Reservoir Analysis of the Echo State Network

Shilpa Dani
School of Computer Science, University of Birmingham.
Supervisor: Dr Peter Tino

Overview

•An **Echo State Network (ESN)** is a type of three-layered recurrent network with sparse, random, and crucially, untrained connections within the recurrent hidden layer. The scale of the internal connections is set so that the networks possess the ***Echo State Property.***

•The *echo state property* [1], which expresses – informally stated – the fact that the influence of inputs on reservoir states fades away gradually. Further, an upper and lower bound are defined for the echo state property that are very easy to compute and depend only on the weight matrix of the reservoirs.

•The **echo state network (ESN)** is a recurrent neural network with a sparsely connected hidden layer (with typically 1% connectivity). The connectivity and weights of hidden units are randomly assigned and are fixed, once it is picked.

•The random connectivity and weights does not give a clear insight in what is going on in the reservoir and how is it related to the performance of the ESN. The main aim of this research is therefore

" To systematically study the influence of the range of reservoir parameters on the learning performance of the ESN."

Objectives

In order to fulfil the aim of the research following were the objectives of the research
•To study the effect of different reservoir topologies on the performance of the ESN.
•To study the effect of different reservoir sizes on the performance of the ESN.
•To study the effect of linear and non-linear nodes types on the performance of the ESN.

Experimental Methods

In order to systematically study the influence of the reservoir topology on the learning performance of the ESN, the research approach include following main steps.

A. Connection Topologies: Six different reservoir topologies with increased level of complexities were used to construct the reservoir. (fig. 2). To remove the effect of random weighing, the experiments were repeated 30 times for each reservoir with different assigned weights.

1. A combination of connections weights from a [0.05,0.1,0.3,0.5,0.7,0.9,0.95, 1,1.2,1.5] was used to generate the reservoir.
2. The reservoir was generated as in 1. The sign of some of the connection weights was changed from positive to negative.
3. The connection weights were randomly for each topology.

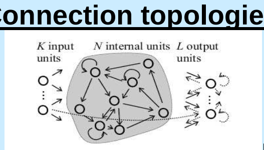
B. Three different datasets namely, *Santa Fe Laser, Nonlinear Communication Channel* and *NARMA System* were used.

C. Reservoir Size : The experiments were repeated for different number of hidden units for each dataset.

D. Connection nodes: All the experiments mentioned in A,B and C were repeated for Linear as well as Non-linear hidden units.

In order to asses the performance of the different topologies the Mean square error (MSE) was observed for different topologies.

Connection topologies



Randomly interconnected reservoir. Hidden units connected to other internal units and/or self connected.

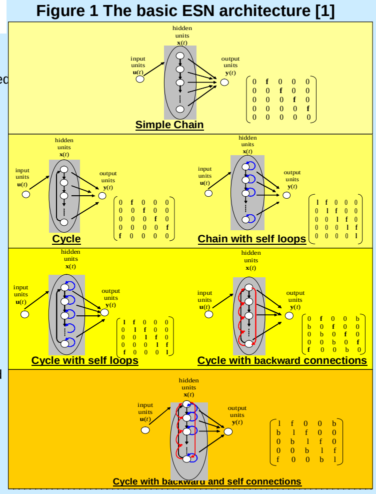
Figure 1 The basic ESN architecture [1]

ESN-like architecture with reservoir composed of units organised in one chain, hence only elements on recurrent weight matrix sub-diagonal have non-zero values(**f**)[2].

Two more complex architectures with cycle and self-loops (**l**) added onto the chain.

Third level of complexity with self-loops (**l**) added onto the cycle and backward connections added onto the cycle.

Fourth level of complexity with self loops, and backward connection onto the cycle.



f – forward connection weight
b – backward connection weight
l – self-loop connection weight

Figure 2 The connection topologies with increased level of complexity

Results

The main aim of the experimentation was to systematically investigate which parameter setting works best towards performance enhancement of the ESN.

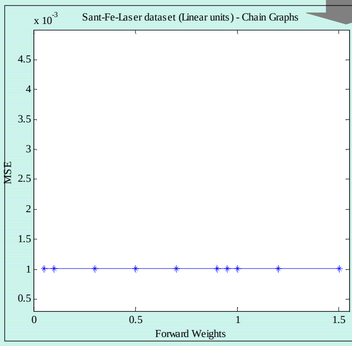


Figure 3(a) Results for the Chain and Cycle topology for Santa-Fe-Laser data. The plot represents results for 4 different reservoir size.

For linear units weights on cycles (3(a)) and loops (3(b)) that are (in absolute value) greater than 1 lead to instability of the system, which was expected.

Figure 3(b) Results for the chain graph with self loops The plot represents results for 10 different self loop weights for reservoir size 30.

The reservoir with non-linear units outperformed the linear units reservoir(see fig.3(a)).

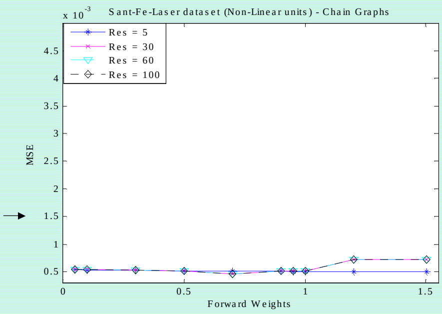


Figure 3(c) Results for the cycle topology for Santa-Fe-Laser data. The plot represents results for 4 different reservoir size.

The increase in the size of the reservoir shows slight improvement in the network performance.

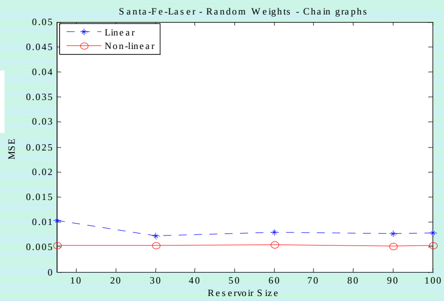


Figure 3(d) Results for the chain topology for Santa-Fe-Laser data. The plot represents results for random weight chain topology for reservoir size 5, 30, 60 and 100.

Conclusion

In the course of data analysis, the following observations were recorded:

- ***Connection topologies***

  The network shows decrease in the performance for the connection weights, for connection weights leading to 1.

  The self loops weights close to 1 the network performance gets worse.

- ***Node complexity***

  The non-linear units perform better than the linear units.

- ***Reservoir size***

  The experimentation showed that, network performance was improved with the increase in the size of the reservoirs.

References

1. Jaeger, H. (2001) "The Echo State Approach to Analysing and Training Recurrent Neural Networks", Technical Report- GMD Report 148, German National Research Center for Information Technology.

2. Cernansky, M., Tino, P.(2008) Predictive Modelling with Echo State Networks, In *18th International Conference on Artificial Neural Networks - ICANN 2008,* Accepted. Lecture Notes in Computer Science, Springer-Verlag, 2008.

Acknowledgements
I would like to express my gratitude to all those who gave me the possibility to complete this dissertation. I am deeply indebted to my supervisor Dr. Peter Tino for his help, guidance and encouragement throughout the second mini-project and the final project.