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Modeling of Track Longitudinal Level Irregularity Based on High Frequency Measured Data

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Abstract: Reduction of the operating cost has long been a major challenge among railway operators. In order to make railway track maintenance, which makes up a large share of operating cost, more efficient, many prediction models for track degradation have been built. The recent development of condition monitoring technology made it possible to obtain track data much more frequently than before by using railway vehicles under operation. In this research, we built two track irregularity models with the method of state-space model, which is applicable to high frequency measured data. As a result, by using Sato model as a system model, it was able to predict longitudinal level irregularity up to 31 days ahead with mean absolute error less than 0.3 mm in most cases.

Keywords: railway track maintenance, condition monitoring, railway track geometry, high frequency measured data, track irregularity modeling, state-space model

1. INTRODUCTION

Railway track requires regular maintenance in order to keep train rides safe and smooth. However, the cost required for maintenance is high both in terms of financial and human resources. Therefore, reduction of maintenance cost has been a big challenge for a long time. Because prediction of future track irregularity will help infrastructure managers to plan track maintenance in a more efficient way, many kinds of researches are conducted to predict track irregularity from track inspection car data.

Following recent development of Internet of Things (IoT) technologies, introduction of Condition Based Maintenance (CBM) in railway field is becoming easier and showing a great progress. In the area of railway track maintenance, track irregularity measuring device which is small enough to be able to install on in-service vehicle is already put to use. Inspecting the railway track with in-service vehicle enables to obtain track data almost every day and hence grasping detailed change over time becomes possible. Without this device, track geometry data could only be obtained from a dedicated track inspection car which runs about every three months on each line. It is highly expected that the reduction of maintenance cost is achieved by accurate track irregularity prediction made from those high frequency measured track data.

When making predictions using high frequency measured data, using conventional

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regression methods is inefficient because an enormous number of past data is used. Therefore, in order to make predictions with high frequency measured data, sequential prediction method should be used.

In this research, we propose state-space model (SSM) as a method for longitudinal level track irregularity prediction using high frequency measured data. Two different track degradation models were built, and the prediction accuracy of each model was investigated in this paper.

2. LITERATURE REVIEW

Because understanding future track irregularity makes possible to optimize rail track maintenance and thus maintenance cost are reduced, many approaches have been developed for track irregularity prediction. Falamarzi *et al.* (2018) categorized previous track degradation models into three groups: mechanistic models, statistical models, and artificial intelligence (AI) models. Statistical models are further categorized into deterministic models, stochastic models, and probabilistic models.

As to approaches that focus on the mechanism of railway track degradation, the relation between track settlement and factors involving track degradation such as track condition or trains passing through are modeled. Sato (1995) described the track settlement after tamping operation as follows:

$$y = \gamma(1 - e^{-\alpha x}) + \beta x \tag{1}$$

where,

y : track settlement,
x : repeated number of loading carried by the track, and
α, β, γ : parameter.

This equation shows that right after the tamping when initial settlement occurs, track settlement proceeds exponentially. After a certain period of time, exponential degradation transitions to linear degradation. Moreover, the author analyzed track irregularity growth data and developed an equation for average track irregularity growth per 100 days as follows:

$$S = 2.09 \times 10^{-3} T^{0.31} V^{0.98} M^{1.10} L^{0.21} P^{0.26} \tag{2}$$

where,

S : track irregularity growth (mm/100 days),
T : number of train passages (million tons/year),
V : train speed (km/h)
M : structure factor,
L : influence factor of jointed rail or continuously welded rail (CWR) (1 for CWR and 10 for jointed), and
P : influence factor for subgrade (1 for good and 10 for bad).

Examples of statistical approaches include research by Kamiyama et al (2011). They attempted to predict the track irregularity of each point, not the representative value of track section. The prediction model has a similar structure as AR (2) model and used present and past track geometry data. Where, AR (2) is meaning second order autoregressive (AR). For

past track geometry data, values of surrounding points were also used. As a result, the prediction error of the model was within 1 mm when track irregularity growth was stable. On the other hand, when track irregularity growth is radical, where there are such structures as railway crossings, the model showed lower accuracy.

Yamamoto et al. (2016) predicted track irregularity by Bayesian modeling with the high frequency measured data following the start of railway track inspection by in-service train. About one data was obtained per day for each point and exponential smoothing was used to remove the influence of abnormal value or measurement error before the prediction. This method had more accuracy than the linear regression model in the 15-day prediction of the longitudinal level and also applicable to points where track irregularity growths are large.

Andrade et al. (2013) analyzed the track degradation of Portuguese Railway line and modeled the deviation of longitudinal level value. By using Hierarchical Bayesian modeling, parameters regarding deterioration were set for each section and thus it was able to express the spatial correlation.

The third group is the models that use AI methods that are currently developing rapidly. Falamarzi et al. (2018) used both regression model and artificial neural network (ANN) model to predict the deviation of gauge value of Melbourne tramway. Tram tracks are divided into 20m segments which have homogeneous characteristics and prediction was done for each segment. Prediction model was built for each combination of the track condition (repaired or unrepaired) and type of tracks (straight or curve). Past gauge values, type of pavement, or type of rail was used for explanatory valuables. As a result, both two methods had similar acceptable prediction accuracy.

Various methods have been proposed for the purpose of track irregularity modeling, however, there are still several problems in current prediction methods. Prediction value from methods that focuses on track degradation mechanism tends to be the same when the track conditions are the same, but actual track irregularity varies from point to point. Deterministic methods such as regression methods are inefficient and not practical when applying to the high frequency measured data because the amount of data used are enormous. Also, they cannot handle abnormal values. AI methods are still under development and there are not much application examples.

Therefore, we propose a prediction method that uses SSM. SSM has flexibly in building a model and thus it is possible to build a model based on the degradation mechanism. Also, predictions of SSM are done sequentially and SSM can handle missing values easily which are big advantages when applying to the high frequency measured data. Moreover, SSM describes the noises that occur during the process of prediction (process noise) and observation (observation noise) and hence it can handle measurement error to a certain degree. Further sections describe the track degradation models built with SSM and discuss the prediction accuracy by applying the model to the actual inspection data obtained from in-service vehicle.

3. PREDICTION OF TRACK IRREGULARITY USING SSM

3.1 State-Space Model

SSM is a method that enables to estimate unobserved inner state from observed data. SSM consists of system model that describes the transition of inner state and observation model that describes the process of measurement at each period. Figure 1 depicts the idea of SSM.

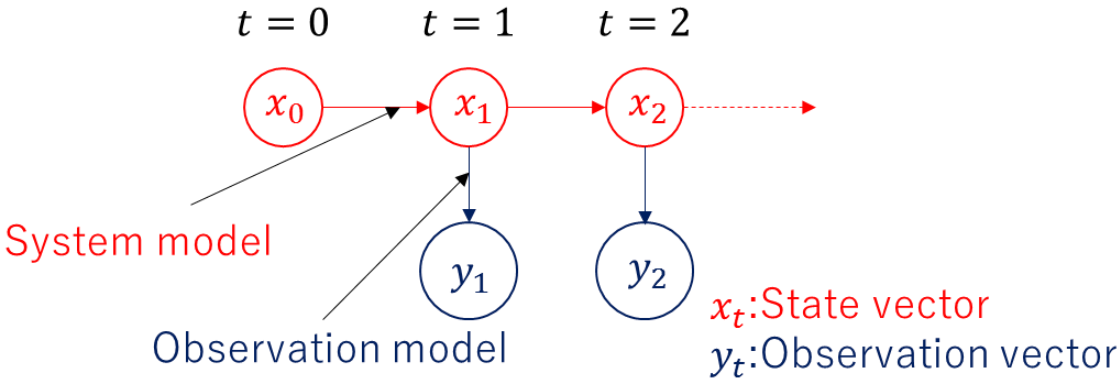

Figure 1. State-Space Model

System model and observation model are equations shown as follows:

$$x_t = F_t x_{t-1} + G_t v_t \tag{3}$$
$$y_t = H_t x_t + w_t \tag{4}$$

where,

x_t : state vector,
y_t : observation vector,
F_t : state transition matrix
G_t : driving matrix
H_t : observation matrix
v_t : process noise, and
w_t: observation noise.

In track degradation model, the system model describes the degradation of railway track by time and observation model describes the observation process of track irregularity by the track irregularity measuring device. Process noise describes the errors occurring during the transition process and observation noise describes the errors occurring during the observation process.

Estimation of SSM has a one-step-ahead prediction process of the state vector and it is possible to make long-term predictions by applying it repeatedly. In this paper, Linear Gaussian State-Space Model in which both system model and observation model are linear, noises are assumed to be Gaussian distribution. Kalman filter is applied to estimate the model.

3.2 Explanation of the Data Applied

In this research, we used longitudinal level irregularity data of both light and left rail measured by track irregularity measuring device equipped on an in-service train. The data contains the irregularity of 11 consecutive points (1m interval). The data starts from October 23, 2016 and ends on April 20, 2017. The irregularity was measured once a day but includes some missing values. For the details of the track irregularity measuring device, please refer to Kasai *et al* (2014). Since the data was the high frequency measured data, measurement error or inconsistency in measurement position caused large short-term fluctuations even though the track irregularity growth was not so large in the long term.

3.3 Track Irregularity Model

Following two track irregularity models were built in the research. Observation models of both models are models that add observation noise to the state vector. Validity of two system models is investigated. One prediction step was set as a day in both models. Maximum likelihood estimation is used to set parameters needed. Maximum likelihood estimation was performed once for the whole section and same parameters were set for all points in next term.

3.3.1 Sato Model (Model 1)

The model 1 is applying Sato model (Equation (2)) for system model. The reason for applying the Sato model to the system model is that the validity of the model has already been verified from many experimental data. Sato model appears on Japanese design standard of railway track and is also a benchmark for track irregularity prediction. Since there was not enough information about track condition other than train speed, we estimated the number of passage and assumed that the whole section has CWR and good subgrade. Also, it should be noted that Sato model calculates the growth per 100 days and thus value was converted to growth per day by dividing by 100. System model and observation model are equations as shown below and value calculated from Sato model is set as an initial value.

$$\begin{pmatrix} x_t \\ s_t \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ s_{t-1} \end{pmatrix} + G v_t \tag{5}$$

$$y_t = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} x_t \\ s_t \end{pmatrix} + w_t \tag{6}$$

where,

s_t : track irregularity growth per day.

3.3.2 ARMA Model (Model 2)

The model 2 is applying the Auto-Regressive Moving Average (ARMA) model for system model. ARMA model is a time series analysis method and consists of autoregressive process and moving average process. The order of each process is represented by (p, q) where p is the order of auto-regressive (AR) part, and q is the order of moving-average (MA) part. In this study, we were setting the p=2 and q=1 respective. Since ARMA model can only be used for stationary process, differenced time series was used for prediction. Hence, the structure of this model is same as ARIMA (2, 1, 1) model. System model and observation model of this model are equations shown as follows:

$$\begin{pmatrix} x_t \\ \varphi_2 x_{t-1} + \theta_1 v_t \end{pmatrix} = \begin{pmatrix} \varphi_1 & 1 \\ \varphi_2 & 0 \end{pmatrix} \begin{pmatrix} x_{t-1} \\ \varphi_2 x_{t-2} + \theta_1 v_{t-1} \end{pmatrix} + \begin{pmatrix} 1 \\ \theta_1 \end{pmatrix} v_t \tag{7}$$

$$y_t = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} x_t \\ \varphi_2 x_{t-1} + \theta_1 v_t \end{pmatrix} + w_t \tag{8}$$

where,

φ_1, φ_2 : parameters regarding autocorrelation and

θ_1 : parameter regarding moving average.

3.4 Predicting Positive and Negative values of Growth

Track irregularity has positive and negative values and hence degradation progresses both in positive and negative direction, varying from point to point. In Model 1, the direction of degradation must be set when setting an initial value, however, there is no information to judge whether track irregularity growth proceeds in positive or negative direction right after the track maintenance. Therefore, we assumed that degradation progresses to the closer maintenance standard value. Even if the misjudge was made by this assumption, it is possible to adjust the prediction using observation data through the update process of Kalman filter.

3.5 Prediction Using the High Frequency Measured Data

In order to validate the track irregularity models built, we applied the models mentioned before to actual high frequency measured data. As shown in Figure 2 the data was split in two. Using the first part of the data, track irregularity of the second part was predicted and then compared with actual observation. During the first part of the data, one-step ahead predictions are done, which functions as a learning process. In the second part, multi-step ahead predictions are done. In this case, maximum prediction term was 31 days.

For evaluation, we used the absolute value of prediction error. Table 1 shows the prediction results of both models.

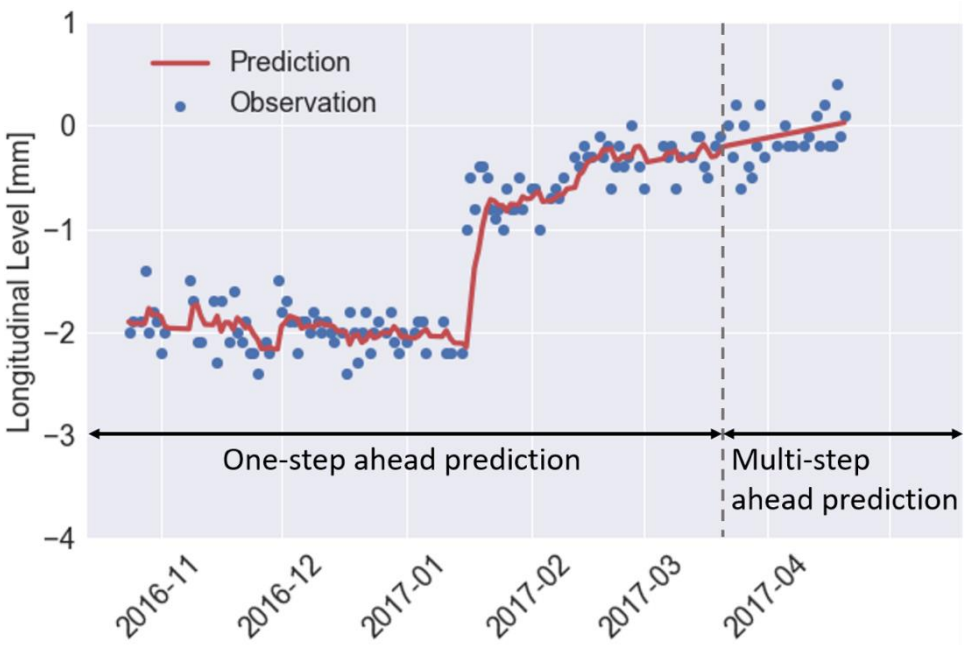

Figure 2. Example of prediction (Model 1)

Table 1. Prediction error

System Model	Model 1	Model 2
Max. Prediction Term [days]	31	31
Number of Data	528	528
Mean [mm]	0.24	0.91
Std. [mm]	0.20	0.92
Max. [mm]	1.45	3.62
Min. [mm]	0.00	0.00

3.6 Discussion

Model 1, which uses Sato model for system model had a very good prediction accuracy with mean prediction error of 0.24 mm. Although the number of such predictions is small, there were predictions with error bigger than 1 mm. In all cases, observation data showed a huge fluctuation which can be considered as a measurement error or an abnormal value. Overall, prediction accuracy of Model 1 will be better without such abnormal values.

Although Model 1 showed good accuracy, there are cases that model mis predicted the positive/negative trend of track irregularity growth. That means prediction accuracy gets worse in longer prediction term. Also, the influence of recent observation is large in this model, which means predictions are affected by the latest trend. Hence, this model cannot adapt to change of trend, especially when positive/negative trend of track irregularity growth turns over.

Model 2 could not perform prediction with sufficient accuracy. It is necessary to review the order of ARMA model or investigate another type of system model. Also, this model requires parameter estimation for each point. Considering that number of data is enormous in whole track, Model 1 is preferable not only in terms of prediction accuracy but also in terms of practical use.

4. CONCLUSION

In this research, we built two track irregularity models, which are applicable to the high frequency measured data by using SSM and investigated the validity. As a result, by using Sato model as a system model, it was able to predict longitudinal level irregularity up to 31 days ahead with mean absolute error less than 0.3 mm in most cases. On the other hand, ARMA model was not suitable for system model, prediction accuracy being around 0.9 mm.

For future research, revision of system model should be considered. As mentioned before, there are cases that growth trend was mis predicted, and the model cannot adapt to change of trend. Also, considering the fact that ARMA model could not make a valid prediction, it is necessary to review the ARMA order or seek a new system model. Since correlation between neighboring points was seen in the data, system model describing such correlation should be effective.

Furthermore, Kalman filter which is used for estimation method for prediction model assumes a linear system/observation model and Gaussian system/observation noise. Improvement in accuracy should be considered by using particle filter or other filtering methods that do not require these assumptions.

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