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Novel Model Based on Wavelet Transform and GA-fuzzy Neural Network Applied to Short Time Traffic Flow Prediction

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Abstract: Precise prediction of short time traffic flow is the key point to realize reasonable traffic control and induce. The intelligent Artificial Neural Network (ANN) can provide effective forecasting performance. However, the prediction precision is influenced greatly by the structure of the ANN. Inadequate design of the ANN prediction model may lead to a low prediction rate. In addition, due to the nonlinear and stochastic of the data, it is often difficult to predict the traffic flow precisely. Hence, a new hybrid intelligent forecasting approach base on the integration of Wavelet Transform (WT), Genetic Algorithm (GA) optimization and Fuzzy Neural Network (FNN) is proposed for the short time traffic flow prediction in this study. The advantages of the proposed method are that the WT can process the nonlinear and stochastic characteristics of the original data and GA-FNN offer optimized ANN model to avoid the influence of the improper ANN structure. By doing so, the forecasting rate can be improved much higher than traditional ways. Three hundred and sixty samples of the practical traffic flow data were collected to validate the proposed prediction model. The analysis results showed that the proposed method can extract the underlying rules of the testing data and improve the prediction accuracy by 15% or better when compared with only ANN approach. Thus, the new WT-GA-FNN traffic flow prediction model can provide practical use.

Key words: Short time traffic flow, prediction, wavelet transform, GA, FNN

INTRODUCTION

Transportation is an indispensable item in the social activities. It is the foundation of the national economy industry and its normal operation ensures the health of the market economy (An *et al*., 2010). Advances in computer science and information technology make it possible to establish high integrated transportation information system. Consequently, the Intelligent Transport System (ITS) becomes a hot topic in the research and application field of transportation construction. Traffic flow prediction is among the most popular research area in the field of intelligent transport system. Accurate and real-time traffic flow prediction is the key fact for traffic control and traffic induce. Short-term traffic flow prediction can make forecast about traffic flow state of the next several minutes to provide real-time effective information for travelers, realize the dynamic route guidance, save travel time, relieve the traffic congestion and reduce pollution, save energy and other purposes (Zamani *et al*., 2010). Therefore, it is imperative to implement short time traffic flow prediction.

Short time traffic flow data is of strong time sequence and belongs to the typical timing time series forecast problems. Some mature prediction models have been applied to short time traffic flow prediction since 1960s (Nejad *et al*., 2009). In general, they can be divided into 4 kinds of prediction methods, i.e., traditional statistical theory based approach, neural network based method and nonlinear theory based method and the integration of the mentioned technologies (Zhao *et al*., 2008; Li *et al*., 2011a; Wen and Lee, 2005). Due to the fact that the traffic system is a complex nonlinear system with time-varying and high uncertainties, the prediction accuracy of existing models can not be satisfactory. The forecasting accuracy need to be improved for real practice applications (Wen and Lee, 2005; Hauser and Scherer, 2001; Heng *et al*., 2009). Since the integration of different analysis techniques can provide better performance than independent use, a new hybrid approach to short-term traffic flow prediction based on Wavelet Transform (WT) and Fuzzy Neural Network (FNN) is proposed in this work. This method has been marked as the advantages of the good nonlinear signal process ability of the WT and the powerful learning

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ability of the FNN. Meanwhile, to achieve the structural parameter optimization of the FNN, the Genetic Algorithm (GA) optimization is employed to obtain good generalization ability of the prediction model. By using the practical dataset for experimental analysis, the results showed that the new method can predict short-term traffic flow effective and the prediction rate is higher than the independent use of the FNN. Hence, the proposed new prediction approach has application importance.

THE PROPOSED METHOD

Due to the interference of inside and external excitations, the short-term traffic flow is a kind of typical non-stationary signal. The different signal components of short-term traffic flow present various characteristics and contribute different roles on the influence on change trend of traffic flow. The general trend of traffic flow is determined by known component and the uncertain interference signals make the actual traffic flow fluctuate nearby the general trend. Available treatment is very important to remove the abnormal interference. WT is a new advanced technique to process non-stationary signal in time-frequency domain (Huang *et al*., 2010). The core of Wavelet Transform (WT) is the multi-resolution analysis. Since, WT can process signals from coarse scale to precise scale, it can reflect not only the overall properties of the signals but also the local information. Because the analysis precision of wavelet transform is adjustable, it can not only locate the high frequency of short composition signal but also analysis the low frequency components. According to different scales of fluctuation, non-stationary signal is decomposed step-by-step into different levels of wavelet sub bands. Each sub band includes signals with varying time-frequency components ranging from low frequencies to high frequencies. Moreover, it can overcome the defect in time domain without any resolution by Fourier analysis and draw more details of the signal information against short-time Fourier transform. Therefore, these wavelet sub bands can reflect the essence and potential rule of the traffic flow more clearly.

In the analysis of short-term traffic flow, the WT is firstly used to decompose the actual traffic flow with 3 levels. Then, the predicted mode for each wavelet sub band is established using FNN and the GA is applied to the FNN optimization. Finally, the traffic flow is obtained by adding up the predictive values of every FNN models.

Wavelet Transform (WT) theory: Statistical characteristic of short time traffic flow shows that the time series of the traffic data can be regards as normal and abnormal components. The normal component always presents low-frequency signals in the measured traffic data which is the main trend of traffic flow while the abnormal component usually presents high-frequency signals. According to the different frequency bands between the normal and abnormal components of the traffic flow, Wavelet Transform (WT) can process the signal and provide both the normal and abnormal components in the low and high frequency bands. Thus, the future traffic trend could be forecasted more precise.

The basic wavelet theory has been introduced in much literature and the detailed derivation of WT is not given in this study. This work describes only a brief introduction about wavelet packet.

Wavelet packet analysis can be seen as the expansion of orthogonal filtering of a function space. It divides the wavelet bands into multi-layers and further decomposes the high frequency part. In addition, it can select proper frequency band adaptively according to the features of the signal to match the signal's frequency spectrum. Wavelet packet involves decomposition and reconstruction. The decomposition procedure can be described as:

$$\left.\begin{aligned} S_{2n}(t) &= \sum_k h_k S_{2n}(2t-k) \\ S_{2n+1}(t) &= \sum_k g_k S_n(2t-k) \end{aligned}\right\} \tag{1}$$

where, signal S (t) is filtered by high pass and low pass orthogonal filters, h_k and g_k. One can be noticed that by reasonable determination of decomposition level the desire width of the frequency bands and the start-stop frequencies can be obtained. Thus, the characteristics and noise in the original signal can be separated. Hence, by signal reconstruction the useful frequency components can be recovered with the noise inference eliminated. The reconstruction procedure can be expressed as:

$$\left.\begin{aligned} S_n(2t) &= \sum_k h_{2k+1} S_{2n}(t-k) + \sum_k g_{2k+1} S_{2n+1}(t-k) \\ S_n(2t-1) &= \sum_k h_{2k} S_{2n}(t-k) + \sum_k g_{2k} S_{2n+1}(t-k) \end{aligned}\right\} \tag{2}$$

Figure 1 shows the Wavelet packet decomposition with three levels, where j (j = 1, 2, 3) denotes the decomposition level, A denotes low frequency band and D denotes high frequency band. The relationship of the original signal and wavelet sub band signals is as follows:

$$S = AAA3+DAA3+ADA3+DDA3+ AAD3+DAD3+ADD3+DDD3 \tag{3}$$

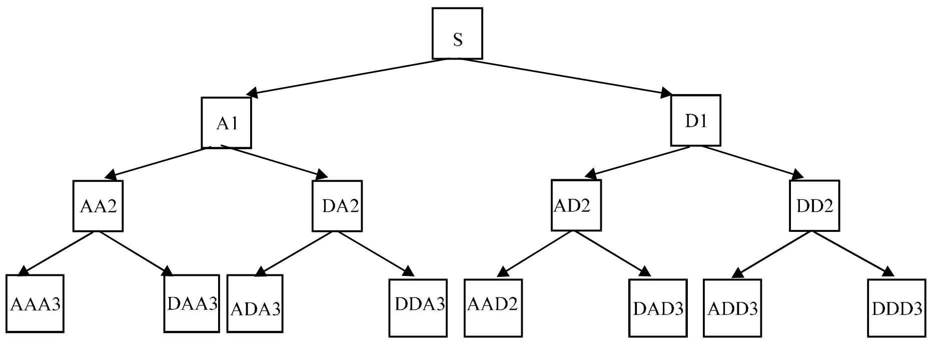

Fig. 1: The tree topology of the Wavelet packet decomposition with three levels

By using wavelet packet decomposition, it is feasible to choose the decomposition level and determine the reconstruction frequency sub bands. That is to say, for the signal with different characteristics, the wavelet packet may relevantly provide the "best" filter group to avoid redundant signal and energy leakage.

GA optimized fuzzy neural network: Fuzzy logic is a new mathematical theory that analyzes analog input values in terms of logical variables that take on continuous values between 0 and 1, in contrast to classical or digital logic which operates on discrete values of either 1 or 0 (true or false, respectively). Fuzzy logic involves with fuzzy concepts-concepts that cannot be expressed as "true" or "false" but rather as "partially true". Fuzzy logic has the advantage that the solution to the problem can be cast in terms that human can understand. This makes it available to carry out missions that are already successfully performed by humans. Thus, Fuzzy method has been widely used in various aspects. However, the determination of membership functions depends on human experts and experiences which decrease the adaptation ability of the fuzzy approach (Li *et al*., 2011b, 2010b; Park *et al*., 2003; Li *et al*., 2010a; Luo *et al*., 2010; Li and Yan, 2011). Since the integrated fuzzy logic and ANN provides more powerful learning ability, we use the Artificial Neural Network (ANN) to auto-tune the membership functions of the fuzzy inference in this study (Li *et al*., 2011a). Figure 2 shows the typical structure of FNN.

The FNN consists of input layer, fuzzy layer, hidden layer and output layer. The input layer connects with input feature vector $P = [p_1, p_2,..., p_a]^T$. The fuzzy layer is used to fuzz each input p_a to get corresponding fuzzy membership values $x_b = \mu_{Aab}(p_\alpha) = [q_{1b}, q_{2b},..., q_{ab}]^T$. The Gaussian function was adopted as the fuzzy membership function that is:

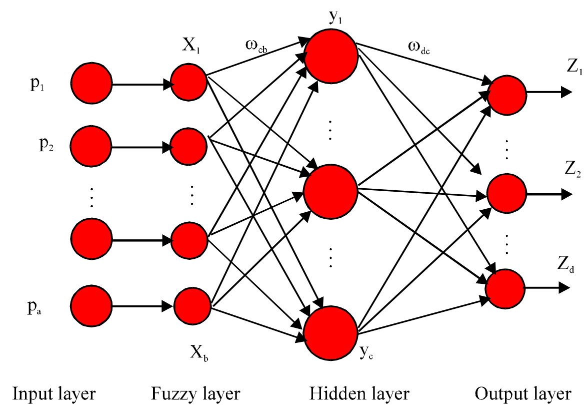

Fig. 2: The typical structure of FNN

$$\mu_{Aab}(p_a) = \exp\left[-\left(\frac{p_a - \alpha_{ab}}{\beta_{ab}}\right)^2\right] \tag{4}$$

where α_{ab} is the center of membership function and β_{ab} is the width of the function. Hence, the output of the fuzzy layer is $X = [x_1, x_2,..., x_b]$. In the hidden layer, for the c neuron nodes, the weights ω_{cb} were used as the fuzzy relation matrix to perform fuzzy inference rules. Then the singleton output of the *c*th fuzzy rule is:

$$y_c(x_b) = \omega_{cb}\, x_b \tag{5}$$

The fourth layer outputs the fuzzy decision of the FNN. The weighted average method for inverse fuzzy was used in this study. One can note that the main purpose of the FNN is to optimize the FNN coefficients. The traditional way is to train the FNN by Back Propagation (BP) algorithm. However, the BP algorithm may lead to local optimal solutions, declining FNN performance. To overcome this problem, the GA was used to train the FNN because of its good global searching ability and strong robustness. It first encodes the coefficient values to form

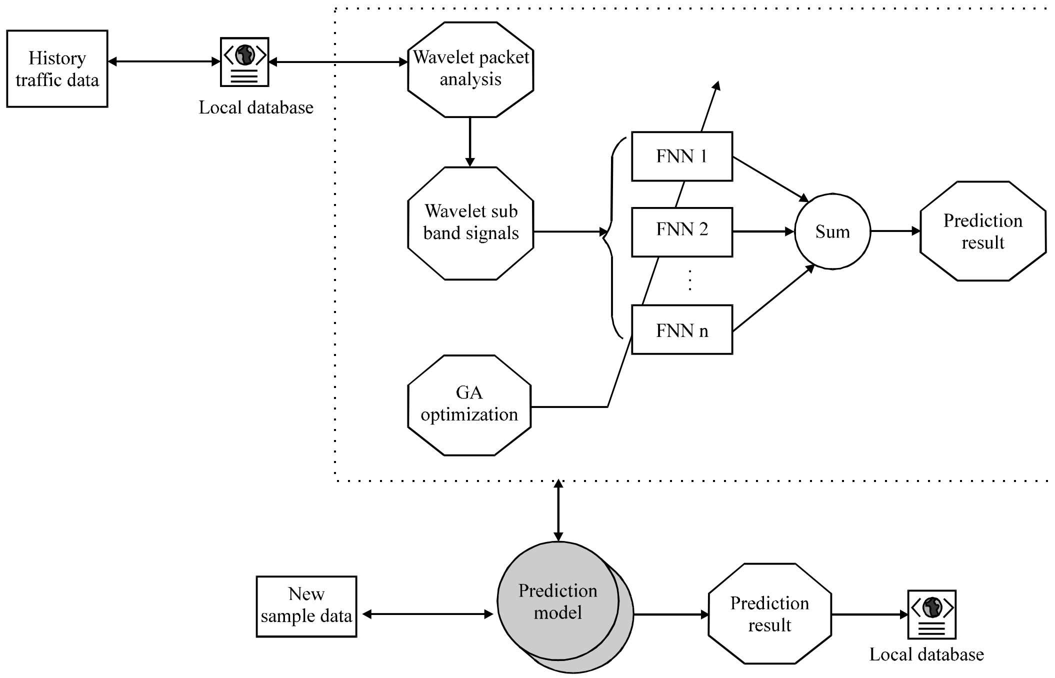

Fig. 3: The workflow of the proposed method

chromosomes and then performs replication, crossover and mutation to evolve the chromosomes. Lastly, use the optimal chromosome to represent network weight and membership function coefficients.

The work flow of the proposed method: Figure 3 shows the workflow of the proposed method for short time traffic flow prediction. The proposed forecasting processes are given as follows:

Step 1: Pretreat traffic data in the local database to uniform the data format

Step 2: Decompose the input data into wavelet frequency sub-bands using WT and extract the reconstruction of the wavelet sub-signals

Step 3: Build FNN prediction models for each sub-signal. Train the FNNs with the GA optimization and sum the outputs of the FNN models to obtain the prediction result

Step 4: Test the performance of the proposed prediction model

EXPERIMENT RESULT AND DISCUSSION

In order to validate the performance of the proposed algorithm, the traffic data is measured and collected every 20 min for 5 days in real practice. Three hundred and sixty data sets are prepared for the traffic forecasting procedure. Two hundred and eighty eight samples of the first 4 days are used to train the prediction model and the rest samples are for test. A portion of the traffic flow time series is shown in Fig. 4.

The original data is firstly decomposed into 3 levels by WT. The time spectra of the sub-bands at 3rd layer are shown in Fig. 5. It can be seen from Fig. 5 that the low-frequency signals embody the overall trend of the original traffic flow and several other sub-signals represent the uncertainty inference. The wavelet decomposition can well identify the different characteristics from the original data and hence benefit the traffic flow prediction through different GA-FNN models.

Then, the GA-FNN models are established to get the prediction component of each sub-signal and their sum indicates the final short time traffic flow prediction value. In the GA optimization, the population size is 250, the crossover probability is 0.9 and the mutation probability is 0.01. After GA optimization, the structure of 1-10-20-1 was chosen for the FNN in this work.

Figure 6 gives the performance of the proposed method for traffic flow forecasting. We have compared the performance of the proposed method with the independent use of FNN and GA-FNN. One can note that the GA optimized FNN has significant improvement to the

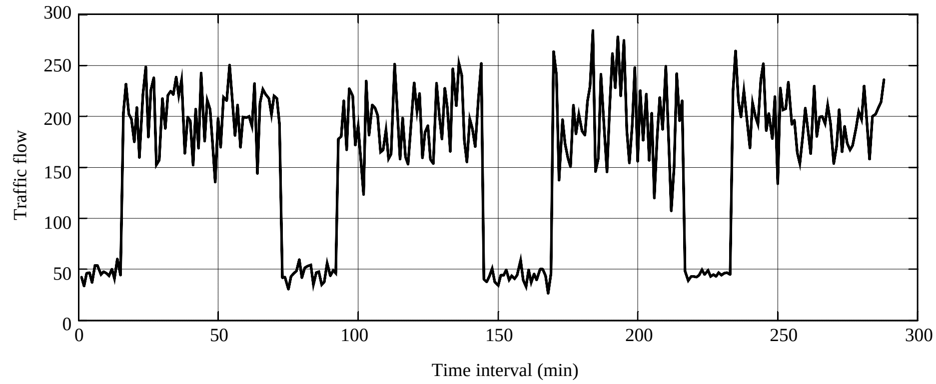

Fig. 4: The original traffic flow time series

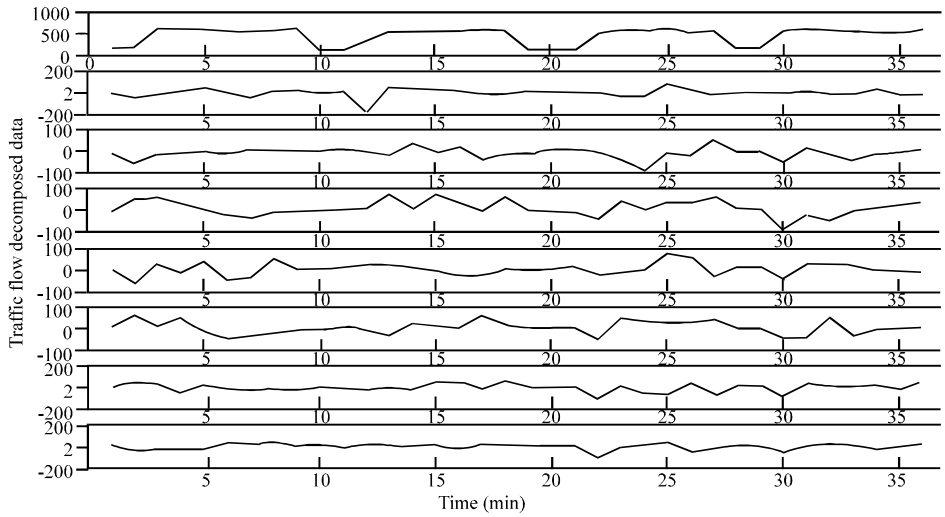

Fig. 5: The sub-signals derived by WT with 3 decomposition level

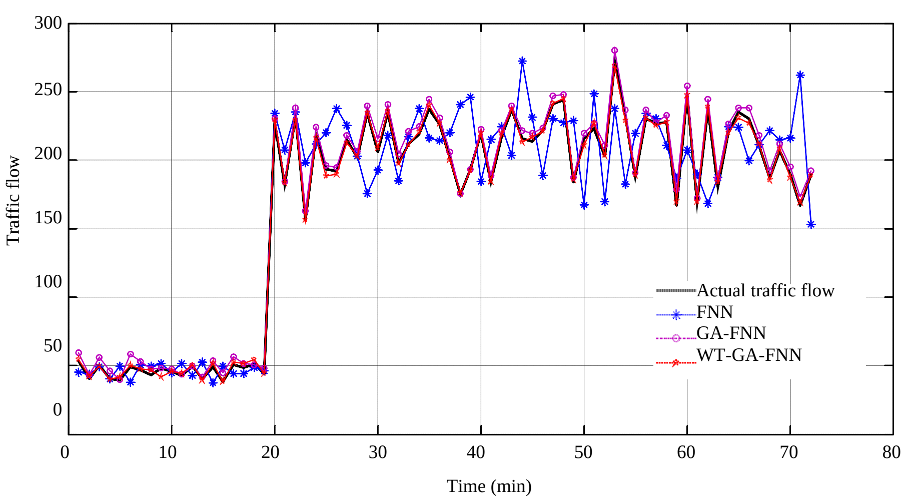

Fig. 6: The comparison of prediction performance using different method

Table 1: The traffic flow prediction results

Models	MAE (%)	Max absolute error (%)	Degree of fitting (%)
FNN	24.5	28.7	0.633
GA-FNN	6.2	9.5	0.953
WT-GA-FNN	3.6	5.1	0.987

Table 2: The comparison results of FNN, GA-FNN and WT-GA-FNN

WT-GA-FNN model (%)				GA-FNN model (%)			
MAE	MSE	MAPE	MSPE	MAE	MSE	MAPE	MSPE
1.27	1.85	1.49	1.53	2.18	2.54	2.79	2.55

prediction accuracy than the traditional FNN model. In addition, the proposed method outperforms the GA-FNN with the respect to the prediction accuracy. The prediction performance of FNN, GA-FNN and WT-GA-FNN is listed numerically in item of quantification in Table 1.

The prediction performance of the WT-GA-FNN model and the GA-FNN model is compared in Table 2. The comparison results show that the proposed method for short time traffic flow prediction is more effective than the GA-FNN. By the WT processing, the nonlinear elements are depressed and thus the forecasting error is decreased by 0.69% or better. One can note that the WT plays an effective role in the improvement of short time traffic flow prediction.

CONCLUSION

Intelligent Transportation management relies on precise traffic flow forecasting. It is necessary to employ advanced data mining approaches to excavate the hidden knowledge of the traffic data. Thus, intelligent method has been widely used in traffic flow prediction. However, the nonlinear components of the data always disturb the forecasting procedure, especially for the short time traffic flow forecasting. Hence, this study presents a new hybrid intelligent model for the short time traffic flow forecasting. This new method combines the advantages of the nonlinear analysis of WT and powerful learning ability of FNN to mine distinct and potential patterns of the traffic data. Moreover, the GA algorithm is applied to optimize the FNN parameters. The experimental test results have proven that the presented prediction approach is feasible and efficient for short time traffic flow forecasting. The prediction rate of the proposed WT-GA-FNN is much better than the model with no WT and GA processing. Thus, the proposed method has application importance.

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