A review on identification of global minima using Radial Basis Function Network in the prediction of chaotic motion

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Abstract:

RBFN stands for Radial Basis Function Network. It is a type of artificial neural network that uses radial basis functions as activation functions. RBFNs are commonly used for various machine learning tasks, including function approximation, pattern recognition, and classification. In an RBFN, the network is composed of three layers: an input layer, a hidden layer, and an output layer. The input layer receives the input data, which is typically a vector of features. The hidden layer contains a number of neurons, each associated with a radial basis function. These radial basis functions compute the similarity between the input data and their respective centers. The radial basis functions in the hidden layer are responsible for transforming the input data into a higher-dimensional feature space. Each function represents a localized "bump" centered at a specific point in the input space. The bumps are typically Gaussian functions, but other radial basis functions can be used as well.

Keyword: Radial basis function network, global minima, mean square error, optimization.

1. Introduction

The output layer of the RBFN combines the activations from the hidden layer to produce the final output. This layer performs a weighted sum of the hidden layer activations, where the weights are adjusted during the training phase to optimize the network's performance on a specific task. The output can be a scalar value for regression tasks or a probability distribution for classification tasks.

Training an RBFN involves two main steps: center selection and weight adjustment. The center selection step determines the positions of the radial basis functions in the input space. Common methods for center selection include clustering algorithms such as k-means or using a subset of the training data points.

Once the centers are selected, the weights of the network are adjusted using techniques like least squares or gradient descent. The goal is to minimize the difference between the network's output and the desired output for the given training data.

RBFNs have several advantages, including their ability to approximate any continuous function to arbitrary accuracy given a sufficient number of radial basis functions. They also tend to have good generalization properties and can handle noisy or incomplete data. However, RBFNs can be computationally expensive to train and may require careful tuning of their parameters.

Overall, RBFNs are a powerful tool in machine learning, particularly for problems that involve non-linear relationships between input and output variables.

The artificial neural network (ANN) architecture as Radial Basis Function Network (RBFN) is widely used by the researcher in their application around the world. Since climate and rainfall are highly nonlinear by its nature so that it is very difficult to predict exactly for chaos forecasting. Artificial Neural Network is an information processing system enthused by biological system such as brain. A biological system consists of highly interconnected neurons. The neurons are connected to each other through links having weight. Just like the human brain, it can get inputs, process them and produces the significant output. A multilayer ANN contains an input layer of neurons, an output layer of neurons and one or more hidden layer of neurons. The pattern recognition and prediction in a deterministic approach through ANN technology on the basis of RBF algorithm is found to be the most competent way. The advantage of artificial neural network is that they can be used to extract data, detect trends. They can predict the pattern which is not provided during training.

RBFN is one of the architecture in ANN. Experimentally available data is feed as the training pairs to the RBFN for learning. The learning rate of RBFN may be modified if desired. Accuracy of the system is dependent on the learning rate and Epochs. Epoch is the number of times the loop of code executed to obtain minimum error. Here, we have designed the RBFN in such a way that it has a higher learning rate and a greater accuracy. The design incorporates the Sigmoid normalization to convert the application data adaptable to the processing of RBFN.

The main objective of this research is to find the point where the rate of MSE is too minimum so called global minima, so with the help of RBFN model we can variate the value of learning rate and momentum factor, and will find those value of learning rate and momentum factor where the rate of MSE is too minimum.

2. Methodology

The various parameters used in the training algorithm are as follows-
The algorithm for training a Radial Basis Function Network (RBFN) typically involves the following steps:

1. **Data Preprocessing:**
- Normalize or scale the input data to ensure that each feature has a similar range or distribution.
- Split the dataset into training and testing sets to evaluate the performance of the trained RBFN.

2. **Center Selection:**
- Determine the centers for the radial basis functions in the hidden layer.
- Common methods include clustering algorithms such as k-means selecting a subset of the training data as centers.

3. **Spread/Width Determination:**
- Set the spread or width parameter for each radial basis function.
- The spread controls the region of influence for each RBF and can be a fixed value or determined dynamically during training.

4. **Compute Activations:**
- Calculate the activations of the hidden layer neurons for each input data point.
- The activation is typically a measure of similarity or distance between the input data and the corresponding RBF center.
- Common choices for the activation function include Gaussian functions or other radial basis functions.

5. **Calculate Weights:**
- Determine the weights connecting the hidden layer to the output layer.
- The weights are typically calculated using techniques like least squares, linear regression, or gradient descent.
- The goal is to minimize the discrepancy between the RBFN's output and the desired output for the training data.

6. **Evaluation and Optimization:**
- Evaluate the performance of the trained RBFN using the testing set.
- Adjust the RBFN's parameters, such as the number of hidden units or the spread, based on the testing results to improve generalization and avoid overfitting.
- Repeat steps 2-6 until the desired performance is achieved or a stopping criterion is met.

7. **Prediction:**
- Use the trained RBFN to make predictions on new, unseen data by propagating the input through the network.
- The output of the RBFN can be a continuous value for regression tasks or a

probability distribution for classification tasks.

It's important to note that there can be variations in the RBFN algorithm depending on the specific implementation, problem domain, and optimization techniques used. The steps outlined above provide a general framework for training an RBFN.

3. Literature Review

Basu & Andharia (1992) found that the rainfall data time series shows a chaotic behavior with its predictors not only to be chaotic in nature but also suffer from epochal changes.

Guhathakurta et al (1999), Rajeevan et al. (2004), Thapliyal & Rajeevan (2003) have found that the identification of internal dynamics of rainfall for long period are approximately difficult.

Guhathakurta (1998, 2000, 2006); Guhathakurtaet al. (1999);Rajeevan (2001); Rajeevanet al.(2004); Thapliyal&Kulshrestha (1992);Thapliyal (1997); Thapliyal & Rajeevan (2003); Krishnamurthy &Kinter (2003);Krishnamurthy & Kirtman (2003) and Sahaiet al. (2002) have found that statistical models have inherent limitations such as the models are not useful to study the highly nonlinear relationships between dependent (i.e., target) and independent (i.e., predictors) parameters, even if one considers models like power regression. It is concluded that the identification of internal dynamics of rainfall for long period (chaos) is approximately difficult From Rumelhart et al. (1986), the Artificial Neural Networks (ANNs) have been proved to be a powerful soft computing technique for prediction of highly complex and nonlinear systems like chaos. ANNs belong to the black box time series models and over a relatively flexible and quick means of modeling. These models can treat the non-linearity of system to some extent due to their parallel architecture.

Guhathakurta (2006) has successfully applied RBFN in long-range forecast of monsoon rainfall over very smaller Indian region ``Kerala''. In this forecast, past recorded rainfall data time series is used to forecast the future value. In many other cases RBFN is found to best for prediction of other climate activities.

Sivanandam et al. (2006) and Kumar (2007) pointed out that a small `α’ is used to avoid major trouble of the direction of the learning, when very unusual pair of training pattern is presented in chaos.

Enireddy et al. (2010) used the RBFN model for predicting the rainfall data time series. 99.8% and 94.3% accuracy were obtained by them during the training and testing period respectively. From these results they concluded that rainfall can be predicted in future using the same method. Sawaitul et al. (2012) and Kowar et al. (2013) also performed experiments on forecasting future weather to arrive at the conclusion that RBFN algorithm can also be applied on the weather forecasting data. Thus it is concluded that the ANNs are capable of modeling in identification of internal dynamics of chaotic motion.

H. El Shafie et al., (2012), have found the RBF neural network model has significantly better stability than the MR model. Despite the fact that using artificial intelligent modeling in forecasting was a reliable way to make a conservative estimate for the actual monitoring data, overall there may be a limit on the RBF neural network. Kowar et al. (2013) have found that the successful applications of ANN models may be in the simulation of chaotic series with high degree of accuracy. A broad literature review from 1986 to 2012 has been carried out. In support of the same experiment of RBFN system in deterministic forecast, we have gone through the literatures.

According to Basu & Andharia (1992); Mohammed (2010); Patil & Ghatol (2010) it is mainly because of the chaotic behavior of rainfall data time series and due to the same reason, researches in these fields are being conducted for a long time, but successes of these models are rarely visible. Many researchers have introduced number of models for chaotic series forecasting. No multiple models have forecasted the same situation in exactly same way with same results. At the same time, no single model is reliable for chaos forecasting.

Cohen S. et al., (2012), introduced the problem of bad initial cluster centers becomes worse when the number of training patterns increases. It is thus more important to correct for this problem in those cases when one expects the size of the data set to be sufficient for robust parameter estimation. the improved performance of the resulting algorithm on 8 data sets and compared his approach with the current state of the art in RBF training algorithms.

Sheela G. K. et al. (2012), proposed RBFN model is accurate than BPN model. Wind speed prediction model is a necessary tool in wind farms. The selection of parameter is important in the performance of models. The model which shows reduces RMSE, uncertainty of prediction and calculation time.

Yue W. et al. (2012), given a comprehensive survey of the RBF network. Various aspects of the RBF network have been described, with emphasis placed on RBF network learning and network structure optimization. Topics on normalized RBF networks, RBF networks in dynamic systems modeling, and complex RBF networks for handling nonlinear complex-valued signals are also described.

Vachkov G. et al. (2014), showed that despite the smaller number of parameters, the simplified RBFN models are able to achieve almost the same accuracy, as the Reduced RBFN models. Therefore the Simplified RBFN could be the preferable choice for creating RBFN models.

Foqaha M. et al. (2016), presented the improve approximation accuracy and reduce the root mean square error and sum square error compared with other approaches. The results of the simulations show that HRBFN-PSO is an effective method that is a reliable alternative for approximation nonlinear mathematical functions. The quality of the results improves the convergence.

Mosavi M. R. et al. (2017), showed that the SFSA algorithm due to a simple structure and the ability to explore the search space is able to provide much better results in terms of convergence speed and classification accuracy in compare to benchmark algorithms. Also due to the simple structure of multi-layer perceptron NN, it can be used as a classifier in future works instead of RBF network.

Awad M. (2018), combining GAs with RBFN applied on a proposed hierarchical topology of sub-RBFNs with the aim of determining the optimal topology of the proposed model and the optimal learning parameters of the training algorithm. Which can be use to improve the model for train ing the network.

Simon S. Du et al. (2019), showed that gradient descent on deep over parametrized networks can obtain zero training loss. Our proof builds on a careful analysis of the random initialization scheme and a perturbation analysis which shows that the Gram matrix is increasingly stable under overparametrization. These techniques allow us to show that every step of gradient descent decreases the loss at a geometric rate.

Ioannis G. Tsoulos et al. (2022) proposed for the Multistart global optimization method. The new technique improves on using a limited number of samples from the objective function in order to construct an estimator of the function. The estimator in the present work was an RBF neural network

4. Conclusion

The identification of internal dynamics of chaotic motion and its prediction for future is very difficult. While RBFN model is sufficient to overcome such shortcomings, with a proper selection of appropriate parameters is all most importance and a challenging task. To identify the global minima, the network will be train for identification of internal dynamics of chaotic motion and in prediction of future values by past recorded data series.

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