SMAR 2017 – Fourth Conference on Smart Monitoring, Assessment and Rehabilitation of Civil Structures

SMAR 2017

A basic research for track maintenance with track facility daily monitoring data

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ABSTRACT:

In Japan, rail track facility monitoring devices have been developed for a highly efficient maintenance system and nowadays running tests of one of these devices in a certain train line are implemented to acquire daily track facility monitoring data. However, it has yet to be shown the effective usage of these monitoring data for track facility maintenance. As a basic research for the effective usage of these monitoring data, this proposal aims to develop a track irregularity monitoring method using statistical approach. ARIMA model and RNNs have been applied with monitoring data and it predicts track irregularity progress.

1 INTRODUCTION

In Japan, the history of rail way began in September 1872, from Tokyo to Yokohama. Through the high economic growth, the railway network has been extended. And now, more than 27,000 km length of the network is managed in Japan. Through Japanese rail way history, the problem of track irregularity still remains to be solved. And it is still a serious issue for the safety of railway operation. Monitoring devices for track facility have been developed for maintenance systems in Japan. Nowadays, as Ryo et al. (2014) reported, running tests of a device installed on passenger trains are implemented to acquire daily data for facility monitoring. It gets various kinds of data in each passage and these data are accumulated rapidly in databases. This device enables railway operators to analyze the current track conditions deeply. In near future, it may enable to predict the track condition and detect track errors. The progress of the monitoring devices technology is remarkable, on the other hand, there are no solid methodologies to analyze track irregularity data or predict the track irregularity. In order to improve the quality of the monitoring data based risk management in track facilities, it is important to figure out the adequate methodology. To address this need, two different types of time series forecast methods, traditional statistical model and Neural Networks, are applied and the prediction accuracies are compared in this paper. The remaining part of this paper is organized as follows: Section 2 explains the background of this paper and methodologies applied to the monitoring data. The empirical example is presented in Section 3. Conclusions and future tasks are mentioned in Section 4

2 BACKGROUND

2.1 Development of Monitoring Devices for Track Irregularities

Atsushi (2014) points out that there are four main benefits of monitoring devices for track irregularities compared with hand-operated monitoring: (1) Improvement of work efficiency, (2) Improvement of monitoring accuracy, (3) Improvement of monitoring frequency, (4) Development of monitoring functions. The work efficiency, monitoring accuracy, and monitoring functions are clearly improved rather than hand-operated monitoring. As for monitoring frequency, thanks to the development of Information and Communication Technology, it has been improved in recent years.

The track irregularities are caused by frequent passages of train on track. Long-wave track irregularities affect the vertical and lateral body vibration resulting in a poor ride and short-wave track irregularities affect the high-frequency vibration resulting in increased load on the track, noise and vibration. Even derailment due to climbing or jumping of the wheel over the rail can occur with the large track irregularities. These factors increase the necessity of frequent maintenance and have been a burden for track maintenance. Kanji et al (1998) describes the control of track irregularities is performed at regular intervals and consists of: (1) inspecting track condition, (2) assessing repair need, (3) planning repair, (4) repairing and (5) confirming repair work. To manage these tasks, a first track inspection car was introduced in the 1960s and has played important roles in inspecting the track condition, pinpointing sections requiring repair and confirming the repair works. Track irregularities are detected based on the relative positions of the measured points (called the'10m chord alignment method'). In order to acquire track condition data more frequently, a track facility monitoring device is under development and running tests of the device installed on passenger trains are implemented to acquire daily data for facility monitoring. It gets environmental variables (gauge, longitudinal level, cross level and alignment) as track irregularity data several times in a day at 25-cm intervals.

2.2 Time Series Analysis

The concepts of time series analysis are widely applied in many areas of research. Massimiliano et al.(2006) studied the autoregressive (AR) model to predict macroeconomic time series and parameters estimation problems. One of the most important time series model is the autoregressive integrated moving average (ARIMA) model. ARIMA can represent several different types of time series model such as AR model, the moving average (MA) model, and the combination of AR and MA (ARMA) model. These models assume time series values can be explained by linear form of models.

Recently, Recurrent Neural Networks (RNNs) have been studied and used in time series forecasting. RNNs can also reflect the target through the historical target values of the time series. The greatest features of neural networks are flexible non-linear modeling capability. Tabatabaee et al. (2013) predicted road pavement condition using the historical pavement condition survey data with RNNs.

3 TIME SERIES PREDICTING OF TRACK IRREGULARITY DATA

3.1 Track Irregularity Data

Track monitoring data can be acquired for each passage in a day. In this paper, the max value of several monitoring data is defined as the representative value in the day and the values of longitudinal level are the subject of this paper. The comparison of track longitudinal level values among three points is shown in Figure 1. These three points are obtained at adjacent measuring points and they have different types of track deterioration processes. There are drastic changes during May 2015 at Point 1, January 2015 at Point 2, September 2014, and September 2015 at Point 3. These indicate that repairs of track rails had implemented at these points. In this paper, pure deterioration processes of track longitudinal level values are focused for analysis. Therefore, as the data for time series modeling and verification, the periods of monitoring data between two times of repairs are used. Figure 2 shows the target datasets for time series modeling. The sample compositions in three datasets are shown in Table 1. The datasets are divided into two samples of training set and test set.

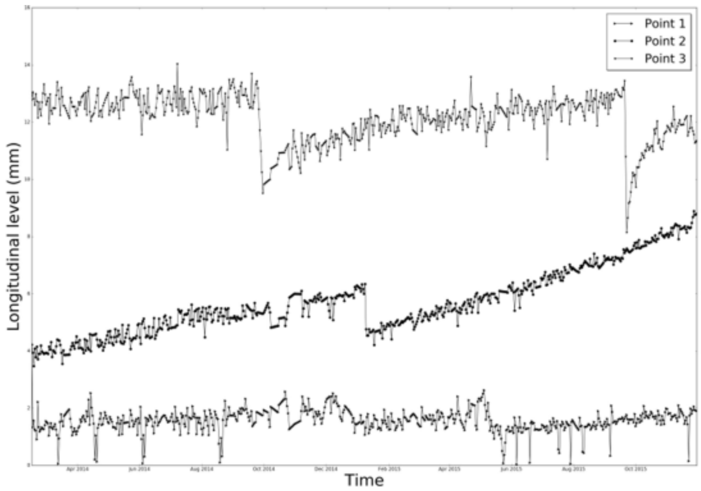

Figure 1. Comparison of track longitudinal level values at 3 points

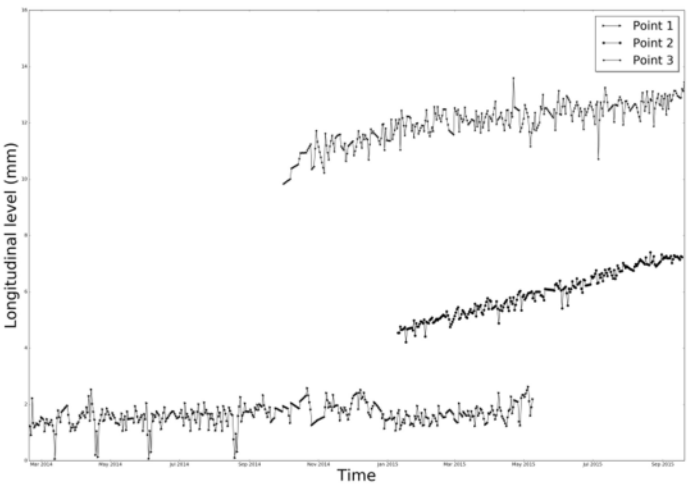

Figure 2. The target data for time series modeling

Table 1. Sample compositions in three data sets

Series	Sample size	Training set (size)	Test set (size)
Point 1	446	18th/MAY/2014-25th/MAR/2015 (357)	26th/MAR/2015-20th/SEP/2015 (89)
Point 2	252	10th/JAN/2015-24th/AUG/2015 (202)	25th/AUG/2015-18th/SEP/2015 (50)
Point 3	355	1st/OCT/2014-16th/AUG/2015 (284)	17th/AUG/2015-20th/SEP/2015 (71)

3.2 *The ARIMA model*

In an autoregressive integrated moving average model, the future value of a variable is assumed to be a linear function of several past observations and random errors. That is, the underlying process that generate time series has the form.

$$\begin{aligned} \mathrm{y_t} = \theta_0 + \ \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} \\ +\epsilon_t - \theta_1\epsilon_{t-1} - \theta_2\epsilon_{t-2} - \cdots - \theta_q\epsilon_{t-q} \end{aligned} \tag{1}$$

Where $\mathrm{y_t}$ and ϵ_t are the actual value and random error at time period t, respectively; $\phi_i(i: 1,2, \dots, p)$ and $\theta_j(j = 0,1, \dots, q)$ are model parameters. p and q are integers and referred to as orders of the model. Random errors, ϵ_t, are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2. If order q = 0, then (1) becomes an AR model of order p. If order p = 0, then (1) becomes an MA model of order q. George et al. (1970) developed three interactive steps of model identification, parameter estimation and diagnostic checking.

3.3 *The RNNs approach to time modeling*

When the linear restriction of the model is not adequate for the data, non-linear structures should to be considered. Recurrent Neural networks is one of non-linear models and used for time series prediction. A recurrent neural network is an extension of a conventional feedforward neural network. The RNNs handle the variable-length sequence by having a recurrent hidden state whose activation at each time is dependent on that of previous time. Formally, given a sequence $\mathbf{x} = (\mathrm{x_1}, \mathrm{x_2}, \cdots, \mathrm{x_\Upsilon})$, the RNNs update its recurrent hidden state $\mathrm{h_t}$ by

$$\boldsymbol{h}_t = \begin{cases} 0, & t = 0 \\ \phi(h_{t-1}, \mathrm{x_t}), & otherwise \end{cases} \tag{2}$$

where ϕ is a non-linear function such as composition of a logistic sigmoid with an affine transformation. Optionally, the RNNs may have an output $\mathrm{y} = (y_1, y_2, \cdots, \mathrm{y_\Upsilon})$ which may again be of variable length. The update of the recurrent hidden state in Eq. (2) is implemented as

$$\boldsymbol{h}_t = g(W\mathrm{x_t} + U\boldsymbol{h}_{t-1}) \tag{3}$$

where g is a smooth, bounded function such as a logistic sigmoid function or a hyperbolic tangent function. To train RNNs, a long short-term memory (LSTM) unit [Sepp et al. (1997)] is applied in this paper.

Table 2. Performance of predictions in three data sets

RMSE	Persistence Model		ARIMA		RNNs	
	In sample	Out-of-Sample	In sample	Out-of-Sample	In sample	Out-of-Sample
Point1	0.35	0.27	0.30	0.25	0.27	0.29
Point2	0.22	0.13	0.18	0.12	0.18	0.12
Point3	0.39	0.35	0.34	0.29	0.36	0.40

3.4 Results

In this paper, the prediction accuracies of ARIMA models and RNNs models are compared at three points. Before that, the persistence model (as known as the naïve) is applied as a benchmark test. This model is where the observation from the previous time step is used as the prediction for the observation at the next time step. To assess the performance of predictions, the root mean squared error (RMSE) is used.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y_t})^2} \tag{4}$$

Where y_t is the observation at time step t and $\hat{y_t}$ is the prediction at time step t. With training datasets, these three models are built and then, one step ahead for each time step is predicted in sample and out of sample. Table 2 shows the result of predictions in three data sets. Compared with Persistence model, the prediction performances of ARIMA model are improved at three adjusted points. On the other hand, the prediction performances of RNNs are improved in Sample datasets but got worse at out of Sample datasets at Point 1 and Point 3. These results indicate that ARIMA model is suitable for the short term prediction of track longitudinal values. The point-to-point comparisons between actual and predicted values are given in from Figure 3 to Figure 5.

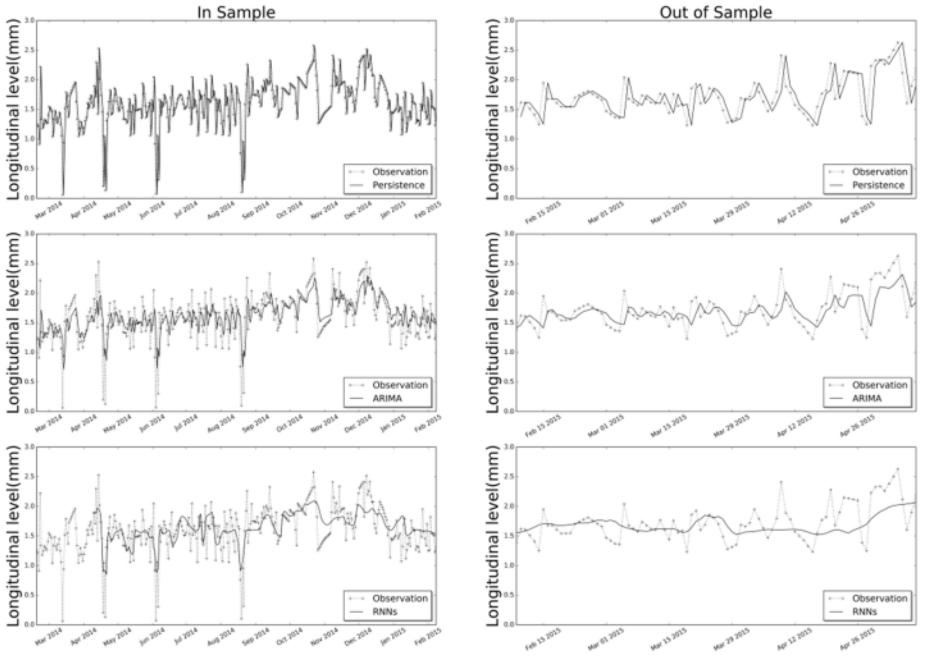

Figure 3. The comparison of the prediction performance at Point 1

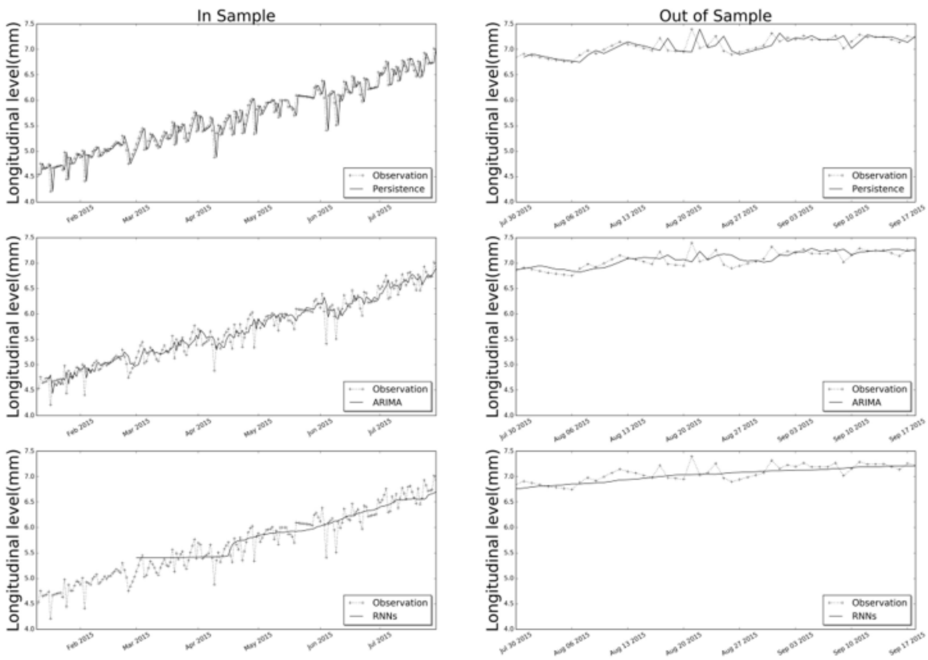

Figure 4. The comparison of the prediction performance at Point 2

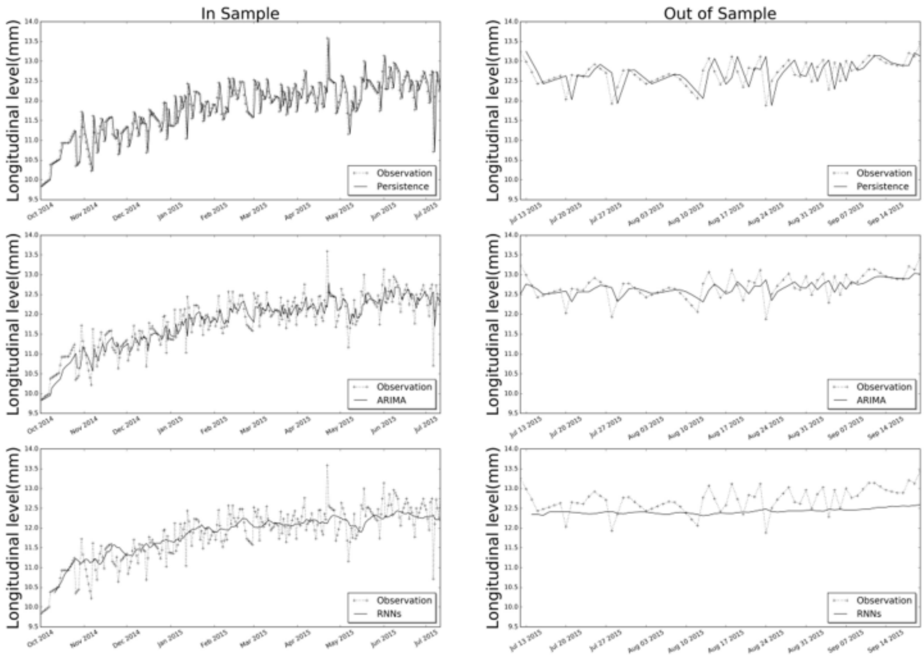

Figure 5. The comparison of the prediction performance at Point 3

4 CONCULUSIONS

The monitoring devices for track irregularities have been developed over the last few decades. Meanwhile, the universal method for the track irregularities prediction has not been developed. Various methods have been proposed both in the area of traditional time series analysis and in the area of neural networks. In this paper, as the basic research of track irregularity prediction, two types of predicting model are applied. From the area of traditional time series analysis, ARIMA model is applied meanwhile recurrent neural networks are applied from the area of neural networks. The results at three adjusted points show the prediction performances with ARIMA model are better than those with RNNs for short-term prediction. In this paper, the values of longitudinal level are the subject as the starting point of track irregularity analysis. However, various kinds of data are obtained through the monitoring and accumulated rapidly. For the adequate assessment of rail track condition, the building of combined models utilizing these data will be the next challenge.

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