Traffic Prediction with Reservoir Computing for Mobile Networks*

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Abstract

The accurate traffic model and prediction of mobile network plays an important role in network planning. It is particularly important for the performance analysis of mobile networks. The study in this paper concerns predicting the traffic of mobile network, which is essentially nonlinear, dynamic and affected by immeasurable parameters and variables. The accurate analytical model of the traffic of the mobile network can be hardly obtained. Therefore a predicting method based on history input-output using correlation analysis ideas and Reservoir Computing (RC) is proposed. Correlation analysis is used to select proper input variables of the model. Reservoir Computing is a recent research area, in which a random recurrent topology is constructed, and only the weights of connections in a linear output layer is trained. This make it possible to solve complex tasks using just linear post-processing techniques. The proposed model has been verified on the data from network monitoring system in China Mobile Heilongjiang Co. Ltd.

1. Introduction

In recent years, a rapidly advancing technology and competitive market have required mobile network to operate in many cases in different cells. The capacity planning, overload warning and congestion control became crucial issue [1]. To accomplish these tasks, an accurate traffic model of the mobile network is needed. There are a lots of studies about the mobile network traffic model and prediction [1]-[5]. Denis Tikunov and Toshikazu Nishimura in [1] present a prediction methods of traffic using Holt-Winter's exponential smoothing, which method predict the traffic using the traffic history. The proposed method is based on the classification of the traffic data. Houda Khedher et. al in [2] review the traffic engineering issues and develop analysis techniques to extract the relevant parameters from measurements realized on an operating GSM network. The authors analyze the characteristics of the traffic and model traffic of some particular type. A method of forecasting traffic systematically based on the user's properties and information about the environment is proposed in [3]. However, the user's properties and information about the environment are not easy to obtain. A traffic model for cellular mobile radio telephone system with handoff are proposed, in which model fixed channel assignment is considered.

In the present mobile network, accurate traffic model plays an important role in network planning and management. However, mobile network traffic is essentially nonlinear, dynamic process and is affected by immeasurable parameters and variables. So it is difficult even impossible to obtain a precise traffic analytical model. To cope with such complex nonlinear problem, researchers has been underway on their identification and prediction using Reservoir Computing based entirely on measured inputs and outputs. The idea is to establish a linear or nonlinear relation between the past inputs and the current outputs. Recently, Reservoir Computing (RC) has shown the powerful ability to modeling complex, nonlinear dynamic system [6]. RNNs have been widely used in many applications such as system identification and control of dynamic system. RNNs have shown to be Turing equivalent for common activation functions, can approximate arbitrary finite state automata and universal approximators [6] However, training recurrent neural networks is hard in practice. Reservoir Computing, a special structure of RNNs, offers an intuitive methodology for using temporal processing power of recurrent neural networks (RNNs) without the hassle of training them [8]. Among the most prominent examples of such architectures is Echo State Network (ESN). Here we will refer to ESN as Reservoir Computing.

In this paper, an traffic model based on Reservoir Computing and self-correlation analysis has been proposed to model and predict the traffic time series of the mobile net-

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work. The traffic from different cells may be have entirely different characteristic. Therefore, in order to model and predict the traffic time series accurately, cells are classified into four group according to the traffic characteristics. After approximately classification of the cells, the proper input variables of the model based on ESN are chosen using the correlation analysis idea. The self-correlation coefficient of the traffic is calculated. The traffic data, which have bigger self-correlation coefficients with expectation output values, are chosen as input variables. Then, a model based on ESN is trained to predict the traffic time series.

The paper is organized as follows. In section II, the Reservoir computing and correlation analysis are introduced. The methods of cells partition ,self-correlation calculation and construction of the traffic model based on ESN are described in section III. Simulation results are provided in section IV. Finally, section V concludes the paper.

2. Prerequisites

2.1. Calculation of Self-correlation Coefficient

The correlation coefficient is a measure of the relationship between two attributes or columns of data. The correlation coefficient is also known as the Pearson product-moment correlation coefficient. However, in time series analysis area, the self-correlation analysis is a simple method which measures the cycle-to-cycle behavior of the time series. It is crucial for accurate prediction to select more correlative input variables with the output in the process of modeling the time series based on history input and output. Now, there is no systematic solutions to select input variables. In common, the input variables are selected according to the experience of the designers. But, in this paper, self-correlation analysis is used to make the selection of the input variables. At first, suppose that temporal signal is real time series $\{x(n)\}$. The self-correlation function definition of random real signals is $R(m) = E\{x(n)x(n+m)\}$. If $x(n)$ go through all states, the collection average of above formula can be realized by time average of single sample $x(n)$. In practical calculation, since the point number N of observing values is finite value, we can calculate the estimated value $\hat{R}(m)$ of $R(m)$ using the equation as follows

$$\hat{R}(m) = \frac{1}{N} \sum_{n=1}^{N-1-m} x(n)x(n+m) \tag{1}$$

It has been proved that $\hat{R}(m)$ is the consistent estimated value of $R(m)$. In process of calculation, in order to make correlation coefficient comparatively, $\hat{R}(m)$ is unitary by calculation according to the following equation

$$\hat{\rho}(m) = \hat{R}(m)/\hat{R}(0) \tag{2}$$

where $\hat{\rho}(m)$ is unitary self-correlation function, and its change range is in $[-1, 1]$.

2.2. Prediction of Time Series with Reservoir Computing

We briefly introduce the Reservoir Computing before introducing the predicting methods using Reservoir Computing. In Reservoir Computing, the reservoir consist of a random recurrent network with analog neurons that is driven by temporal signal. And the activations of the neurons are used to make linear classification/regression. The equations of the Echo State Networks (ESNs) can be written as

$$\begin{aligned} \mathbf{x}(n+1) &= \mathbf{f}\left(W^{in}\mathbf{u}(n+1) + W\mathbf{x}(n) + W^{back}\mathbf{y}(n)\right) \\ \mathbf{y}(n+1) &= \mathbf{f}^{out}\left(W^{out}\left(\mathbf{u}(n+1), \mathbf{x}(n+1), \mathbf{y}(n)\right)\right) \end{aligned} \tag{3}$$

where $\mathbf{u}(n) = (u_1(n), \cdots, u_K(n))$ are the activations of input units at time step n, $\mathbf{x}(n) = (x_1(n), \cdots, x_N(n))$ are the internal units and $\mathbf{y}(n) = (y_1(n), \cdots, y_L(n))$ are output units. Real-valued connection weights are collected in a $N \times K$ weight matrix $\mathbf{W}^{in} = \left(w_{ij}^{in}\right)$ for the input weights, in an $N \times N$ matrix $\mathbf{W} = (w_{ij})$ for the internal connections, in an $L \times (K+N+L)$ matrix $W^{out} = \left(w_{ij}^{out}\right)$ for the connections to the output units, and in a $N \times L$ matrix $\mathbf{W}^{back} = \left(w_{ij}^{back}\right)$ for the connections that project back from the output to the internal units. $\mathbf{f} = (f_1, \cdots, f_N)$, $(f^{out} = (f_1^{out}, \cdots, f_L^{out})$ are the internal unit's output functions and output unit's output functions, respectively. $(\mathbf{u}(n+1), \mathbf{x}(n+1), (y)(n))$ is the concatenation of the input, internal, and previous output activation vectors.

Basic idea of the ESNs learning is the large and fixed "reservoir", from which the desired output is obtained by training suitable output weights. The reservoir has a large number of neurons which are randomly and sparsely connected. Determination of optimal output weights is a linear task of mean-square error (mse) minimization [9].

$$\min_{\hat{w}} \|X\hat{w} - \mathbf{y}_d\| \tag{4}$$

where $X = \left[\mathbf{x}^T(Init), \mathbf{x}^T(Init+1), \cdots, \mathbf{x}^T(Trn)\right]$ and $\mathbf{y}_d = [y_d(Init), y_d(Init+1), \cdots, y_d(Trn)]$. and $Init$ and Trn are the beginning and ending index of the training examples, respectively, and the size of the training set is $N_t = Trn - Init + 1$. $Init$ is usually set to certain value to discard the influence of reservoir initial transient.

In this paper, ESNs implement the direct prediction model of time series. The direct prediction method relate the prediction origin and prediction horizon in a straight-forward way. Next, it is necessary to show how the direct prediction problem can be converted into a dynamic system modeling task [9].

Suppose that $s(n)$ is a temporal signal, $\mathbf{d}(k) = [s(k), s(k-i_1), \cdots, s(k-i_{K-1})]$, so the direct prediction means that we should give a nonlinear dynamic system realizing the dynamic mapping $\mathbf{d}(k) \rightarrow s(k+h)$, where $s(k+i_j), (j = 1, \cdots, K-1)$ denotes the time series value of i_j after time k, h is the prediction horizon. Supposed that the input-output sequences of $\{\mathbf{d}(k), s(k+h)\}$ are from a dynamic system, and RNNS such as ESNs can be used for the modeling task. The predicting task can be implemented by rewriting (3) as:

$$\begin{aligned} \mathbf{x}(n+1) &= \mathbf{f}\left(W^{in}\mathbf{d}(n+1) + W\mathbf{x}(n) + W^{back}s(n+h)\right) \\ s(n+h+1) &= \mathbf{f}^{out}\left(W^{out}\left(\mathbf{d}(n+1), \mathbf{x}(n+1), s(n+h)\right)\right) \end{aligned} \tag{5}$$

The target output of the ESNs is the h-step-head value of the time series, the input-output sequences may be $\{\mathbf{d}(k), s(k+h), k = 1, 2, 3, \cdots, N_t\}$.

3 Traffic Prediction with Echo State Networks

3.1. Activity areas

The traffic data of mobile network used in this study are from network monitoring system in China Mobile Heilongjiang Co. Ltd. In order to obtain an accurate traffic analysis, the traffic of the mobile network, together with other attributes such as short message service (SMS), hand-off and channel hold time and so on, are collected hourly from every cells in Heilongjiang province. In this study, we exclusively focused on the voice traffic. The hourly voice traffic obtained from different cells. They have distinct characteristics. The traffic features, such as the busiest hours in a day, or a 24-hour changing mode in a week in different cells are quite distinct. So is the average value of traffic in different cells. With the further analysis, we find that there are some cells in which the traffic during weekday are higher than it at the weekend. With those analysis, we approximately classify all the cells into four groups: residential district, college campus, business centers and highways, according to the traffic characteristics such as cell size, number of channels and traffic intensity, the average traffic intensity, etc. In this way, all cells belonging to the same group present approximately the same qualitative and quantitative behavior of the traffic intensity. For example, Figure 1 and Figure 2 show the traffic intensity averaged over the hours of the work days and weekends of one business centers and residential district, respectively.

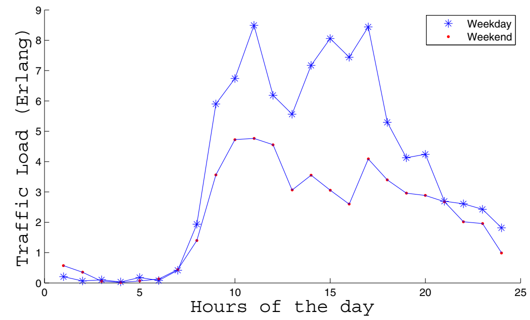

Figure 1. Traffic intensity versus the hour of the day(Business centers).

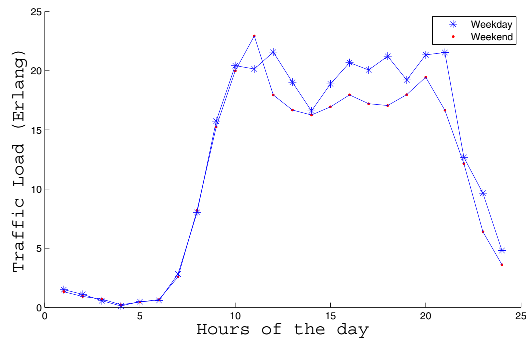

Figure 2. Traffic intensity versus the hour of the day(residential district).

Comparing Figure 1 with counterpart of the residential district, the conclusion can be drawn that there are no behavior similarity between them. The duration of the high traffic and hour they reach the relative high traffic value are different.

In this study, we will investigate the predicting model of traffic time series of business centers. The same methods can be extended to other types of cells easily.

3.2. The Selection of Input Variables

The Mobile Network is a very complicated non-linear system and many factors directly affect the change of daily traffic value. However, during the modeling process, some factors can not be considered because too many factors make it difficult to model the traffic due to excessively numerical computation or collection of many factors. We choose each hour traffic value of some cells from April 1, 2008 to April 30, 2008, there are $24 \times 30 = 720$ data value. Therefore, $N = 720$ in the equations, $\hat{R}(m)$ can be calculated using (2). Then, we can work out the self-correlation function curve between twenty-four o'clock of April 1, 2008 and $24 \times 8 = 192$ hour periods of 8 days before April 1, as Figure 3 shows. In the same way, we can

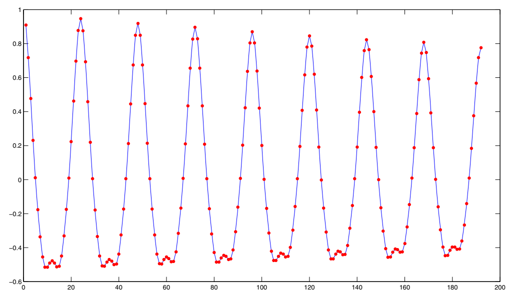

Figure 3. Self-correlation function curve of traffic time series.

also obtain similar curve by calculating the self-correlation function between 23 hour periods of August 5, 2000 and every point of 8 days before April 1, 2008.

$s(n)$ denotes the traffic value at the time n, the traffic value of k hour periods before time n is $x(n-k)$; $\rho(t-k)$ is the correlation coefficient between $x(t)$ and $x(t-k)$. We can get the conclusion from the self-correlation function curve of Figure 3 that in traffic time series, the correlation degrees between the current traffic value and other periods of time before are different.

We compute the self-correlation coefficient of traffic time series from 133 cells of downtown type, the results are similar to the Figure 3. In Figure 3, the correlation coefficients within 2 days between $s(n)$ and $s(n-k)$ whose value are bigger than 0.75 are $\rho(t-1), \rho(t-2), \rho(t-23), \rho(t-24), \rho(t-25)$. Because the purpose of our study is to perform short term prediction of traffic of mobile network, we choose these historical traffic $\mathbf{d}(k) = [s(k-1), (k-2), s(k-23), s(k-24), s(k-25)]$ as the input variables, which is the input variable of system (5).

3.3. Construction of Traffic Model with Reservoir Computing

According to the practical requirements, 24-step-forward predictor of the hourly traffic time series was chosen. As the analysis in the phase of selecting input variables, the system input are the sequential hourly traffic time series from the oldest value until the newest value. As mentioned above, we choose $\mathbf{d}(n) = [s(n-1), s(n-2), s(n-23), s(n-24), s(n-25)]$ as the input vector of the Echo State Networks.

Before creating the system, the values of the average hourly traffic was transformed to normalize the input vector. After that, the minimum value of each input sequence of the equation (5) becomes 0. The transformation is performed as in (6)

$$\mathbf{d}_{trans} = \mathbf{d} - \min(\mathbf{d}) \tag{6}$$

where $\mathbf{d}_{trans}$ is the transformed value whose minimum is 0.

We choose the traffic of the first 29 days of April from 133 cells to train the Echo State Network, and predict the traffic value of the April 30, 2008, that is $h = 24$ in the system (5). After some experimental evaluations, the parameter configuration of the reservoir topology was chosen as following:

(1) The reservoir is composed by 50 units, scaled to a spectral radius of $\lambda = 0.98$.
(2) The input units is connected to the reservoir units by weight scaling between $[-1, +1]$.
(3) The node type is "leaky1_esn".
(4) The activation function is "tanh".
(5) The input Scaling,input Shift, teacher Scaling, teacher Shift,feedback Scaling are 0.1, 0, 0.1, 0.9, 0.3, respectively.

The weights of input with respect to out are used. The Echo state network are trained used the parameters above by running the data of the first 29 days of April, 2008.

4 Results and Analysis

The models performance was measured by the root mean square error (RMSE) specified by equation (7)

$$rmse = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(s(n) - \hat{s}(n))^2} \tag{7}$$

where the $s(n), \hat{s}(n)$ are the traffic value and its corresponding predicted value, respectively. The frequency of RMSE of training and test of the 133 cells are given in Figure 4 and Figure 5, respectively. As the Figure 4 shows, the training errors are in the range of $[0.078, 0.457]$, which mainly concentrate on the ranges of $[0.13, 0.27]$. The number of the cells in which the training error is located in $[0.13, 0.27]$ is 120. As the Figure 5 shows, the training errors are in the range of $[0.1876, 1.0088]$, which mainly concentrate on the ranges of $[0.2, 0.9]$. There are 124 cells whose prediction error are in this range. There is only 1 cell, of which the RMSE of the test error is larger than 1 and the test and training error in almost all cells are acceptable. This means that the proposed the method not only can model and predict the traffic time series but also has strongly robust property. According to analysis and simulation results above, the predictor model created by Reservoir Computing can obtain the characteristic contained in the traffic time series

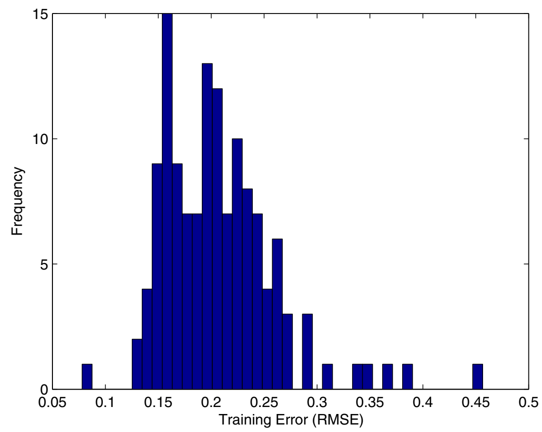

Figure 4. The frequency of cells with RMSE (Training Error)).

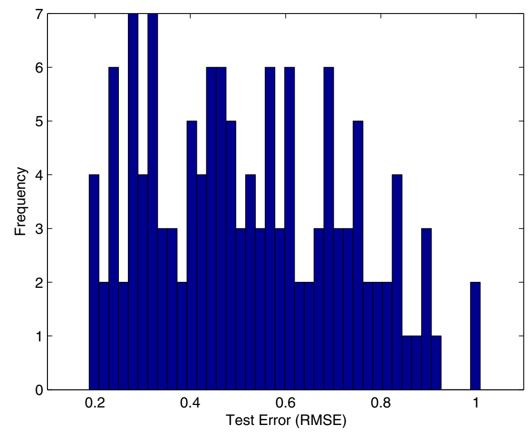

Figure 5. The frequency of cells with RMSE (Testing Error).

and predict the time series accurately. In addition, a proper division of the cells making the traffic time series of cells in one group has a similar characteristics will be another interested research aspects in the future.

5 Conclusions

In this paper, a traffic model based on history value with Reservoir Computing and correlation analysis are proposed to predict the hourly traffic time series. At first, the selection of input variables of the predictor model are performed by using correlation analysis. Then, the predictor model are built with Echo State Networks. The simulations on the practical data from a mobile network show that the proposed method can achieve construction of traffic model and prediction accurately for mobile networks. In addition, the robust property of this new method is proved by further verification in which the modeling and predicting of voice traffic from 133 cells with the same architecture and parameters setting for ESNs is evaluated. However, the architecture and parameters of the Reservoir Computing are obtained using cross validation method in our experiments. In future study, More attention should be paid to propose a systematic method on selecting the architecture and parameters of Reservoir Computing for traffic prediction.

References

[1] D. Tikunov and T. Nishimura. Traffic prediction for mobile network using holt-winters exponential smoothing. *Software, Telecommunications and Computer Networks, 15th International Conference on.*, pages 1–5, September 2007.

[2] H. Khedher, Fabrice, and S. Tabbane. Traffic characterization for mobile networks. *IEEE 56th Vehicular Technology Conference, Proceedings. VTC 2002-Fall.*, 3:1485–1489, Sepember 2002.

[3] Y. Akinaga, K. S., N. Shinagawa, and A. Miura. A proposal for a mobile communication traffic forecasting method using time-series analysis for multi-variate data. *Global Telecommunications Conference, 2005. GLOBECOM '05. IEEE*, 2:1119–1124, November 2005.

[4] S. Bhattacharaya, H. M. Gupta, and S. Kar. Traffic model and performance analysis of cellular mobile systems for general distributed handoff traffic and dynamic channel allocation. *IEEE Transactions on Vehicular Technology*, 57(6):3629–3640, November 2008.

[5] F. N. Pavlidou. Two-dimensional traffic models for cellular mobile systems. *IEEE Transactions on Communications*, 42(2):1505–1511, February 1944.

[6] Benjamin Schrauwen, David Verstraeten and J. V. Campenhout An overview of reservoir computing: theory, applications and implementations. *ESANN'2007 proceedings - European Symposium on Artificial Neural Networks*, pages:471–482, April 2007.

[7] K. H. Yang, G. L. Shan, and L. L. Zhao. Correlation coefficient method for support vector machine input samples. *Proceedings of the Fifth Internaltional Conference on Machine Learning and Cybernetics*, 2857–2861, August 2006.

[8] B. Schrauwen, J. Defour, D. Verstraeten and J. V. Campenhout. The introduction of time-scales in reservoir computing, applied to isolted digits recognition. *LNCS, 4668, Part I*, 471–479, 2007.

[9] Zhiwei Shi and Min Han. Support Vector Echo-State Machine for Chaotic Time-Series Prediction. *IEEE Transactions on Neural Networks*, 18(2):359–372, 2007.