Wireless Spectral Prediction by the Modified Echo State Network Based on Leaky Integrate and Fire Neurons

Yunsong Wang

School of Railway Technology,
Lanzhou Jiaotong University, Lanzhou
730000, Gansu, China

Tao Cai

Gansu Branch of Northwest Air Traffic
Management Bureau, China Civil
Aviation, 730000, Gansu, China

Abstract
With the rapid development of wireless communication technology, the wireless spectrum resources are dwindling. Cognitive radio (CR) is the key technology to solve this problem. In view of the echo state network advantages compared to traditional recursive neural network, we construct the new neural network, echo state network based on leaky integrate and fire neurons (LIF_ESN), and prove that it has a better network performance, when reduce the reserve pool size and to improve the accuracy for time series prediction problem, than the classic ESN. At the same time, we apply this kind of LIF_ESN to the communication problem. The experimental results show that the ESN and LIF_ESN have good performance on spectral prediction. LIF_ESN can obtain better prediction performance when the reserve pool size is small.
Key words: WIRELESS SPECTRAL PREDICTION, COGNITIVE REDIO, LIF_ESN

1. Introduction

Artificial neural network has become a kind of mature computing science and technology, widely used in communication engineering, etc. The first generation of neuron adopted McCulloch-Pitts threshold neuron model. The principle of this kind of neuron is, when it receives the weighted input signal reaches a specified threshold, the neuron will output a high level of binary signals [1].

The second generation of neuron did not use a stepper threshold function to calculate the output signal. It uses the continuous excitation function, making such neuron more suitable for processing of the analog input and output signals. The incentive function of this generation of neuron usually uses hyperbolic tangent function, and current common feed-forward and recursive neural network is made up of this kind of neuron [2]. Real neuron can emit an original firing-rate (A pulse between intermediate frequencies), while continuous activation function can simulate the intermediate output frequency [3].

The third generation of neuron use independ-

ent spikes improved biological implementations, it just like the real neuron allow during transmission and calculation combined signal time and space [4]. These neurons use rate coding, its mechanism of independent sending and receiving peak pulse is similar with the sound signal multiplexing technology based on the frequency and amplitude information, other than low bit rate coding.

A kind of neuron model which is provided with a refractory period characteristics of pulsed is widely used at present, we call it leaky integrate and fire (LIF) neuron. In view of the bottlenecks on traditional echo state network (ESN), the new neural network based on LIF neurons is easy to implement by hardware. Because of its dynamic characteristics, the new neural network keeps a better network performance when we significantly reduce the reserve pool size. We prove that it has the excellent performance by using a series of benchmark experiments on the basis of to fully understand. At the same time, we applied this kind of echo state network based on leaky integrate and fire neurons (LIF_ESN) to the communication problems. According to spectral prediction problem on cognitive radio (CR) system, we predict that the last time the primary user occupied by the LIF_ESN. The experimental results show that, the new echo state network designed in this paper has better prediction performance compared to the classic echo state network.

2. Leaky Integrate and Fire Neuron

The third generation of neuron (spike neuron) uses distributed time coding and processing of information rather than spike rate of analog neuron, so it's closer to biological neuron. The first two generations of the neuron model belong to static neurons, while spike neuron is dynamic neuron, which can solve the dynamic binding problem. The dynamic characteristics of this neuron reflect the process that accumulates of the input signal and issuing to the outside [5].

We assume η as the membrane voltage after the spike neuron produces a spike, u_{rest} as the initial membrane voltage, $\varepsilon(t, u(t))$ as the postsynaptic potential (PSP) signal after the neuron produces a spike in time t.

$$u_i(t) = \sum_j \omega_{ij} \cdot x_j(t) \tag{1}$$

$$y_i(t) = f\left(u_{rest} + \eta(t - t_f) + \sum_{\tau=0}^{t} \varepsilon(t, u_i(\tau))\right) \tag{2}$$

$$f(z) = \begin{cases} z \geq \Theta \wedge \frac{dz}{dt} > 0 \Rightarrow ON \\ else \Rightarrow OFF \end{cases} \tag{3}$$

Equation 2 obtains that after the neuron emit a spike, PSP signal offset the membrane voltage. Because of this type of restraint of the membrane voltage, Neuron turns into the absolute refractory period. Different from the analog neuron's mapping way of conduct down simply, PSP signal remembers the signals from the up one level, and it will be sent at the same time. The memory which will last until the end of the absolute refractory period makes pulse neuron reflecting the characteristics of the time delay after the neuron emit a spike. Therefore it's effective by using network which is made of spike neurons to solve the dynamic problem and to deal with time-varying signals, such as the time series prediction problems in engineering, etc.

A kind of spike neuron model is widely used because of its integral characteristics, we call it leaky integrate and fire neuron.

We define the ignition time $t_i^{(f)}$ to represent the characteristics of the neuron. The lower index i indicates the neuron, the upper index f the number of the spike. Parameter n_i measures the duration inhibiting the load voltage of neuron i. The spike will be processed and influence other neurons' membrane voltage [6]. By this way, stimulation the neuron gains $u_i(t)$ can be expressed as:

$$u_i(t) = \sum_{t_i^{(f)}} n_i\left(t - t_i^{(f)}\right) + h(t) \tag{4}$$

In the equation 4, $h(t)$ is the external response. Commonly used simplified impulse response model is only considered the influence of the refractory period inputting to the last neuron. From mathematical point of view, equation 4 can be changed to:

$$u_i(t) = n_i\left(t - t_i^{(f)}\right) + h(t) \tag{5}$$

Equation 5 obtains that, to the neuron i in the absolute refractory period, postsynaptic membrane potential $n_i\left(t - t_i^{(f)}\right)$ transferred from outside will be combined with the external time event $h(t)$. This mode that changes neuron membrane voltage $u_i(t)$ comprehensively to modify neuron's state inside makes individual LIF neuron sui generis. LIF neuron can calculate independently compared with the analog neuron. If we add many LIF neurons to structure impulse response model, and use them to improve network under the condition of without changing network topology, information mapping will be richer under the condition of the network's macroscopic structure is no longer complex. This model is easy to implement, and it's easier to analyze. Because this model has a "bad memory", we can also call it short-term memory capacity neuron.

3. Echo State Network Based on Leaky Integrate and Fire Neurons

3.1. Model Structure and Stability

We suppose that a traditional ESN include K input, L output and the size of the reserve pool is N. Variable $u = u(t)$ means K d external input, variable $x = x(t)$ means N d reserve pool state, and variable $y = y(t)$ means L d output vector. Connection weights of input, internal, output and feedback is ω^{in}, ω, ω^{out} and ω^{fb}. Continuous time dynamic expression of traditional ESN can be represented as:

$$\dot{x} = \frac{1}{c}\left(-\alpha x + f\left(\omega^{in}u + \omega x + \omega^{fb}y\right)\right) \quad (6)$$

$$y = g(\omega^{out}[x;u]) \quad (7)$$

Among them, $c > 0$ is a global variable of ESN, $\alpha > 0$ is neurons firing rate in the reserve pool, f is a kind of S function, g is output activation function, and $[;]$ means vector of the connection [7].

Because the receiving and sending signal of LIF neuron is spike, we change equation 6 and equation 7 with Euler discretization by step length of δ, and get updating formula about the discretization time sampling of input $u(n,\delta)$:

$$x(n+1) = \left(1 - \frac{\alpha\delta}{c}\right)x(n) + \frac{\delta}{c}f\left(\omega^{in}u\left((n+1)\delta\right) + \omega x(n) + \omega^{fb}y(n)\right) \quad (8)$$

$$y(n) = g(\omega^{out}[x(n);u(n,\delta)]) \quad (9)$$

The Euler discretization above is onlv for small real rendering of continuous time system δ. When δ increases gradually, the discrete approximation value will be deteriorate and unstable [8]. A strictly necessary and sufficient condition is proposed to elaborate the stability of ESN based on LIF neuron: Assume an ESN based on LIF neuron according to equation 8 where the sigmoid f is the hyperbolic tangent function. Then if the matrix $\omega = \frac{\delta}{c}\omega + \left(1 - \alpha\frac{\delta}{c}\right)I$ has a spectral radius $|\lambda|_{max} > 1$, the network does not have the echo state property [9].

3.2. Performance of Benchmark Experiment Base on LIF_ESN

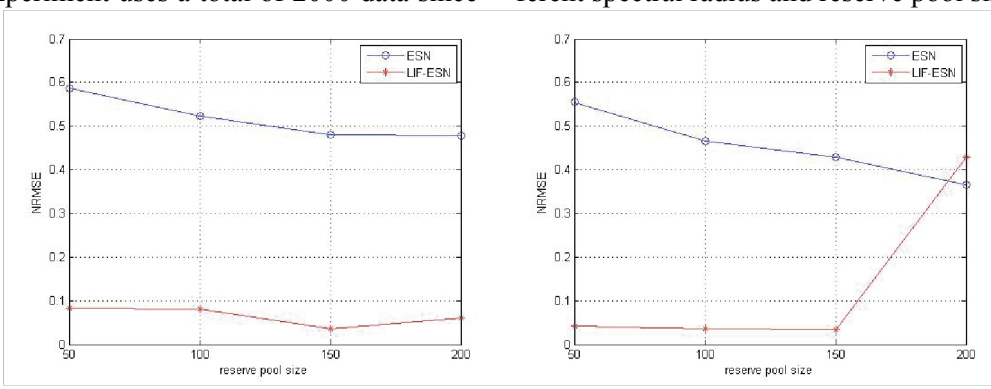
The purpose of this experiment is to verify characteristics of LIF_ESN applied on time series prediction. Experimental data is the monitoring situation of sunspots from National Geophysical Data Center (NGDC). Experiment uses a total of 2000 data since January 1774, selecting the top 1500 data to train network and 500 for testing network.

We carry out on the experimental data smoothing before the prediction. Experiment is designed that spectral radius $\rho(\omega)$ are 0.5, 0.8 respectively, reserve pool sizes N are 50, 100, 150, 200 respectively. Traditional ESN's connection density is 0.1, and LIF_ESN absolute refractory period is 1.2. Normalized Root Mean Square Error (NRMSE) reflects the performance of prediction, and is defined as:

$$\mathrm{NRMSE} = \left\{\frac{1}{N}\sum_{k=1}^{N}[\hat{y}(k) - y(k)]^2\right\}^{1/2} \quad (10)$$

Among them, $y(k)$ is predictor variable in the target $\hat{y}(k)$ is predictive value and N is number of samples.

Figure 1 is the predict performance for benchmark problem when traditional ESN and LIF_ESN in different spectral radius and reserve pool sizes.



(a) Spectral radius is 0.5 (b) Spectral radius is 0.8

Figure 1. Predict Performance of sunspots by ESN and LIF_ESN in different spectral radius and reserve pool sizes

NRMSE values are given by Table 1 to predict traditional ESN and LIF_ESN when the reserve pool size in 50-200 respectively.

Table 1. Performance comparison of ESN and LIF_ESN prediction

		ESN	LIF_ESN

$\rho(\omega) = 0.5$	$N = 50$	0.58611	0.083671
	$N = 100$	0.52363	0.080000
	$N = 150$	0.48000	0.035437
	$N = 200$	0.47886	0.060293
$\rho(\omega) = 0.8$	$N = 50$	0.55484	0.042287
	$N = 100$	0.46596	0.036081
	$N = 150$	0.42922	0.034599
	$N = 200$	0.36504	0.429400

The conclusion can be obtained by Figure 1 and Table 1. When we reduce the reserve pool size, LIF_ESN can keep better performance compared with traditional ESN.

4. Wireless Spectral Prediction by the Modified Network

Wireless spectrum resources are dwindling with the rapid development of wireless communication technology. Cognitive radio is the key technology to solve this problem, and its core idea is to make the wireless communication device discovering and utilizing available spectrum rationally [10]. In order to maximize the spectrum utilization, and make Primary User (PU) and Second User (SU) to minimize the conflicts between the collision rates, Professor Acharya put the prediction mechanism introducing into the cognitive radio spectrum [11]. Neural network method has attracted much attention, because of its good ability of self-learning, and lower computational complexity and higher prediction precision, but traditional recursive network training algorithm is too complex, the network structure is complex and fading memory [12]. In view of the echo state network advantages compared to traditional recursive neural networks, in this paper we use traditional ESN and LIF_ESN to predict the duration of the state of wireless spectrum, and compare the prediction performance.

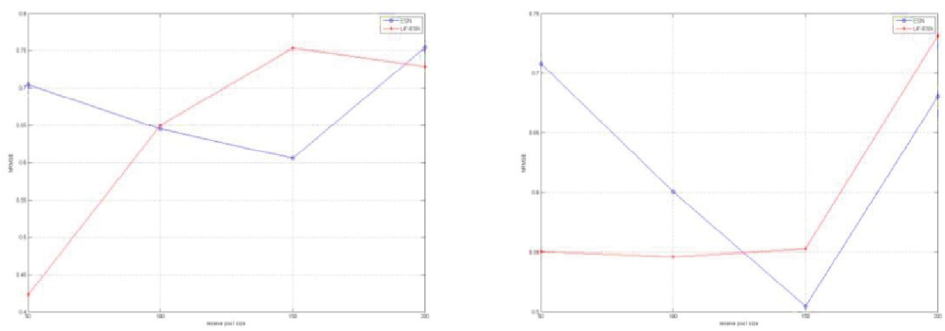
4.1. Experimental Design

According to wireless local area network (WLAN) worked on 2.4GHz 02.11b spectrum, we assume that PU appears the probability of 0.5 obeyed the Poisson distribution and the duration of 0.4 obeyed exponential distribution to generate time series [13]. We sample sequence and calculate the rest of time for the each state from the sampling moment, and generate 800 sequence samples, among them 600 samples are used for training, 200 samples for testing, and use Before 10 data to predict the next state.

The experiment is divided into two groups, predict respectively by using traditional ESN and LIF ESN. Experiment is designed that spectral radius $\rho(\omega)$ are 0.5, 0.8 respectively, reserve pool sizes N are 50, 100, 150, 200 respectively. Traditional ESN's connection density is 0.1, and LIF_ESN absolute refractory period is 1.2.

4.2. Experimental Results and Analysis

Figure 2 is the result of spectral duration prediction based on traditional ESN and LIF_ESN.



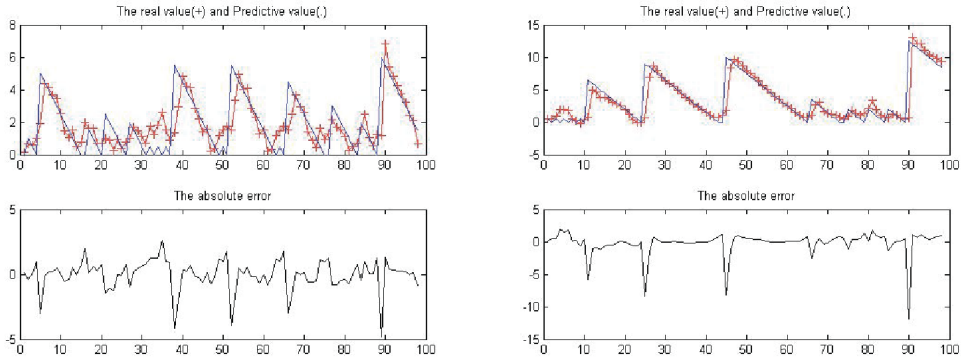
(a) Spectral radius is 0.5 (b) Spectral radius is 0.8

Figure 2. Predict Performance of spectral prediction by ESN and LIF_ESN in different spectral radius and reserve pool sizes

Table 2. Performance comparison of ESN and LIF_ESN prediction

		ESN	LIF_ESN
$\rho(\omega) = 0.5$	$N = 50$	0.70454	0.42302
	$N = 100$	0.6454	0.65028
	$N = 150$	0.60605	0.75323
	$N = 200$	0.75424	0.72908
$\rho(\omega) = 0.8$	$N = 50$	0.70803	0.55084
	$N = 100$	0.60079	0.54621
	$N = 150$	0.50479	0.55322
	$N = 200$	0.68049	0.73150

When we reduce the reserve pool size, LIF_ESN can keep better performance compared with traditional ESN. Figure 3 shows the actual situation of spectral prediction.



(a) ESN (b) LIF_ESN

Figure 3. Actual situation of spectral prediction by ESN and LIF_ESN (spectral radius $\rho(\omega) = 0.8$ and reserve pool sizes $N = 50$)

The conclusion can be obtained by Figure 2, Figure 3 and Table 2. LIF_ESN shows a very superior performance relative to the traditional ESN when reserve pool is small.

5. Conclusion

In order to reduce the reserve pool size and improve the accuracy for time series prediction problem, we construct a kind of echo state network based on leaky integrate and fire neurons. Experimental study of benchmark problem shows that the performance of the modified network is better than traditional ESN when the reserve pool size is small. In spectral prediction problem in cognitive radio system, we adopt the ESN and LIF_ESN to predict the duration of the primary users' spectrum state. The experimental results show that the ESN and LIF_ESN have good performance on spectral prediction. LIF_ESN can obtain better prediction performance when the reserve pool size is small.

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