Prediction of Time-Series Data using PSpice and Runge-Kutta Method

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***Abstract*— Prediction of time-series data in natural world are very important. For example, if nonlinear time-series data are predictable, we can take adequate action for problem of weather. In this study, we propose two prediction methods for time-series data using coupled oscillators system. We predict chaos time-series data like the natural phenomena by these methods. The chaos time-sires data are made by the Chua's circuit. The prediction results of time-series data are compared with two our methods. We show possibility of predictable by actual circuit.**

I. Introduction

Predictions of the time-series data of natural world are very important for human, and a lot of researches are carried out up to now[1][2]. A lot of things of the natural world such as the atom, neurons, and planets are oscillating. These are connected by each other, and operate as a system. Therefore, time-series data of a lot of natural things are oscillatory solutions. Coupled oscillators system can make complex phenomena[3][4].

The time-series data is generally predicted with statistics, a state space model, a Karman filter and so on. We think that the oscillatory solution should be used for the prediction.

In our previous study, we proposed a method using Runge-Kutta method and normalized equations of lattice oscillator[5]. However, the prediction was used numerical equations without features of the OP-Amps. Further, an input signal source was optimized for normalization of circuit equations. Therefore, to make an actual circuit of this prediction system is hard.

In this study, the lattice oscillators constructed by van der Pol oscillators are simulated using Runge-Kutta method and PSpice, and predict the time-series data of the Chua's circuit. Simulations by PSpice include features of OP-Amp, and include the input signal source that is constructed by only a voltage source. Additionally, values of all elements is used realistic values.

The prediction results of time-series data using PSpice are compared from the prediction results using Runge-Kutta method.

We show possibility of predictable by the actual circuit of our method by using PSpice.

II. Prediction using Runge-Kutta method

A. Circuit model for Runge-Kutta method

In this study, 9 van der Pol oscillators are coupled as a lattice by inductors(see Figs. 1(a) and 1(b)), and we predict time-series data by this circuit. In this method, an arbitrary signal $f(t)$, that is synthesized and predicted, is presented as a current of an inductor L_{out2}, because circuit equations should be normalized and simplified(see Fig. 1). Therefore, an input part is substituted the inductor L_{out2} and an arbitrary voltage signal source. An output signal $h(t)$ of the voltage signal source is shown as follows:

$$h(t) = \frac{1}{L_{out2}} \int f(t)dt. \quad (1)$$

In this method, we can predict in ideal condition because the measurement instrument and input power source are considered. Each oscillator are called OSC(k,l). In our method, future time-series data are predicted from past time-series data by a circuit which is like a filter. Therefore, to input past time-series data from outside is needed. The time-series data is input to each oscillator through each outside inductor L_{out}. Each oscillator includes a negative resistance, an inductor L, and a capacitor C. Prediction results are gotten as time-series data of a voltage of OSC(k,l). We want to analyze this circuit by using Runge-Kutta method. Therefore, normalized equations of this circuit should be used. The parameters of this circuit are set as Figs. 1(a) and 1(b). The all oscillators are used same parameters, and the all coupling inductors are used same inductance. All inductors L_{out2} for inputting time-series data are used one value. The voltage of each oscillator is called $v_{(k,l)}$. Moreover, the electric current that flows to the inductor of each oscillator is named $i_{(k,l)}$. An arbitrary time-series data are input from an inductor L_{out2} and voltage signal source. We control the voltage signal source to be a current of L_{out2} is the arbitrary time-series data synthesis and prediction time-series data are output as the current $i_{(1,1)}$ of OSC(1,1). The nonlinear resistance of each oscillator is approximated as follows.

$$f(v_{(k,l)}) = -g_1 v_{(k,l)} + g_3 v_{(k,l)}^3. \quad (2)$$

The circuit equation is normalized by the following equations.

$$t = \sqrt{LC}\tau, \quad i_{(k,l)} = \sqrt{\frac{Cg_1}{3Lg_3}}x_{(k,l)}, \quad v_{(k,l)} = \sqrt{\frac{g_1}{3g_3}}y_{(k,l)}, \quad \alpha_{(k,l)-(m,n)} = \frac{L}{L_{(k,l)-(m,n)}}, \quad \varepsilon_{(k,l)} = g_1\sqrt{\frac{L}{C}}. \tag{3}$$

[corner]

$$\begin{aligned}
\frac{dx_{(k_0,l_0)}}{d\tau} &= y_{(k_0,l_0)}, \\
\frac{dy_{(k_0,l_0)}}{d\tau} &= -x_{(k_0,l_0)} + \alpha_{(k_1,l_1)-(k_2,l_2)}(x_{(k_3,l_3)} - x_{(k_0,l_0)}) \\
&+ \alpha_{(k_4,l_4)-(k_5,l_5)}(x_{(k_6,l_6)} - x_{(k_0,l_0)}) + \alpha_{out(k_0,l_0)}(x_s - x_{(k_0,l_0)}) \\
&+ \varepsilon_{(k_0,l_0)}(y_{(k_0,l_0)} - \frac{1}{3}y^3_{(k_0,l_0)}).
\end{aligned} \tag{4}$$

$(k_0, l_0, k_1, l_1, k_2, l_2, k_3, l_3, k_4, l_4, k_5, l_5, k_6, l_6)$=

$$\begin{cases}
top-left: (0,0,0,0,0,1,0,1,0,0,1,0,1,0), \\
top-right: (0,2,0,1,0,2,0,1,0,2,1,2,1,2), \\
bottom-left: (2,0,2,0,2,1,2,1,1,0,2,0,1,0), \\
bottom-right: (2,2,2,1,2,2,2,1,1,2,2,2,1,2).
\end{cases}$$

[center($k = 1$ and $l = 1$)]

$$\begin{aligned}
\frac{dx_{(1,1)}}{d\tau} &= y_{(1,1)}, \\
\frac{dy_{(1,1)}}{d\tau} &= -x_{(1,1)} + \alpha_{(1,0)-(1,1)}(x_{(1,0)} - x_{(1,1)}) \\
&+ \alpha_{(1,1)-(1,2)}(x_{(1,2)} - x_{(1,1)}) + \alpha_{(0,1)-(1,1)}(x_{(0,1)} - x_{(1,1)}) \\
&+ \alpha_{(1,1)-(2,1)}(x_{(2,1)} - x_{(1,1)}) \\
&+ \varepsilon_{(1,1)}(y_{(1,1)} - \frac{1}{3}y^3_{(1,1)}).
\end{aligned} \tag{5}$$

[side]

$$\begin{aligned}
\frac{dx_{(k_0,l_0)}}{d\tau} &= y_{(k_0,l_0)} \\
\frac{dy_{(k_0,l_0)}}{d\tau} &= -x_{(k_0,l_0)} + \alpha_{(k_1,l_1)-(k_2,l_2)}(x_{(k_3,l_3)} - x_{(k_0,l_0)}) \\
&+ \alpha_{(k_4,l_4)-(k_5,l_5)}(x_{(k_6,l_6)} - x_{(k_0,l_0)}) \\
&+ \alpha_{(k_7,l_7)-(k_8,l_8)}(x_{(k_9,l_9)} - x_{(k_0,l_0)} + \alpha_{out(k_0,l_0)}(x_s - x_{(k_0,l_0)}) \\
&+ \varepsilon_{(k_0,l_0)}(y_{(k_0,l_0)} - \frac{1}{3}y^3_{(k_0,l_0)}).
\end{aligned} \tag{6}$$

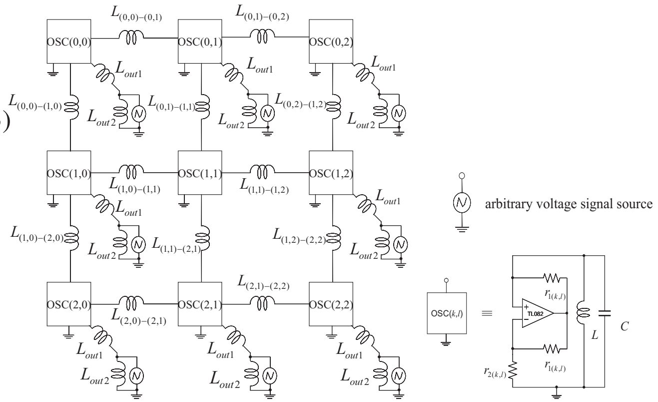
$(k_0, l_0, k_1, l_1, k_2, l_2, k_3, l_3, k_4, l_4, k_5, l_5, k_6, l_6, k_7, l_7, k_8, l_8, k_9, l_9)$=

$$\begin{cases}
top: (0,1,0,0,0,1,0,0,0,1,0,2,0,2,0,1,1,1,1,1), \\
left: (1,0,1,0,1,1,1,1,0,0,1,0,0,0,1,0,2,0,2,0), \\
right: (1,2,1,1,1,2,1,1,0,2,1,2,0,2,1,2,2,2,2,2), \\
bottom: (2,1,2,0,2,1,2,0,2,1,2,2,2,2,1,2,2,2,1,2).
\end{cases}$$

Each nonlinearity and coupling parameter must be adjusted individually, because we synthesize and predict time-series data by these circuit equations. Therefore, each ε and α are renamed as $\varepsilon_{(k,l)}$ and $\alpha_{(k,l)-(m,n)}$.

B. Prediction method using Runge-Kutta method

We use a time-series data of Chua's circuit as an original time-series data. Parameters of Chua's circuit on pp.24 of [6] are used. The original time-series data is assumed as $f(t)$. A prediction of the original time-series data is assumed as $g(t)$. The original time-series data of continuous data are divided by time period of arbitrary length T, and are predicted. Our system is predicted future time-series data from past time-series data. The details of procedure of our method are shown as follows, and an example of synthesis and prediction are shown in Fig. 2.



(a) Lattice circuit. (b) Van der Pol oscillator.

Fig. 1. Circuit model for Runge-Kutta method.

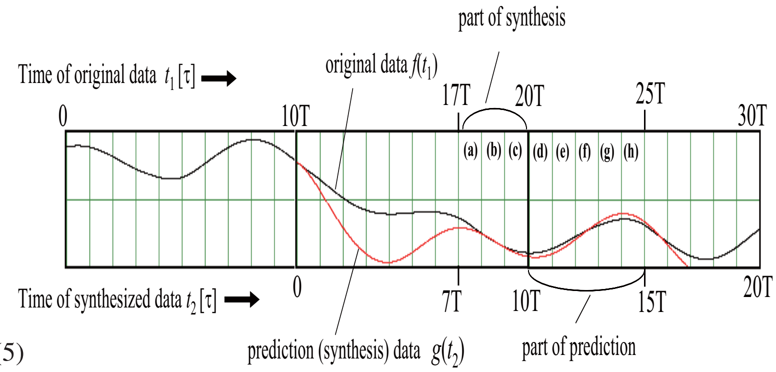


Fig. 2. Relation between synthesis time-series data and original time-series data (Runge-Kutta method).

1) The original data from $f(0)$ to $f(10T)$ is added to our system, and data from $g(0)$ to $g(10T)$ is synthesized at the same time. The original data are shown in Fig. 2. The synthesis data are shown in Fig. 2. In the Fig. 2, time axis of synthesis data differs from time axis of original data.
2) The synthesized data $g(t)$:($7T \leq t \leq 10T$) are adjusted to values close to $f(t)$:($17T \leq t \leq 20T$) by changing each parameter and eighteen initial values of oscillators. Each initial value is set plus $f(10T)$ or minus $f(10T)$ independently.
3) The original time-series data from $f(10T)$ to $f(20T)$ is added to the adjusted system, and time-series data from $g(10T)$ to $g(20T)$ is synthesized at the same time. The synthesis data $g(t)$:($10T < t \leq 20T$) are considered as prediction data.
4) A prediction period is fixed from $10T$ to $15T$ because to predict for long time is difficult.

If the time-series data $g(t)$:($10T < t \leq 15T$) is close to $f(t)$:($20T < t \leq 25T$), we can consider that $g(t)$:($10T < t \leq 15T$) predicts the original time-series data(see Fig. 2). We

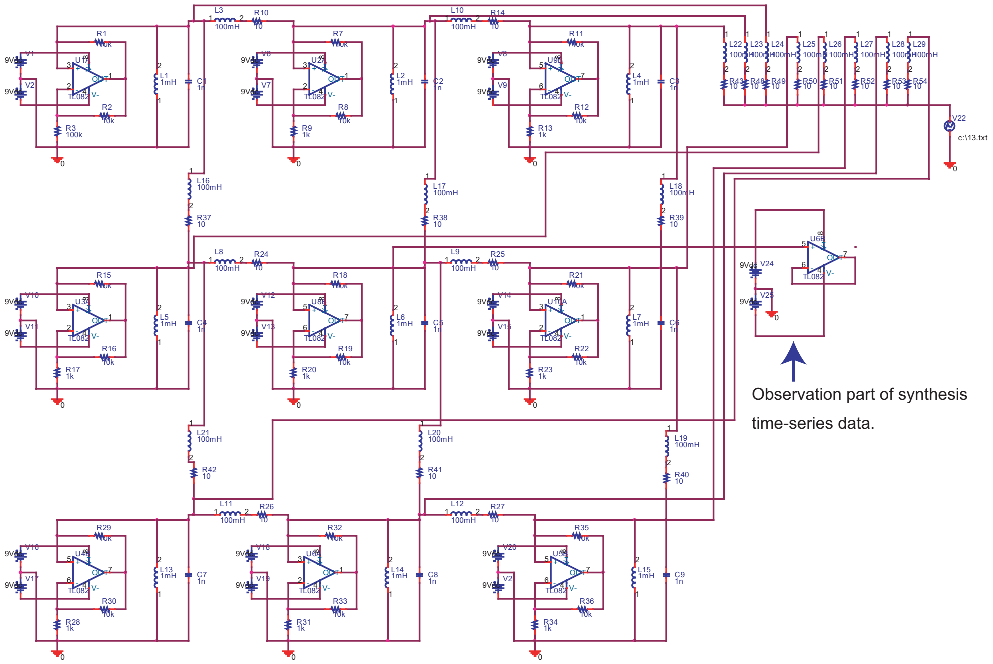


Fig. 3. Circuit model for PSpice(OP-Amp:TL082).

predict long time data repeating this method.

III. Prediction using PSpice

In this section, we predict the same time-series data by PSpice.

A. Circuit model for PSpice

The prediction circuit for PSpice is shown in Fig.3. This circuit and above circuit are same circuit basically. However, in this circuit, we conscious an actual circuit. This circuit includes registers of coupling inductors. Original time-series data are input from an arbitrary voltage signal source. Synthesis and prediction time-series data are output as the voltage $v_{(1,1)}$ of OSC(1,1). The capacitances are used from 1500nF to 1nF. The resistances are used from 10MΩ to 10Ω. The inductances are used from 150mH to 0.1μH.

B. Prediction method using PSpice

We basically predict time-series data by same method, which is shown in above section. The details of procedure of our method are shown as follows, and an example of synthesis and prediction are shown in Fig.4.

1) The original data from $f(0)$ to $f(2T)$ (α) is added to our system, and data from $g(0)$ to $g(2T)$ (β) is synthesized at the same time(see Fig.4).
2) The synthesized data $g(t) : (T \le t \le 2T)$ are adjusted to values close to $f(t) : (7T \le t \le 8T)$ by changing many parameters and many initial values of oscillators. We adjust all parameters as like full solution search. However, when the synthesis data is very close to original data, we stop to adjust the parameters. Therefore, we can think a probability of global minimum, which our results is, is low. Each initial values is set plus $f(6T)$, minus $f(6T)$ or 0, independently.
3) The original time-series data from $f(t) : (2T < t \le 3T)(\gamma)$ is added to the adjusted system, and time-series data from $g(t) : (2T < t \le 3T)(\delta)$ is synthesized at the same time. The synthesis data $g(t) : (2T < t \le 3T)$ are considered as prediction data.
4) A prediction period is fixed from $2T$ to $3T$ because to predict for long time is difficult.

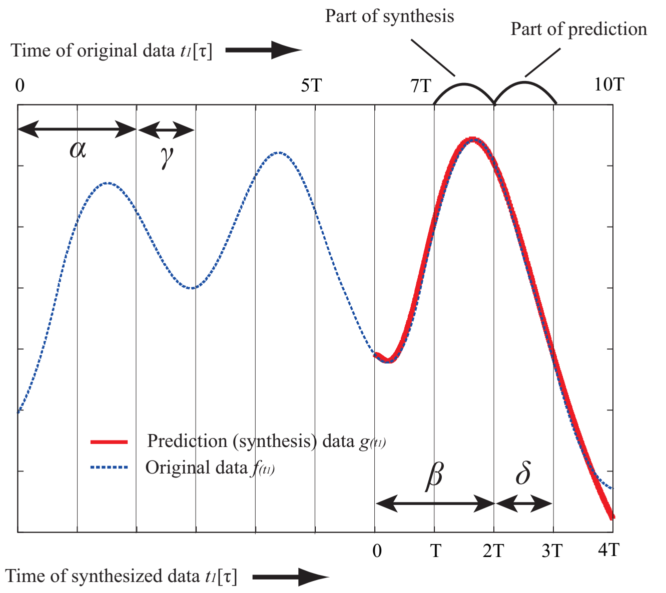
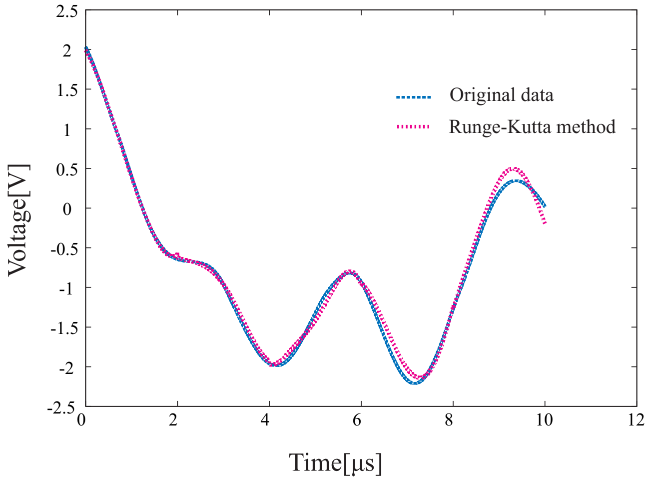
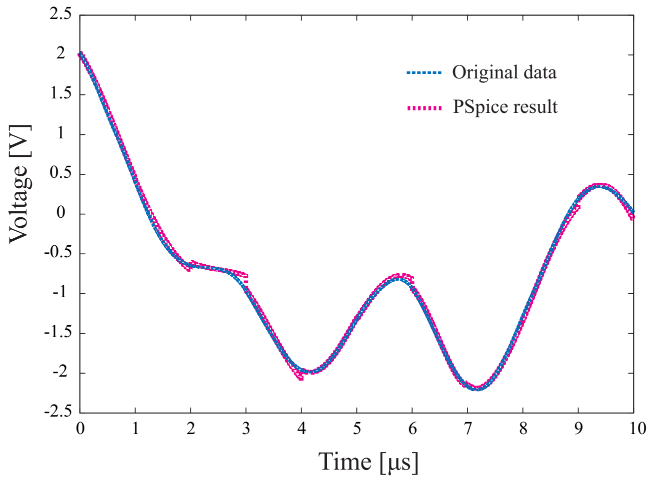


Fig. 4. Relation between synthesis time-series data and original time-series data (PSpice).

If the time-series data $g(t) : (2T < t \le 3T)$ is close to $f(t) : (8T < t \le 9T)$, we can consider that $g(t) : (2T < t \le 3T)$ predicts the original time-series data (see Fig.4). We predict



(a) Prediction results of Runge-Kutta method.



(b) Prediction results of PSpice.

Fig. 5. Prediction results

TABLE I

COMPARISON OF MEAN ABSOLUTE ERRORS AND ERROR RATES.

		0-T	T-2T	2T-3T	3T-4T	4T-5T	5T-6T	6T-7T	7T-8T	8T-9T	9T-10T
Runge -Kutta	Mean absolute errors	0.010766	0.005188	0.009479	0.049336	0.024742	0.043291	0.131468	0.017386	0.084017	0.054813
	Error rate[%]	0.5409	0.8552	0.9861	2.5543	1.2519	3.0564	6.4987	0.8130	6.6471	11.022
PSpice	Mean absolute errors	0.032161	0.037112	0.035688	0.006525	0.001489	0.028941	0.012496	0.006792	0.040905	0.001294
	Error rate[%]	1.5909	5.2871	4.3139	0.2968	0.0749	2.1890	0.5778	0.3102	3.0528	0.3540

long time data repeating this method.

IV. COMPARISON BETWEEN PREDICTION RESULTS OF RUNGE-KUTTA METHOD AND PSPICE.

The composite prediction result using Runge-Kutta method and the original data are shown in Fig.5(a). The composite prediction result using PSpice and the original data are shown in Fig.5(b). We can confirm that the result of PSpice is better than the result of Runge-Kutta method. However, the Runge-Kutta method synthesizes during $3T$, and predicts during $5T$. In other hand, PSpice synthesizes during T, and predicts during T. We can think that to obtain good results by using PSpice are easier than to obtain good results by using Runge-Kutta method. However, the adjustment of our method using PSpice is difficult.

The error rates are shown in Table I.

The mean error rate is calculated as follows:

$$The\ \ error\ \ rate = \frac{Mean\ \ absolute\ \ errors}{Maximum\ \ amplitude} \times 100\ \ [\%] \quad (7)$$

The result of PSpice is better than the result of Runge-Kutta method in 7 domains of 10 domains. The mean error rates of PSpice results are large in the domain where change is sharp. Because the adjustment of our method using PSpice is difficult. In the Runge-Kutta method, a mean error rate between the prediction time-series data and the original time-series data is 3.42%. In PSpice, a mean error rate is 1.80%.

V. CONCLUSION

In this study, the lattice oscillator constructed by van der Pol oscillators was simulated using Runge-Kutta method and PSpice, and we predicted the time-series data of the Chua's circuit using the lattice oscillator. Moreover, the prediction results of time-series data using PSpice were compared with results using Runge-Kutta method. The mean error rates in our methods using Runge-Kutta method and using PSpice were 3.42% and 1.80%, respectively. Therefore, we can say that we were able to predict well. In other words, we can think that possibility of predictable by the actual circuit of our method is shown. However, synthesis using Runge-Kutta method was easier than synthesis using PSpice, because the changed parameter is few, and the time efficiency is good. The mean error rate in our system using Runge-Kutta method enough is small. Therefore, we can think that prediction efficiency is good when the Runge-Kutta method is used.

VI. ACKNOWLEDGEMENTS

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