A Cascading Wavelet-Feed Forward Neural Network Approach for Forecasting Traffic Flow

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ABSTRACT

Predicting Traffic flow in the busiest cities has become a popular research area in the past decades. The rapid development of intelligent traffic management system attracts the software industry to come up with efficient tools for traffic prediction over the roads. In this study, Discrete Wavelet Transformation (DWT) is employed with Artificial Neural Network (ANN) to forecast the traffic flow over the roads by analyzing loop sensor's data. An Information Theoretic Approach has been extended for choosing the number of nodes in hidden layer of Neural Network for the proposed model. The proposed hybrid model was compared with standard Artificial Neural Network (ANN) model. The forecasted results showed that proposed joined Wavelet and Feed Forward Neural Network (WFFNN) worked much well over the experimental data than ANN model.

Keywords

Time series, Discrete wavelet transformation, Feed forward neural network, Traffic flow.

1. INTRODUCTION

Significant statistical information for both past and near future can be extracted by analyzing time-series data. Traffic congestion, volumes, origins, routes and other road-traffic performance metrics are useful for designing urban traffic control systems and these types of data typically exhibit a periodicity in time. Traffic data can be collected manually or via static sensors such as traffic cameras and loop detectors. In this paper, we analyzed time-series loop sensor data and proposed a model for daily traffic forecasting (traffic condition around the day in specific time-gaps) for next upcoming weeks. Two datasets (Dodgers and TSF generated data) have been used for testing purpose of the proposed model [3, 2]. We analyzed and trained the model with 18 weeks traffic counts (car counts of every 5 minutes in a day) obtained from Dodgers loop sensor dataset and forecasted the traffic condition of upcoming seven weeks. Each day contains 288 time-slice predictions. In the similar way, we trained our model with the average velocity of 4000 observations (recorded the average velocity in every five seconds) obtained from TSF generated data and forecasted what will be the next 1000 observations or average velocity of the simulation model. So, the main focus of this paper is analyzing time-series loop sensor traffic data and examine the applicability of wavelet-feed forward neural network based modeling.

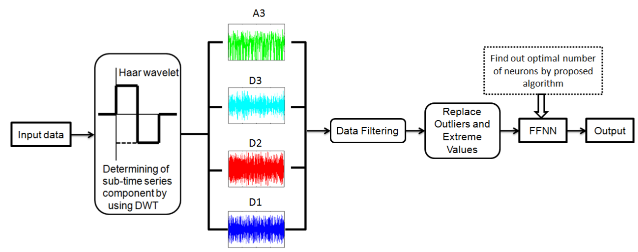

Figure 1: Schematic diagram of the proposed WFFNN model.

In this study, an algorithm has been proposed based on theoretic approach (Jump Method) and it is observed that proposed algorithm works well for choosing the best number of neurons for a neural network. Wavelet-Neural Network approach can be useful for different application fields. Here, we used the technique in analyzing traffic data and added data filtering for different sub-signals before summing up the sub-signals and an algorithm for determining the optimal number of neurons on the training period of the proposed model.

Wavelets analysis is localized in both time and frequency while the Fourier transform is only localized in frequency. So, combine model of wavelets and neural network has been used for analyzing time series data and enhance the prediction performance of neural networks. This paper deals with loop sensor's data and forecasts the traffic congestion by counting the cars or average velocity of vehicles. The main purpose was employing wavelets to analyze large loop sensor time-series traffic information and extract the traffic condition over time.

2. MODELING STRATEGY OF WFFNN

This study employed Discrete Wavelet Transformation cascaded with Feed Forward Neural Network. Here, Mallat Discrete Wavelet Transformation has been adopted. Mal-

Table 1: Testing results of Dodgers loop sensor dataset.

Number of Neurons	Proposed WFFNN Model			ANN		
	MSE	RMSE	MAPE(%)	MSE	RMSE	MAPE(%)
7	8.1524	2.8552	3.9605	37.0948	6.0906	20.9647
8	7.0129	2.6482	3.7494	35.7893	5.9824	16.7499
9	7.1152	2.6674	4.0770	28.7240	5.3594	11.4475
10	7.1354	2.6712	4.1003	32.2587	5.6797	19.8356

Table 2: Testing results of TSF generated data.

Number of Neurons	Proposed WFFNN Model			ANN		
	MSE	RMSE	MAPE(%)	MSE	RMSE	MAPE(%)
4	5.1040	2.2592	2.2678	23.3926	4.8365	12.2045
5	4.9098	2.2158	1.9827	24.2849	4.9279	14.3829
6	4.9194	2.2180	2.2012	20.3916	4.5158	9.5893
7	5.0923	2.2566	2.2156	19.2938	4.3924	6.1047

lat's algorithm can be expressed as follows [5]:

$$\begin{aligned} a_{j+1} &= Qa_j \texttt{ where j=0,1,2,...,J} \\ d_{j+1} &= Ga_j \texttt{ where j=0,1,2,...,J} \end{aligned} \quad (1)$$

Here, in the equation Q and G are low pass filter and high pass filter respectively. If a_o represents the original time series T, then T can be decomposed to $d_1, d_2, d_3, ..., d_j$ and a_j, where J is the scale. a_j and d_j are the approximated coefficients and detail coefficients of original time series.

Firstly, the input data (C_t, car counts in every five minutes in Dodgers loop sensor data and V_t, average velocity in TSF generated data) have been decomposed into a certain number of sub-time series components by DWT. Input time series first decomposed into approximation and detail coefficients. In this way decomposition process is iterated and successive approximation signals being decomposed in turn.

Best results for two data sets have been obtained by three decomposition level. Input data have been decomposed with Haar wavelet function and Daubechies wavelet function. Consequently, D_1, D_2, D_3 were detail time series and A_3 was approximation time series. To get more accurate results we employed Interquartile Range (IQR) for clustering and finding the outliers and extreme values [1]. In this study, outliers have been replaced with mean values of respective data sets. Extreme values have been normalized.

In this study, the wavelets sub series $\{D_1, D_2, D_3, A_3\}$, were summed together after removing insignificant coefficients , which is similar as [4], and feed to a Feed Forward Neural Network at time t and original time series at time $(t+t_f)$ are outputs of FFNN, where t_f is the length of time to forecast. Predicted output sets were later compared with the actual values. Number of neurons of the hidden layer of FFNN has been chosen by proposed algorithm (Algorithm 1) and it is observed that proposed algorithm was very effective for the experimental datasets. The schematic diagram of proposed model is shown in figure 1.

Algorithm 1 Extended Jump Method for Finding Neurons

The MSE (Mean Square Error) d_k equals the variance of residuals generated by fitting the neural network model with k nodes.
for k=1 **to** k_{max} **do**
  Calculate MSE, d_k
end for
for k=1 **to** k_{max} **do**
  Calculate priority factor P_k for d_k (Assigning priority value or weight based on MSE value).
end for
Choose two positive numbers $v > 0$, called the transformation power and $b > 0$, called priority bias factor.
for k=1 **to** n **do**
  if k=1 **then**
    $J_k = b.P_k.d^{-v}$
  else
    $J_k = b.P_k.d_k^{-v} - d_{k-1}^{-v}$
  end if
end for
The best number of nodes is the number k lies between two highest picks such that Node number of $(J_{second\_highest}) <= k <=$ Node number of $(J_{top\_highest})$.

3. EXPERIMENTAL RESULTS

To compare the efficiency of the proposed model, we generated ANN model and tested with the same inputs. Performance indices were presented in Table 1 for Dodgers loop sensor data and Table 2 for TSF generated data. It is clear from Table 1 and Table 2 that MSE (Mean Square Error), RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) values for proposed WFFNN (results of using Haar wavelet have been presented in two tables) model are much better than ANN model.

Although the forecasting accuracy of ANN model in respect of MAPE is 11.4475% for Dodgers loop sensor data and 6.1047% for TSF generated data. Best result for the Dodgers loop sensor data by using WFFNN model found at neuron number 8 with Haar wavelet and MAPE is 3.7494%. Best result for TSF generated data came up with Haar wavelet function by using 5 neurons in the hidden layer and there MAPE value is 1.9827%, which is very much acceptable.

4. CONCLUSION

This paper presented a hybrid prediction approach and it's application based on discrete wavelet transformation and feed-forward neural network. Our proposed model can provide good accuracy in predicting real time traffic and works well over loop detector or sensor data. It can be used as a useful tool for Advanced Intelligent Transport Systems.

5. REFERENCES

[1] F. M. Dekking. *A Modern Introduction to Probability and Statistics: Understanding why and how.* Springer, 2005.

[2] P. Gora. Traffic simulation framework. In *Computer Modelling and Simulation (UKSim), 2012 UKSim 14th International Conference on*, pages 345–349. IEEE, 2012.

[3] J. Hutchins. *Freeway Performance Measurement System (PeMS), "http://pems.eecs.berkeley.edu".*

[4] O. Kisi and M. Cimen. A wavelet-support vector machine conjunction model for monthly streamflow forecasting. *Journal of Hydrology*, 399(1):132–140, 2011.

[5] S. G. Mallat. A theory for multiresolution signal decomposition: the wavelet representation. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 11(7):674–693, 1989.