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Investigation of Biometric Date Input to Multi-Layer Perceptron

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Abstract

In this study, we propose a network model with input of biometric data to the hidden layer neurons of the Multi-Layer Perceptron (MLP). The injecting of the noise is known to be effective to the improvement of the performance of the MLP. We inject the biological pulse wave as a source of this noise. We investigate the performance of the MLP when the sampled data of biological pulse waves obtained from real biological experiments are injected into the neurons. Computer simulated results show that the performance of the biological pulse wave is better than the case of random noise. Further, we investigated the characteristics of the proposed method,

1. Introduction

In this study, in order to investigate the effect of chaotic oscillations of real biological signals on information processing ability, we investigate the performance of the Multi-Layer Perceptron (MLP) with input of biometric data. The pulse wave is a change of the volume caused by the blood current and is measured from the surface of various parts of the body. Biological signals including the pulse wave, the brain wave, and the heart beat wave are said to exhibit chaotic behaviors [1][2]. We refer the biological pulse wave as the chaotic pulse wave. Some reports suggest that healthy biological systems possess chaotic features and periodic states indicate sick or fatal conditions.

On the other hand, many algorithms injecting chaotic oscillations into the neural networks have been proposed in order to avoid the local minimum problems [3]. We have also investigated various methods to exploit chaotic features to enhance the ability of the neural networks [4]-[9]. However, in the past studies, only mathematical abstract models, e.g. the logistic map and the cubic map, are considered as chaotic source.

In this study, we inject the chaotic pulse wave as a source of the chaotic oscillations into the MLP. By computer simulations, we investigate the effect of the chaotic pulse wave. We also compare the results with the cases of random noise and sine wave.

2. MLP with chaotic pulse wave

The MLP is the most famous feed forward neural network and is composed of some neuron layers. In general, the MLP is learned by Back Propagation algorithm (BP) which was proposed by D.E. Rumelhart [10]. This network can solve various kinds of tasks, for example, pattern recognition, pattern classification, data mining and so on. In this study, we consider the case that the MLP consists of three layers (where the number of the neurons are 2-40-1) and the hidden layer neurons has inputs as shown in Fig. 1. The neuron has multi-

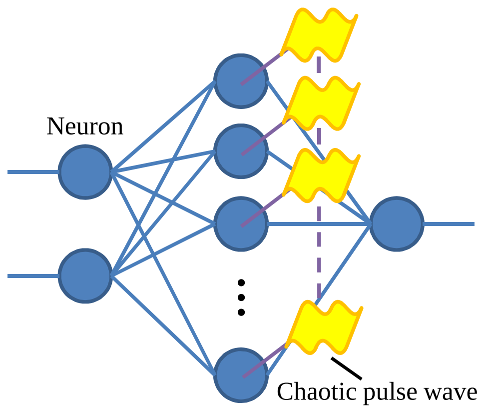

Figure 1: MLP with chaotic pulse wave.

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input and a single output. The standard updating rule of the neuron is defined by Eq. (1).

$$y_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)x_j(t) - \theta_i(t)\right), \quad (1)$$

where y is an output of the neuron, f is an output function, w is a weight of connection, x denotes the output of other neurons, and θ is a threshold of neuron. For this equation, the weight of connections and the threshold of neurons are learned by BP algorithm.

Next, I show a proposed updating rule of the neuron. We inject the chaotic pulse wave into the threshold of neurons. The updating rule is described in Eq. (2) and is used to the neurons in the hidden layer.

$$y_i(t+1) = f\left(\sum_{j=1}^{n} w_{ij}(t)x_j(t) - \theta_i(t) + \alpha\psi_i(t)\right), \tag{2}$$

where ψ is the chaotic pulse wave, α denotes the strength of the chaotic pulse wave. In this equation, the weight of connections and the threshold of neurons are learned by BP algorithm as same as the standard updating rule.

In Eqs. (1) and (2), the output function f is a sigmoidal function described as:

$$f(a) = \frac{1}{1+e^{-a}}. \tag{3}$$

3. Chaotic pulse wave

We have obtained pulse waves from real biological experiments. The sampling frequency of the data is 200Hz and measurement time is 5 minutes. The time waveform of the pulse wave and the corresponding reconstructed attractor are shown in Fig. 2 and Fig. 3, respectively. We calculate the averaged Lyapunov exponent as 4.5032 and hence we can say that this pulse wave is chaotic.

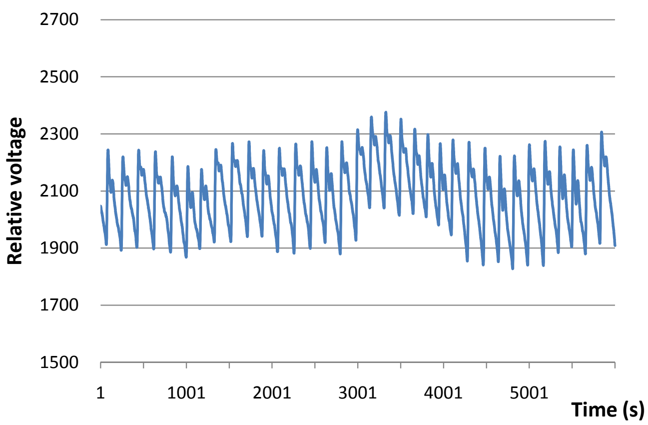


Figure 2: Example of pulse waves.

In order to inject this chaotic pulse wave into the MLP, we normalize the wave and use only one of every 7 samples.

4. Simulation

In this section, the difference in the performance of the proposed MLP with input of biometric data and the conventional MLPs is investigated.

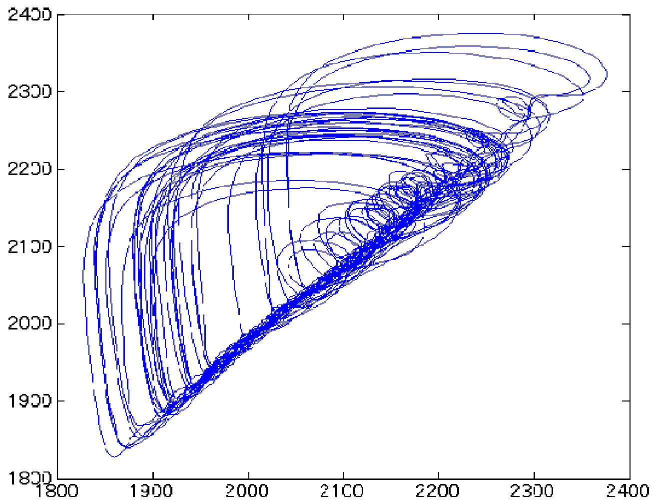


Figure 3: Example of reconstructed attractors of pulse wave.

4.1. Two-spiral problem

We apply the proposed network for solving the Two-Spiral Problem (TSP) [11]. TSP is a problem which classifies two spirals drawn on the plane, and it is famous as a highly nonlinear problem. The MLP learns points on the two spirals by using BP algorithm. We prepare 98 data on the two spirals as shown in Fig. 4. The number of learning times is fixed as 500000. We investigate the error which is defined as Eq. (4).

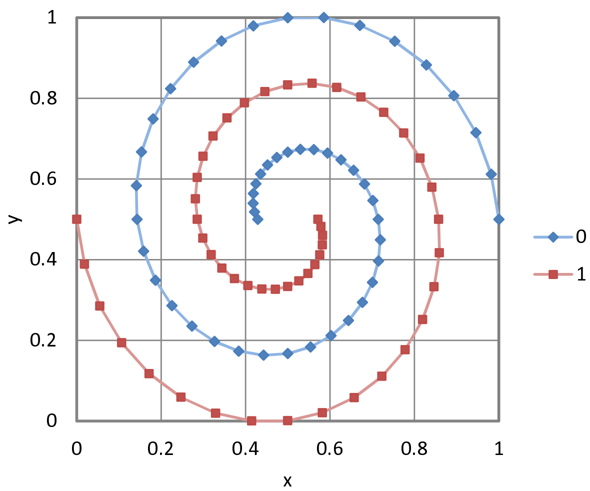


Figure 4: Two spirals problem (target points).

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(T_n - O_n)^2, \tag{4}$$

where T is the target value and O is the output value.

4.2. Learning performance

We compare the results with the conventional, random noise case, sine wave case, and the chaotic pulse wave case (proposed). The simulated results are summarized in Table 1. From this table, the average error of the MLP with chaotic pulse wave is the smallest of all. The conventional MLP is the worst because the conventional MLP often falls into a local minimum. Figure 5 is an example of learning curves of four MLPs. From this curve, we can confirm a good performance of the proposed MLP with chaotic pulse wave.

Table 1: Learning performance.

	Ave.	Min.	Max.	Std. Dev.
Conv.	0.0978	0.0006	0.2518	0.0790
Random	0.0717	0.0003	0.2369	0.0534
Sin	0.0720	0.0085	0.2480	0.0608
Pulse wave	0.0516	0.0005	0.2452	0.0640

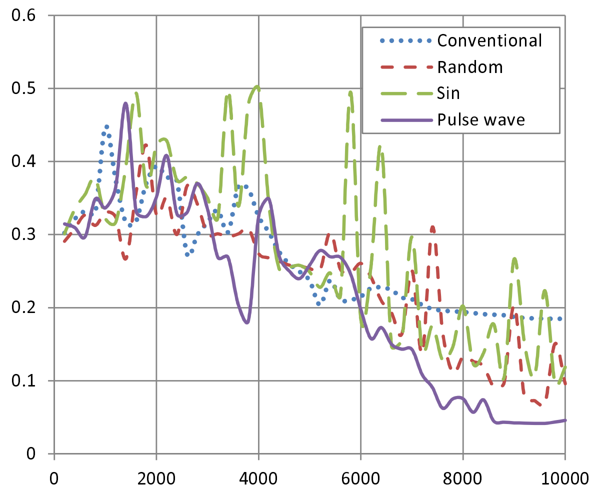


Figure 5: Example of learning curves.

4.3. Classification of two spirals

Next, we investigate the ability of the MLPs to classify points spread over the space to two spirals when the x and y coordinates in the intervals $0.0 \leq x \leq 1.0$ and $0.0 \leq y \leq 1.0$ are inputted to the MLPs. The simulated results are summarized in Table 2 where the target classification is shown in Fig. 6.

An example of the obtained results is shown in Fig. 7. These results are the best results for each MLP in 100 simulation trials. We can see that the proposed MLP can classify the points more smoother than the others.

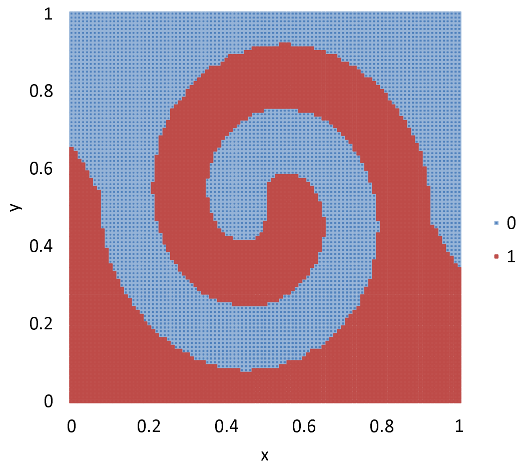


Figure 6: Two spirals problem (ideal classification).

Table 2: Learning performance.

	Ave.	Min.	Max.	Std. Dev.
Conv.	0.2030	0.0910	0.4503	0.0932
Random	0.1725	0.0776	0.2924	0.0428
Sin	0.1760	0.0836	0.5003	0.0895
Pulse wave	0.1600	0.0925	0.5022	0.0836

5. Conclusion

In this study, we have proposed a network model with the injection of biometric data. We injected chaotic pulse wave into the hidden layer neurons of the MLP. By carrying out computer simulations, we confirmed that inputting chaotic pulse wave to MLP gains a good effect for MLP learning.

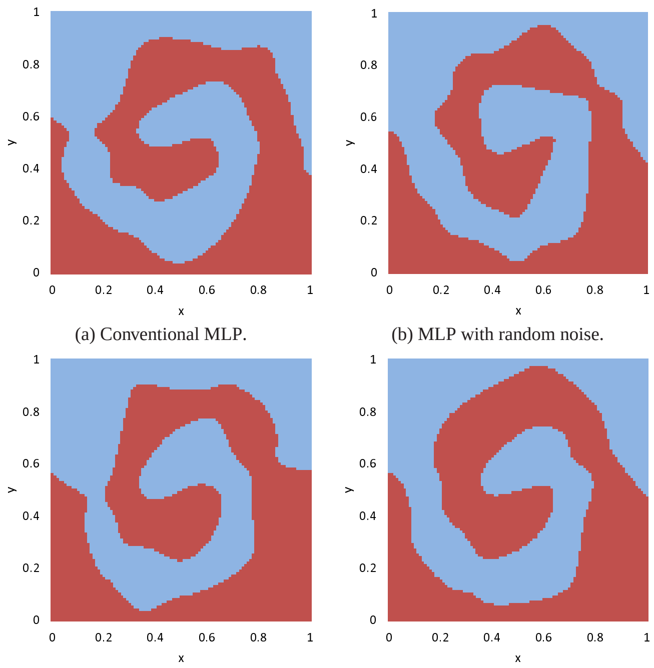
References

[1] C.D. Wagner and P.B. Persson, "Chaos in cardiovascular system: an update," Cardiovascular Research, vol.40, no.2, pp.257-264, Nov. 1998.

[2] A. Das, P. Das and A.B. Roy, "Applicability of Lyapunov exponent in EEG data analysis," Complexity International, vol.9, pp.1-8, 2002.

[3] Y. Hayakawa and Y. Sawada, "Effects of chaotic noise on the performance of a neural network model for optimization problems," Physical Review E, vol.51, no.4, pp.2693-2696, 1995.

[4] Y. Uwate, Y. Nishio, T. Ueta, T. Kawabe and T. Ikeguchi, "Performance of chaos and burst noises



(a) Conventional MLP. (b) MLP with random noise.

(c) MLP with sin wave. (d) Proposed MLP.

Figure 7: Example of classification results.

injected to the Hopfield NN for quadratic assignment problems," IEICE Transactions on Fundamentals, vol.E87-A, no.4, pp.937-943, Apr. 2004.

[5] Y. Uwate and Y. Nishio, "Search of many good solutions of QAP by connected Hopfield NNs with intermittency chaos noise," RISP Journal of Signal Processing, vol.8, no.6, pp.439-447, Nov. 2004.

[6] Y. Tada, Y. Uwate and Y. Nishio, "Performance of chaotic switching noise injected to Hopfield NN for quadratic assignment problem," Proceedings of IEEE International Symposium on Circuits and Systems, pp.5519-5522, May 2006.

[7] Y. Tada, Y. Uwate and Y. Nishio, "Effective search with hopping chaos for Hopfield neural networks solving QAP," Proceedings of IEEE International Symposium on Circuits and Systems, pp.1783-1786, May 2007.

[8] Y. Tada, Y. Uwate and Y. Nishio, "Solving ability of Hopfield neural network with scale-rule noise for QAP," Proceedings of IEEE International Symposium on Circuits and Systems, pp.105-108, May 2008.

[9] S. Aono, Y. Nishio and D. He, "Solving ability of coupled map lattice with 2-opt algorithm for traveling salesman problems," RISP Journal of Signal Processing, vol.13, no.4, pp.303-306, Jul. 2009.

[10] D.E. Rumelhart, G.E. Hinton and R.J. Williams, "Learning representations by back-propagating errors," Nature, vol.323-9, pp.533-536, 1986.

[11] J.R. Alvarez-Sanchez, "Injecting knowledge into the solution of the two spirls problem," Neural Computing & Applications, vol.8, pp.265-272, 1999.