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Global Synchronisation on Multilevel Time Series Prediction

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A B S T R A C T

In this paper, the problem of stochastic synchronization analysis is investigated for a new array of coupled discrete- time stochastic complex networks with randomly occurred nonlinearities (RONs) and time delays. The discrete-time complex net- works under consideration are subject to: 1) stochastic nonlinearities that occur according to the Bernoulli distributed white noise sequences; 2) stochastic disturbances that enter the coupling term, the delayed coupling term as well as the overall network; and 3) time delays that include both the discrete and distributed ones. Rapidly evolving businesses generate massive amounts of time-stamped data sequences and cause a demand for both univariant and multivariate time series forecasting. For such data, traditional predictive models based on auto regression are often not sufficient to capture complex nonlinear relationships between multidimensional features and the time series outputs. In order to exploit these relation- ships for improved time series forecasting while also better dealing with a wider variety of prediction scenarios, a forecasting system requires a flexible and generic architecture to accommodate and tune various individual predictors as well as combination methods.

Keywords- Global Synchronization, Feature Generation and Selection, Ensemble Generation, Model Diversification, neural network randomly occurred nonlinearity (RON), stochastic complex networks, stochastic coupling.

Introduction

The need to understand large, complex, information-rich data sets is common to virtually all fields of business, science, and engineering. In the business world, corporate and customer data are be- coming recognized as a strategic asset. The ability to extract useful knowledge hidden in these data and to act on that knowledge is becoming increasingly impor- tant in today's competitive world. The entire process of applying a computer-based methodology, including new techniques, for discovering knowledge from data is called data mining.

Data mining is an iterative process within which progress is defined by discovery, through either automatic or manual methods. Data mining is most useful in an exploratory analysis scenario in which there are no predetermined notions about what will constitute an "interesting" outcome. Data mining is the search for new, valuable, and nontrivial information in large volumes of data. It is a cooperative effort of humans and computers.

The two primary goals of data mining tend to be prediction and description. Prediction involves using some variables or fields in the data set to predict unknown or future values of other variables of interest. Description, on the other hand, focuses on finding patterns describing the data that can be interpreted by humans. Therefore, it is possible to put data-mining activities into one of two categories:

1) Predictive data mining, which produces the model of the system described by the given data set, or
2) Descriptive data mining, which produces new, non- trivial information based on the available data set.

II. Proposed Work Approach

In this proposed system, a generic architecture is proposed for combining predictors and describes on possible implementation with neural networks generating the individual forecasts. This approach is applied not only to the univariate time series but also flexible enough to deal with multivariate series or other more general prediction tasks. In this approach we undergoes the following steps such as feature selection, training of the individual models, model selection and post processing of outputs.

Feature Generation and Selection

In this module we are presenting the data mining approaches for the generation and the selection of the features from the given input data. The temporal dimension of the data increases the potential scope of the M-feature space to M. L dimensions where L denotes the length of the time series. This means that whatever set of M features describes the actual problem, its temporal variability also enforces consideration of the whole available history of feature series as potential inputs to the predictive model. Careful selection of features is, therefore, of much greater importance in comparison to the static-data prediction problem. On the other hand, temporal feature selection depends strongly on the availability of features in their temporal relation to outputs as well as the depth of outputs prediction.

Individual Predictors

Here in this section due to the continuous nature of typical time series of outputs, this model should be capable of handling multiple inputs and multiple outputs. Neural networks are considered to be a universal nonlinear regression model with the ability to control its complexity and high predictive diversity that can be further encouraged by varying network architectures and initialization conditions, cross-training and even simple injection of noise to the data. Given all these advantages, we decided to choose a simple Feed forward Multilayer Perception (MLP) as a base model that would be used to test the presented architecture against standard predictors and combiners and to take part n the NN3 and NiSIS competitions. The chosen NN is trained using an efficient iRPROP+ algorithm that scales linearly with the number of parameters to be optimized.

Ensemble Generation

In this module we describe an ensemble generation method to makes the model to perform better. The ensemble concept has a slightly different notion than the combinations mentioned earlier, as ensembles group individual methods sharing one functional approach, but differ in, for example, parameterization or training data used. There are many ways the individual models can be combined in an ensemble: the simplest is just by averaging the individual models' outputs, and another popular method is the linear combination of outputs. Complexity of such systems dramatically increases, but it can be controlled by adjusting the number of individual models and their internal complexity.

Model Diversification

In order to make the model more generalization ability, we apply a set of diversification strategies are applied to increase the complementarily of the constituent ensemble member models. Here we used an ensemble of M neural networks with different randomly selected architectures of hidden layers limited. All individual models were cross-trained on exclusively selected subsets of data additionally subjected to the injection of up to 5 percent of noise. The networks were trained up to varied numbers of epochs after which the iRPROP+ learning terminated the model building process. The whole training process has been integrated with the k-fold cross-validation error estimation method that produces M error rates used further for model selection and combinations at later stages of the prediction process. Overall, the training process involves M individual models' learning processes and scales linearly with the size of ensemble.

Model Selection

Here we have presented architecture with the ensemble of neural networks; the first level is occupied by k groups of predictors with on average M/k predictors in each group. Each group is trained on different parts of the data, which have been randomly permutated and partitioned to obtain k disjoint data subsets. Our selection strategy promotes a single best predictor from each of the k cross-validation groups to the next step, at which a subset of the desired number of best predictors is selected and their outputs are ultimately combined by means of an average operator to return the final prediction.

Post-processing And Tuning

In this module due to overcome or to reduce the impact of certain errors and any other problems, we present a post-processing stage into our architecture. In our case, the post-processing covers an original smoothing technique applied to the predicted series obtained for the validation set. The parameters of this smoothing have been fitted to minimize the error rate on the validation set and once fixed, they are kept constant to deliver smoothed predicted series on the testing set. The proposed model comes in two stages. First, a filtering procedure is used to remove high-level noise components. It compares the predicted signal with the bidirectional k-step moving average of this signal and replaces the original signal with the aggregated signal where the difference between the two signals is greater than r times the standard deviation of the original signal. There suiting signal is further smoothed using the same bidirectional n-step moving average yet in general using different steps for the aggregation.

Accuracy of Neural Network

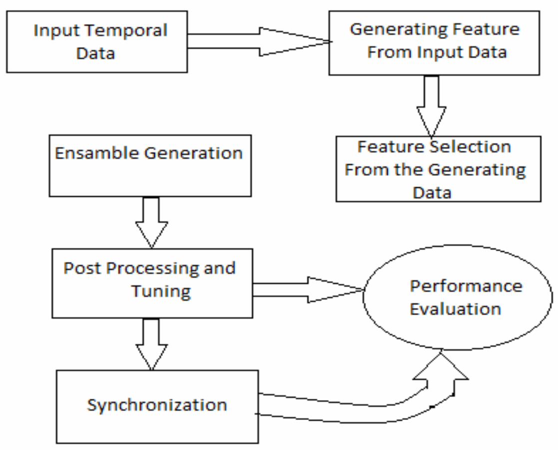
Here in this module Phase Only Correlation is used to enhance the recognition accuracy of neural network and reduce the time required for POC by refining its input. The first five high response values of neuron are selected from forty responses for POC post processing. This amalgamation of data from two recognition techniques have enabled us to look into the new dimension of not only improving the accuracy of neural network but also to decrease the computational and time cost of phase only correlation.

Global Synchronization

The proposed approach is enhanced again by a Global synchronization method. By employing the linear matrix method and stochastic analysis theories, several delay dependent sufficient conditions were obtained which ensures the asymptotic synchronization in mean square sense for the continuous or discrete time stochastic complex networks with time delays.

Performance Evaluation

Finally in this module we evaluate the performance of the proposed approach with the existing techniques in this time series prediction problem.



III. Result

By adopting the new architecture with the ensemble of neural networks as described the strength of the architecture is evaluated by direct comparisons of prediction performances carried out on the same data. But the training procedure of the neural network is one of the complex and time-consuming job. With increasing the number of subjects, the number of epochs also keeps on increasing. The training time directly relates to the accuracy produced by neural net. As the individual implementation of POC based face recognition requires 40,000 comparisons (correlations) which requires 10.335 sec/image. The time required for Neural network is .1550 sec/image but the accuracy is not enough, therefore proposed technique provides a good substitute keeping time (1.2297 sec/image) and accuracy intact.

By using a global synchronization method non linearity and time delay can be improved. So by synchronizing the performance can be much better than usual neural networking method and also POC method. Mean square error (MSE) can be checked for all epochs and evaluation can be done.

IV. Conclusion

This work promotes a new architecture for time series prediction, tackling recently arising challenges of a generally increasing volume of time series data exhibiting complex nonlinear relationships between its multidimensional features and outputs. It combines a multilevel architecture of highly robust and diversified individual prediction models with operators for fusion and selection that can be applied at any level of the structure. Additionally, the system applies an intelligent smoothing algorithm as an example of the post prediction step that often leads to significant performance gains, particularly, if the predicted time series contains a significant noise component.

The individual MLP-type neural networks were included as examples of universal regression. They have been highly diversified by means of varied internal architectures, different weight initializations, and cross training on different partitions of the training data with an injected noise component. All these diversification techniques are aimed at creating highly complementary predictors with better generalization abilities than any individual model. The model building process is supported by the simple, yet effective, greedy feature generation method. The predicted output signal is further validated using an original smoothing technique to remove excessive noise.

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