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Particle Swarm Optimized Radial Basis Network for prediction of Neural Network Benchmark Series

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Abstract- Prediction of chaotic series is a problem in biomedical applications. The exact nature for future samples cannot be predicted accurately from the present and past values of the signals such as Electro Encelphogram, Electro Cardiograph, and Electro Mio-graph etc. Setting accurately the spread factor for prediction network such as Radial Basis networks (RBN) leads to frustration and time consuming. Particle Swarm Optimization (PSO) when applied over spread factor for Radial Basis Network reduces the time complexity and produces more accurate results than random selection of spread factor. We considered benchmark series of neural network to predict the future samples, the Mackey Series. The PSO optimized spread for radial basis network produced exact replica of the future sample with minimum mean squared error than with spread 0.05 and 0.1 randomly selected. With proper parameter setting the PSO based spread can give remarkable results in prediction of any chaotic series.

Index Terms- Chaotic series, spread factor, Particle Swarm Optimization, Radial Basis Network, benchmark, mean squared error, prediction.

1. INTRODUCTION

Time series prediction involves predicting the system behavior in future based on information of the current and the past status of the system. Prediction of time series has widespread applications in the fields of science, engineering, medicine and econometrics, among others. Several methods have been used for prediction of real life complex, nonlinear time series commonly encountered in various such application domains [1-3]. In recent years, there is also a growing interest in incorporating bio-inspired computational algorithms, commonly termed as computational intelligence (CI), in discovering knowledge from data, both in education and research [4-9].

Among various CI techniques, artificial neural networks (ANNs) have been developed in form of parallel distributed network models based on biological learning process of the human brain. Various neural network structures have been widely used nowadays for various applications including perceptrons, feed forward neural networks, self organizing maps and radial basis networks. These networks are tuned with different parameters for applications and have proved a boon to many researchers. But still researchers are facing problems with setting different parameters to find the best network.

Global optimization is concerned with finding the best possible solution to a given problem. As there are no efficient algorithms to achieve this goal in general, heuristic global optimization methods like evolutionary algorithms are often used to optimize neural networks. Alternatively, it is sometimes acceptable to find a local optimum, which is as good as all solutions in its neighborhood. Local search methods are comparatively well understood, and local optima can often be found efficiently even for problems in which global optimization is difficult. Evolution of connection weights at the lowest level and the learning algorithm at the highest level (using 1st and 2nd order error information) could be considered as a hybrid learning approach wherein the initial weights determined by the evolutionary learning process is fine tuned by the local search method. The parameters of the local search algorithm could be optimized using the evolutionary search process.

Another CI technique, namely, particle swam optimization (PSO) was proposed by Kennedy and Eberhart [5] as a population based stochastic optimization technique inspired by the social behavior of bird flocking. PSO is a computationally simple algorithm based on group (swarm) behavior. The algorithm searches for an optimal value by sharing cognitive and social information among the individuals (particles). PSO has many advantages over evolutionary computation techniques like genetic algorithms in terms of simpler implementation, faster convergence rate and fewer parameters to adjust [6, 7]. The popularity of PSO is growing with applications in diverse fields of engineering, biomedical and social sciences, among others [7-9].

In this paper PSO is used to search the optimum value for spread for radial basis network for prediction. The following sections includes database used, results and conclusions.

2. DATABASE USED - MACKEY SERIES

500 samples were trained for Mackey series and another 500 samples were predicted. Samples were taken as x(t-18), x(t-12), x(t-6) and x(t) and the predicted sample was x(t+6). Samples started from 101 to 600 and test samples started from 601 to 1100. 500 samples started from 101 and 601 respectively for train and test data in four columns. The network was trained for 500 samples and then test for another 500 samples.

3. RESULTS

Mean Squared Error with PSO optimized Spread factor - 5.2698e-005
Mean Squared Error with spread=0.05 - 0.00014478
Mean Squared Error with spread=0.1 - 0.00058642

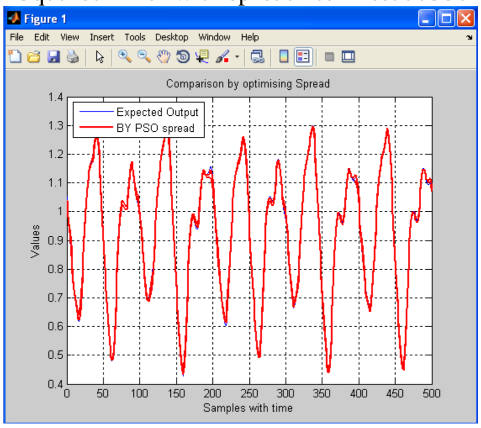

Figure 1 – Prediction of Mackey series using optimized spread with PSO.

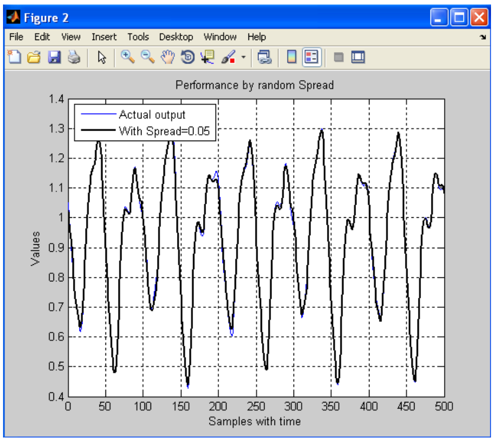

Figure 2 – Prediction of Mackey series using random selected spread for RBN = 0.05.

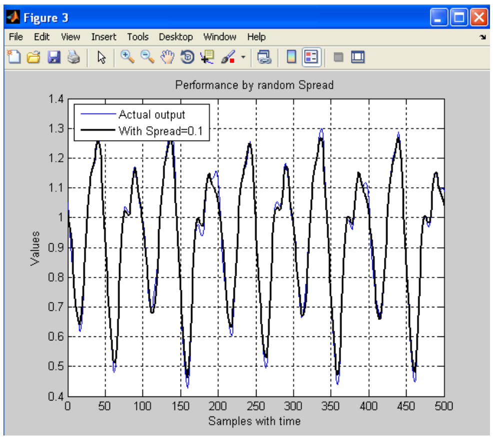

Figure 3 – Prediction of Mackey series using random selected spread for RBN = 0.1.

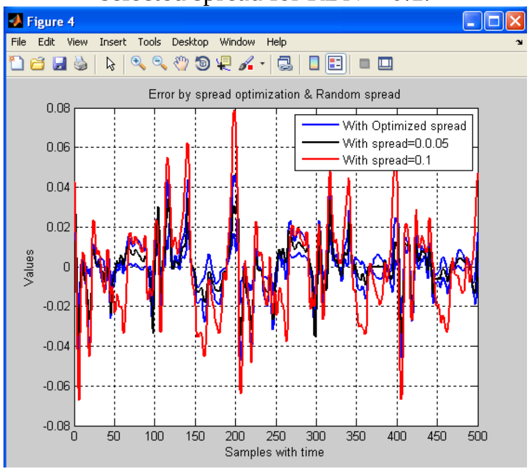

Figure 4 – Error plot for optimized spread, random spread 0.05 and random spread 0.1.

4. PARAMETERS USED

The population size for swarm was taken to be 30 particles. 50% data was taken for training and 50% was taken for testing. That is 500 samples for training and testing. Initial swarm and their velocities were randomly initialized. The other parameters considered or set were,

% Maximum Iterations
maxiter=10;

% Inertial weight factors
wmax=0.9;
wmin=0.5;

% Maximum and Minimum Value of velocity
vmax=2;
vmin=0;

% Maximum and Minimum value for particle position - spread
popmax=5;
popmin=0.00001;

The velocity, position, inertial weight and constants C1 and C2 were calculated according to,

```
% Velocities update
v(i,:)= w*v(i,:)+ c1*rand*(pbest(i,:)-
pop(i,:))+c2*rand*(gbest-pop(i,:));
```

pbest and gbest are the local best and global best values of the particle.

```
% Update the position of the particle
pop(i,:)=pop(i,:) + v(i,:);

% Inertial weight

w=wmax-(wmax-wmin)*j/maxiter;

%Constant C1 and C2
c1= (c1f-c1i)*j/maxiter+c1i;
c2= (c2f-c2i)*j/maxiter+c2i;
```

Further the maximum and minimum values for particle position and velocities were restricted after updating. Also the constants for calculating C1 and C2 were generalized. The radial basis network was trained and tested with PSO obtained spread factor.

5. CONCLUSIONS

It can be seen that PSO based spread gives better result. The mean squared error seen above is negligible for PSO based RBN as compared to that for random spread. It is tedious to select the spread factor for an application from a range [0 1]. PSO converges the system faster with optimum value and improves prediction. The number of iterations required for optimizing the spread factor was only 10.

REFERENCES

[1] De Gooijer, J. G. and Hyndman, R. J. 25 years of time series forecasting. International Journal of Forecasting, vol. 22, 2006, pp. 443-473.
[2] Box, G.E.P., Jenkins, G.M., and Reinse, G.C. Time Series Analysis: Forecasting and Control, Prentice Hall, Englewood Cliffs, NJ, 1994.
[3] Mackey, M. and Glass, L. Oscillation and chaos in physiological control systems. Science, vol. 197, 1997, pp. 287-289.
[4] Haykin, S. Neural Networks: A Comprehensive Foundation, 2nd Edition, Prentice Hall, New Jersey, USA, 1999.
[5] Kennedy, J. and Eberhart R. C. Particle swarm optimization. Proc. IEEE Intl. Conf. on Neural Networks IV, Piscataway, NJ: IEEE Service Center, 1995, 1942–1948.
[6] Kennedy, J., Eberhart, R.C., and Shi, Y. Swarm Intelligence, Morgan Kaufmann Publishers, San Francisco, CA, 2001.
[7] Poli, R., Kennedy, J., and Blackwell, T. Particle swarm optimization an overview. Swarm Intelligence, vol. 1, 2007, pp. 33-57.
[8] Samanta, B. and Nataraj, C. Use of particle swarm optimization for detection of machine condition. Engineering Applications of Artificial Intelligence, vol.22, 2009, pp. 308-316.
[9] Samanta, B. and Nataraj, C. Prognostics of machine condition using soft computing. Robotics and Computer-Integrated Manufacturing, vol. 24, 2008, pp. 816-823.
[10] Pratik Hajare, Dr. Narendra Bawane, "PSO optimized Feed Forward Neural Network for offline Signature Classification", Int. Journal of Engineering Research and Applications, Vol. 5, Issue 7, (Part - 1) July 2015, pp.100-105.
[11] Pratik R. Hajare, Dr. Narendra G. Bawane, "Initial Weights and Biases to Backpropagation in Feed Forward Neural Network by Particle Swarm Optimization", International Journal of Multidisciplinary Research & Advances in Engineering, ISSN: 0975-7074, Vol.7, No. III, July 2015.
[12] Pratik R. Hajare, Dr. Narendra G. Bawane, "Optimum weights and Biases for Feed Forward Neural Network by Particle Swarm Optimization", International Journal of Granular Computing, Rough Sets and Intelligent Systems, Screening completed, Under Review.
[13] Pratik R. Hajare, Dr. Narendra G. Bawane, "Neural Network Optimization by Swarm Intelligence for Prediction & Classification", International Conference, Shaastrarth-2015, Rungta College of Engineering & Technology, Bhilai.