

A NEURAL NETWORK MODEL FOR URBAN TRAFFIC VOLUMES COMPRESSION

OU Xiaoling, ZHANG Yi, REN Jiangtao, YAO Danya
Institute of System Engineering, Department of Automation,
Tsinghua University, Beijing 100084, P. R. China

ABSTRACT

Traffic data are the information source for traffic control and management. With the development and integration of Intelligent Transportation Systems, many applications and their respective sensors and detectors are a rich source of data about transportation system characteristics and performance. However, because of the limitation of databases and devices, the huge amounts of traffic data can not be stored without reduction. In this paper, an approach for urban traffic volume compression based on artificial neural network is proposed. The lossy compression of data is realized by using a set of three-layer back-propagation neural networks to remove the correlation within traffic volumes. The model has both a small reproduction error and a relatively high compression ratio.

Keywords: ITS, Data Compression, Artificial Neural Networks

1. INTRODUCTION

The Intelligent Transportation System (ITS) has become more and more popular and achieved a wonderful progress in recent years, especially with the development of information technology. Its information-oriented application systems are then the typical results ([1] and [2]). One of the most creative progresses is the integration of ITS-related control and management systems. It leads to the problems of data management, fusion and application, for example, the management of ITS data in the huge scale, the storage of real-time ITS data and the wide application with the ITS-related data fusion ([8]). The increasing interests in this field have generated the numerous questions ([3]). Obviously, it is not easy to have some solutions to the problems so far due to the limitation of the

traditional database systems. It is thus of great importance to find an efficient data compression approach, which can be used basically for the data compression and furthermore for the other intentional applications.

With the consideration of different data compression approaches, it is clear that, from the information theory by Shannon ([4]), there is always the redundancy existing in the information sources. The redundancy indeed is deduced from the correlation of information sources as well as the non-uniformity probability distribution of information sources. Therefore, the efficient compression of data can be achieved, if the above correlation could be found and removed or a method could be formed to change the distribution of information sources from the non-uniformity probability to the uniformity probability. Based on it, the methods of data encoding and decoding are adopted for the data compression. Recently, the artificial neural network (ANN) has been used wildly and successfully in the data compression to remove the correlation existing in the information sources, such as, for the image and video compression ([5]), electrocardiogram compression ([6]) and ultraviolet-visible spectrum compression ([7]), etc. The application of ANN in the ITS data compression should then be expended.

In fact, there are the different implicit attributes of similarity existing in ITS information. For example, for a certain urban intersection, the traffic volumes on any Wednesday could be similar with those on the next Wednesday in the normal operations. It can be taken as one of similarity attributes in the time domain existing implicitly in ITS information. It can also reflect the correlation within the information sources. With the consideration of this attribute, an approach of the lossy data compression for urban traffic volumes via a set of simple three-layer feed-forward neural networks is then discussed in the paper. For the inverse, the data

can be restored using the data compression model with the high fidelity and compression ration up to about 20:1.

The paper is organized as follows. The data compression model using ANN is given in the part 2. After the evaluation criterions are defined in the part 4, the performance of data compression approach can be assessed. The implementation of data compression is then undertaken in the part 5 to demonstrate the application of the new approach for data compression, including the data collection, pre-processing and results. Finally, the conclusion is outlined in the part 6.

2. DATA COMPRESSION MODEL OF ANN

Consider the fact that the traffic volumes in the whole day have a quite large range of variation in the whole day, a set of three-layer back-propagation artificial neural networks are used in this model to enhance the data compression and restoring. The structure of each network is shown in Fig 1. Each ANN should be chosen appropriately according to the different characteristics of variation in the different period in one day. After some experiments, 4 segments should be considered for the ascending, the first peak, the second peak and the declining, as shown in Fig 2. A neural network can be defined and trained to compress the traffic volumes in each segment. Thus, the total of 28 ANNs is needed in the data compression model for 7 days in the week.

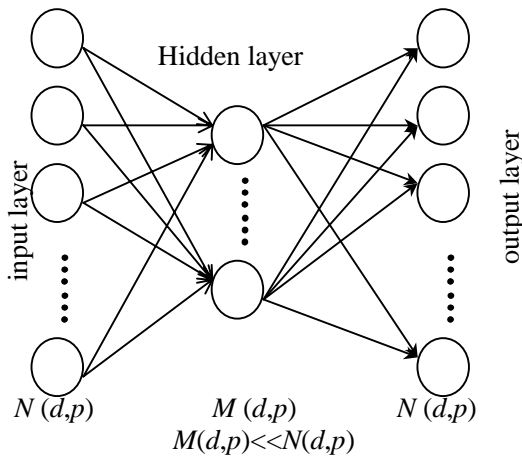


Fig 1: Neural Network Diagram

Consider the traffic volumes in any day are taken as a vector, that is, a time sequence. The set of all vectors in the same weekdays and weekend days in a period then can be described as

$$Set(d) = [f_1, f_2, \dots, f_{n_d}]$$

where $d=1,2,\dots,7$ represents Monday, Tuesday, ..., Saturday, Sunday, respectively. f_i represents the i^{th} vector and n_d is the total number of the vectors in $Set(d)$. Then here, $Net(d,p)$ denotes the ANN for compression of traffic volumes in the p^{th} segment of $Set(d)$, where $p = 1, 2, 3, 4$ and $d = 1, 2, \dots, 7$.

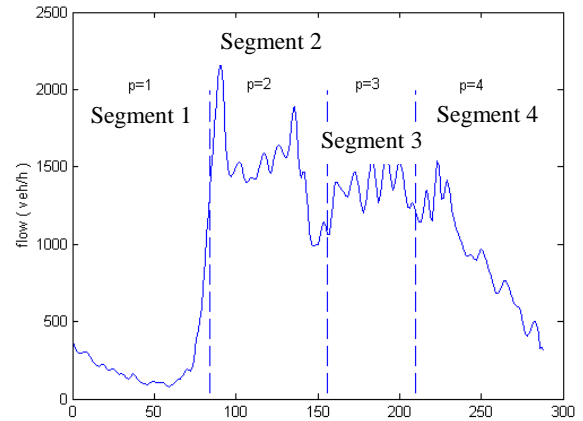


Fig. 2: Assignment of Segments

In each ANN $Net(d,p)$, the number of output neurons is the same as that of input neurons, $N(d,p)$. It is also the dimension of the vectors in p^{th} segment of the $Set(d)$. Obviously, the number of hidden neurons $M(d,p)$ is much small compared to the numbers of input and output neurons. All hidden neurons are fully interconnected to both of the input and output neurons.

After being scaled to the range of (0,1), the vector of original traffic volumes is fed to the input neurons as the training sample. The network can then be trained using the supervised data that is the same as the inputs. Once the network has been trained, the weights

$$W(d,p): \{w_{lm}, w_{mn}; l=1,2,\dots,M(d,p), m=1,2,\dots,M(d,p), n=1,2,\dots,N(d,p)\}$$

and the thresholds

$$B(d,p): \{b_m, b_n; m=1,2,\dots,M(d,p), n=1,2,\dots,N(d,p)\}$$

of the network are fixed as the common specifications extracted out of original vectors. The differences of individual day vectors are found at the output of hidden neurons and stored instead of the original input data as

$$H(d): \{h_{mk}; m=1,2,\dots,M(d,p), k=1,2,\dots,K_d\},$$

where K_d is the number of vectors in $Set(d)$.

Because of the abnormal situation always existing in the urban traffic, such as traffic jams and accidents, the traffic volume will have the variation in the form of

large ascending or declining in the short time, which is beyond the general consideration. In these cases, if the same model with fixed weights and thresholds is used for the data compression without any compensation, the big error must be induced in the progress of data restoring. That is, the volumes in the abnormal situations cannot be restored with the high fidelity. The errors between the output of the j^{th} neuron and the inputs of the corresponding neuron in the sample k must then be stored as $\{d, j, k, e(d, j, k)\}$ when the error exceeds the acceptable error margin T . Thus, the restoring of traffic volumes can be implemented via the inverse of compression using the compression model and have the volumes modified by the abnormal volumes stored in $\{d, j, k, e(d, j, k)\}$. In fact, the choice of T is a tradeoff between the data restoring accuracy and compression ratio. Obviously, the compression ratio is high and the data restoring accuracy is poor when T is large.

3. PERFORMANCE EVALUATION

Since 4 segments have been taken to compress the traffic volumes for each $Set(d)$, 4 ANN should be considered in the performance evaluation of ITS-related data compression model for each d . Due to the differences of similarity existing in the urban traffic volumes among the different $Set(d)$, the performance evaluation should be undertaken corresponding to the different $Set(d)$.

There are several criterions, which can be adopted to assess the performance of data compression model.

The fitness of ANNs is a basic aspect to be considered in the assessment of performance. It is evaluated using the average mean square error (AMSE) of data sequences between the inputs and outputs for 4 ANN in the same $Set(d)$. The AMSE can be described as:

$$AMSE(d) = \frac{\sum_{i=1}^{K_d} \left\{ \sum_{p=1}^4 \sum_{j=1}^{N(d,p)} [I(j) - O(j)]^2 / N \right\}}{K_d},$$

where N is the total number of traffic volume samples in one day. $I(j)$ is the input at the j^{th} input neuron and $O(j)$ the output at the j^{th} output neuron in ANN.

Secondly, the average percentage relative mean-square root error (APRE) between the original data sequences and the restored ones using ANN is introduced to investigate the performance of the proposed model on the data compression. The APRE can be described as:

$$APRE(d) = \frac{\sum_{i=1}^{K_d} \sqrt{\sum_{j=1}^N [(X(j) - X_r(j))^2] / \sum_{j=1}^N X^2(j)}}{K_d},$$

where $X(j)$ represents the original data sequence and $X_r(j)$ represents the restored data sequence.

Finally, the compression ratio is introduced here to assess the compression ratio as:

$$CR = \frac{\text{Bytes of Original Volume Sequence}}{\text{Bytes of Compressed Data}}.$$

Usually, these criterions are enough to evaluate the performance of data compression model. But some other criterions may be needed for the performance evaluation in the special cases.

4. IMPLEMENTATION OF DATA COMPRESSION

DATA COLLECTION AND PRE-PROCESSING

Take the urban traffic volumes in 144 days from Apr.1st to Aug.31st at the interchange of Zhangzhizhong Road and North Dongsu Street in Beijing city as the data source. All of volumes are collected using loop detectors and linked to the SCOOT Traffic Information Database in the Traffic Control and Management Center at Beijing. The primary volumes are sampled on each lane with 30-second intervals. Due to the limited capability of the database server, the primary traffic volumes have been merged into carriageway traffic volumes with 5-minute intervals and managed by database systems, that is, 288 data points a day ($N=288$).

Table 1: Assignment of Urban Traffic Volume Vectors

p	Number of data points	Time period	Specification
1	84	0:00-7:00	The ascending
2	72	7:00-13:00	The first peak
3	54	13:00-17:30	The second peak
4	78	17:30-24:00	The declining

As the discussion above, take the time sequence of traffic volumes in one day, totally 288 traffic volumes, as a data vector. All traffic volume vectors are classified to 7 sets, like $Set(1)$, $Set(2)$, ..., $Set(7)$, corresponding to 7 sets of days for Mondays,

Tuesdays, ..., Saturdays and Sundays. All vectors in each $Set(d)$ is further subdivided into 4 segments as described in Table 1. Finally, the traffic volumes should be scaled to (0, 1) in order to be suitable for ANN inputs.

RESULTS AND ANALYSIS

Adopt a three-layer back-propagation ANN for the traffic volumes compression as described as before. During the progress of ANN training, the number of hidden neurons in the network is determined by the fitness of ANN and the desired compression ratio. The original traffic volumes can then be restored by the stored outputs of hidden units in ANN with the high fidelity.

Fig.3 shows the comparison of restored traffic volumes based on the ANN model with the original ones for all Wednesdays, for example, in 4 segments separately. Both of the restored traffic volumes and original ones for each segment are displayed in the same sub-figure for the period. That is, for each segment, the traffic volumes in any week are followed directly by ones in the following week. For the comparison in convenience, the restored traffic volumes for the continuous 7 weeks are displayed in the lower curve and the original traffic volumes in the same weeks in the upper curve. The original inputs of $Net(3,p)$, where $p=1, 2, 3$ and 4 , is normalized from $Set(3)$ and the restored data between hidden and output layers into $H(3,p)$, where $p=1, 2, 3$ and 4 . The number of d, p and the hidden neurons $M(d,p)$ used in each ANN are listed at the top of each plot.

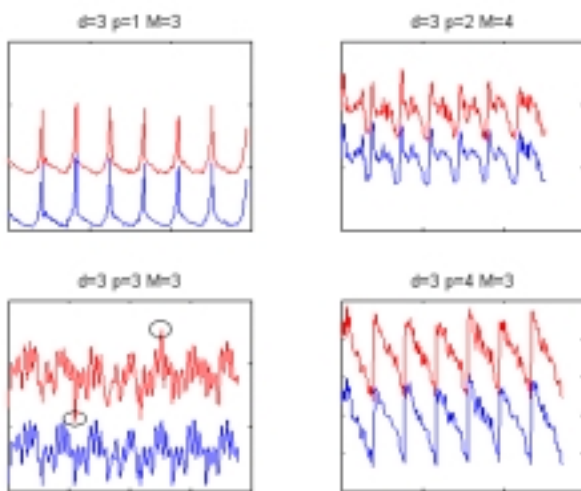


Fig. 3: Comparison of Normalized Original Data with Restored Data Using ANN

From the comparison of the restored traffic volumes with the original ones for 4 segments in one day as shown in Fig.3, it is clear that in the scale of (0, 1), the outputs of ANNs coincide basically with the original inputs except for several points in some peaks, where the traffic volumes are not restored accurately. That is, all of the volume vectors can be restored using only 13 outputs of hidden units while the abnormal points where the volumes cannot be restored accurately can be retrieved via the vector of abnormal points $e(j,k)$. The abnormal points, for example, marked using the small circle as shown in Fig. 4, can be determined when the error between the output of the j^{th} neuron and the input of the corresponding neuron in the sample k exceeds the acceptable error margin T . The vector of abnormal points $e(j,k)$ is indeed formed with all of abnormal points, in which the serial number of output neuron j and the number of sample k are included, such that, the positions of abnormal points can be searched easily in the data restoring. Thus, it can be concluded that the ultimately restored traffic volumes can have the high accuracy.

The different criterions for the performance evaluation of each ANN, like $AMSE$, $APRE$ and other related parameters are summarized in Table 3, where T_e is the total number of abnormal points $e(j,k)$ stored when the error margin is defined as $T = 4\sqrt{AMSE}$ during weekdays and $T = 3\sqrt{AMSE}$ during weekends.

Table 2: Performance Evaluation for Data Compression

d	1 <i>Mon</i>	2 <i>Tue</i>	3 <i>Wed</i>	4 <i>Thu</i>	5 <i>Fri</i>	6 <i>Sat</i>	7 <i>Sun</i>
K_d	20	20	20	21	21	21	20
M_p	p=1	3			3		
	p=2	4			4		
	p=3	3			4		
	p=4	3			3		
$AMSE(d)$ ($\times 10^{-4}$)	7.32	5.04	6.89	6.37	5.82	8.42	8.34
T_e	4	3	4	4	4	11	9
$APRE(d)$ (%)	6.26	6.46	5.98	5.79	5.50	6.57	6.36
CR	21.9	21.9	21.9	21.8	21.8	19.8	19.9

Consider the intentional criterions described in the

paper. It is clear that the average *AMSE* represents the overall restoring error of ANNs with 0.000698, the average *APRE* between the restored traffic volumes and original ones is 6.13% and the compression ratio is about up to 20:1.

By the way, it is obvious that the data restoring errors of ANNs are higher and the number of hidden neurons is larger in *Set(6)* and *Set(7)* than in other sets. That is, the similarity is little bit weak in the weekends. On the other hand, it is the fact that to increase the abnormal points can decrease the compression error induced from the ANN. It leads to the data restoring errors (*APRE*) of weekend days can be similar with those of weekdays finally.

5. CONCLUSION

A neural network model for traffic volume data compression was proposed here based on the similarity attributes existing in the urban traffic volumes. From the implementation and evaluation of the proposed data compression model, the ANNs can be used to extract the similarity of ITS-related data included in their weights, thresholds and also the outputs of hidden neurons. Once the outputs of hidden neurons are stored with the abnormal points where the volumes cannot be restored accurately, the original volume data can be restored using the ANNs between the hidden and output layers. It is clear indeed that the ANN-based approach discussed in the paper is valuable in the urban traffic volume compression with a quite high accuracy and a considerable compression ratio. It is also possible for this approach to be applied to other ITS-related information applications as long as there are some similarity attributes existing.

On the other hand, the modification to the approach to enhance the performance of ANN model is under the consideration and investigation. For example, from our preliminary study, it is clear that there is a universal similarity existing in fact for the traffic volumes in the period from 0:00am to 7:00am in all days in the week. This result makes it possible to adopt an ANN instead of 7 nets for the same p ($p=1$) in the case described in the paper. It will certainly enhance the compression efficiency without the loss of the accuracy for traffic volume compression and restoring.

6. REFERENCE

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