A spike trains encoding and decoding solution for the spiking neural networks

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Received 11 Sep. 2023; Revised 20 Oct. 2023; Accepted 10 Nov. 2023; Published 25 Nov. 2023.
DOI: https://doi.org/10.54939/1859-1043.j.mst.91.2023.28-34

ABSTRACT

This paper proposes a spike train encoding and decoding solution to process input and output signals for the spiking neural networks. The efficiency of the proposed solution is verified by the experimental tasks: The XOR classification problem and the aerodynamic coefficients identification of an aircraft from the data sets are recorded from flights. The results show that the proposed encoding and decoding solution has a higher convergence rate to the set values, and the mean squared error smaller than another solution is introduced in this research.

Keywords: Spike encoding; Spike decoding; Spiking neural network; Latency encoding.

1. INTRODUCTION

Spiking neural networks (SNNs) are also known as the third generation neural network, which has been interesting in recent times and has a lot of advantages over the previous two generations [1]. Its principle closely resembles biological neurons in higher animals, this is particularly suitable for applications where fast and efficient computation is required [2].

The spiking neurons in the SNNs use spike trains, instead of the analog signal to transmit information to neighboring neurons [3, 4]. For the applications of SNNs, the input signal of the network needs to be encoded into spike trains, respectively, the spike trains after training must be decoded into the analog signal at the output of the SNNs [5].

The study of encoding and decoding schemes for SNNs began with the continuous development of rate coding, which is applied to second-generation neural networks (ANN) [1]. After that, a series of other encoding schemes were born to overcome the limitations of rate coding as Latency and its variations encoding [6-8], Binary encoding [6, 7], Phase encoding [9, 10], Rank order coding [6, 11, 12], Burst encoding [9]. One of the encoding forms for SNNs that is most popularly applied to implement SNNs on hardware devices is latency encoding, due to its simplicity and high accuracy [13].

In this research, we propose a new variation of latency encoding called firing delay encoding. It will improve the accuracy in the encoding and decoding stages for SNNs. The simulation results have shown that the accuracy of the proposed solution is higher than the other solution in [8] on the data set in the aircraft parameters identification.

The contents of this paper are arranged as follows: Part 1 introduces an overview of SNNs and encoding and decoding methods for input and output signals of SNNs. Part 2 analyzes the mathematical basis for the firing delay encoding. Part 3 tests the effectiveness of the proposed encoding solution for the XOR classification problem and the aerodynamic coefficients identification of an aircraft from flight data using the Spikeprop algorithm. Section 4 provides some conclusions and further development in the future.

2. THE PROPOSED ENCODING SOLUTION

2.1. Mathematical basis

The general functional diagram describes the input-output signal encoding and decoding in the SNN for identification issues:

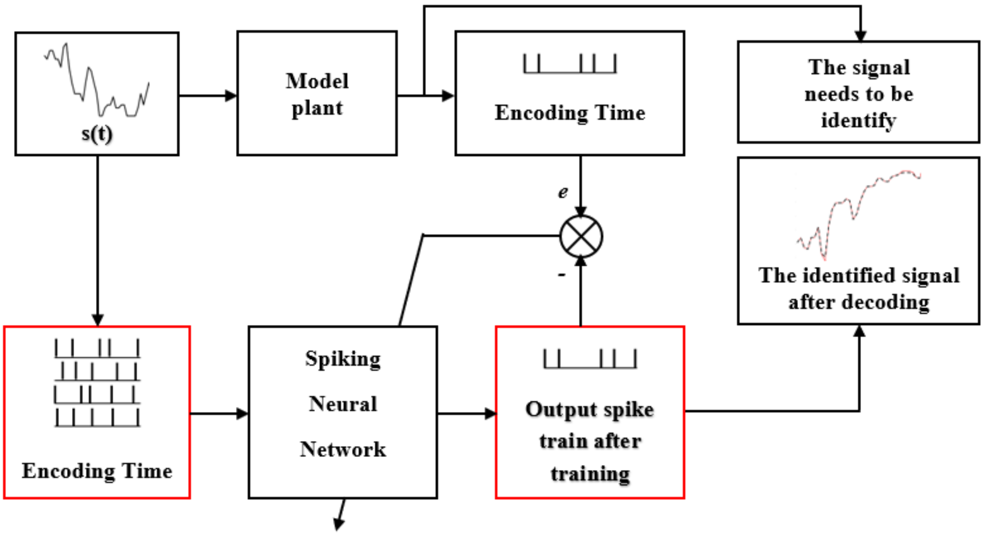

Figure 1. *The diagram describes the input–output signals encoding and decoding in the SNNs.*

To deal with the signal processing in the SNNs, the first thing needs to convert the input analog signal into the firing times, at which spikes occur and are delivered to the input layer. A form of time coding in [8, 14] is called the Old encoding scheme, which is represented as:

$$t_i(s) = t_{max} - round\left(t_{min} + \frac{(s_i - s_{min})(t_{max} - t_{min})}{(s_{max} - s_{min})}\right) \quad (1)$$

Where $t_i(s)$ is the ith spike time, t_{min} is the earliest spike time, t_{max} is the latest spike time, s_i is the present value, s_{min} is the minimum value, and s_{max} is the maximum value of the input stimulus, respectively.

Analyzing Eq. (1), we find as:

- When $s_i = s_{max}$ with rounding error that $t_i(s) = 0$, ie, the spike occurs immediately when the input stimulus has the maximum value;

- When $s_i = s_{min}$ with rounding error that $t_i(s) = t_{max} - t_{min}$, ie, the spike occurs immediately when the input stimulus has the minimum value.

The spike response model (SRM) is most popularly applied to many works in the SNNs [15-17]. The output responses of the input layer neuron to the output of the final hidden layer by using the SRM model are shown as [17]:

$$x_j(t) = \sum_{i=1}^{N_{l+1}} \sum_{k=1}^{K} \sum_{g=1}^{G_i} w_{ij}^k \varepsilon(t - t_i - d^k) + \eta(t - t_j) \quad (2)$$

Where N_{l+1} is the number of presynaptic neurons in the layer $l+1$, K is the number of synapses between the presynaptic neuron *i* and postsynaptic neuron *j*, G_i is the number of spikes fired by the presynaptic neuron *i*, $\varepsilon(\mu_i)$ is the spike response function is defined as [18]:

$$\varepsilon(\mu_i) = \left[\exp(-\frac{\mu_i}{\tau_1}) - \exp(-\frac{\mu_i}{\tau_2}) \right] H(\mu_i)$$
$$\mu_i = t - t_i - d^k \tag{3}$$

Where $H(\mu_i)$ is the Heaviside step function, is defined as:

$$H(\mu_i) = \begin{cases} 1, & if \quad \mu_i > 0 \\ 0, & otherwise \end{cases} \tag{4}$$

Where τ_2 is the rise time constant, τ_1 is the decay time constant, and η is the restored action potential function of the neurons to the resting potential value after firing a spike. This function has the form as [17-19]:

$$\eta = \begin{cases} -2\vartheta e^{\frac{-\mu_i}{\tau_R}} & if \quad \mu_j > 0 \\ 0 & if \quad \mu_j \le 0 \end{cases} \tag{5}$$

Where ϑ is the fired threshold of the neurons and τ_R is the recovery time constant.

From Eq. (1) and Eq. (2), the authors find that:

- There is a difference in the firing time when $s_i = s_{max}$, that is, the firing time after encoding to neurons in the input layer can appear immediately at the $t_i(s) = 0$, while from the input layer onwards there is always a delay time d^k;
- There is a difference in the firing time when $s_i = s_{\min}$, that is, the firing time is not guaranteed at the $t_{\max}$.

Therefore, the authors propose a new encoding scheme to solve the above differences and minimize errors for applications of SNNs.

2.2. The proposed encoding and decoding scheme

The proposed encoding scheme determines the exact firing time of the *i*th spike in a considered time window $[t_{min}, t_{max}]$. In order to construct the proposed scheme, the values of the stimulus signal need to be first shifted in the domain $[0 \div 1]$ by computing as:

- Compute $s + |s_{min}|$ if $s_{min} < 0$, after $(s + |s_{min}|) / max(s + |s_{min}|)$;
- Compute $s - |s_{min}|$ if $s_{min} > 0$, after $(s - |s_{min}|) / max(s - |s_{min}|)$.

Therefore, the analog input signal is normalized to have values in the domain $[0 \div 1]$ that are represented as follows:

$$s_{new} = \frac{(s_i - s_{min})}{max(s_i - s_{min})} \tag{6}$$

The authors propose the formula to determine the *i*th spike time in the considered time window as follows:

$$t_i(s_{new}) = t_{min} + round\left((t_{max} - t_{min}) * \left[1 - \frac{(s_i - s_{min})}{max(s_i - s_{min})} \right] \right) \tag{7}$$

From Eq. (7), several conclusions can be drawn as:

- When $s_i = s_{max}$, that is $(s_i - s_{min}) = max(s_i - s_{min})$, a spike is fired at $t_i(s_{new}) = t_{min}$;
- When $s_i = s_{min}$, that is $(s_i - s_{min}) = 0$, a spike is fired at $t_i(s_{new}) = t_{max}$;
- When $(s_i - s_{min}) \in (0, max(s_i - s_{min}))$, the spikes are fired at $t_i(s_{new}) \in (t_{min}, t_{max})$.

From Eq. (7), the decoding formula is drawn as:

$$\hat{s}_i = \left[1 - \frac{(t_i - t_{min})}{(t_{max} - t_{min})} \right] max(s_i - s_{min}) + s_{min} \tag{8}$$

In order to test the proposed encoding and decoding scheme, the authors will evaluate the signal encoding and decoding efficiency in the following section.

3. EXPERIMENT AND DISCUSSION

3.1. The XOR data set

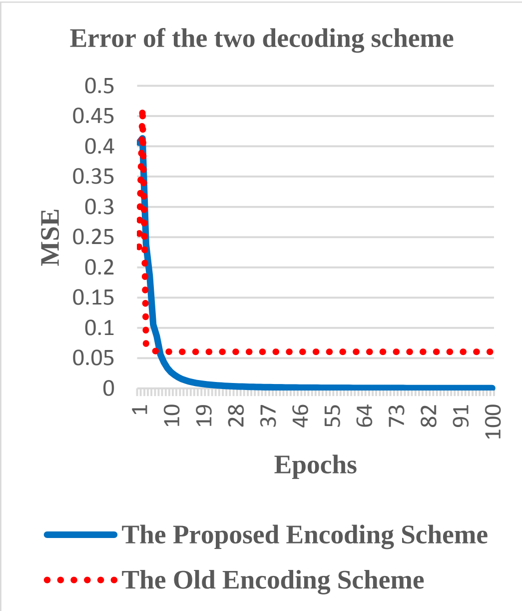

Figure 2. *The MSE of the proposed and old encoding scheme for the XOR problem.*

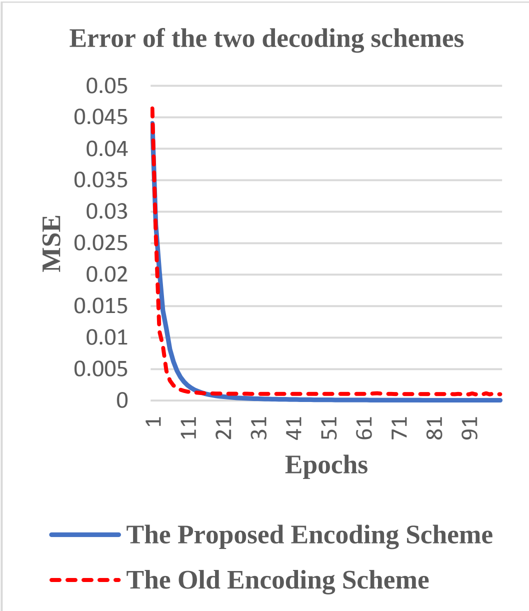

Figure 3. *The MSE follows the two encoding solutions for the lift coefficient identification.*

In this experiment, the authors use the spike response model (SRM), which is described in [15] with a structure such as three neurons in the input layer, five neurons in the hidden layer, and one neuron in the output layer; synaptic weights $w = [-1,1]$, the time constants $\tau_1 = 5\text{ms}, \tau_2 = 12\text{ms}$; the delay of synapses $d^k = 3\text{ms}$; learning rate

$\eta = 0.01$; the considered time window to ensure a spike firing with t_{min} = 5 ms and t_{max} = 30 ms. The XOR data set consists of 100 data samples [15]. The results are averaged over 100 trials and errors to ensure statistical validity. The efficiency of the proposed encoding scheme is compared with the old encoding scheme in [8].

Specifically, the mean square errors (MSE) of the proposed scheme is smaller than the old scheme, whereas the epochs of these two schemes are the same as in Fig. 2. The successful classification rate of the proposed scheme is bigger than the old scheme as in table 1.

***Table 1.** The xor classification results of the experiment.*

Encoding Scheme	Learning Rate	Number of Trials	Successful rate
Old encoding scheme	0.01	100	93%
Proposed encoding scheme	0.01	100	97%

3.2. Lift coefficient identification of an aircraft from the flight data set

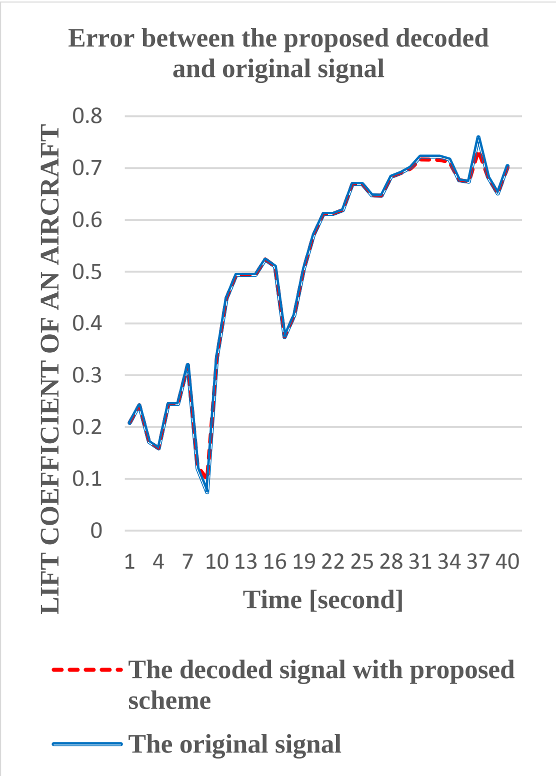

***Figure 4.** The difference between the proposed encoded-decoded signal and the original signal.*

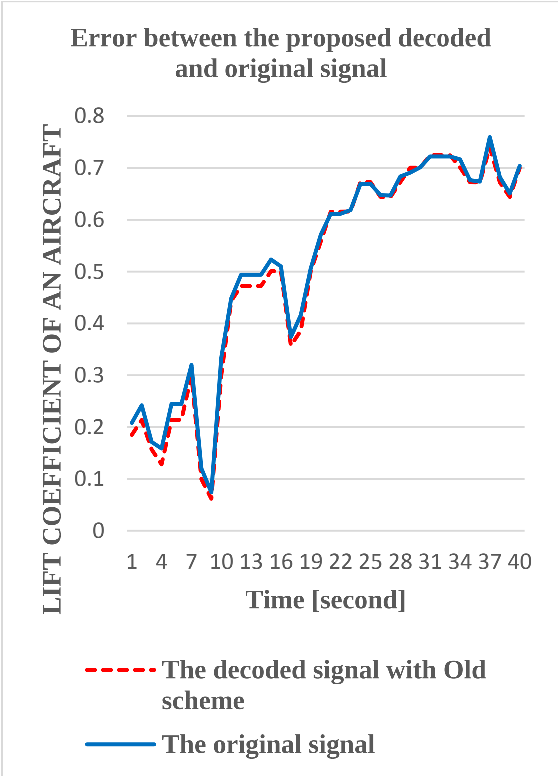

***Figure 5.** The difference between the Old encoded-decoded signal and the original signal.*

In this experiment, the authors use the spike response model, which is described in [15] with a structure such as two neurons in the input layer, fifteen neurons in the hidden layer, and one neuron in the output layer; the parameters of the network are the same in tested above. The considered time window to ensure a spike firing with t_{min} = 5 ms and t_{max} = 30 ms. The data set is determined from actual flights such as in [20]. The efficiency of the proposed encoding scheme is better than that of the Old encoding scheme in [8]. For the encoding, with a large enough number of epochs (epochs > 20), the MSE of the proposed solution is smaller than the old solution as in Fig. 3. For Decoding, the results based on visualization, can be seen that the quality of lift coefficient identification according to the proposed solution has higher accuracy than the old solution (Fig. 4 compared to Fig. 5).

Table 2. *The accuracy of lift coefficient identification.*

Encoding Scheme	Learning Rate	Number of Trials	MSE
Old encoding scheme	0.01	100	3.3423.e-04
Proposed encoding scheme	0.01	100	2.9618.e-05

From the two experiment tasks above, it can be seen that the convergence speed to the zero neighborhood of the mean squared error of the old method is not significantly faster than the proposed solution as shown in Fig. 2 and 3. This is due to the old encoding scheme (1) fired earlier than the considered time window, specifically $[0, t_{max}\text{-}t_{min}]$ instead of $[t_{min}, t_{max}]$ as the proposed scheme in (7)-(8), but the identified parameters of the proposed solution have a higher convergence rate to the set value than the old method as shown in Fig. 4 and 5. This is because the proposed encoding and decoding scheme has met the theoretical satisfaction of the spiking neural network.

4. CONCLUSIONS

Through the experiments and results in part 3, it can be seen that the proposed encoding and decoding solution has a higher successful classification rate than the old encoding and decoding solution introduced in part 2.1 about 4% on the XOR classification problem. In addition, the MSE of the proposed scheme is smaller than the old scheme about 10% on the identification issue. In the future, we will investigate some problems as:

- Apply to different firing models;
- Anti-noise ability of the proposed solution;
- Test the proposed solution with more complex problems;
- Consider the fit for the input data set with different degrees of jitter.

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TÓM TẮT

Một giải pháp mã hóa và giải mã các chuỗi đột biến cho mạng nơron đột biến

Bài báo đề xuất một giải pháp mã hóa và giải mã các chuỗi đột biến để xử lý tín hiệu vào và ra cho mạng nơron đột biến. Tính hiệu quả của giải pháp đề xuất được kiểm chứng bởi các tác vụ thực nghiệm: Vấn đề phân loại XOR và bài toán nhận dạng hệ số khí động của một máy bay từ tập dữ liệu được ghi lại từ các chuyến bay. Các kết quả đã cho thấy, giải pháp mã hóa đề xuất có tỷ lệ hội tụ tới giá trị đặt cao hơn và sai số trung bình bình phương nhỏ hơn một giải pháp khác cũng được giới thiệu trong nghiên cứu này.

Từ khoá: Mã hóa đột biến; Giải mã đột biến; Mạng nơron đột biến; Mã hóa độ trễ.