Feasibility Analysis of Introducing Negative Number to Improve Spiking Neural Network

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Abstract. The aim of this paper is to investigate the feasibility of adding negative numbers to the traditional Leaky Integrate-and-Fire (LIF) for Spiking Neural Network (SNN). Currently the mainstream Spiking neuron is LIF. It is well utilized in some spiking models, but the outputs of these models can only be 0 and 1, implying that they somehow reduce the information transfer represented by negative numbers. This implies that the current SNN research on introducing negative numbers is inadequate. In this paper, by borrowing the idea of Hyperbolic tangent function and the phenomenon of biological neurons transmitting inhibitory and excitatory transmitters, the Ternary Leaky Integrate-and-Fire model (TLIF) which can output 0, -1 and 1 is proposed by improving the LIF model. And by designing a simple recognition model and comparing the recognition accuracy of LIF and TLIF models under the same dataset training, it is found that TLIF can have a better recognition effect in dealing with some datasets, but its performance is worse than LIF when facing more complex data. As the result, the introduction of negative numbers is feasible for SNNs, but further research is needed for the specific improvement methods. improvement methods and neural network design need further research.

Keywords: Spiking neural network, Negative number, Ternary Leaky Integrate-and-Fire.

1. Introduction

Spiking Neural network (SNN) is the new generation neural network, which is a neuromorphic algorithm. It has important applications and potential in low power neuromorphic hardware [1]. The former mainstream neuron model is Leaky Integrate-and-Fire (LIF), which simulates the dynamic changes in the membrane potential of neurons with leaky properties. This model reflects the dynamic characteristics of the model concisely and efficiently, but it has certain limitations, one of which is that there is a problem like ReLU function killing neurons [2]. The output value of negative input value in the neuron is 0, and the role of negative numbers in this model is weakened. LIF could only simulate the biological current signal, but it could not simulate the effect of neurotransmitters after the current signal. This is because the current signal can only be excited or not excited in two states. The excited current is transmitted through the axon to the synapse to promote the secretion of different types of neurotransmitters, which can be divided into inhibitory and excitatory neurotransmitters in nature. LIF output 0 and 1 only represent the unexcited and excited state of the current, but could not represent inhibition and excitability.

The Hodgkin-Huxley model (HH) could describe the effects of sodium, potassium and leakage current on membrane potential in a more detailed way than the LIF model. But it also could not reflect the output of negative current, and the calculation is more complicated. Therefore, it is speculated in this paper that if the neuron model is transformed from the original output values of 0(inhibition) and 1(excitation) to -1(inhibition), 0(deactivation) and 1(excitation). The process of neuron imitating electric current signal could be extended to the process of electric current to chemical neurotransmitters. This makes the mechanism of neuromorphic algorithms more similar to biological neurons to some extent. By adding -1 to the output of the LIF model, it can be seen that mimic inhibition, deactivation and excitation. By using the hyperbolic tangent of artificial neural network for reference, this paper hopes to improve the LIF model of SNN. To improve the LIF model for negative input problems.

2. The Principle of Spiking Neural Network

2.1. The Basic Elements of Spiking Neural Network

Artificial Neural Network (ANN) as an important part of artificial intelligence, it has undergone several generations of development and evolution, and a more mature neural network system has emerged. The first generation of ANN is called perceptual machine, such as the two-layer neural network constructed in the United States in 1958 [3], has a certain perceptible ability; The second generation of ANN is a multi-layer neural network, representative of the convolutional neural network (CNN). CNN are mainly used for image recognition [3, 4], which has significant progress. However, the current ANN still an existence of the interpretability, a problem of power consumption efficiency. The mutual promotion of brain science and artificial intelligence in research has led to the development of brain-like computing, in which the SNN occupies an important position. This model is the neural network model closest to the operation of the brain, which is considered to be the new generation of neural networks [5]. The computational unit of SNN is the spiking neuron, which is also the main difference between SNN and ANN. ANN adopts the simple sigmoid neuron, tanh activation function, while SNN adopts non-differential neuron models with memory, such as Hodgkin-Huxley model (HH), Leaky Integrate-and-Fire model (LIF), which focus on portraying the biological features, which makes SNN has the advantages of low power consumption for operation and preservation of spatial-temporal characteristics.

The main components of SNN include neuronal model, synaptic plasticity mechanism, information coding, learning algorithm, etc. This paper mainly discusses the neuronal model, especially analyzes some limitations of mainstream neuronal algorithms and proposes improvement suggestions.

2.2. The Difference Between Artificial Neural Network and Spiking Neural Network

2.2.1 The Leaky Integrate-and-Fire Model and Hyperbolic Tangent Model

Activation function is a common function in ANN, where the input signal determines the output signal of a neuron through its activation function, enabling the neural network to introduce nonlinear features. Common activation functions are Sigmoid, ReLU, etc.

Hyperbolic Tangent(tanh) is a common type of activation function in ANN and its expression is shown in equation (1):

$$\tanh(x) = \frac{\mathrm{e}^{\mathrm{x}} - e^{-x}}{\mathrm{e}^{\mathrm{x}} + e^{-x}} \tag{1}$$

Tanh(x) mapping the input value between [-1, 1] and is a singular function, which means that this activation function can alleviate the gradient vanishing problem and can accelerate the convergence of the neural network.

Because SNN uses spiking signals as the information transfer method of the organism, the activation function of ANN is not used. Although there is no activation function, there is a similar mechanism to describe neurons, which is the spike neuron model. Common spike neuron models are Leaky Integrate-and-Fire model, which is a model proposed by Lapicque in 1907, where the input spike can be integrated into the membrane potential, and if a defined threshold is reached, the output generates a spike and the membrane potential falls back to the resting potential. The LIF model is one of the most important types of the I&F neuron model, which increases the membrane potential of leakage [6, 7].

$$U^{t+1} = (1 - \frac{dt}{\gamma})U^t + \frac{dt}{\gamma}\sum_j w_{ij} o_j^{t+1} o_j^t = \begin{cases} 0, V_{th} > U_j^t \\ 1, V_{th} < U_j^t \end{cases}, \ \frac{dt}{\gamma} \epsilon (0,1) \tag{2}$$

Where $\frac{dt}{\gamma}$ is the membrane potential decay constant, j denotes the index of the presynapse, V_{th} is the threshold of the firing spike, o_j^t is the corresponding presynaptic spike, where the value of the spike is either 0 or 1, o_j^t= 0 means that there is no peak activity in the jth neuron, and o_j^t=1 means that there is peak activity in the jth neuron, and w_{ij} is the synaptic weight between $neuron_i$ and $neuron_j$. U^{t+1} denotes the membrane potential at time step t+1, which consists of the membrane potential U^t of the former neuron at the current time step t+1 and the membrane potential U^t of the time step t that has not exceeded the threshold in a certain ratio, thus realizing the leakage of the membrane potential.

$$Output = \frac{U(t)}{timesteps} \quad (3)$$

Where Output is the final output process of the spike neural network, U(t) is the output spike value of the last neural layer, and timesteps is the total number of time steps of the network operation. This equation (3) represents the final output value of the LIF model.

2.2.2 Disadvantage of the LIF Model and Advantages of the tanh(x)

Despite the simplicity advantage of LIF, the model struggles to respond to spiking output in the face of a large proportion of negative inputs. If there is a LIF neuron with a resting potential of -70mV and a threshold potential of -65mV, and this neuron is input with randomly distributed spikes ranging from -100mV to 100mV, it can be seen from Figure 1 that the probability of the LIF responding to the inputs is very low and the potentials are affected by negative values. It is below the resting potential for most of the time.

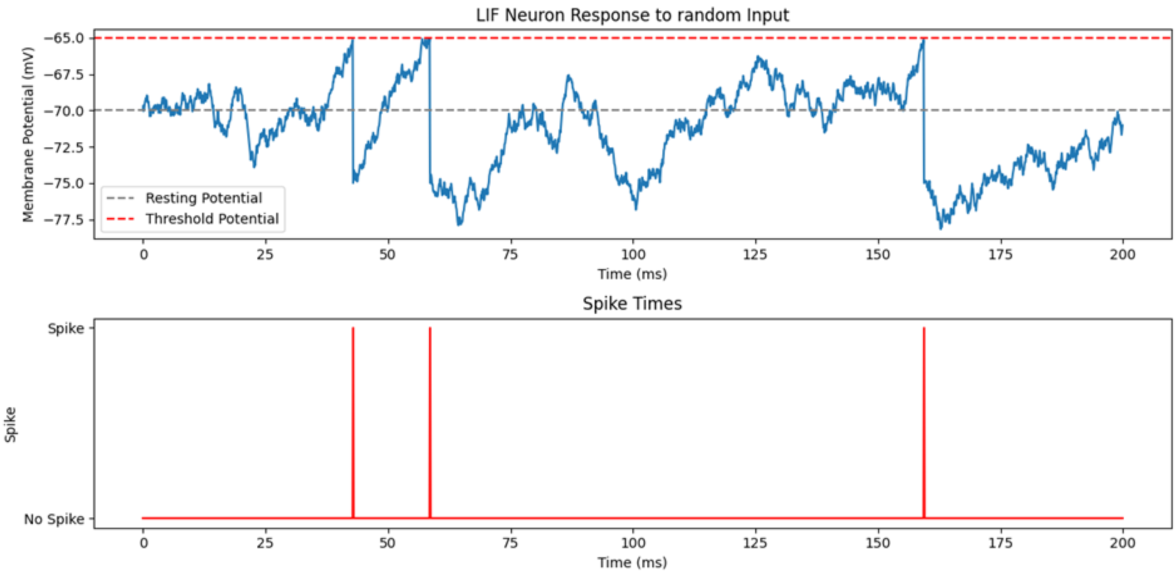

Fig. 1 LIF response to random input

This suggests that LIF is less responsive to the presence of a large number of negative inputs, a feature that leads to the fact that LIF models tend to ignore the information that negative numbers convey in neural networks. This leads to a situation where the LIF model “kills” the information represented by negative numbers in a similar way that the Sigmoid function kills neurons.

Therefore, the LIF model still has some limitations. The tanh function is widely used because its activation function output range is between [-1,1], which alleviates the problem of gradient vanishing to a certain extent. And tanh(x) has symmetry and smoothness compared with the output range of the function in [0,1], which ensures that the network has stability and good convergence speed during the training process. If the advantages of the tanh function and the LIF model can be effectively combined to make up for the problem of the LIF model's stability and fast convergence speed, the LIF model will be able to achieve the same result.

3. The Research Significance of Negative Numbers in Spiking Neural Network

3.1. The Process of Signal Transmission by Biological Neurons

Neurons are the substances involved in information processing and information transfer in the nervous system. Depending on their function, neurons will have different morphologies, but most neurons will contain the four structures of cell bodies, dendrites, axons and synapses.

Information is transmitted unidirectionally between neurons through synapses, which are located between the synapse of the message-sending neuron and the cell body membrane or dendritic membrane of the message-receiving neuron, and the message is transmitted from the synapse to the cell membrane of the other cell [8]. When a neuron receives a stimulus from another neuron, it generates a potential change in the cell membrane, forming an action potential, which is conducted along the axon and reaches the terminal clasp, at which point the neurotransmitter is released from the end of the neuron and is transmitted s to the next neuron, triggering a change in the potential of the next neuron.

The whole process of transmitting signals can be broadly divided into: stimulus generation, propagation of action potentials and neurotransmitter transmission. In the central nervous system, the complex processing and integration of signals allows organisms to perform complex propagation of signals, which enables organisms to perceive, think, and other functions.

3.2. The Significance of Introducing Negative Numbers to Spiking Neural Network

In the research of deep learning and biological neural network models, the choice of activation function is crucial to the learning effect of the network. Tanh activation function is therefore widely used in some specific occasions, while LIF can only output non-negative values, which makes the LIF model too simple in dealing with the negative values, resulting in the information of the negative number itself is ignored, which reduces the recognition accuracy to a certain extent.

Therefore, this paper draws on idea of tanh(x) and proposes to add output values such as -1 to the original LIF model. To increase from the original 0 or 1, to -1, 0 and 1. From a biological point of view, neurons are the cells involved in information processing and information transfer in the nervous system [8]. And most neurons have four regions or structures, namely, cell body, dendrites, axons, and synapses. And the information is transmitted unidirectionally through synapses.

After the message reaches the cell body, it causes a series of reactions, and after reaching a certain level, it causes an action potential to be generated. The action potential is conducted through the axon, and the end point of this spike is the terminal clasp, which is the small bump that is created when the axon branches several times during its travel. When the spike is conducted to the synapse, the synapse secretes different kinds of chemicals, neurotransmitters, which excite or inhibit the receptor cell. And neurotransmitter determines whether or not an action potential is generated in the axon of the receptor cell.

Adding -1 to the output value of the LIF model actually extends the original 0 for inactivation potential and 1 for excitatory action potential to -1 for the secretion of inhibitory neurotransmitters by the synapse, 0 for no action potential and 1 for the secretion of excitatory neurotransmitters.

4. The Spiking Neural Network after Introducing Negative Numbers

4.1. Introducing the LIF Model of Negative Number

Based on the original LIF model, a negative threshold is set. The new threshold has the same absolute value as the original threshold, and at the moment when the spike accumulates below the negative threshold, the spike neuron fires a spiking with a value of -1, or does not fire a spiking if the spike accumulates a value between the two thresholds. The above can be expressed by equation (4).

$$U^{t+1} = (1 - \frac{dt}{\gamma})U^t + \frac{dt}{\gamma}\sum_j w_{ij} o_j^{t+1} o_j^t = \begin{cases} 1, +V_{th} < U_j^t \\ 0, others \\ -1, -V_{th} > U_j^t \end{cases}, \frac{dt}{\gamma} \epsilon (0,1) \tag{4}$$

For ease of representation, this improved LIF model is referred to in this paper as the ternary LIF model (TLIF). This is because the outputs of this model are only -1, 0 and 1, the same as the elements of a balanced ternary [9,10].

4.2. Changes in Model Performance after the Introduction Of Negative Number

4.2.1 Model Design

In order to compare the performance difference between the traditional LIF model and the TLIF model, this paper designs a neural network architecture based on a linear layer and a LIF/TLIF neuron for the task of recognizing and classifying certain datasets. The experiment is based on the implementation of spikingjelly [11,12]. This architecture is represented in Figure 2.

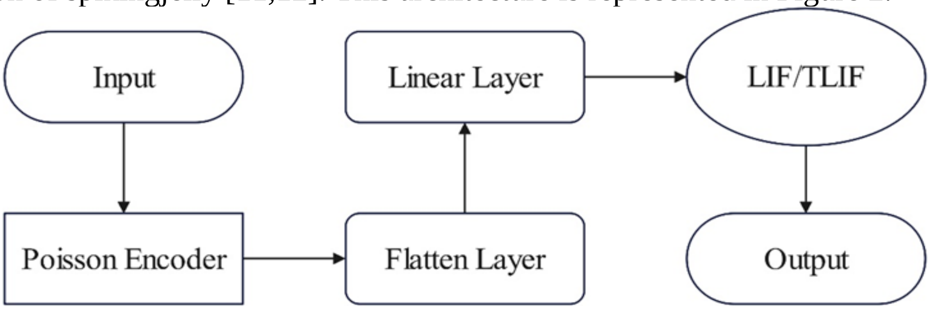

Fig. 2 Neural network architecture.

Given a 4D image sequence $I \in R^{B\times C\times H\times W}$. B is batch size, C is channel, H×W is the size of images. Then the input image is converted into spike signals with only 0 and 1 by Poisson Encoder. Poisson Encoder generates spikes based on the input pixel values and the spike firing rate is proportional to the pixel values to simulate the characteristics of biological neurons in response to the stimulus. Flatten layer flattens the 2D image for easy processing by Linear Layer. The LIF/TLIF neuron receives the output from Linear Layer and generates the spike signal with the output dimension [B, L], which represents the spike issuance of L neurons (L means the number of labels). The Linear Layer weights are updated using Stochastic Gradient Descent (SGD) by calculating the mean square error loss between the spike issuance frequency and the target label. If the n^{th} spiking neuron corresponds to a high frequency of spike issuance in a given recognition, then this input category is the corresponding nth class. It is expressed in the following formulas:

$$X_1 = Encoder(I),\ X_1 \in R^{B\times C\times H\times W} \tag{5}$$

$$X_2 = Flatten(X_1),\ X_2 \in R^{B\times (C\times H\times W)} \tag{6}$$

$$X_3 = LIF/TLIF(Linear(X_2)),\ X_3 \in R^{B\times L} \tag{7}$$

Experiment

MNIST and CIFAR10 dataset were selected to test the loss function and accuracy of LIF and TLIF models in these two cases to compare the performance of TLIF and LIF respectively.

The MNIST dataset is a large repository of handwritten digits with 10 labels created by researchers such as Mr. Yann LeCun. The CIFAR-10 dataset is a small image dataset widely used in computer vision and especially machine learning research. It contains color images of 10 different categories.

By tuning the parameters of the neural network model, the model can handle MNIST and CIFAR10 graphs. Recording the recognition accuracy (ACC) of epoch at 10 and 100 times allows comparing the performance of the two networks. The accuracy probability of the CNN model in processing MNIST is also recorded to compare the gap between the TLIF model and the existing mature models in table 1

Table 1. The accuracy of TLIF in MNIST or CIFAR10 classify mission.

Model	*Epoch*	*MNIST*	*CIFAR10*
		ACC	*ACC*
LIF	*100*	*77.46%*	*31.93%*
TLIF	*100*	*84.27%*	*27.98%*
LIF	*10*	*55.41%*	*20.63%*
TLIF	*10*	*65.12%*	*17.68%*
CNN	*10*	*98.92%*	-

And recorded the loss values of the neural network in figure 3:

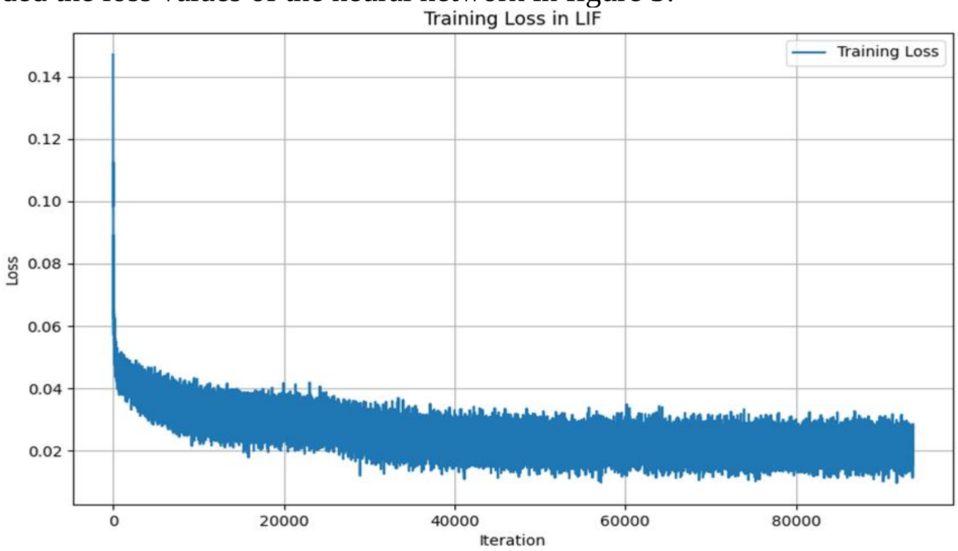

Fig. 3 Loss of LIF and TLIF when inputs were MNIST.

It can be concluded from the results of the experiment that the recognition accuracy of TLIF is 84.27%, while the recognition accuracy of LIF is only 77.46%. It shows that TLIF recognizes the MNIST dataset better than LIF. By observing the Loss image, it can be concluded that although the fitting speed of LIF in the early epoch is faster than that of TLIF, the overall fitting effect is not as good as that of TLIF model. And judging from the trend, the TLIF model may still be able to achieve better results at more epochs. However, in the experiments, the computational speed of TLIF is significantly slower than the LIF model, and the gradient computation is more complex, in order to prevent the gradient explosion problem, this paper makes a restriction on the output of the spiking neuron, and restricts the absolute value greater than 10, so as to alleviate the problem of gradient. Meanwhile, the TLIF model does not recognize CIFAR10 well, only 27.98%. This may be because MNIST contains a simpler dataset than CIFAR10. If the complexity of this model is increased a bit, then the results may be better. But TLIF still shows potential for recognizing the CIFAR10 dataset.

5. Discussion

It can be observed from the experiments that the accuracy of TLIF model in recognizing MNIST (84.27%) is higher than that of LIF model (77.46%), but both of them have lower accuracy in recognizing CIFAR10. The Loss function curve of TLIF indicates that the model performs better in convergence with more batches, and it has the potential to further improve the recognition ability. This confirms the feasibility of improving LIF from a biological perspective by extending the outputs from 0 and 1 to 0, -1 and 1 assumptions. The presence of -1 allows the SNN to convey negative information somewhat better. Compared to the idea of combining the traditional LIF model with other mechanisms (e.g., self-attention), this paper starts from improving the LIF model, and proves that the improvement of TLIF is feasible by comparing the recognition ability of the LIF model and the TLIF model. However, this paper does not try to replace LIF with TLIF, such as in Spikingformer [10], to explore the performance of TLIF in more complex models. And the performance of TLIF in recognizing CIFAR10 is worse, which may be due to the simplicity of the experimental network model. Finally, TLIF is slower than LIF and does not converge as fast as the LIF model. TLIF may be more effective if an attempt is made to design a better network structure. An important future research direction is to design better equations for the 0, -1 and 1 ideas, such as improvements in the selection of negative thresholds. Thus, TLIF will show better effectiveness in future iterations.

6. Conclusion

In this paper, by adding the output of -1 to the traditional LIF model, the TLIF model succeeds in further modeling biological neurons, which makes the performance of spiking neural networks further improved. Experiments with datasets such as MNIST. Finding that TLIF performs slightly better than the LIF model in the recognition task, which suggests that the introduction of -1 to LIF is feasible and fills the gap of using negative numbers for spiking neurons. However, the performance difference between the two models is not significant in complex datasets, suggesting that the model architecture of the experiment is too simple. It also shows that the TLIF model still needs to be improved. Hopefully, in the future, some improvements can be made to TLIF and a suitable network architecture can be found to bring out the performance of this model better.

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