A Study on Spiking Neural Network Design

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Abstract

A Spiking Neural Network (SNN) is defined as an Artificial Neural Network (ANN) that has developed rapidly in the last decade. There are some difficulties in implementing these networks, especially in supervised machine learning. The main limitation is that classical learning approaches such as backpropagation cannot be directly applied to SNNs. We created a model to enable backpropagation, using a biological neuron model instead of the activation function of the ANN network. This study, a deep neural network that can work in both ANN and SNN modes was designed to classify the feature vectors obtained from the wavelet coefficient of magnetoencephalography signals taken from the human brain. Thus we propose a hybrid network that can operate in both conventional and firing modes by replacing the activation function of the traditional neural network with Izhikevich neurons. Our proposed network has been tested in classifying 4-class motor imaginary signals and the results are presented comparatively. We hope this work, which blends computational neuroscience and machine learning, will bring a different perspective to fired network design.

1. Introduction

ANN (Artificial Neural Network), which is the basis of deep learning is a groundbreaking machine learning method in artificial intelligence by modeling the biological brain in a computer environment. This definition, which started with AlexNet [1], has been used in many tasks, especially image classification [2] tasks. Although ANNs are inspired by the biological brain, they do not consist of neurons with a firing mechanism, as in the Hodgkin-Huxley neuron model [3]. The most recent version of ANNs activated by this biological firing mechanism of the real neuron is the Spiking Neural Network. In addition to the advantage of being sensitive to the temporal properties of information transmission occurring in biological nervous systems, SNNs can offer the opportunity to analyze noise and stochastic parameters that cannot be fully simulated with ANNs [4]. The use of SNNs in machine learning applications is rapidly increasing [5, 6]. However, SNNs present some challenges. The transfer function of ascending neurons is generally undifferentiated, which precludes the use of backpropagation, which is an effective method of error reduction in neural networks. Classical learning approaches such as backpropagation cannot be applied directly to SNNs. This limitation has been solved by different approaches [7].

In this study, unlike the literature, we propose a model that enables backpropagation by replacing the activation function of a traditional ANN network with Izhikevich [8] neurons. The neural network we propose has a hybrid structure that can operate in both ANN and SNN modes, allowing the combined analysis of both modes.

2. Materials and Methods

2.1. Dataset

In the study, data belonging to dataset III presented in the Brain Computer Interface IV competition were used. The dataset includes direction-modulated Magnetoencephalography (MEG) activity recorded while performing wrist movements in four different directions of two different healthy subjects. The data set includes 160 trials in total, 40 trials for each class for training, 74 trials for subject 1, and 73 trials for subject 2 for testing. Brain signals were presented by resampling to 400 Hz after the experiment [9].

2.2. Wavelet Transform

The Wavelet Transform represents a signal as a weighted sum of shifted and scaled versions of a Wavelet function, preserving the time and frequency characteristics of the signal. ψ and W_{coeff} represent the Wavelet function and transform coefficients given by Eq. 1, respectively.

$$W_{coeff}(a, b) = \int_{-\infty}^{+\infty} x(t)\psi_{(a,b}(t)dt \tag{1}$$

If the scales and shifts of the transform are chosen to have a base equal to 2, the transformation is called the Discrete Wavelet Transform (DWT), which is a more efficient method. The DWT calculation is given by Eq. 2 [10].

$$DWT(i, l) = \sum_{i} \sum_{l} x(l)2^{-i/2}\psi(2^{-i}n - l) \tag{2}$$

The desired frequency components of the signals can be obtained with wavelet transform. Studies are using Delta (0-4Hz) and Theta (4-8Hz) frequency bands of brain signals [11, 12]. To obtain the relevant frequency bands, DWT coefficients are calculated from the 5th-order transform using the Daubechies Wavelet function.

2.3. Izhikevich Neuron Model

The membrane potential of the Izhikevich neuron model [13] is formulated by Eq. (3).

$$\frac{dV}{dt} = \frac{k(V - V_r)(V - V_t) - U + pI + I_{ext}}{C} \tag{3}$$

$$\frac{dU}{dt} = a(b(V - V_r) - U) \tag{4}$$

if $V \geq V_{peak}$, then $V \leftarrow c$, $U \leftarrow U + d$

The V, $C = 100\ \mu F/cm^2$, V_r, V_t, U, I represents the membrane potential, the capacity of the cell membrane, the resting membrane potential, the instantaneous threshold potential, the recovery current and the input current arriving to the neuron values respectively. The base parameters (a, b, c, d) of the Izhikevich model [14] given in Eq. eq:4) are also represented by recovery position constant, the input resistance, the voltage reset value, and the downstroke inrush current during spike respectively.

The parameters of the Izhikevich neuron are also given in Table 1. This type was chosen because it produces proportional spikes to the input current.

Table 1. The parameters of Izhikevich neuron model.

Parameter	Value	Description
k	0.7 $nSmV^{-1}$	Sodium channel gain
V_r	-60 mV	Resting potential
V_t	-40 mV	Threshold voltage
C	100 pF	Membrane capacitance
a	0.03 ms^{-1}	Recovery position constant
b	-2 nS	Input resistance
c	-50 mV	Voltage reset value
d	100 pA	Downstroke inrush current
V_{peak}	35 mV	Action potential peak
V_{t-min}	20 mV	Minimum voltage

The firing rates produced by the Izhikevich neuron, whose parameters are given in Table 1, in response to different input currents under normal conditions are given in Fig. 1. As can be seen from the Fig. 1 inset, the model cannot generate spikes up to approximately 51.4 μA current applied to it, and exhibits ReLu-like proportional firing frequencies at currents above this value. To increase the similarity of the model to the ReLu activation function, it is applied an external direct current of approximately $I_{ext} = 51.4\ \mu A$ to the model. By current I, even the smallest input currents applied to the model are provided to produce spikes. Besides, with the coefficients p and q corresponding to the input current I and the firing rate FR, respectively, we move the model to a more proportional input-output space. In this way, by amplifying the input current applied to the model with the coefficient p, we also normalize the number of spikes produced in response to this increased current with q. Findings that a similar modulation process takes place in the brain biologically have been shown with the effect of astrocytes in the formation of synaptic current in mice [15]. In the aforementioned study, it was found that Bergmann glial cells, a type of astrocytes in the cerebellum, function effectively as an excitatory signal amplifier. Thanks to this modulation, our spiking network can produce outputs similar to the ReLu activation function for the normalized values of the network. We call this proposed model the rectified Izhikevich model. In Fig. 2, the output of the rectified Izhikevich neuron in the $[-1, 1]$ is given in comparison with the ReLu activation function. The values of p and q were chosen as 10^4 and 10^{-6}, respectively, to obtain the closest outputs to the ReLu activation function.

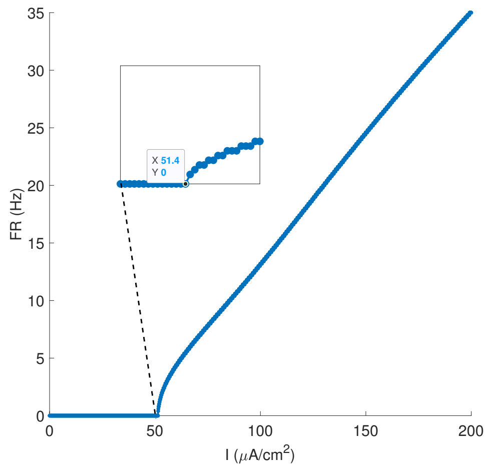

Fig. 1. The firing rates of Izhikevich neurons in response to constant current.

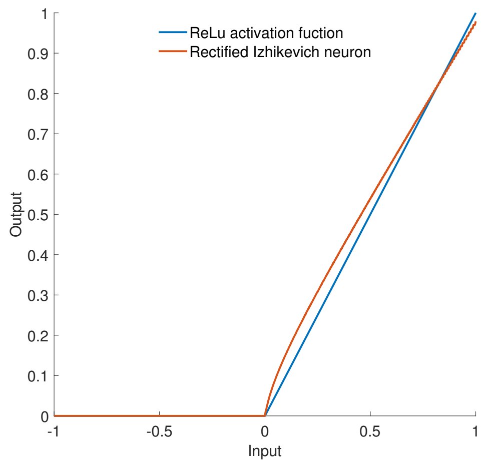

Fig. 2. The output of ReLu activation function and Rectified Izhikevich neuron.

The pseudo-code of the rectified Izhikevich neuron model that we suggested is also given in Algorithm 1. The spiking state is controlled according to the V_t value of the differential membrane potential calculated by the forward Euler method. The V membrane potential that oscillates between V_t and $V_t - 5\ mV$ is considered as a spike by checking the *Control* variable. The $Peak_{Count}$ keeps the number of spikes produced by the neuron in response to the current I applied to the neuron during $T = 1000\ ms$.

2.4. Network Model

Fig. 3 shows the structure of deep neural networks with 3 layers used in this study. These networks exhibit ANN or SNN behavior according to the activation mechanism used in each layer. The neurons of designed deep neural networks are activated by the ReLu or Izhikevich neuron model. The average firing rate of the rectified Izhikevich neuron, which is used as the activation mechanism in the SNN mode of the networks, is determined as the output of the neuron. Each value given to the input of the networks as a column matrix represents the current applied to the Izhikevich neuron. In each layer of the networks, the current I from the previous layer is multiplied by w, which is the weight of the network (green blocks), normalized (pink blocks), and transformed to nonlinear form with the activation function (blue blocks). The spike production of the rectified Izhikevich neuron is guaranteed by the externally applied I_{ext} to the neuron. The network given in Fig. 3 consists of 2064 neurons. The classification result is obtained with the softmax layer at the end of the network.

Algorithm 1 Rectified Izhikevich Model

Input:
I: Image Column Matrix;
Output:
FR: Average Firing Rate

Description:

Define parameters: $k, V_r, V_t, V_{peak}, C, a, b, c, d$
Define time constants: T, dt
Define levels of current: p, q, ϵ
$V \leftarrow Vr$
$U \leftarrow 0 * V$
$Peak_{Count} \leftarrow 0$
$Control \leftarrow 1$
for $(i = 1; (T/dt) - 1; i + +)$ **do**
  $V(i + 1) = V(i) + dt * (\frac{k(V-V_r)(V-V_t)-U+pI+I_{ext}+\epsilon I_{chaos}}{C})$
  $U(i + 1) == dt * (a(b(V - V_r) - U))$
  if $V_{i+1} >= V_{peak}$ **then**
    $V_i = V_{peak}$
    $V_{i+1} = c$
    $U_{i+1} = U_{i+1} + d$
  end if
  if $V_i >= V_{t-min}$ and $Control == 1$ **then**
    $Peak_{Count} = Peak_{Count} + 1$
    $Control = 0$
  end if
  if $V_i >= V_{t-min} - 5$ **then**
    $Control = 1$
  end if
end for
$FR = Peak_{Count}/T$
$FR = Peak_{Count} * q$

2.5. Performance Evaluation

We assessed the classification performance of the research with Accuracy and Cohen kappa coefficients which are given in Eq. (5) and (6). The accuracy (Acc) represents the ratio of the correctly classified instances to that of the total number of instances. Kappa values, which range from 0 to 1, are close to 0, indicating high consistency and accuracy.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$k = \frac{p_o - p_e}{1 - p_e} \tag{6}$$

In Eq. (**??**), p_o represents the sum of the number of samples that are correctly classified within each category. That metric provides overall classification accuracy obtained by dividing the total number of samples. The p_e given in Eq. (**??**) calculates by Eq. (7). The $m1$, $m2$, ..., m_c and n_1, n_2, ..., n_C express the predicted number of samples in each category and the total number of samples (N) respectively.

$$pe = \frac{m_1 x n_1 + m_2 x n_2 + ... + m_c x n_c}{N x N} \tag{7}$$

Kappa refers to a measure of consistency with values between 0 and 1. The values of Kappa move away from 1 indicate low consistency and accuracy. [16].

3. Experimental Results

The MEG dataset is classified by using deep neural networks given in Fig. 3 that can operate in both ANN and SNN modes. Initially, the feature vectors of 15x10 are obtained from the DWT of each trial for the ten channels. The nodes of the neural networks given in Fig. 3 exhibit the ANN feature when activated with the ReLu function, while they exhibit the SNN feature when activated with rectified Izhikevich neuron. In both modes, the feature vectors are transformed into a column matrix. When using the deep neural networks with Izhikevich neurons, each value of the column matrix represents the current I applied to neurons during T ms. The initial weights of the network are randomly assigned, and the weights are updated by the error rate after each

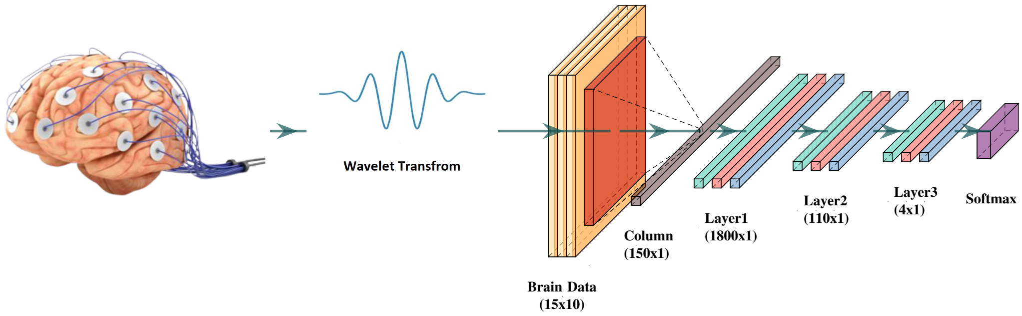

Fig. 3. The structure of the hibrit neural network model with 3 layers.

iteration. The learning rate α is chosen as $7x10^-7$. Simulations are coded originally in MATLAB 2021b without using any toolbox. For the simulations, a computer equipped with an i7 2.8 GHz processor and 16GB RAM on the Windows 10 Professional operating system is used. The simulation times have been reduced by approximately 1/3 with the parallel programming commands. The classification results and Kappa values achieved as a result of the training process consisting of 100 iterations are given in Fig. 4.

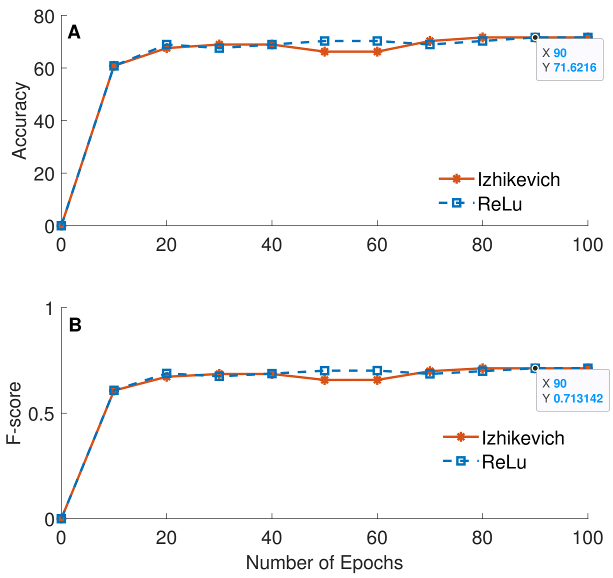

Fig. 4. The classification performance of the neural network for MEG dataset, (A) accuracies by ReLu and rectified Izhikevich neuron model, (B) F-score values by ReLu and rectified Izhikecivh neuron model ($\alpha = 7x10^{-7}$).

More detailed evaluation metrics are given in Table 2. When the given Figure 4 and Table 2 are examined, it can be seen that for data sets consisting of 4 classes, SNN consisting of rectified Izhikevich neurons exhibits at least as successful results as an ANN with the same structure.

Table 2. Comparison of the average evaluation metrics for MEG dataset on different Network Modes.

Network Mode	Kappa	Accuracy	Precision	Recall	F-score
ANN (ReLu)	0.61	0.72	0.72	0.72	0.71
SNN(Izhikevich)	0.61	0.72	0.72	0.72	0.71

As seen in Fig. 4, an SNN composed of rectified Izhikevich neurons exhibits similar classification results to ANN when nodes are activated by the ReLu function. It is seen that 3 layers-deep neural networks in SNN mode are at least as successful as in ANN mode which uses ReLu activation function. The iteration times of the networks in ANN and SNN modes are also given in Table 3. The computational cost per iteration are shown in Table 3 for $T = 1000ms$.

Table 3. Comparison of iteration times of neural network mods.

Neuron Type	Iteration Time ms $\approx$
ANN (ReLu)	0.128
SNN (Izhikevich)	0.539

Since SNNs can model biological neurons more realistically, they also allow more realistic parameters such as chaotic current [17, 18], magnetic field [19] etc. to be examined compared to ANNs.

4. Conclusion

In this study, a deep neural network with three layers that can operate in both ANN and SNN modes is designed. The neural network using rectified Izhikevich neuron and Relu activation function in SNN and ANN modes respectively has been successfully tested on motor imaginary dataset that presented in BCI competiton IV as dataset III. It is shown that SNNs have a classification success at least as good as ANNs on motor imaginary tasks in this study. Since SNNs have the ability to express biological neurons more realistically, it is possible to analyze the effects of natural parameters such as noise and chaotic signals on networks composed of real biological neurons. Future studies can be extended to investigate the effects of the mentioned biological parameters on SNNs. We hope this study will lead to further research in this area.

5. References

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