Modeling Chaos Neural Networks for Classification of EEG Signals

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Abstract

This work proposes essential improvements based on Chaos theory to enhance adaptive ability of Feed-forward Neural Network (FFNN). A novel structure of a single neuron is proposed with a feedback connection and a periodic active function. The proposal model obtained the best results on least mean square error as well as dramatic decrease of training time. Results are also illustrated and compared through XOR problem, 7-point problem and application for classification of EEG data.

Keywords: Chaos Neural Networks, backpropagation, electroencephalogram (EEG)

1 Introduction

Artificial Intelligent (A.I) Computation always reaches higher ability to be adaptive with changes of realistic environments. Neural Networks is one of the most interesting areas of A.I. of which the well-known characteristic is the learning ability. However the training of networks is being argued to improve it. Freeman (1991) decided that chaos may be the chief property that makes the brain different from an artificial-intelligence machine. K. Aihara [2] said that a usual neuron model is a simple threshold element transforming a weighted summation of the inputs into the output through a non-linear. However from the viewpoint of neurophysiology, there is a firm criticism that real neurons are far more complicated than simple threshold elements.

One of the problems associated with the backpropagation algorithm is its parameterization. Beforehand, the value of a number of parameters needs to be specified. It has been found that very small variations in these values can make the difference between good, average or bad performance. This also implies that one can never be sure to have found the optimal solution. Furthermore, the backpropagation algorithm can converge in a local minimum or oscillate between two (or more) different solutions shown in Fig. 1.

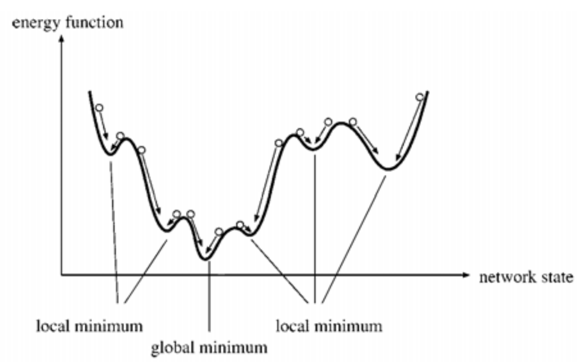

Fig. 1. Error surface of FFNN.

The rule for weight-modifications shows some similar structures with a well known chaotic equation, so a possible explanation for the hyper-sensitive and sometimes problematic behavior of the backpropagation algorithm may be found in chaos theory shown by K. Bertels and *et. al* in[5].

This work follows the approach considering neural networks as a Chaos dynamic system which has been proposed by K. Aihara [2], and M. Nakagawa [1]. Many of applications were examined in [1] such a chaotic memory retrieval model, image processing, telecommunication signal synchronous.

EEG signals classification have been carried out with many different methodologies as Autocorrelation in [7], Neural Networks in [8], Fuzzy logic in [9]. This work proposes a novel neural network with some improvements based on Chaos theory to speed up the learning time and to escape the local optimum. The present learning model is properly characterized in terms of periodic chaos neuron to involve a chaotic dynamics as well as external or autonomous control of the periodicity. The obtained results are examined by XOR problem, 7-point problem and application for classification of Electroencephalogram (EEG) signals. In addition illustrations are compared to some conventional neural networks.

2 Electroencephalogram (EEG)

Electroencephalogram (EEG) signals provide one possible means of human–computer interaction, which requires very little in terms of physical abilities. By training the computer to recognize and classify EEG signals, users could manipulate the machine by merely thinking about what they want it to do within a limited set of choices.

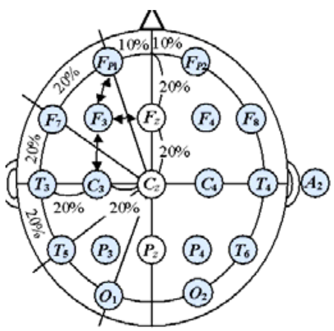

Fig. 2. EEG data acquisition.

The reliable operation of brain–computer interfaces (BCIs) based on spontaneous electroencephalogram (EEG) signals requires accurate classification of multi-channel EEG. The design of EEG representations and classifiers for BCI are open research questions whose difficulty stems from the need to extract complex spatial and temporal patterns from noisy multidimensional time series obtained from EEG measurements.

3 Models

3.1 The conventional Neuron

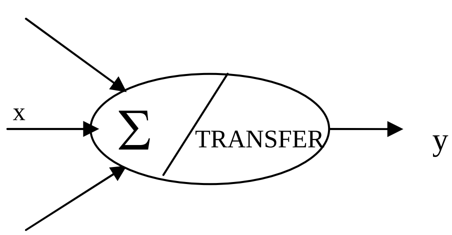

Fig. 3. Conventional NN model.

The standard FFNN is usually 3 layers following: Input layer: X= $\{x_1, x_2, \ldots, x_N\}$, hidden layer and output layer. All neurons are connected by weights and their output s value are calculated through net value and transfer function.

Net value:

$$net = \sum_{i=1}^{N} w_{ij}.x_i + \theta \qquad (1)$$

Transfer function is usually used a saturation function such sigmoid function.

3.2 A Periodic Chaos Neural Network Model

This work mentions a novel FFNN with periodic active functions and a feedback factor, k, from the output to the inputs of a neuron. It is shown that a neuron with an ability of dynamic memory feedback is better the conventional model with such a monotonous mapping as a sigmoid function. The utility of periodic chaos is used to escape from local minimum values and speed up the learning time. In addition the global minimum value could be reached efficiently since chaos region in bifurcation diagram.

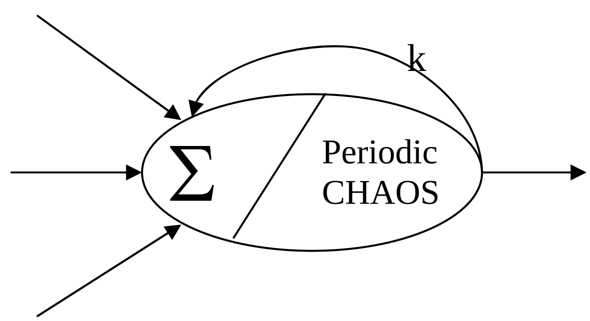

Fig. 4. Chaos Neural Network Model.

Modified net value:

$$net(t+1) = k.net(t) + (\sum w.x + \theta) \qquad (2)$$

Periodic chaos transfer function:

$$Y(t) = \sin(\frac{net(t)}{\tau(t)}) \qquad (3)$$

Where:

$$\tau(t+1) = \tau(t) + ke.\tau(t).(1-\tau(t)) \qquad (4)$$

The use of chaos functional help networks independent on the initial conditions and can not trap in the saturation of transfer function. In addition, this speeds up the training time of network and can avoid the local minimum.

4 Results

The proposed model is compared to the conventional model within the same conditionals such as number of neurons, number of layers, initial values of weights, 10^{-3} in tolerance square error, and upper limit of learning epochs as 10^4 times.

4.1 XOR problem

Conventional Model: with 2 hidden neurons, logsig transfer function, learning rate=0.8. The conventional model result is Epochs =10.000, Tolerated error = 0.0619shown in Fig. 5.

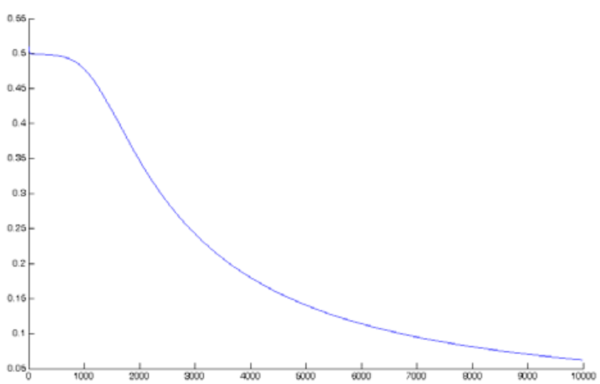

Fig. 5. Tolerance square error of conventional FFNN.

Result of Chaos Neural Networks Model is shown in Fig. 6. with Epochs=48, Tolerated error = 0.001

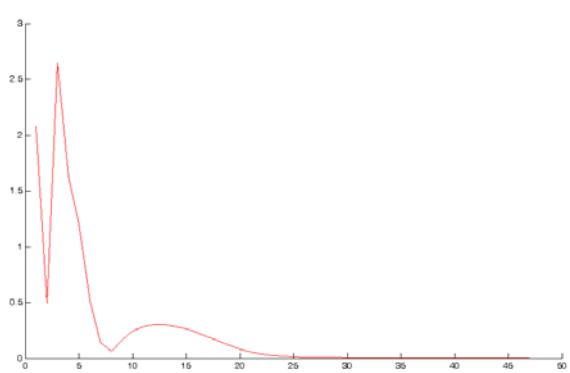

Fig. 6. Tolerance square error of Chaos Neural Networks.

4.2 7-point problem

This problem has 7 patterns with 2 inputs and 1 output. X_1=[0 0 1 1 0.5 0.25 0.75], X_2=[0 1 0 1 0.5 0.75 0.25], and Y=[0 1 1 0 1 0 0]. Conventional Model: 7 hidden neurons, logsig transfer function, learning rate=0.8.The conventional model result is Epochs =10.000, Tolerated error = 0.3884 shown in Fig. 7.

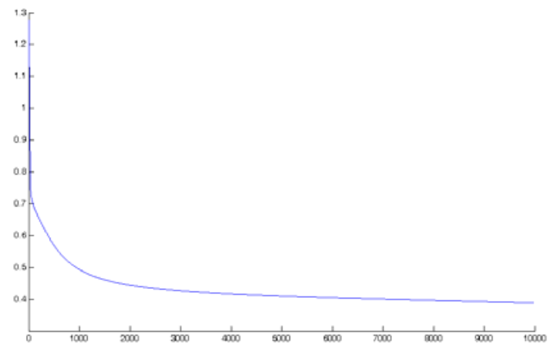

Fig. 7. Tolerance square error of conventional FFNN.

Result of Chaos Neural Networks Model is shown in Fig. 8. with Epochs=22, Tolerated error = 0.001

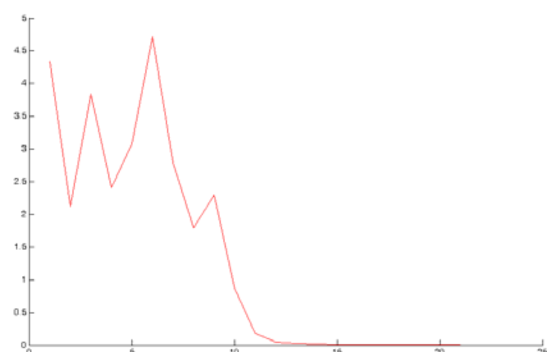

Fig. 8. Tolerance square error of Chaos Neural Networks.

4.3 Classification of 2 EEG types

Two types of EEG data used to examine are foot moving and left-hand moving. These data are obtained from 16 channels and they are equivalent to 16 inputs of Neural Models. Result of Chaos Neural Network classifies EEG data into 2 groups with Tolerance error= 0.1. The output errors are shown in Fig. 11.

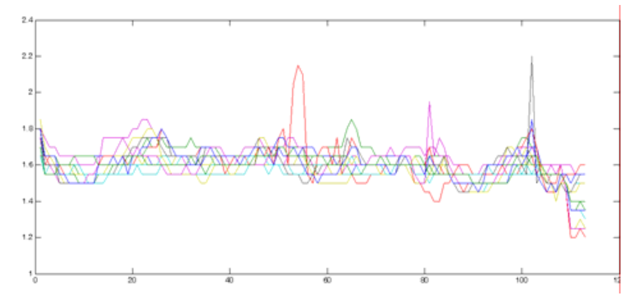

Fig. 9. EEG data of foot moving.

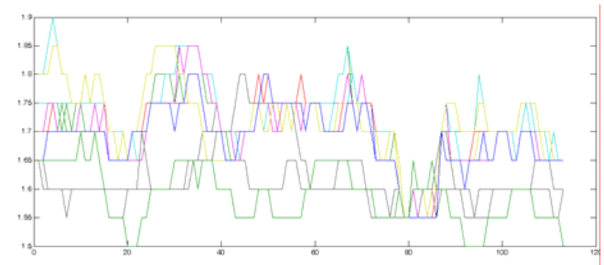

Fig. 10. EEG data of left-hand moving.

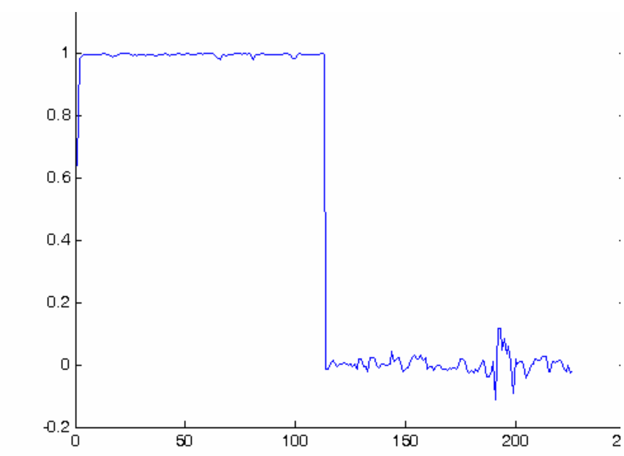

Fig. 11. Output error of classification 2types EEG data.

This results is just limited in 2 types of EEG signals, however the proposed neural network model is clearly adaptive with the kinds of EEG data. With more than 2 signals, the binary output will be extended with more than 1 neuron.

5 Conclusion

From conventional neural networks with the back-propagation learning algorithm, this work proposes some improvements based Chaos theory such as modifying net value with a feedback factor and changing the transfer function to avoid the saturation of outputs. However, all intelligent computing algorithms need to examine adaptive characteristic through realistic applications. Therefore, other applications of the proposals will be investigated in future works.

Acknowledgements

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