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Verification of Model-Based Adhesion Estimation in the Wheel-Rail Interface

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Low adhesion in the wheel/rail contact or the 'leaves on the line' problem is a large operational issue for the railway industry. There is currently a shortage of up to date information about the running conditions of rails with respect to short term adhesion trends (over a daily period) and macro trends (across seasons). This can lead to costly over application of mitigation actions such as rail head cleaning to combat the problem.
The generally established methods of assessing areas of low adhesion involve mapping activations of wheel slide and wheel slip protection events to track locations. These methods are reactive and rely upon a slip/slide event to be initiated by the application of traction or braking. The RSSB managed project T959 is forwarding previous fundamental research into methods of low adhesion detection (LAD) in real time using 'modest cost' inertial sensors mounted to in service vehicles. The LAD system proposes that the motions of a railway vehicle (in both lateral and yaw movements) vary as the adhesion conditions under the vehicle change. If the changes in the running dynamics as a result of low adhesion can be observed and interpreted, they can infer the adhesion at all points across a network and not just when slip/slide events are triggered.
The main focus of the research has been to use a linearised model of a rail vehicle suspension system to define a Kalman-Bucy filter. The creep forces, that are unable to be measured directly, are outputted from this filter as augmented states. By comparing the estimated values of creep forces against measurable vehicle dynamics, an estimation of adhesion level can be realised. This approach has been verified against rail vehicle simulations performed by DeltaRail using the multi-body physics software VAMPIRE®.

1. Introduction

Low adhesion or the 'leaves on the line' problem is a large issue often misunderstood by the industry and general public alike. There is currently a lack of information about the changing picture of areas of low adhesion with respect to short term trends (over a daily period), and macro trends (across the seasons). The direct measurement of adhesion, or even the contact forces, experienced in the wheel/rail contact is currently not possible for in-service vehicles, meaning it is difficult to assess the current operating risk experienced by vehicles. The generally established methods of identifying areas of low adhesion involve mapping activations of wheel slide and wheel slip protection events to track locations. This lack of knowledge of current adhesion conditions can cause over application of costly mitigation methods such as railhead cleaning.
The research described in this paper has been performed as part of a RSSB managed project T959. This follows on from RSSB project T614 which investigated advanced methods of detecting areas of low adhesion in real time using 'modest cost' inertial sensors mounted to in service vehicles. It was proposed that the motion of a railway vehicle (in both lateral and yaw directions) varies as the adhesion conditions at the wheel/rail interface change (Charles, 2008). Fundamentally, this means that if the changes in the running dynamics as a result of low adhesion can be observed and understood, the adhesion at all points across a rail network can be inferred, i.e. not only when slip/slide events are triggered.

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A number of methods have been proposed to analyse data provided by inertial sensors mounted on the wheelsets, bogie and vehicle body. The main focus of the research has been developing a 'model-based' approach (Charles, 2008) that uses a fundamental understanding of the physics of a rail vehicle to estimate wheel-rail creep forces that can't be measured directly. This method was tested against linear suspension simulation models (Ward, 2011) and later against more realistic simulations produced in the multi-body physics software VAMPIRE® (Hubbard, 2012). A derivation of the model-based creep force estimator is included in section 2.

Initially, (Kalker, 1982) suggested that dynamic differences due to adhesion variations only occur as the creep forces approach saturation levels. Contrary to this, studies of low adhesion using a tribometer train (Pearce, 1986) suggested that the changes are seen not only in the saturation levels, but in the initial slope of the creep force to creep curves. Further studies in laboratory conditions (Fletcher, 2012) established that the initial creep slope is a physical phenomenon, quantifiable for different friction modifying materials such as: water; oil; and simulated leaf contaminant. This means that if an approximation of the creep forces experienced at normal operating conditions could be found by the methods suggested previously, they could be analysed to identify the level of adhesion at which they were generated.

Deriving a value of adhesion from known creep forces would ideally use a measure of the track irregularity experienced – even if this was in only a statistical sense. Creep forces are generally generated by the irregularities in the track causing a dynamic vehicle response which in turn results in differential movement between track and wheel. Therefore knowledge of the input in terms of these irregularities would be useful. However, due to the complexities and costs involved of storing and reusing accurate track information there is a market driver to produce a solution that is independent of route information. As such, only the use of on-vehicle dynamic measurements should be used to derive an estimation of adhesion from creep force. The investigation into a potential solution to this is provided in section 3.

As part of the project, DeltaRail provided a large variety of VAMPIRE® (DeltaRail, 2011) test runs whereby the vehicle simulation was subject to a number of changing operating conditions. These simulations provide a basis to test the model-based estimator in a variety of realistic operating profiles and evaluate its performance. The results of this work are presented in section 4.

2. Model-Based Creep Force Estimator Development

The technique of using a model-based approach to estimate contact forces under normal running conditions has been proven against linear suspension models in a MATLAB/Simulink environment (Ward, 2011). Part of the progression of the work within this project is the verification of creep-force estimation using simulation data taken from VAMPIRE®. This data is treated as if it were from an in-service vehicle and provides a suitable level of validation of the capability of the creep force estimator.

2.1 Methodology

The model-based estimator used here is one based around the use of the well-known Kalman-Bucy filter (Kalman, 1960). The fundamental building block of the model is a linear description of the systems dynamics, which in this case will be a mathematical description of the vehicle suspension system. It can be shown (Garg, 1984) that the yaw and lateral motions of railway vehicle components (i.e. wheelset, bogie and vehicle body) contain the dominant stability characteristics of the vehicles response to track irregularities (Wickens, 2003). Therefore, a linear dynamic model considering the physics of the suspension in these planes of motion can be produced that should appropriately represent the main dynamic characteristics.

The primary problem in this application is that creep forces cannot be measured directly. The solution to this involves manipulating the Kalman filter by defining 'augmented states' that represent these forces. The numerical values of these states are defined by attribution to the 'left-over' values from the force/balance equation. For this method to work, an accurate linear model is required as any processing noise will be interpreted as additional creep forces.

2.2 Development of Creep Force Model-Based Estimator

The vehicle model chosen for this work is a generic modern passenger vehicle, based loosely on the British Rail class 158 design. This suspension is appropriate for this application as it is has largely linear characteristics around the operating region that are more closely related to contemporary bogie design. Figure 1 shows a schematic of the primary suspension system of the modern passenger vehicle being used in this study.

The linear dynamic model can be formed by first considering the force and moment balance equations taken around the wheelset, and neglecting minor terms:

$$m\ddot{y}_{FF} = F_{Ry} + F_{Ly} + F_g + F_{sy} \quad (1)$$

$$I_{wx}\ddot{\psi}_{FF} = R_{Ry}F_{Rx} - R_{Ly}F_{Lx} + M_g + M_{sy} \quad (2)$$

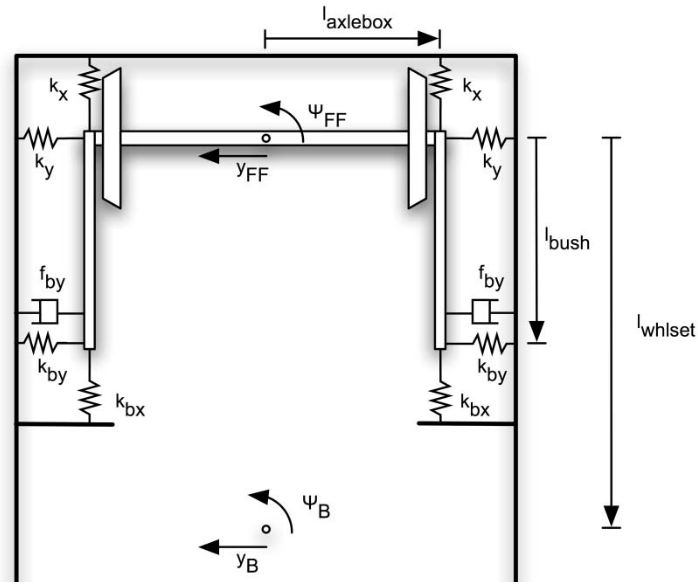

Figure 1: Schematic showing the simplified, linear, plan-view representation of the modern passenger vehicle primary suspension system.

Where: F_R, F_L are the lateral (y) and longitudinal (x) forces acting on the wheelset on the right and left wheels, F_g, M_g are the gravitational stiffness – the resultant normal force due to the contact angle, R_{Ry}, R_{Ly} are the moment arms from the wheelset centre of mass to the contact points and F_{sy}, M_{sy} are the reactive suspension forces due to the wheelset and bogie movement. Previous work has shown that the Kalman-Bucy filter cannot distinguish between the creep forces and the gravitational stiffnesses, so these are grouped into a single term, as shown in equations 3 and 4.

$$F_{FF} = F_{Ry} + F_{Ly} + F_g \quad (3)$$

$$M_{FF} = R_{Ry}F_{Rx} - R_{Ly}F_{Lx} + M_g \quad (4)$$

This provides the terms F_{FF} and M_{FF} that represent the total lateral contact force and the total contact moment acting on the front wheelset.
The suspension forces of F_{sy} and M_{sy} are largely the result of the differential positions between the wheelset and the bogie. The damping terms were found to be very small in comparison to these and as such are neglected here. Assuming the suspension deflection angles are small, the following equations (5, 6) can be derived:

$$F_{sy} = 2k_y\big((y_b + \psi_b l_{bush}) - y_{FF}\big) + 2k_{by}\Big(\big(y_b + \psi_b(l_{whlset} - l_{bush})\big) - (y_{FF} + \psi_{FF} l_{bush})\Big) \quad (5)$$

$$M_{sy} = 2k_{by}\Big(\big(y_b + \psi_b(l_{whlset} - l_{bush})\big) - (y_{FF} + \psi_{FF} l_{bush})\Big) l_{bush} + 2(k_x + k_{bx})(\psi_b - \psi_{FF}) l_{axlebox}^2 \quad (6)$$

The equations 1-6 can be combined and rearranged to into standard state space form:

$$\dot{\boldsymbol{X}} = \boldsymbol{A_k X} + \boldsymbol{B_k U} \quad (7)$$

Where the states and inputs are chosen to be:

$$X = [y_{FF}\ \dot{y}_{FF}\ \psi_{FF}\ \dot{\psi}_{FF}\ F_{FF}\ M_{FF}]^T \tag{8}$$

$$U = [y_B\ \dot{y}_B\ \psi_B\ \dot{\psi}_B]^T \tag{9}$$

As described in detail by previous work done (Christopher Ward, 2011) the Kalman-Bucy filter is tuned primarily via the 'Q' matrix which identifies a degree of certainty with each of the state models. By setting the contact force state models as highly uncertain compared to the vehicle dynamics state models, the filter can be used to approximate the creep forces.

2.3 Verify the Creep Force Estimator

This method was tested with two very simple cases. In each case, the vehicle travelled a length of perfectly smooth track at full line speed (defined here as 200kph), with the addition of a single lateral step change of 5mm in track position. The vehicle wheelset and bogie dynamics were used to provide the input of the model-based estimator, and the time history of the estimation and recorded creep forces were compared. Figure 2 shows the time history for the creep moment when the vehicle is subject to 'dry' adhesion conditions and 'low' adhesion conditions. In each case, the estimator performs well with very small margins of error. The lateral creep force time history gave similar, good results.

3. Post Processing for Adhesion Estimation

The model-based estimator was subject to more demanding test scenarios whereby the vehicle was subject to a more realistic transit. In these cases a realistic track profile was used in that irregularities existed both laterally and vertically, and they were statistically representative of typical high speed track. Figure 3 shows a comparison of the creep moment values (recorded by VAMPIRE®) to the estimated creep moment values using the model-based approach. The figure shows the results of three 60 second tests at three different levels of adhesion; dry ($\mu = 0.56$), low ($\mu = 0.072$) and very low ($\mu = 0.038$). The data output has been subject to a 5s moving RMS window.

It can be seen that the overall level of creep moment reduces with adhesion under normal operating conditions, and the estimator follows this fall. There is a discrepancy between the recorded values and the estimated values of contact force which is attributed to minor modelling discrepancies. As highlighted earlier, these differences will result in errors in the approximation of the state. Also, there is variation of RMS values within the course of each run. This is a result of the variation in the levels of track irregularity over the period at which the RMS is taken.

In order to attempt to normalise the data against track irregularity, the creep moment estimates were divided by each of the on-board dynamics in turn (having been subject to the same 5s RMS) to observe which gave the best results. It was found that using wheelset yaw acceleration gave the best results.

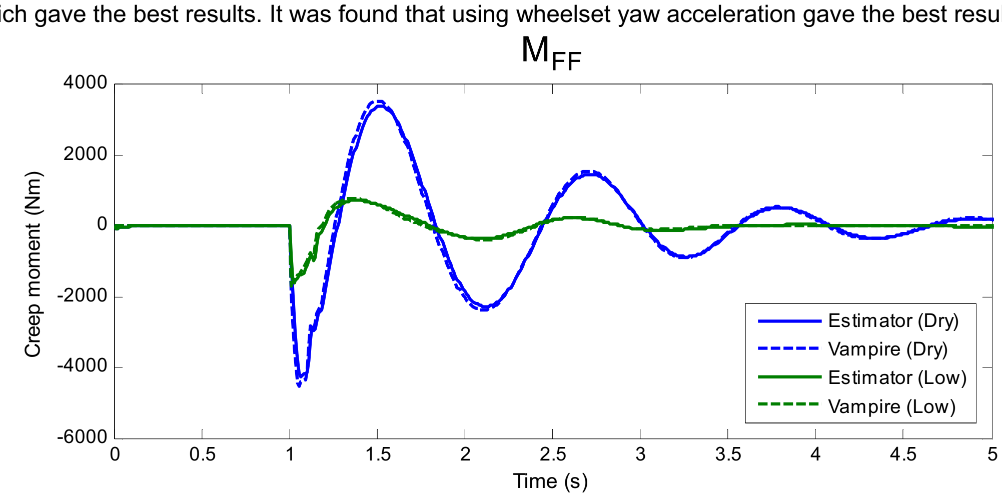

Figure 2: Time response of recorded and estimated contact moment with a single lateral step of 5mm as an input at both dry levels and low levels of adhesion ($\mu = 0.56, \mu = 0.072$ repsectively)

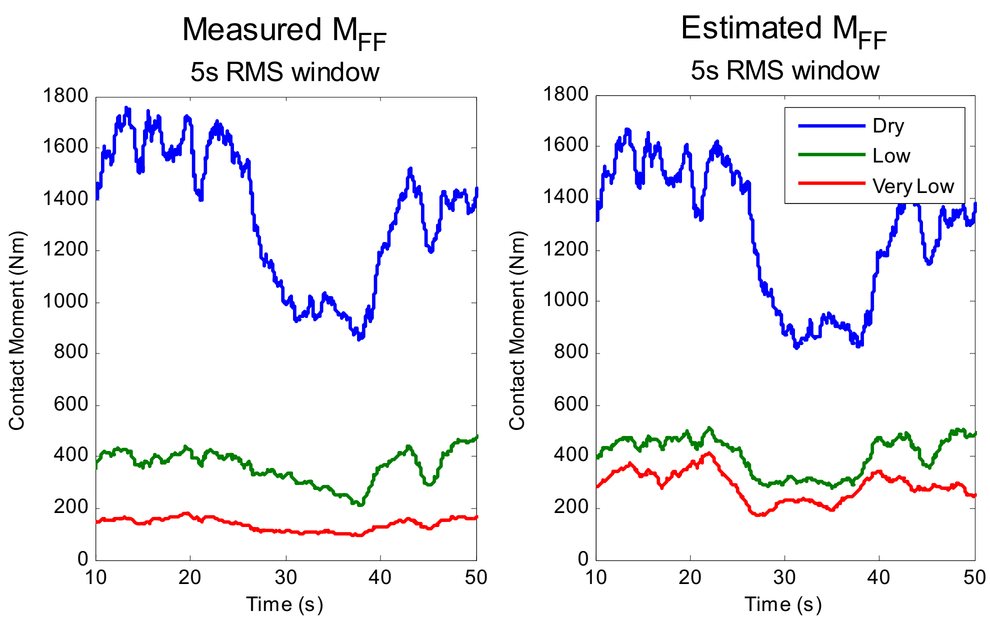

Figure 3: Comparison of recorded creep moment and estimated creep moment with each subject to a 5s moving RMS window. This test was performed at three adhesion levels: dry ($\mu = 0.56$), low ($\mu = 0.072$) and very low ($\mu = 0.038$).

In order to obtain an estimate of adhesion from this result, the average value of $M_{FF(RMS)}$ to $\ddot{\psi}_{FF(RMS)}$ can be used as calibration data for a linear look-up table for each adhesion level tested. Evidently, this method will incorporate some delay in attaining an estimation to allow time to evaluate an RMS.

4. Verification against VAMPIRE® Test Data

The method described above was applied to the same three test runs as were described in section 3. For each of the three adhesion levels of the run, an observation was made about the amount of time that the estimated adhesion remained with 20 % of the 'safe' side of the actual adhesion level. This tests if the estimator is correctly identifying the overall level of operational risk experienced by the vehicle. The summary of this test is found in Table 1. It can be seen that for the riskiest of operating conditions, the estimator correctly identifies this (albeit slightly pessimistically) for 99% of the time.

Table 1: Constant Adhesion Test Summary

Qualitative Condition	Adhesion Level (μ)	Region (μ)	Percentage time in region
Dry	0.56	μ >0.44	69
Low	0.072	0.089 > μ	75
Very Low	0.038	0.045 > μ	99

A separate condition tested is one whereby the vehicle experiences a step change in adhesion level. Figure 4 shows the time history of the adhesion estimation for two conditions; a step from dry to low adhesion and a step from dry to very low adhesion. It can be seen that five seconds after the step occurs, the estimator correctly follows the adhesion level.

5. Conclusion

This paper has shown how an augmented state method can be useful for estimating values that are unable to be measured directly for the purposes of condition monitoring. Furthermore, a solution has been presented to scale these values to changing environmental inputs (i.e. track irregularities) that also cannot be measured.

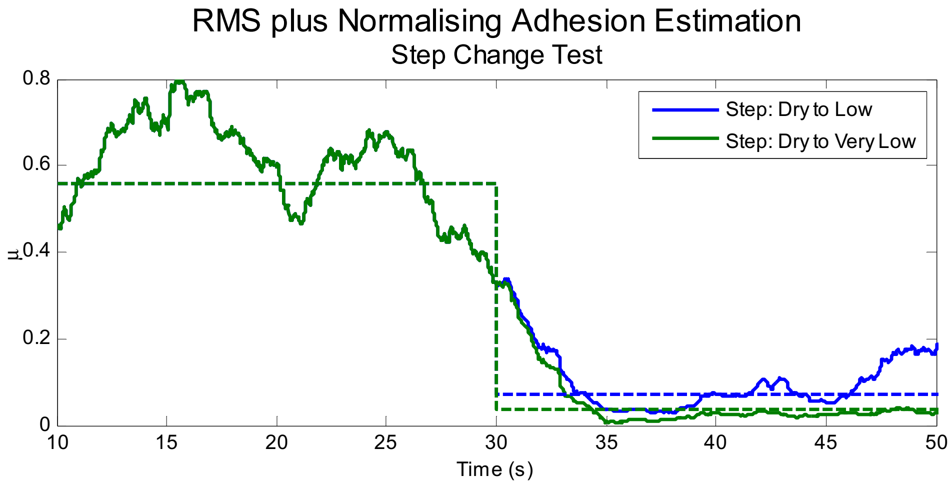

Figure 4: Time history response of adhesion estimation. The dashed lines show the level of adhesion.

5.1 Results Comments

The results presented here show that a reasonable approximation of operational risk of a rail vehicle can be identified by this method. This method requires a processing delay to attain this value which means that it would be unable to inform the control of a braking system in real time. It would, however, provide live track information if the data collected was disseminated correctly throughout the wider system. This could better inform decisions on train scheduled and track cleaning or maintenance.

5.2 Further Work

Improved methods of post processing the creep force estimations are in progress. There is a focus on assessing the frequency content of the signal as more vehicle dynamic information is contained in the range below 10 Hz. This would filter high frequency noise introduced by modelling discrepancies.

There is also a desire to identify better methods of normalising the data due to the track irregularities. The current technique using yaw acceleration as a normalisation method provides only a rough estimate and introduces a 5 second delay to obtain an estimate. An investigation was performed to assess the possible use of vertical irregularities to provide a description of the lateral irregularities. Although a rough correlation exists, it is not clear enough to use in this application. Measurement systems for track irregularity also exist, but do not align with the aim of using only 'modest cost' sensors on in-service vehicles.

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