MODEL-BASED CONDITION MONITORING FOR RAILWAY VEHICLE SYSTEMS

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Abstract

Although modelling techniques for railway vehicle dynamics are well-developed, much of the development in railway vehicle condition monitoring has relied on the knowledge-based techniques where no analytical system model is employed and only qualitative or empirical system knowledge are used for fault diagnosis. In this paper, the model-based approach is proposed as an alternative for railway vehicle condition monitoring and the basic idea behind the approach is presented. The performance of the proposed method is evaluated through simulations and some preliminary results are provided.

1 Introduction

Condition monitoring for railway vehicle systems has received increasing attention both from academia and railway industry. This development is mainly stimulated by the growing demands on cost efficiency, reliability and safety for railway vehicle and rail services. The research presented in this paper is a part of the research project known as ERCIR (Enhanced Rail Contribution by Increased Reliability) which is funded by UK Department for Transport. The project aims to improve the performance of rail-related fault prediction and diagnosis via in-service condition monitoring of both vehicles and track.

The problem of fault detection and isolation (FDI) in dynamic systems has attracted considerable attention world-wide and has been theoretically and experimentally investigated with different types of approaches, as can be seen from a large number of survey papers [14], [4], [1], [3] and books (see e.g. [12], [2]) on the subject. The FDI approaches appearing in literature fall into two major categories — model-based approaches and knowledge-based approaches. Model-based approaches rely on the idea of analytical redundancy, the essence of the idea being the comparison of the system’s available measurements with a priori information represented by the system’s mathematical model. In contrast, knowledge-based approaches complement the model-based approaches and can be used in the case where the mathematical model of the monitored system is not available or in the case where the modelling uncertainty is noticeable. Clearly a perfect analytical model (if available) represents the deepest and most concise knowledge of the system. Hence, in the case of information-rich system where the dynamic behaviour of system can be well-described by mathematical model, the analytical model-based methods are by nature the most powerful fault diagnosis methods.

Although, in the past three decades, model-based FDI has been thoroughly studied and a large variety of analytical model-based methods have been proposed and successfully used to solve many practical FDI problems in various areas, very few results on model-based FDI for railway vehicle dynamic systems are reported. Most of the methods for FDI in railway vehicle/track systems that have appeared in literature (see e.g. [13]) can be grouped into the knowledge-based approach mentioned above where no mathematical models describing the dynamical behavior of the railway vehicle system are employed. This means that some a priori knowledge or information on railway vehicle dynamics is lost and there is the potential of improvement in FDI performance if the knowledge or information is fully used. On the other hand, modelling techniques and specific models for railway vehicle dynamic systems are well-developed [7], [11], and considerable progress on the model-based state estimation for railway vehicle has also been made in recent years [10], [6]. However, these were principally developed for simulation and controller design. In this paper, the modelling techniques for railway vehicle are combined with the idea of the model-based FDI and a Kalman filter based method is proposed to be used in the railway vehicle condition monitoring system for diagnosing faults in railway vehicle suspension system. The paper is organized as follows. Section 2 develops a plan view dynamic model to be used in model-based FDI design, then the Kalman filter based approach to FDI of the railway vehicle suspension system is presented in Section 3. Section 4 provides some results from applicability studies and Conclusions are drawn in Section 5.

2 Modelling of railway vehicle dynamics

The first step for model-based FDI is to develop suitable models to describe the dynamic behaviour of the railway vehicle system. Although very complex non-linear simulation models are available using MBS tools, these are too complicated and it is necessary to develop appropriately-simplified models which capture the essential dynamic characteristics related to the problem being considered. The authors’ work has focussed upon the problem that affects running stability for which the lateral and yaw modes are important, and Figure 1 shows a plan view of a conventional bogie vehicle and the configuration of the sensors. The wheelsets and bogie have two degrees-of-freedom (lateral and yaw), and a half-vehicle model is being used so the vehicle body just has the lateral degree-of-freedom. The corresponding equations of motion of the vehicle traveling on straight track are derived as follows:
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To develop the model-based FDI schemes, a state-space form of the plan view dynamical model can be derived from (1) as:

$$\dot{x} = Ax + G\beta$$

where

$$\mathbf{x} = \begin{bmatrix} \dot{y}_{w1} & y_{w1} & \dot{\Psi}_{w1} & \dot{y}_{w2} & y_{w2} & \Psi_{w2} & \Psi_{w1} & \dot{w}_{b} & y_{b} & \dot{\Psi}_{b} & \dot{y}_{bd} & y_{bd} & d_1 & d_2 \end{bmatrix}^T$$

and

$$\mathbf{\beta} = \begin{bmatrix} \dot{y}_{t1} & \dot{y}_{t2} \end{bmatrix}^T$$

matrices \(A\) and \(G\) can be readily derived from the equations (1) and \(\beta\) can be approximated as zero mean white Gaussian noise (see e.g. [6]) with variance \(4\pi^2A_r\sigma^2\) to represent track irregularities, where \(A_r\) is the track roughness factor.

Since a direct measurement of lateral displacements and wheel-rail deflections is not feasible in practice, five sensors (a gyro \((G_b)\) and four accelerometers \((A_1, A_2, A_b, A_{bd})\)) are chosen as shown in Figure 1 which can measure the lateral accelerations of the two wheelsets \((\dot{y}_{w1} \text{ and } \dot{y}_{w2})\), the lateral acceleration and yaw velocity of the bogie \((\dot{y}_{b} \text{ and } \dot{\Psi}_{b})\) and the lateral acceleration of the vehicle body \((\dot{y}_{bd})\). The measurement equation is given as follows:

$$\mathbf{y} = \mathbf{Hx} + \mathbf{v}$$

where, \(\mathbf{y} = \begin{bmatrix} \dot{y}_{w1} & y_{w1} & \dot{\Psi}_{w1} & \dot{y}_{w2} & y_{w2} & \Psi_{w2} & \Psi_{w1} & \dot{w}_{b} & y_{b} & \dot{\Psi}_{b} & \dot{y}_{bd} \end{bmatrix}^T\). \(\mathbf{v}\) represents the measurement noise vector and the measurement matrix \(\mathbf{H}\) is obtained readily from the system matrix \(\mathbf{A}\).
For most practical applications, the measurements are usually sampled-data (i.e. discrete) resulting from the digital implementation and the discrete version of the above model is given as follows (see e.g. [9]):

\[
\begin{align*}
x_k &= Fx_{k-1} + \Gamma w_k \\
y_k &= Hx_k + v_k
\end{align*}
\]

where, \(F = e^{AT}\), \(\Gamma = \int_0^T e^{A\tau} G d\tau\) and \(w_k, v_k\) are white Gaussian noises of appropriate strength, \(T\) is the sampling period for measurements.

3 Model based FDI design

3.1 Background

The general procedure of model-based FDI can be split into two steps: generation of fault accentuated signals (known as residuals in FDI literature) on the basis of the available measurements and a mathematical model of the system; residual evaluation, namely decision on the occurrence of a fault and isolation of the faulty element based on the residuals generated. The heart of procedure is the generation of residuals. There are many approaches to constitute the residual generator in the literature (see e.g. [4], [12], [3], [2]). A straightforward method is based on parameter estimation (see e.g. [4]), in which the parameters of the monitored system are estimated using the measurements available and the resulting estimates are compared with their nominal values. The difference is then taken as the residual signal for FDI decision. This approach is particularly useful for the detection and isolation of the incipient or drift-like faults where the parameters associated with the faults to be detected can be considered as constant during a short period of time within which the measurement is made. The key of the approach is the parameter estimation method employed. However, our earlier research [8] has shown that direct estimation of specific parameters associated with the faults to be detected in the railway vehicle suspension system described by equations (2) and (3) is not straightforward. The solution to the problem involves the combined parameter and state estimation which was usually posed as a nonlinear filtering problem. The popular extended Kalman filter (EKF) based method has been tried for the problem but failed and a Rao-Blackwellized particle filter (RBPF) based method has been developed in [8] to address the issue. However, the RBPF based method is in general computationally expensive and can only be used in the case where the detection time is of minor importance, hence the method is of major relevance in connection with condition monitoring and maintenance problems where early detection of worn equipment is required. In the rest of the paper, we shall focus on the detection of abrupt (or hard) faults which usually need immediate attention and hence the on-line detection.

3.2 Innovation-based FDI design

One of the main difficulties in fault detection of the stochastic system described by (4) and (5) is due to the presence of unknown and unmeasured state variables \(x\). The commonly used approach to deal with it is estimation. For linear Gaussian system, the states are estimated using a Kalman filter according to the following equations:

\[
\begin{align*}
\dot{x}_k &= Fx_{k-1} + K_k r_k \\
P_k &= Fp_{k-1}F^T + \Gamma Q \Gamma^T \\
K_k &= Fp_{k-1}H[Hp_{k-1}H^T + Q_v]^{-1} \\
P_k &= P_{k-1} - K_k Fp_{k-1} \\
r_k &= y_k - H\hat{x}_{k|k-1}
\end{align*}
\]

where, \(r_k\) is the innovation given by:

\[
r_k = y_k - H\hat{x}_{k|k-1}
\]

It is well-known that, under fault free or normal operation, the innovations are zero mean Gaussian with covariance

\[
Q_r = HP_{k|k-1}H^T + Q_v
\]

Any faults or changes in system dynamics can therefore be detected by a change in the weighted squared residual (WSR) measure

\[
l_k = r_k^T Q_k^{-1} r_k
\]

which is \(\chi^2\) distributed with \(m\) degrees of freedom, where \(m\) is the dimension of measurement vector \(y\). This however can lead to false alarms occurring at a particular instant due to disturbances and noise and a more robust decision function for fault detection is the weighted sum squared residual (WSSR) (see e.g. [5] [14]) defined as follows:

\[
d_k = \sum_{j=k-W+1}^{k} l_j = \sum_{j=k-W+1}^{k} r_j^T Q_j^{-1} r_j
\]

where \(W\) is the length of the sliding window within which the residual measure is summed. In the absence of a fault this quantity is a chi-squared random variable with \(Wm\) degrees of freedom, and so fault detection can be achieved by a chi-squared hypothesis test. The window length \(W\) should be chosen in accordance with the requirement for detection time and the fault alarm is set at time \(k\) when the condition

\[
d_k > h
\]

is satisfied, \(h\) being the threshold which is chosen according to the required false alarm probability, window length and chi-squared tables. For the given threshold, window length provides a trade-off between fast detection and false alarm rate.

The information for fault isolation can also be obtained by analysing the components of the innovation vector \(r\) separately, for example, by calculating the r.m.s or performing power spectral density (PSD) analysis for each component of \(r\).

4 Applicability studies via simulations

Since our aim is to monitor the condition of vehicle suspension systems and the solid state inertial sensors have been selected for taking measurements which are much more reliable and cheaper than the conventional mechanical inertial sensors, sensor faults will not be considered here. In the following simulation studies, the attention will be focused on the monitoring
of changes in damping coefficients as the damper faults have been identified as the common faults in railway vehicle suspension system and are difficult to test in situ. In particular, we will focus on the detection and isolation of the abrupt (or “hard”) faults in secondary lateral and anti-yaw dampers which lead to the abrupt changes in the values of damping coefficients $C_{yb}$ and $C_{yb'}$.

In the simulations, the data are generated using model (2) and (3) developed in Section 2 with constant forward speed. The sampling frequency for measurement is chosen as $f_s = 1kHz$. The faults are simulated to occur at time 2.5(sec) at which point the faulty parameters $C_{yb}$ or $C_{yb'}$ in Figure 1 are reduced by 50%. The Kalman filter is designed based on model (4) and (5) with nominal parameter values given in the Appendix and the WSSR detector defined by (10) and (11) with $W = 100$ (i.e. 100mS) is used to detect these faults.

The WSSR ($d_k$) calculated by (10) and the PSD of the innovations from the bogie yaw gyro and the vehicle body accelerometer before and after the onset of the faults are plotted in Figures 2 and 3. It can be seen, from these figures, the faults can be detected by thresholding WSSR ($d_k$), and once the fault alarm is set, the innovations from the bogie yaw gyro and the vehicle body accelerometer recorded just before and after fault alarm can be used for PSD or r.m.s calculation, fault isolation can then be achieved by comparing the PSDs or the r.m.s calculated using the innovation data before and after fault alarm.

![Figure 2: PSD of innovations (+ line—before fault, solid line—after fault) and WSSR with fault in $C_{yb'}$](image1)

![Figure 3: PSD of innovations (+ line—before fault, solid line—after fault) and WSSR with fault in $C_{yb}$](image2)

The PSDs of the innovations in Figures 2 and 3 before and after fault onset time show that the faults affect only the low frequency components in certain innovation sequences, which suggests that low-pass filtering the innovations before r.m.s calculation would help to isolate different faults. Figure 4 shows the r.m.s of innovations from the vehicle body accelerometer and the bogie yaw gyro under different fault conditions. A 3rd order standard Butterworth low pass filter with cutoff frequency $f_c = 10Hz$ is used in calculation (10Hz is chosen from a priori knowledge that the main dynamic modes of the chosen vehicle are below 10Hz). It can be seen, from these figures,
that the lateral damper fault will not affect the r.m.s of the innovation from the bogie yaw gyro, whereas, the anti-yaw damper fault will not affect the r.m.s of the innovation from the body accelerometer. The resulting Kalman filter based FDI procedure to be used in the railway vehicle condition monitoring system is depicted in Figure 5.

5 Conclusions

A Kalman filter-based innovation method has been proposed in this paper for detecting and isolating faults in railway vehicle suspension system based on the derived vehicle dynamic model. The method is computationally efficient and has rapid response to the abrupt fault, thus suitable for using on line to detect and isolate the abrupt or "hard" faults which usually need immediate attention. This complements the RBPF based parameter estimation method developed in [8]. As such, a combination of both methods is believed to be the most appropriate solution to the model-based railway vehicle condition monitoring problem. Further work will be carried out to address the robustness issues and integrate the model-based methods with the knowledge based processing so as to improve the overall performance of the railway vehicle condition monitoring system, and results from an experimental programme on a real railway vehicle are also being assessed.

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References


Appendix. Symbols and parameter values for the railway vehicle dynamical model

\( m_w \) Wheelset mass(1000kg)
\( I_w \) Wheelset yaw inertia(600km^2)
\( m_b \) Bogie mass(2000kg)
\( I_b \) Bogie yaw inertia(2300km^2)
\( m_{bd} \) Vehicle body mass associated with the bogie(8720kg)
\( K_y \) Primary lateral stiffness per wheelset(4000kN/m)
\( K_{yf} \) Primary yaw stiffness per wheelset(4000kN/rad)
\( K_{yb} \) Secondary lateral stiffness per bogie(160kN/m)
\( C_{yb} \) Secondary lateral damping per bogie(16kNs/m)
\( C_{yf} \) Secondary anti-yaw damping per bogie(500kNs/rad)
\( f_{31} \) longitudinal creep coefficient(7.4MN)
\( f_{22} \) lateral creep coefficient(6.2MN)
\( a_0 \) Semi wheel-wheel spacing(1.05m)
\( l_0 \) Half gauge(0.75m)
\( \lambda \) Conicity (0.15)
\( v \) Vehicle forward velocity(20m/s)
\( r_0 \) Wheelset radius(0.37m)
\( A_r \) track roughness factor(0.33 \times 10^{-6})