores the pre-calculation of dendrites. If X is the input and f is the nonlinear activation function, the output y can be represented by,

$$y = f(W^{21}X) \quad (1)$$

Where W^{21} is the weight matrix, $\{1, x_1, x_2, \dots, x_n\} = X$. In the back-propagation procedure, the weight matrix can be updated with,

$$W_{new}^{21} = W^{21} - \eta \frac{\partial E}{\partial W^{21}} \quad (2)$$

Where W_{new}^{21} is the updated weight matrix for W_{21} , E is the cost function or errors from the later layer in back-propagation, and η is the learning rate.

B. Novel Gang artificial neuron

For the biological neurons, the XOR operation is performed in the dendrites with dCaAPs [32], [33], and AND/OR operations are performed at the soma and at tuft and basal dendrites with sodium and NMDA spikes [38]–[40]. The XOR/AND/OR operation means the pre-processing to the interaction information of input data. In the task of understanding a picture, it refers to the relationship between parts of an input-picture. In the task of understanding an article or a speech, it refers to the relationship between words of sentences. However, traditional artificial neurons only simulate the soma.

Fig. 2. Novel neuron. (a) Gang artificial neuron. (b) Gang imitation to biological neuron.

Fig. 3. Generalized dendritic module. ‘|’ expresses ‘or’. The dotted line represents any of them.

1) *Dendrite processing section ($\circ X$)*: In previous studies, we presented dendrite modules and introduced logical relationship of inputs [34], [41]. The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ X \quad (3)$$

Where A^{i-1} and A^i are the input and output of the module, respectively, and X is the original input.

In figure 2a, the dendrite is simulated by one module. The “dendrite” contains the interaction item between both inputs and can be represented as follows.

$$A = W^{10} X \circ X \quad (4)$$

Where A is the output of dendrite or the input of the cell body.

Additionally, the dendrite can also be simulated by using more modules. The “dendrite” in Fig.4 contains the interaction items between multiple inputs. The number of modules plus 1 is the number of interactive inputs. For example, if we use two

Fig. 4. Gang artificial neuron with multiple dendrite modules.

Fig. 5. Generalized Residual Dendrite module. ‘|’ expresses ‘or’. The dotted line represents any of them.

modules to simulate the dendrite, the “dendrite” contains the interaction items among three inputs and can be represented as follows.

$$\begin{cases} A^1 = W^{10} X \circ X \\ A^2 = W^{21} A^1 \circ X \end{cases} \quad (5)$$

Where A^2 is the output of dendrite or the input of the cell body.

The operation of the “dendrite” only consists of matrix multiplication and Hadamard product. Thus, the computational complexity is lower [34], [41]. Additionally, the mapping capacity of Gang neuron can be adjusted by the number of dendrite modules.

2) *Generalized Dendrite module ($\circ A^i$)*: Figure 3 shows a generalized dendritic module. The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ A^{0|1|2|\dots|i-1} \quad (6)$$

Where A^{i-1} and A^i are the inputs and outputs of the module, respectively. $A^{0|1|2|\dots|i-1}$ is any of A .

We can adjust the promotion degree or the number of interactive variables added for the single module by $A^{0|1|2|\dots|i-1}$. When we add a module, the degree of network can increase by at least one and by i at most.

When $A^{0|1|2|\dots|i-1} = A^0$, the degree increases by 1 for one module, which is similar to Horner’s method. The degree increases with the number of modules linearly. For a certain degree of network, the computational complexity is $n - 1$, where n expresses the number of modules.

When $A^{0|1|2|\dots|i-1} = A^{i-1}$, the degree increases by i for one module. The degree increases with the number of modules exponentially. For a certain degree of network, the computational complexity is approximate $\log_2^n$, where n expresses the number of modules. This is similar to exponentiation by squaring. However, exponentiation by squaring is only used for calculation, and the modules in this paper are used for approximation. The weight matrix in Fig. 3 can be solved for by error backpropagation.

Here, I give a off-topic special USES. when this module is connected in series, it is used for polynomial calculation (Fig. 3). When $A^{0|1|2|\dots|i-1} = A^{i-1}$, there is no doubt that its computational complexity is far lower than Horner’s method. This can change many things.

The typical functions (e.g., $\sin$) are stored in the form of polynomial coefficients in the computer. The value of the function is calculated by polynomial when we invoke these functions.

We can solve for the polynomial coefficients of my new module ($A^{0|1|2|\dots|i-1} = A^{i-1}$) and store these coefficients in the computer. The value of the function is calculated by the network in Fig. 3 when we invoke these functions.

3) *Generalized Residual Dendrite module ($\circ A^i$)*: In order to make DD deeper, a residual strategy can be used (see Fig. 5) [42]. The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ A^{0|1|2|\dots|i-1} + W^{i,i-1} A^{i-1} \quad (7)$$

Where A^{i-1} and A^i are the inputs and outputs of the module, respectively. $A^{0|1|2|\dots|i-1}$ is any of A . $W^{i,i-1}$ is a weight matrix.

4) *ResDD-X or Residual Dendrite module ($\circ X$)*: Figure 7 shows the Residual Dendrite module-X (ResDD-X). The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ X + W^{i,i-1} A^{i-1} \quad (8)$$

Where A^{i-1} and A^i are the inputs and outputs of the module, respectively. X is the inputs of DD. $W^{i,i-1}$ is a weight matrix.

Figure 6 (a) shows ResDD-X code for MNIST dataset in references [34]. The number of modules can be adjusted according to the task.

(a)

```
class ResddNet_X(nn.Module):

    def __init__(self):
        super(ddNet, self).__init__()

        # xw+b
        self.fc0 = nn.Linear(28*28, 256, bias=False)
        self.dd = nn.Linear(256, 256, bias=False)

        self.fc2 = nn.Linear(256, 10, bias=False)

    def forward(self, x):
        # x: [b, 1, 28, 28]
        x = self.fc0(x)
        c = x
        # b1 = x@w1*x
        for i in range(4):
            g=self.dd(x)
            x=g*c+g
        x = self.fc2(x)
        return x
```

(b)

```
class ResddNet_A(nn.Module):

    def __init__(self):
        super(ddNet, self).__init__()

        # xw+b
        self.fc0 = nn.Linear(28*28, 256, bias=False)
        self.dd = nn.Linear(256, 256, bias=False)

        self.fc2 = nn.Linear(256, 10, bias=False)

    def forward(self, x):
        # x: [b, 1, 28, 28]
        x = self.fc0(x)
        #c = x
        # b1 = x@w1*x
        for i in range(4):
            g=self.dd(x)
            x=g*x+g
        x = self.fc2(x)
        return x
```

(c)

```
class ResddNet_XW(nn.Module):

    def __init__(self):
        super(ddNet, self).__init__()

        # xw+b
        self.fc0 = nn.Linear(28*28, 256, bias=False)
        self.dd = nn.Linear(256, 256, bias=False)

        self.fc2 = nn.Linear(256, 10, bias=False)

    def forward(self, x):
        # x: [b, 1, 28, 28]
        x = self.fc0(x)
        c = x
        # b1 = x@w1*x
        for i in range(4):
            x=self.dd(x)*c+self.dd(x)
        x = self.fc2(x)
        return x
```

(d)

```
class ResddNet_AW(nn.Module):

    def __init__(self):
        super(ddNet, self).__init__()

        # xw+b
        self.fc0 = nn.Linear(28*28, 256, bias=False)
        self.dd = nn.Linear(256, 256, bias=False)

        self.fc2 = nn.Linear(256, 10, bias=False)

    def forward(self, x):
        # x: [b, 1, 28, 28]
        x = self.fc0(x)
        #c = x
        # b1 = x@w1*x
        for i in range(4):
            x=self.dd(x)*x+self.dd(x)
        x = self.fc2(x)
        return x
```

Fig. 6. ResDD code for MNIST dataset in references [34]. Figure(a) shows $A^i = W^{i,i-1}A^{i-1} \circ X + W^{i,i-1}A^{i-1}$. Figure(b) shows $A^i = W^{i,i-1}A^{i-1} \circ A^{i-1} + W^{i,i-1}A^{i-1}$. Figure(c) shows $A^i = W^{i,i-1}A^{i-1} \circ X + W^{i,i-1}A^{i-1}$. Figure(d) shows $A^i = W^{i,i-1}A^{i-1} \circ A^{i-1} + W^{i,i-1}A^{i-1}$.

Fig. 7. ResDD-X code for MNIST dataset in references [34].

Fig. 8. ResDD-XW code for MNIST dataset in references [34].

Fig. 9. ResDD-A code for MNIST dataset in references [34].

In addition, we can also add a weight matrix to the short-circuit route. Figure 8 shows the Residual Dendrite module-XW(ResDD-XW). The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ X + W_R^{i,i-1} A^{i-1} \quad (9)$$

Where A^{i-1} and A^i are the inputs and outputs of the module, respectively. X is the inputs of DD. $W^{i,i-1}$ and $W_R^{i,i-1}$ are two different weight matrixes.

Figure 6 (c) shows ResDD-XW code for MNIST dataset in references [34]. The number of modules can be adjusted according to the task.

5) *ResDD-A or Residual Dendrite module ($\circ A^{i-1}$)*: Figure 9 shows the Residual Dendrite module-A(ResDD-A). The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ A^{i-1} + W^{i,i-1} A^{i-1} \quad (10)$$

Where A^{i-1} and A^i are the inputs and outputs of the module, respectively. $W^{i,i-1}$ is a weight matrix.

Figure 6 (b) shows ResDD-A code for MNIST dataset in references [34]. The number of modules can be adjusted according to the task.

In addition, we can also add a weight matrix to the short-circuit route. Figure 10 shows the Residual Dendrite module-AW(ResDD-AW). The module is represented as follows.

$$A^i = W^{i,i-1} A^{i-1} \circ A^{i-1} + W_R^{i,i-1} A^{i-1} \quad (11)$$

Where A^{i-1} and A^i are the inputs and outputs of the module, respectively. $W^{i,i-1}$ and $W_R^{i,i-1}$ are two different weight matrixes.

Figure 6 (d) shows ResDD-AW code for MNIST dataset in references [34]. The number of modules can be adjusted according to the task.

For the ease of description, this paper describes the Gang neuron with the best-represented architecture ($\circ X$). In use, you can replace ($\circ X$) by ($\circ A^{0|1|2|\dots|i-1}$) or ResDD.

Fig. 10. ResDD-AW code for MNIST dataset in references [34].

6) *Architecture-Gang neuron with one module*: Figure 2 shows the Gang artificial neuron with one module. The architecture of Gang artificial neuron can be represented as

$$\begin{cases} A = W^{10} X \circ X \\ y = f(W^{21} A) \end{cases} \quad (12)$$

Where W^{10} and W^{21} are the weight matrix, $\{1, x_1, x_2, \dots, x_n\} = X$. In the back-propagation procedure, the weight matrix can be updated with,

$$W_{new}^{21} = W^{21} - \eta^{21} \frac{\partial E}{\partial W^{21}} \quad (13)$$

$$W_{new}^{10} = W^{10} - \eta^{10} \frac{\partial A}{\partial W^{10}} \frac{\partial E}{\partial A} \quad (14)$$

Where W_{new}^{21} and W_{new}^{10} are the updated weight matrix for W^{21} and W^{10} respectively, and E is the cost function or errors from the later layer in back-propagation. η^{21} and η^{10} are the learning rates. The learning rates of “dendrite” and cell body can be different.

7) *Architecture-Gang “neuron” of unicellular organism*: In nature, there are unicellular organisms, such as bacteria and fungus. The first organisms to appear on Earth were presumably single-celled [43]. Thus, figure 4 shows the Gang artificial “neuron” with multiple interactions to imitate unicellular organisms. The architecture can realize excellent nonlinear expression [34], [41] and can be represented as follows.

$$\begin{cases} A^1 = W^{10} X \circ X \\ A^2 = W^{21} A^1 \circ X \\ \vdots \\ A^l = W^{l,l-1} A^{l-1} \circ X \\ y = f(W^{l+1,l} A^l) \end{cases} \quad (15)$$

Where l represents the number of the dendrite modules.

8) *Architecture-simplified Gang neuron*: The weight matrix of the cell body W^{21} in Fig.2 or $W^{l+1,l}$ in Fig. 4 is defined as a constant matrix where all its elements are 1. [Considering batch training, we describes it as a matrix rather than a vector.]

Thus, the architecture in figure 2 can be represented as

$$y = f(W_{ones}(W^{10} X \circ X)) \quad (16)$$

And the architecture in figure 4 can be represented as

$$\begin{cases} A^1 = W^{10} X \circ X \\ A^2 = W^{21} A^1 \circ X \\ \vdots \\ A^l = W^{l,l-1} A^{l-1} \circ X \\ y = f(W_{ones} A^l) \end{cases} \quad (17)$$

III. ANNS USING GANG ARTIFICIAL NEURON

A. Single-layer network

Figure 11 shows the single-layer network. This architecture imitates the intricate dendrite of multiple neurons. Multiple neurons may obtain the same signal [32], [33], [43]. “ $f(\dots)$ ” in Fig. 11 can be set as the function that you plan to use for application. For example, when “ $f(\dots)$ ” is set as *softmax*, it can be used for classification.

B. Multi-layer perceptron (MLP) using Gang artificial neuron

MLP is the most typical neural network. Here, Fig. 12 shows a MLP using Gang artificial neuron with one module. The forward propagation can be represented as follows.

$$\begin{cases} A_h = W_h^{10} X \circ X \\ H_h = f(W_h^{21} A_h) \end{cases} \quad (18)$$

$$\begin{cases} A_o = W_o^{10} H_h \circ H_h \\ Y_o = f(W_o^{21} A_o) \end{cases} \quad (19)$$

Fig. 11. Single-layer network.

Fig. 12. MLP using Gang artificial neuron.

Where $H = [1; H_h]$, W_h^{10} , W_h^{21} , W_o^{10} , and W_o^{21} are the weight matrix, $\{1, x_1, x_2, \dots, x_n\} = X$. The backpropagation can be represented according to formula 13 and 14.

Additionally, when the simplest form of Gang artificial neuron is used, MLP can be represented as follows.

$$\begin{cases} H_h = f(\sum (W_h^{10} X \circ X)) \\ Y_o = f(\sum (W_o^{10} H_h \circ H_h)) \end{cases} \quad (20)$$

C. Information fusion network

Figure 13 shows the information fusion of different neurons. This information interaction is common in the biological brain [38]–[40]. The architecture in Fig. 13 can be expressed as follows.

Fig. 13. Information fusion network.

$$\left\{ \begin{array}{l} A_x^1 = W_x^{10} X \circ X \\ A_x^2 = W_x^{21} A_x^1 \circ X \\ \vdots \\ A_x^l = W_x^{l,l-1} A_x^{l-1} \circ X \\ h_1 = f(W_x^{l+1,l} A_x^l) \\ \vdots \end{array} \right. \quad (21)$$

$$\left\{ \begin{array}{l} A_z^1 = W_z^{10} X \circ X \\ A_z^2 = W_z^{21} A_z^1 \circ X \\ \vdots \\ A_z^l = W_z^{l,l-1} A_z^{l-1} \circ X \\ h_e = f(W_z^{l+1,l} A_z^l) \end{array} \right. \quad (22)$$

Where $\{1, x_1, x_2, \dots, x_n\} = X$, $\{1, z_1, z_2, \dots, z_k\} = Z$, and $\{1, h_1, h_2, \dots, h_e\} = H$. e is the number of neurons. The network architecture can be trained by error backpropagation according to formula 13 and 14.

In fact, these network architectures using Gang neuron can be trained by *PyTorch* expediently. [Note that the inputs and outputs are normalized to $[-1, 1]$.] The architectures presented in this paper are like some plugins and can be used to other larger architectures where you want to design to improve networks' mapping capacity.

Fig. 14. Convolution layer using Gang neuron or traditional neuron.

IV. SOME TYPICAL ANNS ARCHITECTURE USING GANG NEURON

A. Convolution layer using Gang neuron

Figure 13 compares the architecture of using a Gang neuron with a traditional neuron in the convolution layer (an example). The Gang neuron extracts information about the interactions among inputs.

The network using Gang neurons can delete the Fully-connected Layers of traditional networks. In other words, the parameters of the Fully-connected Layer are assigned to a single neuron, which reduces parameters of network for the same mapping capacity. **The Fully-connected Layers do not exist in human brain.**

For example, the number of parameters in the Fully-connected Layer is 10000×100 . When the parameters are assigned to a single neuron, the number of parameters can be $100 \times 10 \times 10$. [**100** expresses the number of Gang neurons.]

B. Schematic diagram of RNN using Gang neuron

Figure 15 compares the architecture of using a Gang neuron with a traditional neuron in the schematic diagram of RNN. The Gang neuron extracts information on the interactions between inputs about time. Where x represents the currents input and h represents the outputs of the previous time.

V. BIOMIMETIC ARCHITECTURE USING GANG NEURON

A. Module 1: Retina, attention(focus), and convolution-like scan

Fig. 16 shows a retina module. This module imitates the focus mechanism of the human eye when we observe things. At the focus, our eye extracts the multiple relationships of the picture, and then, the extracted texture is more and more rough along the direction of focus diffusion. Additionally, **Attention** in Fig. 16 can scan the entire picture, which happens to be similar to convolution. However, my architecture contains gradients related to focus, and the maximum receptive field can be set as the entire picture (Of course, you can also set a small range of receptive field with gradient). I show a 4th-order gradient in Fig. 16. The number of gradients can be adjusted by dendrite modules appropriately. For specific details, please see the specific formula in the Fig. 16.

Fig. 15. Schematic diagram of RNN using Gang neuron.

Fig. 16. Module 1: Retina, attention (focus), and convolution-like scan. The gap between the 'squares' only aims to distinguish the 'squares' in drawing. The calculation of each color block consists of two steps (see Fig. 14): 1) Transform X into a 1-dimensional input; 2) use the dendritic modules. In terms of the activation function, you can use what you want, such as *relu*. Besides, linear activation function (e.g., $Y = WA$) also can be used because the dendritic module has the nonlinear mapping capacity. Additionally, as an example, the figure shows the calculation process of one channel. For more channels, each channel can be calculated separately. Then, the outputs of channels are averaged in the same position.

Fig. 17. Module 2: Population coding in brain. Refer to Fig. 15 for the calculation of neurons. Besides, as an example, the figure shows the calculation process of one channel. For more channels, each channel can be calculated separately. Then, the outputs of channels are averaged in the same position.

B. Module 2: Population coding in brain

The dendrites of neurons are crisscrossed. In population coding of biological brain, the primary afferent fibre whose receptive field centre is closest to the point of stimulation will produce more action potentials than those on the periphery (Fig. 17, the green fibre has a greater action potential frequency than the blue fibres) [44].

Fig. 17 shows a biomimetic population coding module. Two points are important to emphasize.

1) Biomimetic dendrite is staggered; 2) When we design a network by multilayer Module 2 in Fig. 17, the dimension of output decreases as the layer.

C. Application methods

This paper shows three usage.

- 1) In the existing networks, the convolutional layers can be replaced by module 1. (Compared with the existing convolution, module 1 has a larger receptive field and can extract the position information.)
- 2) Multi-layer modules 2 are interconnected to build a new neural network.
- 3) Module 1 and Module 2 are used together. There is a special architecture imitating the biological brain. The first layer is designed by module 1, and all the later layers are designed by module 2.

VI. DISCUSSION AND CONCLUSION

In this paper, I compared the development of artificial neural networks with biological neural networks. As expected, the direction of their research fields is different. Researchers in ANNs pay attention to the architectures for different applications, while researchers in biology focus on exploring the neural mechanisms. Both directions achieve success. It may be time to learn from each other.

As we know, artificial neural networks are inspired by biological neural networks. Seventy years ago, people designed artificial neurons by the knowledge about biological neurons at that time. Today, we have a better understanding of how the work of neurons, especially dendrites.

The traditional artificial neurons ignore a fact that dendrites participate in pre-calculation in a biological neuron or biological neural network. More specifically, biological dendrites play a role in the pre-processing to the interaction information of input data. Two examples can be mentioned in this regard. In the task of understanding a picture, biological dendrites play a role in extracting the relationship between parts of an input-picture. In the task of understanding an article, biological dendrites play a role in extracting the relationship between parts of an article.

Therefore, this paper improved the neuron of ANNs by introducing the dendritic module and presented a novel neuron, named Gang neuron.

VII. OUTLOOK

This paper shows some basis architecture using Gang neuron. In fact, these network architectures using Gang neuron can be trained by *PyTorch* expediently. [Note that the inputs and outputs are normalized to $[-1, 1]$.] These architectures in this

paper are like some plugins. They can be used to other larger architectures where you want to design to improve the mapping capacity of networks.

There is an interesting phenomenon. Some data augmentation methods, such as flipping and zooming in or out pictures, improve networks' performance. I believe this shows that the existing networks can not fully extract some simple information, such as flipping and zooming in or out pictures. However, our brains do this well.

Application letter :

I'm Gang Liu, 26 years old, a 2nd year Ph.D. candidate from the Institute of Robotics and Intelligent Systems, Xi'an Jiao Tong University, P. R. China. I am crazy about math and computer. I plan to apply for a Chinese National Fund program, which will support those Ph.D. candidates in China to study in some world-class Universities. This program is a short time (6-24 months) co-education experiences.

If you're interested in my work and give me a chance to study in your team, please contact me.

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