International Journal of Smart Home
Vol. 9, No. 7 (2015), pp. 73-84
http://dx.doi.org/10.14257/ijsh.2015.9.7.08

An Adaptive Network Prediction and Judgment Method for Unstable Communication on Moving Medical Vehicles

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Abstract

To evaluate the wireless network condition on moving medial vehicles and make reasonable judgment among multiple network channels, an automatic network judgment method is presented for unstable communication environment based on adaptive network speed analysis and prediction method. Historical network observation data are collected; time series analysis method and ARMA model are employed to build prediction model using historical data statistics with periodical update mechanism. Predicted network speed value is then compared with real speed value and a criterion to identify the condition of network is summarized from comparison result analysis. Experiments are conducted in both normal network and interfered network situations. Empirical studies results show that the adaptive prediction method could be used for wireless network speed prediction on moving vehicles. Under different network environments, the fit value of each group of data varies and this value could be used for network problem identification.

Keywords: *wireless network, ARMA model, time series analysis, data prediction*

1. Introduction

Nowadays, the need for information communication on moving vehicles increases in many scenarios such as medical rescue [1, 2]. For emergency medical rescue, the stability of network is important to the information transmission. However, many major disaster medical rescue practices indicated that existing emergency rescue management decisional support system lacked of efficient information sharing due to poor network environment [3]. In this environment, wireless network is the first choice, yet the quality of wireless network is much less poor than wired network. To maintain stable communication under poor network environment, multiple communication channels are generally prepared as backup. Once the quality of in use channel deteriorates below the user requirement, the backup channel should be used instead. On moving vehicles for medical rescue, it is difficult to judge the signal quality of an in use channel. Firstly, the wireless network speed fluctuates dramatically even in static manner, not to mention on moving vehicles, so it is difficult to evaluate the quality of wireless network. Secondly, due to the changing environment outside vehicles, it is difficult to choose a certain user requirement threshold value accordingly. Thus, how to judge the quality of communication channel under unstable environment and to determine whether the quality deteriorates dramatically is the key problem to tackle.

In existing work to deal with the unstable wireless network problem on moving medical vehicles, authors presented a multi-channel network platform, in which three kinds of 3G wireless network and two kinds of satellite network were integrated in one device [4]. The network quality was indicated by a light of each channel, thus network monitoring process was only accomplished by person according to the lights. The

ISSN: 1975-4094 IJSH

network quality was not analyzed quantitatively and manual monitoring might introduce many uncertainties to the judgment of network selection. In other work describing a communication platform for MDSS [3], a dynamic communication channel switch mechanism was predefined for different types of information. The whole process was built on the availability of different networks, but detailed availability analysis wasn't presented. In a word, an automatic network quality quantitative analysis method is needed to make better decisions for network selection.

To deal with the above problem, this paper proposes an automatic and adaptive network analysis and prediction method for network judgment. Since the network speed data changes dramatically from time to time, time series data analysis methods are employed to evaluate the historical network speed data and to provide a more precise prediction method. If the real speed is much less than the predicted speed value for a certain amount of time, the condition of this network must deteriorate during this time, which means this channel might be considered as backup channels instead. The following sections are organized as follows, first of all, the network speed prediction and judgment problem is formulated and an adaptive prediction model is then proposed using ARMA. After that, a network judgment method is presented based on network speed prediction followed by the experiments and result analysis.

2. Problem Formulation

Although multiple kinds of network can be used simultaneously, the parallel working could also cause the problem of message segmenting, packing/unpacking and retransmitting, which also slows down the whole transmission process. Under dynamic environment, it will be more reliable to use one network channel at a time as long as the bandwidth allows. To evaluate the network condition in mathematical manner, quantitative network condition indicators should be chosen for network analysis. Among serval indicators, network speed perceived by end users, is chosen as the indicator for network quality.

Assume that at time t, the perceived network speed from the user side is defined as x_t. As the time t increases, x_t forms a time series data set $\{x_t\}$ .Given the historical data of x_{t-1}, x_{t-2} ,…, x_{t-n}, if the value of x_t decreases under a threshold value, the network quality must declines and it should be switched to other network. So, it is important to choose the threshold network speed value as it decides when to use one channel and when to abandon it. Under dynamic changing network environment, it is impossible to choose a certain threshold value for network judgment. As the network speed varies with the environment changes, the value of the speed is also relative to the historical data. So a threshold value of x_t could be summarized from the historical data of x_{t-1}, x_{t-2} ,…, x_{t-n}, unless dramatic change happens. That is to say, the network quality could be analyzed from the comparison result between the observed network speed value x_t and the predicted value $\hat{x}_t$ from historical data.

3. Adaptive Network Prediction Method Using ARMA Model

Generally speaking, the network speed data follows the time series pattern and time series data analysis method will be used to analyze the pattern. Among kinds of methods for time series data analysis such as neural network [5] and wavelet analysis [6], ARMA is a relative mature model suited for short-time prediction. Thus, ARMA model is used in this section to conduct the network speed prediction and an adaptive model update method is built later.

3.1. ARMA Model

Assume X_t is the time series value at time t. In a stationary process, if the value X_t on time t not only depends on its previous times' value $X_{t-1}, X_{t-2}, \ldots, X_{t-n}$, but also has interdependent relationship with noises $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-n}$, Box and Jenkins described this system as an autoregressive moving average system and the structure was referred to as ARMA model [7]. For a stationary process $\{X_t\}$, a *p*-order auto-regression and *q*-order moving average model, ARMA (*p*, *q*) can be expressed as Equation 1 [8]:

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \ldots + \varphi_p X_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q} \tag{1}$$

where φ_i $(1 \le i \le p)$ and θ_j $(1 \le j \le q)$ are undetermined coefficients.

3.2. Network Speed Prediction and Evaluation

Assume that the network speed is time series $\{x_t\}$. Although the value of $\{x_t\}$ fluctuates with time, it is normally a non-zero mean stationary process. Given the historical data of $x_{t-1}, x_{t-2}, \ldots, x_{t-p}$, the predicted network speed value $\hat{x}_t$ is calculated through Equation 2:

$$\hat{x}_t - \mu = \hat{\varphi}_1 (x_{t-1} - \mu) + \hat{\varphi}_2 (x_{t-2} - \mu) + \ldots + \hat{\varphi}_p (x_{t-p} - \mu) + \varepsilon_t - \hat{\theta}_1 \varepsilon_{t-1} - \hat{\theta}_2 \varepsilon_{t-2} - \ldots - \hat{\theta}_q \varepsilon_{t-q} \tag{2}$$

where φ_i and θ_j are coefficients that satisfy stationary and ε_{t-i} inevitability conditions, and ε_{t-i} is an uncorrelated random variable with zero mean and constant variance σ_ε^2. $\hat{\varphi}_i$ And $\hat{\theta}_j$ represent the estimated value of φ_i and θ_j. μ Is the coefficient standing for the estimated mean value of $\{x_t\}$, which could make the time series data become mean-zero process. Define the zero mean stationary process as $\{\overline{x}_t\}$, $\overline{x}_t = x_t - \mu$. Let $\mathrm{var}(\overline{x}_t)$ and $\sigma_{\overline{x}}$ stand for the variance and standard deviation of $\{\overline{x}_t\}$. γ_k Stands for the covariance between $\{\overline{x}_t\}$ and $\{\overline{x}_{t+k}\}$, as Equation 3. The autocorrelation function ρ_k could be calculated as Equation 4.

$$\begin{aligned} \gamma_k &= \mathrm{cov}(\overline{x}_t, \overline{x}_{t+k}) \\ &= \frac{1}{N-k} \sum_{t=1}^{N-k} (x_t - \mu)(x_{t+k} - \mu), k = 0,1,\ldots N-1 \end{aligned} \tag{3}$$

$$\rho_k = \frac{\gamma_k}{\mathrm{var}(\overline{x}_t)} = \frac{N \sum_{t=1}^{N} (x_t - \mu)(x_{t+k} - \mu)}{(N-k) \sum_{t=1}^{N} (x_t - \mu)^2} \tag{4}$$

3.3. Coefficients Estimation

For the ARMA model, Bayesian information criterion (BIC) is often used for the estimation process of order p and q [9]. Let $\hat{\sigma}_\varepsilon^2$ represent the variance of regressive residual. The value of $\hat{\sigma}_\varepsilon^2$ could be calculated as the square sum of regressive residual divided by the difference between the number of used observations and the number of order. The value of $\hat{\sigma}_\varepsilon^2$ relative to the order p, q is shown as Equation 5. $BIC(p,q)$ is calculated as Equation 6.

$$\hat{\sigma}_\varepsilon^2 (p,q) = \frac{1}{(N-p) - (p+q+1)} \sum_{t=1}^{N} (x_t - \hat{x}_t)^2 \tag{5}$$

$$BIC(p,q) = \ln \hat{\sigma}_{\varepsilon}^{2}(p,q) + \frac{p+q}{N}\ln N \tag{6}$$

If any p_0 and q_0 satisfy $BIC(p_0,q_0) = \min_{1\le p,q\le n} BIC(p,q)$, p_0 , q_0 is the optimized order. Three steps are employed to predict the left coefficients. Firstly, matrix estimation is used to calculate the initial value of $\hat{\varphi}_i$ as Equation 7. Secondly, the covariance value of a series data set $\{y_t\}$ as $y_t = \overline{x}_t - \hat{\varphi}_1\overline{x}_{t-1} - \hat{\varphi}_2\overline{x}_{t-2} - \ldots - \hat{\varphi}_p\overline{x}_{t-p}$ is calculated as Equation 8. Thirdly, since $y_t \cong \varepsilon_t - \hat{\theta}_1\varepsilon_{t-1} - \hat{\theta}_2\varepsilon_{t-2} - \ldots - \hat{\theta}_q\varepsilon_{t-q}$, Equation 9 is built including the unknown coefficients $\hat{\theta}_j$.

$$\begin{bmatrix} \hat{\varphi}_1 \\ \hat{\varphi}_2 \\ \ldots \\ \hat{\varphi}_p \end{bmatrix} = \begin{bmatrix} \rho_q & \rho_{q-1} & \cdots & \rho_{q-p+1} \\ \rho_{q+1} & \rho_q & \cdots & \rho_{q-p+2} \\ \ldots & \ldots & \ldots & \ldots \\ \rho_{q+p-1} & \rho_{q+p-2} & \cdots & \rho_q \end{bmatrix}^{-1} \begin{bmatrix} \rho_{q+1} \\ \rho_{q+2} \\ \ldots \\ \rho_{q+p} \end{bmatrix} \tag{7}$$

$$\gamma_k(y_t) = \mathrm{cov}(y_t, y_{t+k}) = \sum_{i,j=0}^{p} \varphi_i\varphi_j\gamma_{k+j-i}, \ \varphi_0 = -1 \tag{8}$$

$$\begin{cases} \gamma_0(y_t) = \sum_{i,j=0}^{p} \varphi_i\varphi_j\gamma_{j-i} = (1+\theta_1^2+\ldots+\theta_q^2)\sigma_\varepsilon^2 \\ \gamma_k(y_t) = \sum_{i,j=0}^{p} \varphi_i\varphi_j\gamma_{k+j-i} = (-\theta_k+\theta_{k+1}\theta_1+\ldots\theta_m\theta_{m-k})\sigma_\varepsilon^2 \end{cases} \tag{9}$$
$$k = 1, 2, \ldots, q$$

The value of $\hat{\theta}_j$ could be obtained through solving Equation 9. To improve the accuracy of estimated parameters, the above value could be used as the initial value of least squares estimation method to acquire more accurate solutions.

3.4. Adaptive Network Prediction Model Update Method

As the time increases, the amount of historical data grows accordingly and the pattern of the time series data may change slightly according to time and environment. To improve the accuracy of prediction result, more recent data should be used to optimize the prediction model. As a result, after certain amount of time T , ARMA model should be refreshed using the new collected set of time series data and the coefficients in this model should be recalculated. If the value of T is too large, the accuracy of prediction model may decrease. However, if the value of T is too small, unstable network epochs might be neglected due to the prediction model change. For continuous historical observation data, the value of T should meet the requirement of Equation 10. $m\big|_{t_s}^{t_e}$ is the number of epochs during time t_s to t_e , for which the difference between predicted speed value and real speed value exceeds threshold. $m_T\big|_{t_s}^{t_e}$ denotes the according number of epochs during the same period of time with the model refresh interval T and new calculated set of parameters. ϕ Is a small threshold value allowing the difference between $m\big|_{t_s}^{t_e}$ and $m_T\big|_{t_s}^{t_e}$. The optimization objective represents the average value of prediction residuals with refresh interval T . The constraint stands for maintaining the number of unstable epochs during time T . The value of T could be estimated from solving the Equation 10.

$$\begin{aligned} &\min \frac{1}{t_e - t_s - T} \sum_{t_i = t_s}^{t_e - T} \left(\frac{1}{T} \sum_{t = t_i}^{t_i + T} (x_t - \hat{x}_t)^2 \right) \\ &s.t. \left| m \Big|_{t_s}^{t_e} - m_T \Big|_{t_s}^{t_e} \right| \le \phi \end{aligned} \tag{10}$$

4. Network Judgment Procedure Based on Adaptive Prediction Method

4.1. Network Analysis and Judgment Based On Speed Prediction

After predicting network speed $\hat{x}_t$ at time t from the historical observation data $x_{t-1}, x_{t-2}, \ldots, x_{t-p}$ using the ARMA model, the real network speed x_t is collected and the comparison result between $\hat{x}_t$ and x_t indicates the change trends of network speed. If the value of x_t is much less than $\hat{x}_t$, the epoch would be taken as unstable epoch. As the value of network speed changes frequently, the difference between $\hat{x}_t$ and x_t is evaluated using the square sum of residual $\hat{\sigma}_\varepsilon^2 = (x_t - \hat{x}_t)^2$. Define m as the number of unstable epochs, as Equation 11, where $\sigma_\varepsilon^2(p,q)$ is the pre-calculated value through Equation 5. t_s And t_e denote the start and end time to evaluate the network stability and $t_e - t_s$ is the fixed amount of time. If the number of unstable epoch is too large $m > \lambda_2(t_e - t_s)$, the network could be taken as un-stable. λ_1 And λ_2 are pre-calculated coefficients summarized from the historical data analysis.

$$m = \sum_{t = t_s}^{t_e} l_t, \quad l_t = \begin{cases} 1, & \text{if } \hat{\sigma}_\varepsilon^2 > \lambda_1 \sigma_\varepsilon^2(p,q) \\ 0, & \text{else} \end{cases} \tag{11}$$

4.2. Automatic Network Prediction and Judgment Procedure

Considering the normal procedure ARMA model, the whole framework of our network analysis method is summarized as Figure 1. The according steps are listed as follows.

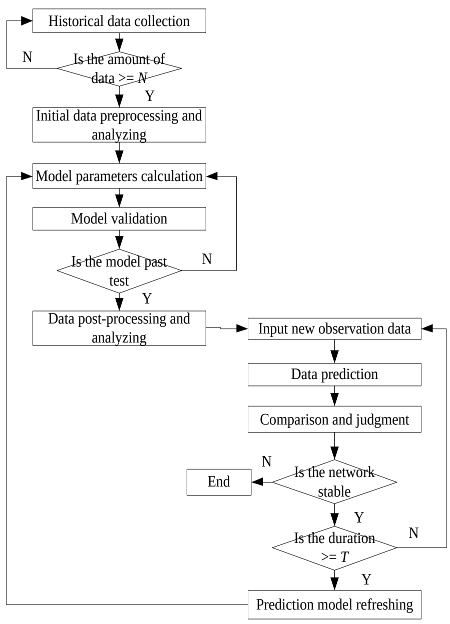

Figure 1. Network Prediction and Judgment Procedure

Step1. Historical data collection: When the network is working norming, collect the network speed data x_t , $t = 1, 2 ...$ the whole data set is divided into two groups. The first group $\{x_t\}$ is used for model estimation and the second one $\{x_t'\}$ is kept for model validation.

Step2. Initial data preprocessing and analyzing: Preprocess the data $\{x_t\}$ to get the mean μ and variance $\mathrm{var}(x_t)$.

Step3. Model parameters calculation: For any value of p_k and q_k , use matrix estimation and least squares estimation to obtain the group of parameters $\hat{\varphi}_i$ and $\hat{\theta}_j$ according to Equation 7, 8 and 9. After estimation, calculate $BIC(p_k, q_k)$ according to Equation 6. For each combination of p_k and q_k , compare $BIC(p_k, q_k)$ accordingly and the combination of p_0 and q_0 that satisfies $BIC(p_0, q_0) = \min_{1 \le p_k, q_k \le n} BIC(p_k, q_k)$ is the optimized pair of order, and the corresponding parameters $\hat{\varphi}_i$ and $\hat{\theta}_j$ are also kept as for model validation.

Step4. Model validation: The validity of built model is checked against the other data set $\{x_t'\}$. The main task is to check the independence of the residual sequence $\{\varepsilon_t\}$, which is accomplished by F-test, γ^2 -test and so on [10]. If the model passes the validation, next step is executed, otherwise, the procedure returns to Step 3 and new group of parameters is estimated.

Step5. Data post-processing and analyzing: Once prediction model is validated, data post-processing is conducted including calculating $\hat{\sigma}_\varepsilon^2$ for each epoch. The value of λ_1 , λ_2 and ϕ is summarized through the value of $\hat{\sigma}_\varepsilon^2$. Value of refreshment time duration T is also computed from solving the Equation 10.

Step6. Data prediction: After new observation data x_{t+1} is obtained, the predicted network speed value $\hat{x}_{t+1}$ is calculated through prediction model.

Step7. Comparison and judgment: The stability criterion m is calculated for several epochs according to Equation 11. If $m > \lambda_2(t_e - t_s)$ stands, the network is unstable and the whole procedure will stop, otherwise, the time duration of the model being used will be checked. If the duration is larger than pre-computed T , prediction model is updated and the procedure returns to Step 3, otherwise, the procedure returns to Step 6 for new data input.

5. Second and Following Pages Empirical Studies

5.1. Experiment Settings

To test and verify the network prediction and judgment method, several groups of wireless network speed data are collected using the implemented device [4], as Figure 2. Three kinds of 3G network provided by China Telecom, China Mobile, China Unicom are integrated in this device. Since China Unicom has the strongest signal in our previous test [3], it is used as the main channel.

Figure 2. The Structure of Prototype System

Using this terminal, different group of network speed data in different environments is used for further experiments. Frist of all, a group of normal network speed data of China Unicom is collected from the device on a moving vehicle, from which one thousand continuous epochs of data is selected for further analysis, shown by Figure 3(a). Secondly, another group of data is recoded as follows: the first four hundred epochs of data are collected under normal environment while the second half is collected under network interference and the network speed is less than the value of ordinary network speed. The network speed is shown by Figure 3(b).

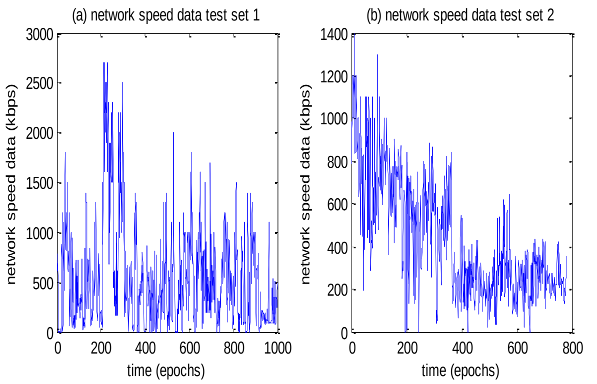

Figure 3. The Network Speed Data Value of Two Test Datasets

5.2. Experiments on Network Prediction Using Time Series Analysis

First of all, an ARMA model is built using the first dataset according to the adaptive prediction procedure as: x_t=-0.03064x_{t-1}+1.763x_{t-2}+0.1429x_{t-3}-0.8756x_{t-4}+ε_t+0.67ε_{t-1}-1.229ε_{t-2}-0.8183ε_{t-3}+0.3255ε_{t-4}+0.09773ε_{t-5}. The comparison of one-step prediction results and the observed data is shown in Figure 4.

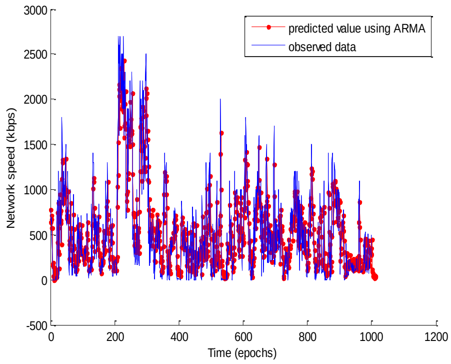

Figure 4. The Comparison between Predicted Value and Observed Data

The residuals between predicted data and observed data are shown in Figure 5 and the autocorrelation and partial autocorrelation value of residuals are shown in Figure 6.

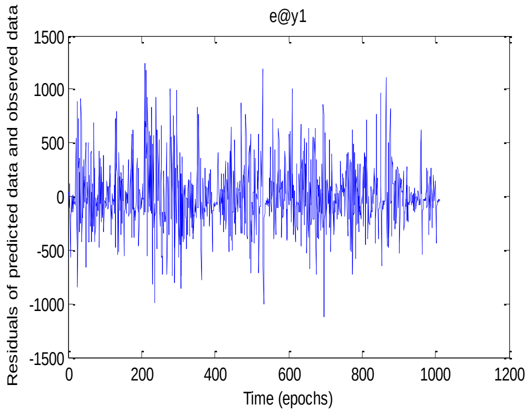

Figure 5. The Residuals between Predicted Data and Observed Data

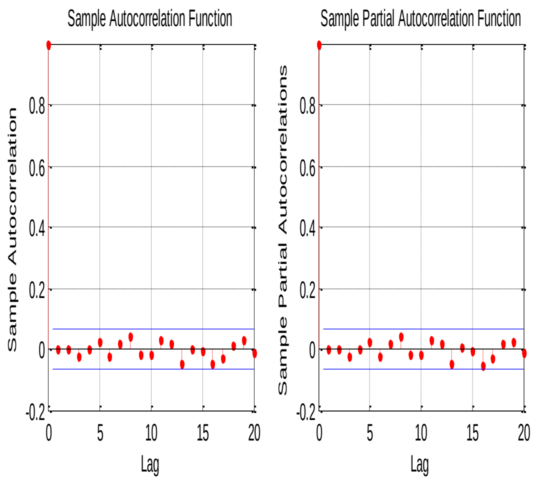

Figure 6. Autocorrelation and Partial Autocorrelation of Network Speed Data

These two kinds of values show that except for the first several nodes, network speed value generally obeys the pattern of time series data. To conduct a more detailed stationary test, Dickey-Fuller test is employed and the results are shown in Table 1. The P-value of each kind of test indicates the error probability caused by differences in sample data. Statistics result in Table 1 indicates that network speed value satisfies the stationary process pattern.

Table 1. Dickey-Fuller Test Results for Network Prediction

Significance level	0.05	0.001	0.01
Stationary test	Pass	Pass	Pass
P-value of stationary test statistics	0.001	0.001	0.001
least squares estimate values	-7.2311	-7.2311	-7.2311
Critical value of least squares estimate	-1.9416	-3.2900	-2.5694

Experiments in this section indicate that time series analysis method could be used for network prediction in changing network environment.

5.3. Experiments on Network Judgment Based On Prediction Result

For the two different datasets, the experiments on network judgment are conducted in this section. The whole dataset is divided into two halves. While the first half set of data is used as training dataset for building prediction model, the other half is used for prediction model validation and test to identify network change. Figure 7(a) shows the comparison between predicted data using ARMA model and the observed data using the first training dataset and the comparison result using the second training dataset is illustrated by Figure 7(b).

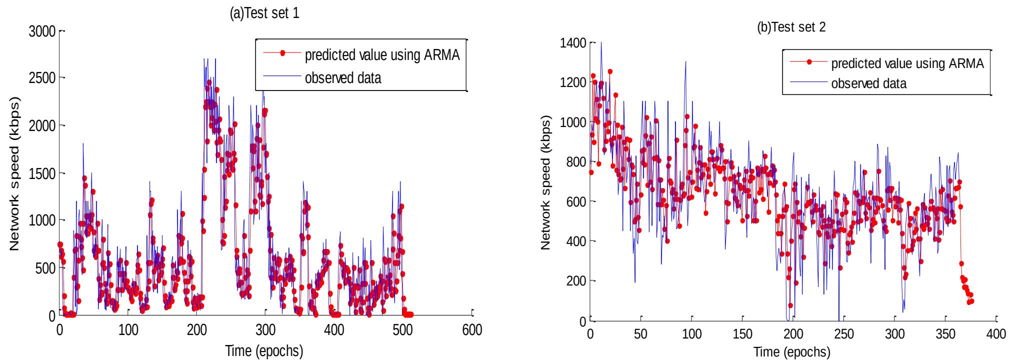

Figure 7. Network Speed Data Comparison Using Two Training Datasets

The prediction model is then used for data analysis using the testing datasets and the comparison between predicted data and observed data is shown in Figure 8.

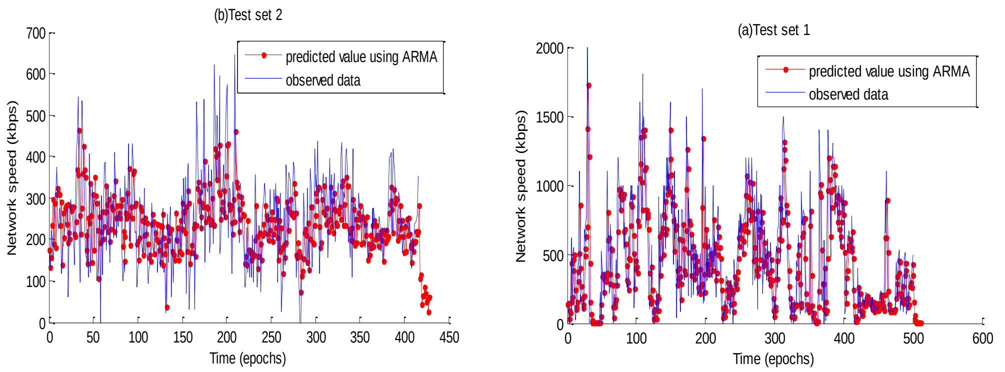

Figure 8. Network Speed Data Comparison Using Two Testing Datasets

Comparing the two figures, a conclusion can be drawn that using the first dataset, the prediction model performs generally the same on both the training sets and testing sets. On the contrary, the performance of prediction model using the second testing data set is less poor than its performance using the corresponding training set, which indicates that changes may occur during the time of the testing data.

To make a clear clarification, the fit value of prediction model to the testing data set is shown in Table 2. The fit value is calculated as the proportion of epochs in the whole number of epochs, the residuals of which are in the reasonable range: 1-m/N. m denotes the number of epochs calculated through Equation 11 and N is the overall number of epochs. The fit value in the second dataset drops dramatically when using the testing data.

Table 2. Fit Value of Prediction Model to the Testing Data Set

	Test set 1	Test set 2
Fit value using training data	46.28%	34.44%
Fit value using testing data	41.16%	10.79%

According to the fit value, conclusions can be drawn that there are errors in the second half of network speed data in dataset 2, which actually is in accordance with the real situations during test data collection.

6. Conclusion and Future Work

To evaluate and judge the wireless network condition in unstable environment, e.g. on moving medical vehicles, a network speed value prediction and judgment method is proposed in this paper. For any in use communication channel, historical network data is taken use of to predict the future network speed in a period of time based on the ARMA model and this model is updated periodically according to statistics results. The predicted network speed value is then compared with the observed network speed and the stability of the network is indicated by the comparison results. Experiment results prove a general case for network situation judgment. When the network works normally, the fit value between predicted value and observed data maintains generally the same between testing sets and training sets. On the contrary, a dramatic change can be observed from the comparison results when the network is interfered and abnormal network speed value is collected.

Based on the research in this paper, in the next step of work, automatic network switch mechanism should be proposed on the network analysis and judgment method for moving medical vehicles. Furthermore, the adaptive prediction method should be improved to provide more precision prediction in changing environment.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (No. 61309005) and the National Key Technology R&D Program (No.2012BAI21B04).

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