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Auto Associative Neural Networks for Nonlinear Principal Components Analysis of Sea Surface Temperature Anomalies in Indian Ocean

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Abstract—*Auto-associative Neural Network model has been used for non linear principal component analysis (NLPCA) to generate nonlinear features in the Reynolds reconstructed SST time series. It has been found that the Non linear empirical orthogonal function (EOF) analysis provides a new reduced set of features which contain the important variations in the data and which could not be derived using linear PCA. It is expected these feature vectors will be used as predictors for the future SST anomalies using the artificial neural network (ANN) model.*

Keywords*: Sea Surface Temperature, Auto- associative Neural Network, Principal Component, Non Linear Principal Component Analysis, Correlation Coefficient]*

1. INTRODUCTION

Owing to the large spatial span of the ocean, it may not be feasible to investigate the variability of the SST on point to point basis. Principal Components Analysis (PCA) [1], also known as Empirical Orthogonal Functions (EOF) Analysis, has been widely used in the analysis of variance in the atmospheric or oceanic parameters where the dimension of the data set is large [2]. PCA reduces the dimension of the data. The purpose is to transforming the data from highly-correlated variables domain to one described by a set of (Orthogonal) eigenvectors. Linear PCA extracts the linear latent dimension. If the data is inherently nonlinear, the linear PCA will not identify the hidden dimensionality correctly and there will be no effective computational gain. In such cases nonlinear PCA may prove to be a vital tool. NLPCA equivalent of nonlinear generalization of traditional PCA. It generalizes the principal components form linear mapping to nonlinear mapping. Kramer [3] has proposed a neural network technique for generalizing the concept of PCA in its nonlinear form, and is now used by the researchers in many fields. Monahan [4] perform comparisons between the NLPCA and PCA methods. Although Monahan [5] analyzed the tropical pacific SST by NLPCA.

AANN is special kind of a feed forward multilayered neural network where the target data set is identical to input data set and the input and output layers are connected via weights. In training we have to adjust the network weights till the outputs matched the inputs. The value of the weights will show relationship between various input processing elements. AANN are being increasingly used to solve various problems like signal processing, pattern recognization, speech recognization etc. Moumi [6] has proposed a method for image recognition with the use of auto ANN. Bishop [7] have demonstrated the auto ANN is a feed forward neural network with desired output. NLPCA using three-hidden-layer feed-forward neural networks to perform the identity mapping, where the output of the network and the network input are non-unique. The hidden layer of the network (containing one neuron) work as a bottleneck layer of the network, which forces the reduction of data dimensionality for data interpretation and for forecasting

In the present study we analyze the SST anomalies in the Indian Ocean region for effective nonlinear dimension reduction of using auto-associative neural network model. Comparison with traditional PCA is done and it is observed that NLPCA explains better variance of the data. Methods to reduce the dimension of the gridded data in spatial sense are discussed. Scope of similar approaches for doing NLPCA is outlined.

2. METHODOLOGY

The method essentially involves time series prediction. The monthly extended reconstructed SST called ERSST data from January 1871 to may 2004 has been used for the present analysis. SST anomaly is then calculated. Autocorrelation analysis was done for the determination of predictors for which lag 1-24 has been used. Based on the results, three predictors are selected that is lag1, lag 12 and lag24 as they have been found to have maximum correlation (more than 0.5).Then normalization of data is done:

$$Xn = (((a-b) * (Meanx - amin)) / (bMax - aMin)) + b \qquad 2.1$$

Where a is 0.2 and b is 0.8, Meanx is the SST anomaly, aMin is the minimum anomaly for the month, bMax is the maximum anomaly for the month and Xn is the normalized value of the anomaly.

After determining the predictors, the entire time series has been divided in to training and testing set where 1300 data points are used for training the data and 296 used for testing the data.

These predictors are used to find the EOF. The results of the EOF analysis shall provide a new reduced set of features which will contain the important variations in the data without losing much information. Separate auto-associative neural network model have been designed. The NLPCA method uses AANN topology to generate nonlinear features. The particular network architecture employed three hidden layers, including an internal bottleneck layer of fewer nodes than either input or output layers. AANN is created, with three neurons in the input layer and 4 neurons in first hidden layer, one in second hidden layer, 4 in third hidden layer and three neurons in output layer. Activation function tan sigmoid is used in hidden layer where as purelinear activation function is used in output layer. Trainlm function is used for training the network. Thus identical mapping is performed by the network in such a way that input and output are identical.

Variance of PCA and NLPCA is calculated.

3. RESULTS AND DISCUSSION

Fig. 3.1 shows the plot between the lag and CCs of the SST time series. In the (Fig. 3.1) Autocorrelation analysis was done for the determination of predictors for which lag 1-24 has been used. Based on the results, three predictors are selected that is lag1, lag 12 and lag24 as they have been found to have maximum correlation (more than 0.5).

Fig. 3.1 shows the plot between the lag and CCs of the SST time series.

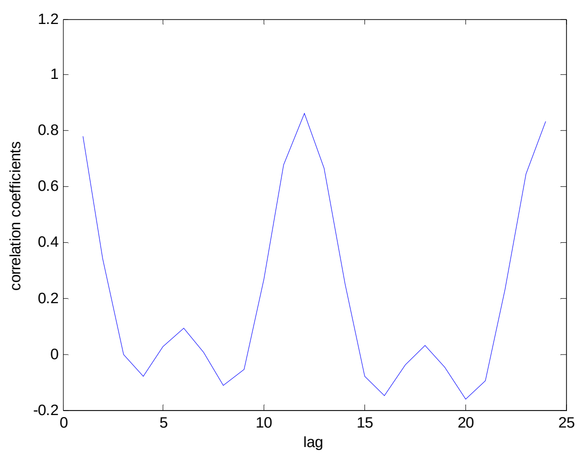

Fig. 3.1: Plot of autocorrelation (with lag 1 to 24) of the SST time series.

Fig. 3.2 shows the 3-D distribution of SST anomalies and the leading principal component extracted through simple statistical method of covariance matrix. The dots shows the SST anomalies (scaled). The red line shows the first linear PC of the three predictors. Fig. 3.3 shows the 3-D distribution of SST anomalies and the first nonlinear principal component extracted by using auto associative ANN model. The dots shows the SST anomalies (scaled). The red line shows the NLPCA of the three predictors. It is found that NLPCA explains **81.42%** variance of the data which is better than **80.71 %** variance explained by the linear PCA.

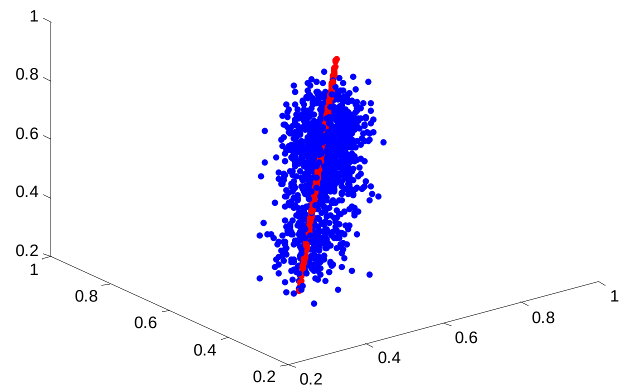

Fig. 3.2: Plot the first linear Principal Component (PC) of the three predictors (XYZ).

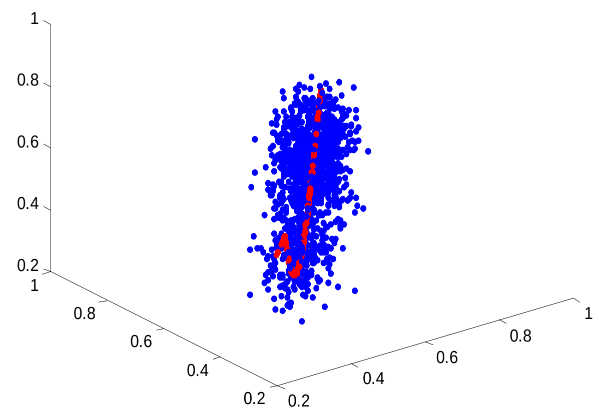

Fig. 3.3: Plot the NLPCA of the three predictors. Based on AANN

4. CONCLUSION AND FUTURE SCOPE

EOF Analysis or PCA has been in use for the dimension reduction problem in meteorology and oceanography since long. SST being spanned in a large spatial domain contains significant correlations among various indices which can be removed by working in the latent dimensions domain rather than in the domain of the SST itself. Same is true about the temporal variability. EOF analysis is a tool for the identification of such hidden dimensions.

A limitation of traditional EOF analysis approach is that it can discover only linear correlations in the data and hence the principal components that are obtained by the EOF analysis are linear principal components. NLPCA is a new approach deployed to discover such nonlinearity in the data. Thus we get the principal components that are nonlinear and explain better variance in the data. AANN has been designed to extract nonlinear features among the predictors. It is observed that first NLPC explains slightly better variance of the data than the linear PC.

It is expected the linear as well as nonlinear PCs will be use as a predictors for prediction of the Indian Ocean SST.

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