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Determination of railway track longitudinal profile using measured inertial response of an in-service railway vehicle

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ABSTRACT: The use of sensors fixed to in-service trains has the potential to provide real time track condition monitoring to inform maintenance planning. An Irish Rail intercity train was instrumented for a period of one month so that a numerical method developed to find track longitudinal profile from measured vehicle inertial responses could be experimentally tested. A bogie mounted accelerometer and gyrometer measured vertical acceleration and angular velocity as the train made regular service operations between Dublin and Belfast on the island of Ireland.

Cross Entropy optimisation is used to find a track longitudinal profile that generates a numerical inertial response that best fits the measured response. Tolerance limits are used to inject variance where required to ensure a good match between measured and modelled signals. A section of track with known track settlement history is selected as a case study. A level survey was undertaken during the measurement campaign to characterise the longitudinal profile through the test section. Bandpass filters are used to compare inferred profiles and the surveyed profile. Good agreement is found between the two profiles although improvements in accuracy and reproducibility are required before conformance with current standards is achieved.

KEYWORDS: Measurement; Railway Track; Track Settlement; Longitudinal Profile; Drive-by; Vehicle Dynamics; Cross Entropy, Optimisation.

1.0 INTRODUCTION

In any structural health monitoring system, effectiveness of condition monitoring in identifying maintenance issues can benefit from real-time automated systems [1]. This is especially true for railway track considering the value of the asset and the implications of track failure [2]. Track recording vehicles (TRVs) are typically used to measure geometric properties of railway track to ensure that the track conforms to a suitable standard for the safe running of trains [3]. Outputs from TRVs are also used to plan maintenance. However, high running costs and the need for occupation of track limit the number of measurement operations undertaken annually. This means there is a risk that track faults may go undetected between TRV operations and the measured data lacks the frequency required to enable statistical analysis to identify trends in fault progression and track deterioration.

Measuring the response of in-service trains using low-cost inertial sensors has the potential to provide more regular information on track condition which can be used to complement the data acquired by the TRV [4]. A higher rate of data acquisition enables estimation of remaining service life and aids efficient maintenance planning. This field of research has received increased interest in recent years partly due to the reduction in the cost of inertial sensors, improvements in computing technology and increased track occupancy [5]. Many authors have reported on methods using on-board sensors to detect a variety of track issues such as track profile [6–17], corrugation [18–21], squats [22,23] and other faults [24,25].

TRV's are intended to measure loaded track so that the parameters recorded are influenced not only by track irregularities but also by variations in track stiffness. This is preferable so that the profile experienced by in-service trains on loaded track is known. However, the level of loading varies between different TRVs and may be below typical in-service train loads, meaning that load-sensitive parameters such as changes in track stiffness may go undetected or are underestimated. A minimum axle load of 5 tonnes is stipulated [3], which is significantly below allowable axle loads for passenger and freight vehicles [26]. For example, the axle load for the Irish Rail train instrumented as part of this study varies from 12 – 16 tonnes. Furthermore, the Irish Rail TRV uses optical sensors placed between the axles to measure the track, meaning that the track is not fully loaded at the point of measurement. Therefore, measurements taken using sensors fixed to in-service train bogies or axle boxes may provide a more realistic measure of the track condition actually experienced by the rolling stock.

According to the European track geometry quality standard [3], longitudinal level is measured for individual rails and defined as the vertical deviation of consecutive top of rail levels from the mean vertical position. Measurements can be optical or inertial. Mean vertical position is calculated using consecutive measurements taken at maximum 0.5 m intervals over a distance that is twice the higher wavelength in the band of interest, but typically taken as 200 m. The mean vertical position is close to zero in practice and the standard allows for the use of zero to peak values. Three wavelength intervals are defined in the standard for analysis of track with increasing line speeds. The wavelength interval of interest for this study is the D1 interval (3 – 25 m) for line speed ≤ 160 km/h. In this paper sensors fixed to the centre of the bogie are used to determine longitudinal track profile which, while not a standard measurement, can give a good indication of general track condition.

Ahmadian [27] details how mid-chord measurements used by many optically based TRVs can attenuate some profile wavelengths while amplifying others. Transfer functions define the relationship between measured data and actual track profile based on the effective chord length of the TRV. Yazawa and Takeshita [7] attempt to rectify this through development of an inertial mid-chord offset method which combines characteristics of both optical and inertial methods. They report on the development of a sensor unit capable of being attached to in-service trains to record full track geometry.

More recently, techniques to determine individual elements of track geometry have been developed using inertial sensors fixed to in-service trains. Measured vehicle vibration signals are influenced by track features such as rail irregularities, corrugation, vertical alignment, track stiffness, weld depressions, and changes in rail bending properties due to the presence of welds, cracks or other defects. Various techniques are used to monitor the track for these defects. Most employ frequency based analysis so that short- and long-wave defects can be differentiated. Long-wave features can be determined using measurements taken from the bogie or car body. Short-wave defects such as corrugation generally require high frequency measurements taken at the axle box [5].

Weston *et al.* [9] determine mean vertical track profile using a gyrometer and displacement transducers mounted on the bogie of an in-service vehicle with good estimates achieved for track profile wavelengths 6 m and above. Complementary accelerometers mounted on the ends of the axle box are used to identify wavelength content below 6 m for the left and right rails. The same authors determine lateral track alignment in a related study [10].

Tsai *et al.* [14] measure the response of an in-service train using a velocimeter installed in the car body and axle mounted accelerometers, to avoid the filtering of signals through the vehicle suspension systems. Measured data is processed using the Hilbert-Huang Transform and good agreement is found between irregularities found in a defined wavelength and TRV data. Additional analysis of the data to develop a bridge structural health monitoring technique is reported in [16].

Odashima *et al.* [17] use car-body accelerations and a Kalman filter based technique to return a 10 m versine measurement for a section of track in Japan comparable to the Japan Railways track measuring standard. Magnitude-Phase-Combination (MPC) metrics are used to test the accuracy of the result compared to that measured by a TRV.

Bocciolone *et al.* [20] use vertical and lateral sensing accelerometers attached to a Milan metro train to detect corrugation and side wear in curved sections. The sensors are attached to the axle box to remove the effect of mechanical filters in the vehicle suspension system. However, the authors also installed a triaxial accelerometer to the car body floor to determine long-wave variation in track profile due to track settlement. Caprioli *et al.* [21] analyse data gathered by the same measurement campaign using wavelet techniques to locate track defects.

This paper describes the field testing of a numerical method presented in OBrien *et al.* [28] using a calibrated vehicle model detailed in Quirke *et al.* [29]. This is an inverse technique whereby inertial measurement of an Irish Rail train is used to find the longitudinal track profile that generated the measurement. By installing the sensors on the train bogie, a loaded track profile is inferred by the method, considering both the track longitudinal profile and the variation in longitudinal track stiffness. Cross Entropy (CE) optimisation [30] is used in the technique. CE is an iterative method which uses Monte Carlo simulation to generate a population of trial solutions from a mean and standard deviation for each variable being sought. The population is updated and improved in each iteration based on an analysis of the optimum results in the previous iteration. The method is particularly suited to multi-variate problems with large solution spaces as is typical in civil engineering [31–34].

A description of the test and the sensors used is provided in the following section. The 2D car vehicle model used in the optimisation technique is described in section 3. The methodology used to find the track longitudinal profiles is presented in section 4 before a discussion of the results in section 5.

2.0 DESCRIPTION OF TEST APPARATUS

Vehicle response data was acquired using inertial sensors installed on the trailer (non-powered) bogie of an Irish Rail Hyundai Rotem InterCity fleet car. The installation was carried out in December 2015 on the leading car (22337) of Set 37, a 5-car train set. This set was configured for operation in both Northern Ireland and the Republic of Ireland to replace the Dublin-Belfast Enterprise service while it was being refurbished. This meant that the set would serve the route exclusively, providing the maximum line repeatability possible for any train in the Irish Rail fleet.

A tri-axial accelerometer and tri-axial gyrometer were installed as close to the bogie centre of mass as possible (see Figure 1). The trailer bogie was chosen to avoid noise contamination from the power train. A suitable mounting location was found on the Electronic Train Protection and Warning System (E-TPWS) unit (see Figure 2). This meant that the sensor was offset from the centre of mass of the bogie as shown in Figure 1. The properties of both sensors used are listed in Table 1. A sampling frequency of 500 Hz was adopted for most of the testing.

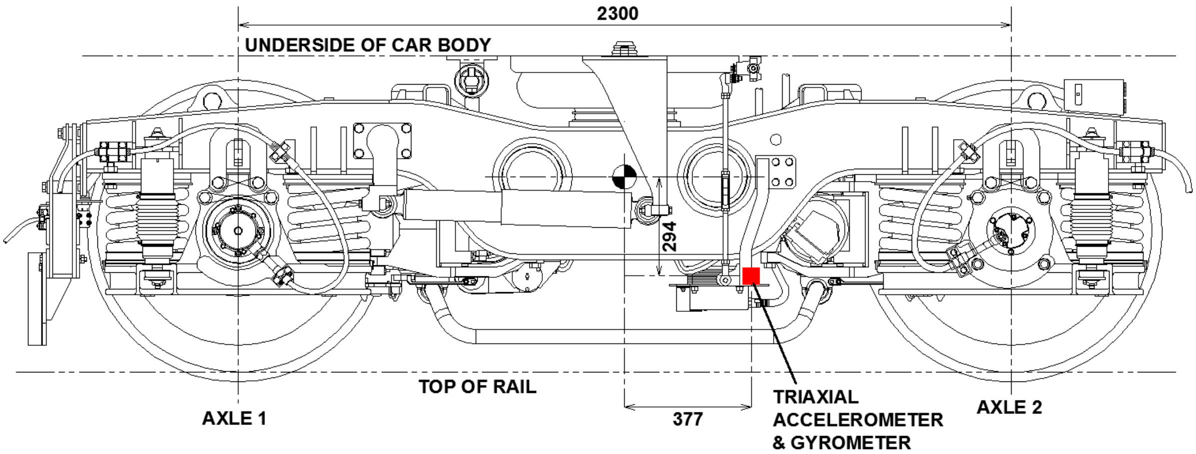

Figure 1. Sensor installation locations on trailer bogie (dimensions in mm). (CAD drawing sourced from Tokyu Car Corporation).

Table 1. Properties of sensors

Sensor Location	Type	Name	Range
Bogie – Bounce	Triaxial Accelerometer	Disynet-DA3802-015g	±15 g
Bogie – Pitch	Triaxial Gyrometer	Crossbow VG400CC-200	±200 °/s

Figure 2. Bogie mounted gyrometer and accelerometer

Figure 3. HBM Somat eDAQ lite data logger in disused train coupler box

A Global Positioning System (GPS) antenna was used to detect train movement and approximately geo-locate the measured data. Vehicle position was recorded at a frequency of 5 Hz. A HBM Somat eDAQ-lite data logger was used to collect and store the measured sensor and GPS data. The logger was installed in a disused train coupler box (see Figure 3), avoiding the need to run data cables into the main carriage of the train. Power was supplied through a spare circuit breaker.

Once train movement was detected by the GPS, a trigger was used to initiate recording of data captured by the sensors 30 s prior to the movement. The logger storage capacity was 32 GB.

Alternatively, data could be downloaded via a secure Wi-Fi router, avoiding the requirement to access the logger directly.

Testing took place on the Dublin-Belfast line from 13th January to 3rd February, 2016. During this period 57 return journeys were made on the line. The train typically made 3 return journeys each week day (including Saturdays) and two return journeys on Sundays. Samples from datasets are labelled ‘Morning’, ‘Afternoon’ or ‘Evening’ accordingly. The Irish Rail network is measured in miles and yards; however, SI units are used in this paper (1 mile = 1.60934 km).

3.0 MODEL DESCRIPTION

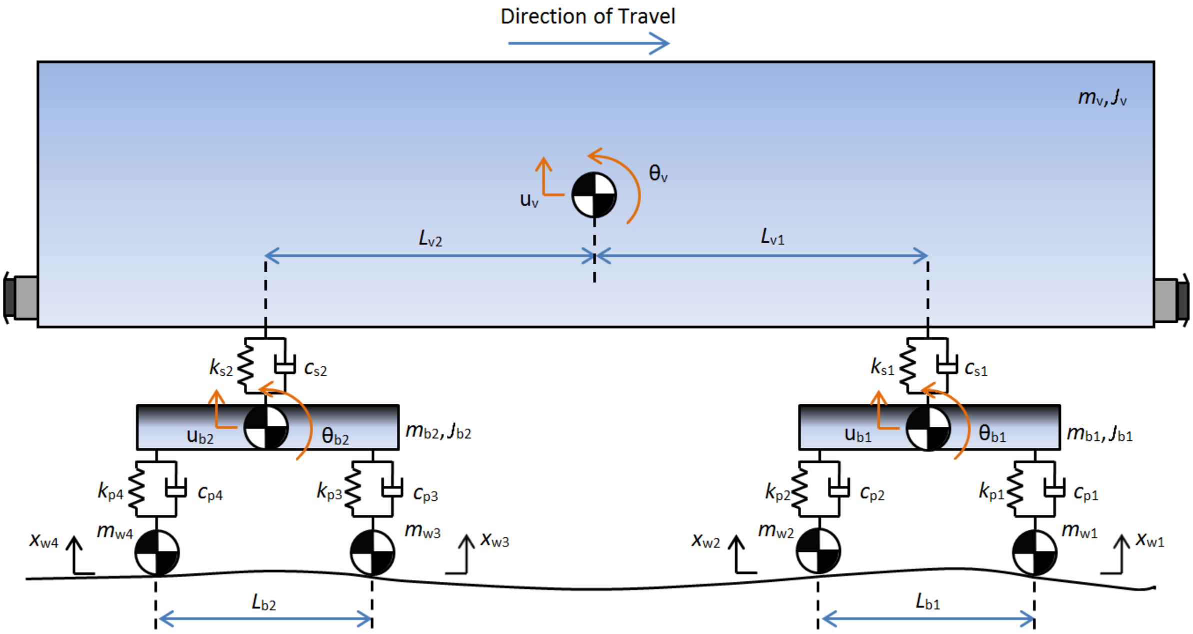

Figure 4. 2D car model (symbols defined in the text and in Table 2)

A numerical vehicle model is used in the optimisation technique described in this paper to find track profiles that generate an inertial response on the vehicle bogie that best fits the measured data from the in-service train. A multi-body 2D car model, shown in Figure 4, is chosen over a 3D model to reduce the computational effort needed to run the simulations required in the optimisation procedure. The model uses rigid bars to represent the car body and bogies. Spring-damper combinations are used to model the behaviour of the primary and secondary suspensions. This vehicle is used in many numerical studies [35] and leads to a good approximation of vehicle behaviour, provided that suitable values are used for the parameters defining it. When coupled to the track profile, the model contains 6 degrees of freedom: car body vertical translation, u_v, car body rotation, θ_v, vertical translation for both bogies, u_{b1}, u_{b2}, and rotation for both bogies, θ_{b1}, θ_{b2}.

Parameters for the Hyundai-Rotem train car are found through a calibration exercise carried out using data from the same measurement campaign. Frequency domain decomposition of measured inertial response to randomly selected sections of the Dublin-Belfast line was used to find dominant vehicle frequencies in [29]. Cross Entropy optimisation was used to calibrate a 2D vehicle model. The model output was validated by comparison to measured data. Calibrated properties and critical dimensions for the instrumented car are listed in Table 2.

Table 2. Properties of Irish Rail Hyundai-Rotem Intercity car [36]

Property	Unit	Symbol	Value
Car body mass	kg	m_v	36 852
Bogie mass	kg	m_{b1}, m_{b2}	3 910
Axle mass	kg	$m_{w1}, m_{w2}, m_{w3}, m_{w4}$	1 407
Mass moment of inertia of car body	kg m^2	J_v	560 342
Mass moment of inertia of bogie	kg m^2	J_{b1}, J_{b2}	10 024
Primary suspension stiffness	N/m	$k_{p1}, k_{p2}, k_{p3}, k_{p4}$	2 779 145
Primary suspension damping	Ns/m	$c_{p1}, c_{p2}, c_{p3}, c_{p4}$	29 400
Secondary suspension stiffness	N/m	k_{s1}, k_{s2}	991 748
Secondary suspension damping	Ns/m	c_{s1}, c_{s2}	60 000
Distance between car body centre of mass and bogie pivot	m	L_{v1}, L_{v2}	8
Distance between axles	m	L_{b1}, L_{b2}	2.3

4.0 METHODOLOGY

The aim of this investigation is to find the longitudinal profile of a railway track from the measured inertial response of an in-service train. Measured data is used as input to a numerical optimisation method executed in Matlab [37]. Multiple datasets are used to infer track longitudinal profiles though a section of track with a known settlement so that comparisons to surveyed track longitudinal profile can be made.

4.1 Track Section Case Study

A section of track on the Dublin-Belfast railway line was identified for this study due to historical issues with track settlement. The track is located in an area known as Red Bog, near Castlebellingham, Co. Louth, Ireland. The settled section of track is located on an embankment over an area of poor ground between 78.08 km and 78.16 km, a distance of approximately 80 m. A photograph of the track section is shown in Figure 5 where the settled section can be observed in the central part of the photograph.

A level survey was carried out on the northbound line in this section of track on the 21st January, 2016. The stated accuracy of the survey is ±2 mm. The surveyed track longitudinal profile is taken as the average of the left and right hand rails. The profile is shown in Figure 6. The 'ideal profile' shown in Figure 6 is the presumed design vertical profile through the section and is used to highlight the track settlement that has occurred in the section. A dip in the profile of approximately 80 mm over the 80 m section can be observed. For cross-reference between the two figures, the bridge in the background of Figure 5 is located at 77.92 km and was used as the starting point for the survey.

Figure 5. Track settlement location. (Photograph: C. Bowe).

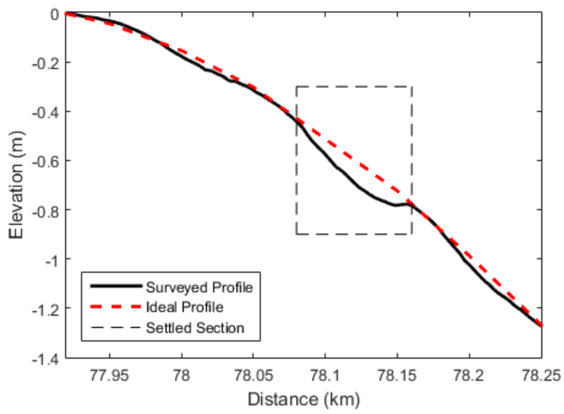

Figure 6. Level survey of track longitudinal profile for northbound line (average of left and right hand rails).

4.2 Measured Data

Bogie vertical acceleration and bogie angular velocity data are extracted from the datasets between 77.85 km and 78.45 km, approximately 250 m from the track settlement section in both directions. This is achieved by means of GPS windowing. Datasets from Belfast-bound services are used as the instrumented bogie was at the front of the train, enabling inference of rail profiles using the leading bogie of the numerical model, m_{b1}. The raw data is filtered using a 6th order Butterworth bandpass filter (0.25 – 25 Hz) to remove the effects of sleeper spacing, drift, temperature and other noise. Samples of the unfiltered and filtered bogie angular velocity through the track settlement section are shown in Figure 7. As detailed in Quirke *et al.* [29] a post-measurement calibration factor of 23.9 is applied to the bogie angular velocity prior to being used as input to the optimisation technique. The factor is required to account for the sensor offset from the bogie centre of mass and the calibration error caused as a result which was not considered at the time of installation. It is required to convert the measured data from °/s to rad/s for comparison to numerical model output. Samples of raw and filtered bogie vertical acceleration from the same dataset are shown in Figure 8. The train forward velocity for the data presented in Figures 7 and 8 is 33.5 m/s, which is the typical line speed for this section of track.

The optimisation technique assumes a zero value for the first elevation in the inferred profile estimates. Therefore a start point is chosen in the measured data where the filtered vertical acceleration and angular velocity are close to 0. The start point must also be remote from any irregular peaks occurring in the data.

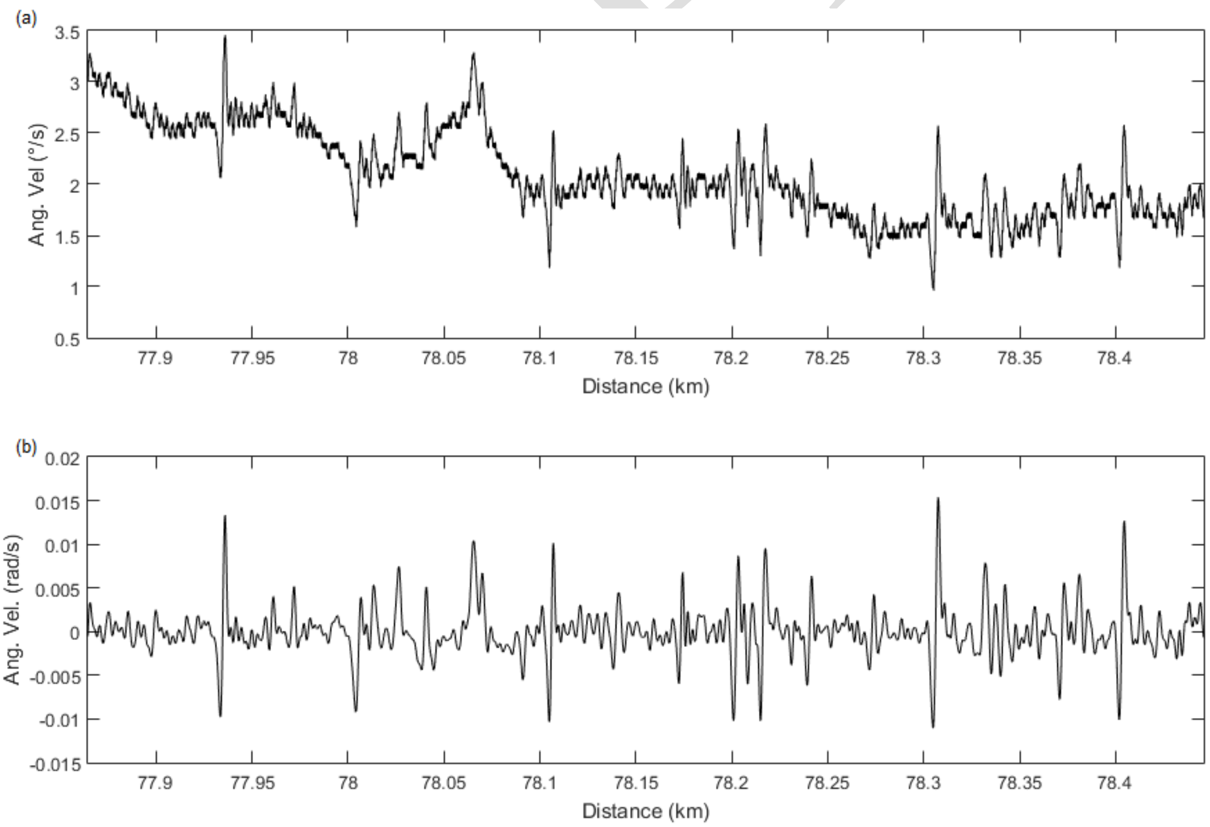

Figure 7. Bogie angular velocity signal (pitch velocity) (13th January 2016 – Morning) as a function of distance from the start point (Dublin); a) Unfiltered signal; b) Bandpass filtered signal (0.25 – 25 Hz)

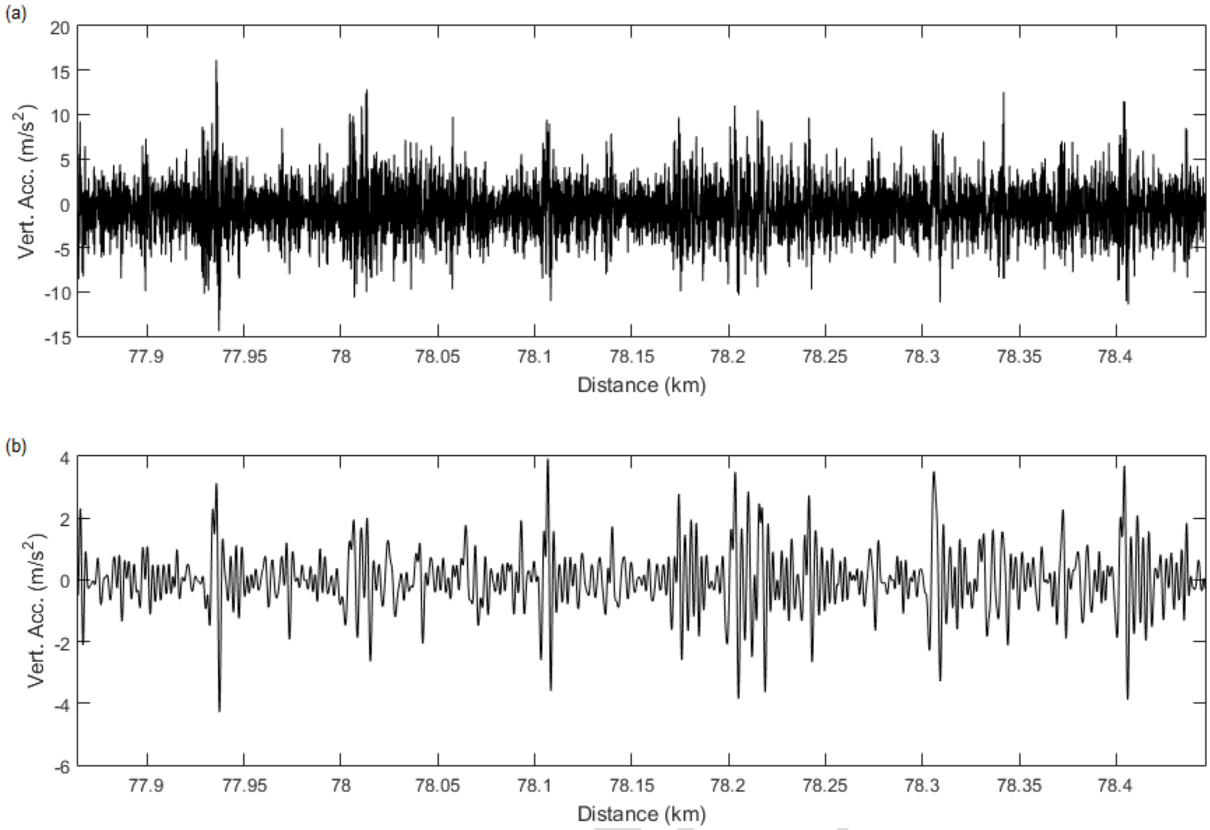

Figure 8. Bogie vertical acceleration signal (13th January 2016 – Morning) as a function of distance from the start point (Dublin); a) Unfiltered signal; b) Bandpass filtered signal (0.25 – 25 Hz).

The method for inferring track longitudinal profiles presented in OBrien *et al.* [28] is a numerical approach that assumes a constant vehicle forward velocity. In reality train forward velocity changes along the track and will differ between datasets. This variation in velocity must be accounted for in the numerical model. A sample of train forward velocity sampled from selected datasets is shown in Figure 9. The velocity is calculated using the GPS data and, as such, is only as accurate as the GPS accuracy. Obstructions to the line of sight of the GPS antenna affect GPS accuracy and hence the measured train forward velocity. For example, the velocity profile for '15th January 2016 – Morning' shows a sudden drop at 77.92 km. This is most likely due to a bridge crossing over the railway at this point momentarily obstructing the line of sight of the GPS (see Figure 5).

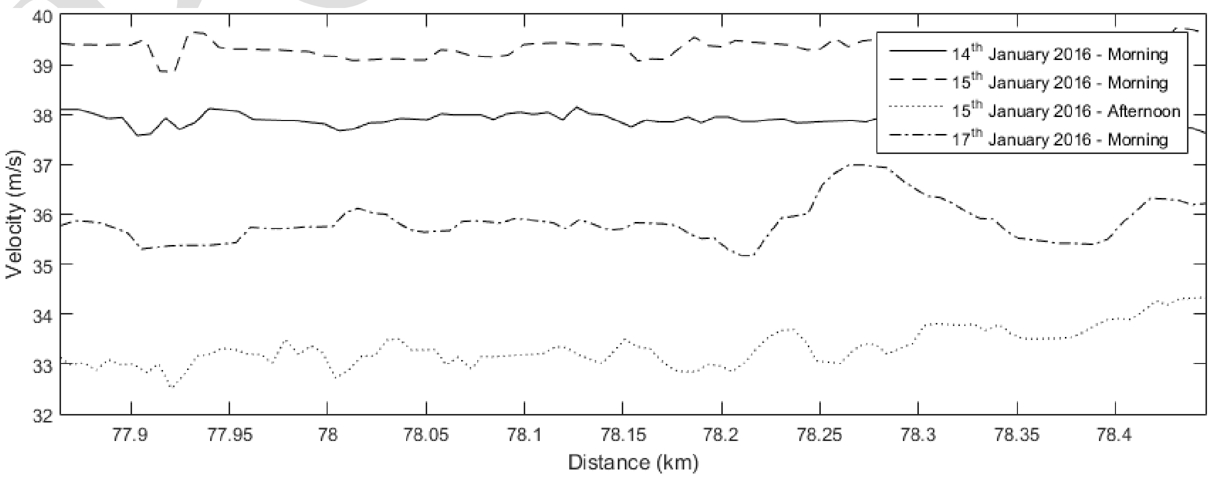

Figure 9. Train forward velocity as a function of distance from the start point (Dublin) taken from selected datasets.

4.3 Cross Entropy Optimisation

Cross Entropy (CE) optimisation is used in this paper to find track longitudinal profile from measured inertial response of an in-service train. The CE method uses Monte Carlo simulation to generate a population of trial solutions from a mean and standard deviation for each variable being sought. In this study a population of trial track longitudinal profiles is generated for both axles on the leading bogie of a vehicle model. Numerical outputs, generated by running the vehicle over the profiles in the population of estimates, are compared to measured data to find an elite set of profiles. This set is used to improve the population of estimates until the method converges to the solution.

There is no track model considered in the interaction, i.e. the track profile is assumed to be supported on an infinitely stiff track. Changes in track stiffness will be manifested in the inferred track profile. Independent profiles are required under both axles to compensate for the rigidity of the track in the model. It is not necessary to consider independent profiles for axle 3 and 4 on bogie m_{b2} as their influence on the inertial response of the measured bogie, m_{b1} is insignificant.

In order to avoid local minima during the optimisation and thus converge to the global optimum, the dimensionality of the problem must be kept to a suitable level. This is controlled by limiting the number of variables considered at a given time. In this case each profile elevation is taken as a variable in the optimisation. To keep the dimensionality of the problem low, a limited number of elevations are considered. However, elevations are required at regular intervals to adequately define the longitudinal profile. Therefore, in order to infer a longitudinal profile over hundreds of metres the algorithm steps through the data in phases, inferring a small section of the profile in each phase. The inferred profile is then used to set the mean and standard deviation for the generation of profile estimates in the next phase. This stepping technique, and the vector transfer methodology required to enable it, are described in detail in OBrien *et al.* [28].

In the space-time discretisation used, there exists an elevation in the inferred profile for each scan in the measured data. Therefore, the spacing between elevation values in the inferred profile is a function of the vehicle forward velocity and the sensor scan rate. In each phase, 16 elevation unknowns are considered in each profile corresponding to a data segment containing 16 values for both bogie vertical acceleration and bogie angular velocity. The distance between the unknowns is calculated using the vehicle forward velocity inferred from the GPS measurements.

The first elevation in the initial population of rail profiles for axles 1 and 2 is randomly generated using an initial mean and initial standard deviation. Subsequent elevations are generated using a random walk process. The value of the previous elevation and the initial standard deviation are used to randomly generate the next elevation. The random walk method is used for the first generation of profile estimates only. Subsequent generations use statistical mean and standard deviation from best fitting elevations in the preceding generation. Profiles for axles 3 and 4, on the second bogie, are interpolated from the inferred profile for axle 1. Zero values are used until the inferred profile for axle 1 is greater than the vehicle wheelbase.

A moving average filter is applied over 4 elevations in the profile. The filter is used to smoothen the population of profiles estimates, thereby avoiding the generation of unrealistic sudden changes in profile and spikes in numerical output. An example of an initial population of possible solutions generated for the profile under the first axle is presented in Figure 10(a) with the corresponding filtered profiles presented in Figure 10(b).

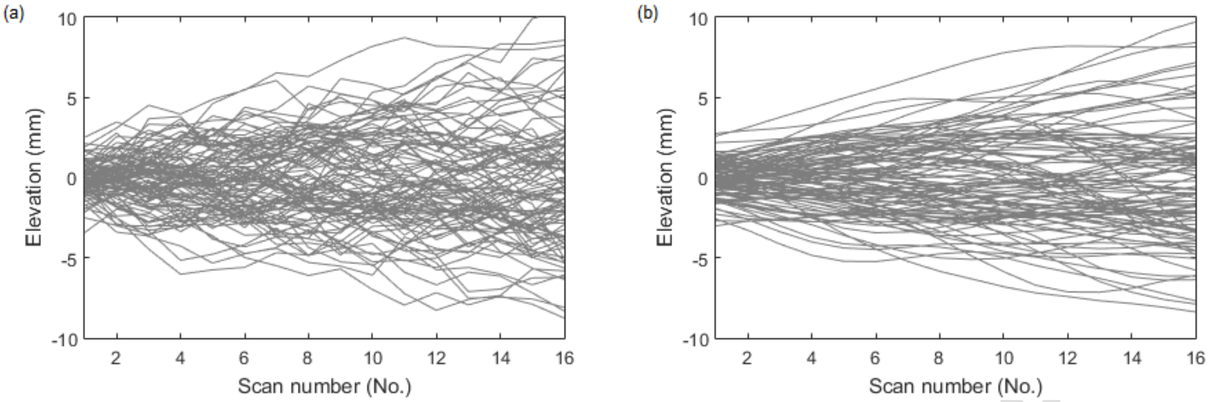

Figure 10. Example of initial population of profile estimates for axle 1 generated using the random walk process. a) Unfiltered profiles; b) Profiles filtered using moving average filter.

The vehicle model is run over each set of profiles (under axle 1 and axle 2) in the population of estimates to generate numerical responses that can be compared to the measured data. To account for the offset of the accelerometer from the bogie centre of mass described in Section 2, simulated outputs for bogie vertical acceleration are corrected according to Equation (1). This is done so that simulated outputs are comparable to the measured accelerations.

$$\ddot{u}_{b1}^{*} = \ddot{u}_{b1} - \frac{x_A}{\sqrt{{x_A}^2 + {z_A}^2}} \ddot{\theta}_{b1} \tag{1}$$

where x_A is the horizontal offset of the sensor from the centre of mass equal to 0.377 m and z_A is the vertical offset equal to 0.294 m. The elevation estimates for each profile in the population are ranked by minimising the value of an objective sub-function, O_i, where i is the scan number corresponding to the elevations in the profiles. The objective sub-function is calculated at each scan number, i, as follows:

$$O_i = W_A\left(\ddot{u}_{b1,i}^{*} - \ddot{u}_i^{\circ}\right)^2 + W_R\left(\dot{\theta}_{b1,i} - \dot{\theta}_i^{\circ}\right)^2 \tag{2}$$

where W_A and W_R are weighting factors for the bogie vertical acceleration and angular velocity respectively. Measured signals are denoted with the superscript '°'. The weighting factors are required due to the different orders of magnitude between the bogie vertical acceleration and angular velocity. Furthermore, the weighting factors can be changed to influence the value of the objective sub-function, providing a bias towards acceleration or angular velocity if necessary. Weighting factors are calculated as the ratio of the sum of squared differences between the bogie acceleration, SS_A, and angular velocity, SS_R, calculated as follows:

$$SS_A = \sum_{i=1}^{m} \left(\ddot{u}_{b1,i}^{*} - \ddot{u}_i^{\circ}\right)^2 \tag{3}$$

$$SS_R = \sum_{i=1}^{m} \left(\dot{\theta}_{b1,i} - \dot{\theta}_i^{\circ}\right)^2 \tag{4}$$

$$W_A = \frac{\overline{SS_R}}{\overline{SS_A} + \overline{SS_R}} \tag{5}$$

$$W_R = 1 - W_A \tag{6}$$

where m is the number of unknowns in the profile. An elite set of elevations is formed by selecting those values associated with the lowest 10% of objective sub-function values. The elite set is used to calculate the mean and standard deviation for each elevation in the two profiles. An improved population of profile estimates is then generated using the means and standard deviations for the elite set. Another set of numerical outputs are calculated by running the vehicle over the updated population. The process iterates until convergence is achieved.

Convergence is achieved when the squared difference between the sum of standard deviations (for all scan numbers) for consecutive generations falls below a convergence threshold. As the standard deviation diminishes through the generations there is less variance in the population of estimates, indicating that the process has converged to a solution.

4.4 Tolerance Limits

In multi-variate optimisation there is a risk of premature convergence, finding local minima or multiple solutions where the variables are dependent. While the CE method is generally effective at avoiding these outcomes, additional measures are applied here to ensure that a good match between model outputs and measured data is achieved.

Tolerance limits are introduced as a positive and negative offset from the measured signals to ensure that, if exceeded by the model output, convergence is blocked and additional variance is introduced to the population of profiles in the next generation of estimates. Rather than assessing each signal output for the population of estimates individually, the mean of the difference between the measured signal and modelled output signals for the entire population is calculated. T_A (Equation (7)) is the mean of the difference between the bogie vertical acceleration signals while T_R (Equation (8)) is the mean of the difference between the bogie angular velocity signals.

$$T_A(i) = \frac{1}{N}\sum_{n=1}^{N}\left(\ddot{u}_{b1}^{*}(i) - \ddot{u}^{\circ}(i)\right) \tag{7}$$

$$T_R(i) = \frac{1}{N}\sum_{n=1}^{N}\left(\dot{\theta}_{b1}(i) - \dot{\theta}_{i}^{\circ}(i)\right) \tag{8}$$

where N is the size of the population of estimates. If the value of T_A or T_R exceed their respective tolerance limit in three iterations at the same scan number in the signal, the corresponding mean is changed to the average of the mean of the adjacent profile elevations and the standard deviation for the corresponding profile elevation is doubled.

In some cases, a match between the measured signals and the numerical response of the vehicle model to the profile may not be achievable within the initial tolerance limits. The optimisation may become stuck in local minima or there may be some inaccuracy in vehicle properties due to changing vehicle load for example. It must be acknowledged that the vehicle model is a linear 2D idealisation of a 3D non-linear system and outputs may not always perfectly match the measured response of the real train. Elements of the vehicle model such as the primary damping and the secondary suspension system are non-linear in reality and their linear representations will inevitably contain error. Car body mass and centre of mass will vary from assumed constant values due to variations in fuel loads and passenger numbers between different services. Additionally, the signal will contain content that is not related to the profile wavelength being sought and cannot be simulated by the model through variation of the profile alone (e.g. short wavelength rail defects, joints, welds, breather switches, points and crossings).

To account for this, and to allow the algorithm to progress past sections of signal where a good match cannot be achieved, the tolerance limits, TL_A and TL_R, are forced to widen incrementally after 100 generations according to the following relationship:

$$TL_A = TL_A(0.01G) \tag{9}$$

$$TL_R = TL_R(0.01G) \tag{10}$$

where G is the number of generations. Once the tolerance limit is widened sufficiently, the block on convergence will be lifted and convergence to a solution will take place as no further variance will be injected into the profile estimates. An example of the application of tolerance limits in a typical phase is shown in Figure 11. It can be observed that for the population of profiles (axle 1) shown in Figure 11(a), the mean bogie vertical acceleration generated (Figure 11(b)) exceeds the tolerance limit at four scan numbers, 9, 10, 11 and 12. Profiles for axle 2 are not shown for brevity. The mean bogie angular velocity (Figure 11(c)) is within the limits. As described above, if the exceedances are repeated at the same scan number, the algorithm injects variance into the next generation of profiles, thereby potentially forcing the method out of the local minimum.

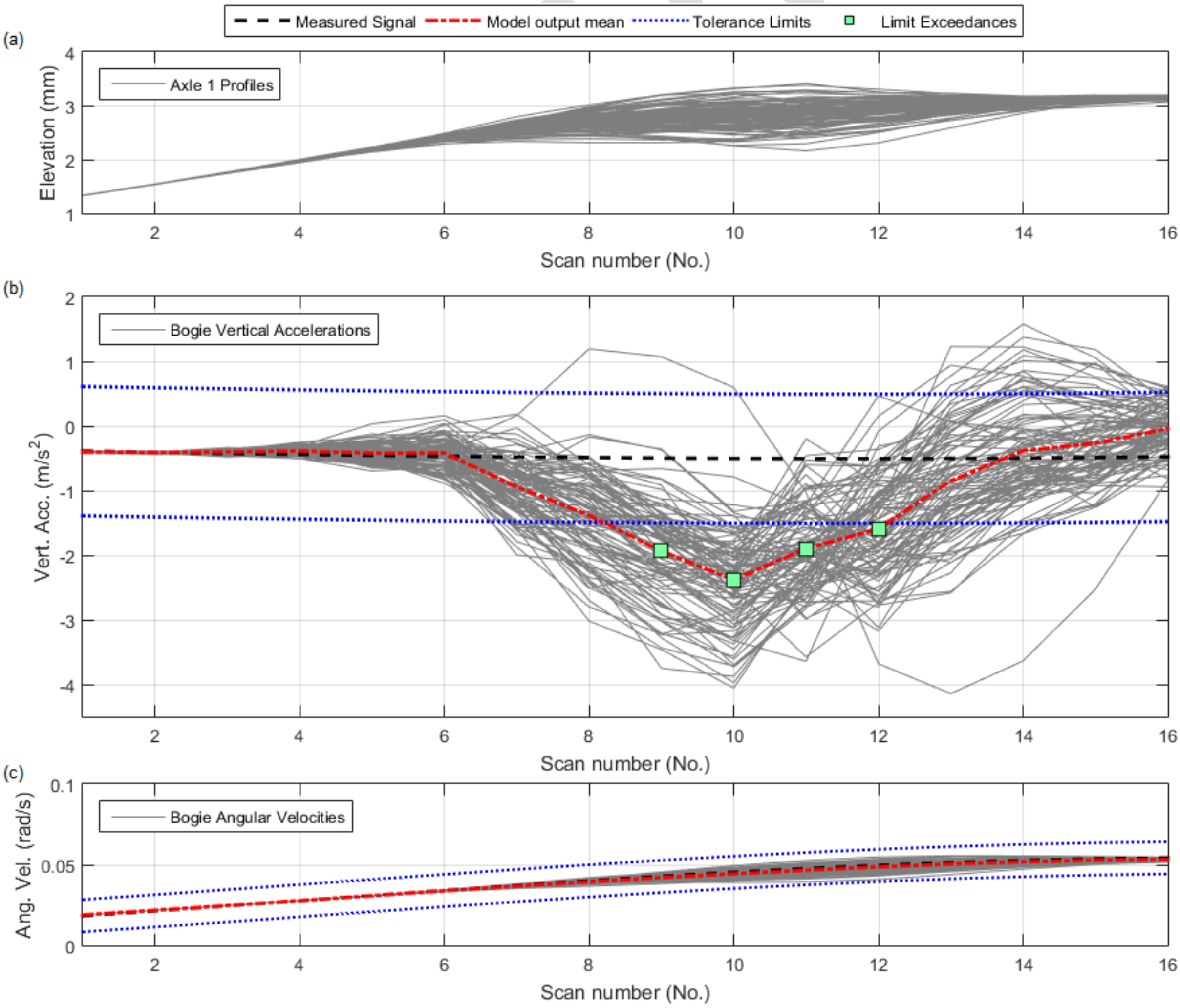

Figure 11. Example of tolerance limit exceedance; a) Population of profile estimates for axle 1; b) Bogie vertical acceleration for population of profile estimates in relation to measured data and tolerance limits. Exceedances are highlighted as shaded squares; c) Bogie angular velocity for population of estimates in relation to tolerance limits.

4.5 Multiple solutions and compensation

The geometry of the bogie can affect the ability of bogie-mounted sensors to detect track profile [9]. For example, track wavelengths equal to twice the bogie wheelbase produce no vertical acceleration but will produce angular velocity. Similarly, for bogie mounted gyrometers, no angular velocity is generated at wavelengths equal to the bogie wheelbase. These issues are overcome in part by use of a combination of both sensors.

The geometry of the bogie is the cause of another issue when using optimisation to find track profiles. There may be multiple profile combinations that generate the same angular velocity response in the bogie. Three combinations of profiles for axles 1 and 2 are shown in Figure 12(a) and (b) respectively. The true profiles are represented by the solid black lines. The differences between the true profile and the two alternative profiles (dashed and dotted curves) for axle 1 are compensated by equal but opposite changes to the profiles for axle 2 at an offset distance equal to the bogie wheelbase. Figure 12(c) shows that the angular velocity generated by the 3 profile combinations is the same. However, the bogie vertical acceleration, as measured at the sensor location, Figure 12(d), is different in each case.

In multiple trials, it was found that considering angular velocity and vertical acceleration in the objective function gave good results whereas considering vertical acceleration alone did not perform well. A weighted combination of results was found to be most effective, i.e. the profile was found that gave a best fit to a weighted squared difference between measured and theoretical data for each of the two sensors. In well performing trials, the angular velocity term was weighted more highly than the acceleration term. The axle profiles that gave the weighted best fits were not the same, something that is not likely for axles of similar weight. As the angular velocity was highly weighted, possible bias due to the dominance of this term was corrected to determine the final unique profile as follows:

$$r(x) = r_{w1}(x) - r_{w2}(x - L_{b1}) \tag{11}$$

where r_{w1} and r_{w2} are the inferred profiles for axles 1 and 2 respectively.

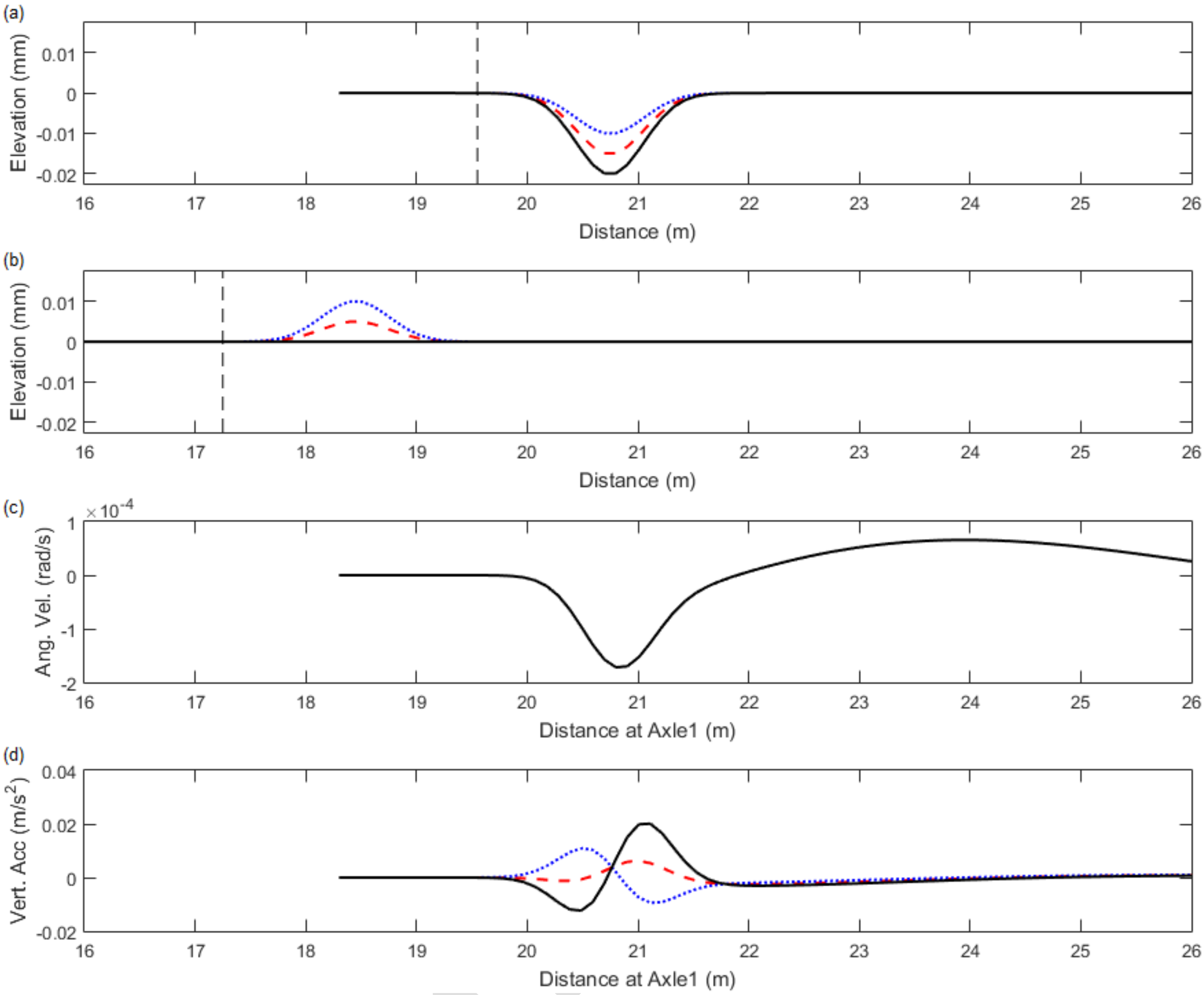

Figure 12. Example of multiple possible solutions; a) Axle 1 profiles; b) Axle 2 profiles; c) Bogie angular velocity; d) Bogie vertical acceleration at sensor location. The vertical dashed lines represent the locations of axles 1 and 2 in the same instant.

4.6 Summary of Optimisation Parameters

The parameters controlling the optimisation are listed in Table 3. It is important to note that these parameters have been chosen empirically. It is hypothesised that the accuracy and efficiency of the method could be improved through adjustment of the parameters but this is outside the scope of this study and could be a topic for future work.

Table 3. Optimisation parameters

Property	Value
Number of scans in each phase	16
Initial mean	0
Initial standard deviation	1 mm
Size of population of estimates, N.	100
Size of elite set (percentage of population of estimates)	10 %
Acceleration signal tolerance limits, TL_A	±1 m/s^2
Angular velocity signal tolerance limits, TL_R	±0.01 rad/s
Maximum allowable number of limit exceedances at scan number	3
Convergence threshold for termination of phase	4×10^{-10}

5.0 RESULTS AND DISCUSSION

The process of inferring track longitudinal profiles through optimisation, as described in the previous section, is applied to 46 datasets recorded during the testing period. As a typical example, the ‘13th January 2016 – Morning’ dataset, extracted from the GPS window for the track settlement case study, contained 2 981 samples/scans. Considering that there are 16 scans in each phase, and an overlap of 8 scans between phases, a total of 372 phases are required in the optimisation.

Inferred longitudinal track profiles are filtered using a 6th order Butterworth band-pass filter between wavelengths of 3 – 25 m to match the D1 wavelength interval specified by the track geometry standard, EN 13848. The resulting profiles are compared to the filtered track level survey in Figure 13. The downward trend in elevation in the surveyed track profile, visible in Figure 6, is filtered out. However, the settled section is still visible between the downward slope at 78.08 – 78.09 km and the upward slope between 78.15 – 78.16 km. There is a small rise in elevation in the middle of the settled section at 78.11 – 78.12 km.

The inferred profiles through this section are aligned using a cross-correlation function as the GPS lacks the accuracy and repeatability necessary for this task. Figure 13 presents the compensated track profiles inferred from bogie inertial response data, measured through the case study section in 46 different runs. Aside from a surveyed dip at a track distance 78.03 km, all other predominant features are detected. Generally, the magnitude of the elevation changes appear to be overestimated by the algorithm by a factor of 2. Errors in the gyrometer calibration may be partially responsible for the poor match to the elevation profile in terms of magnitude. The use of a 2D vehicle model and possible inaccuracies in vehicle calibration, resulting in a poor representation of the vehicle dynamics, may also be a factor. Furthermore, the track was not loaded during the level survey, while the inertial measurements are taken on the train bogie and hence are from a loaded track. This may be a factor for the overestimation of the elevation profile where the inferred profile is less than the surveyed profile.

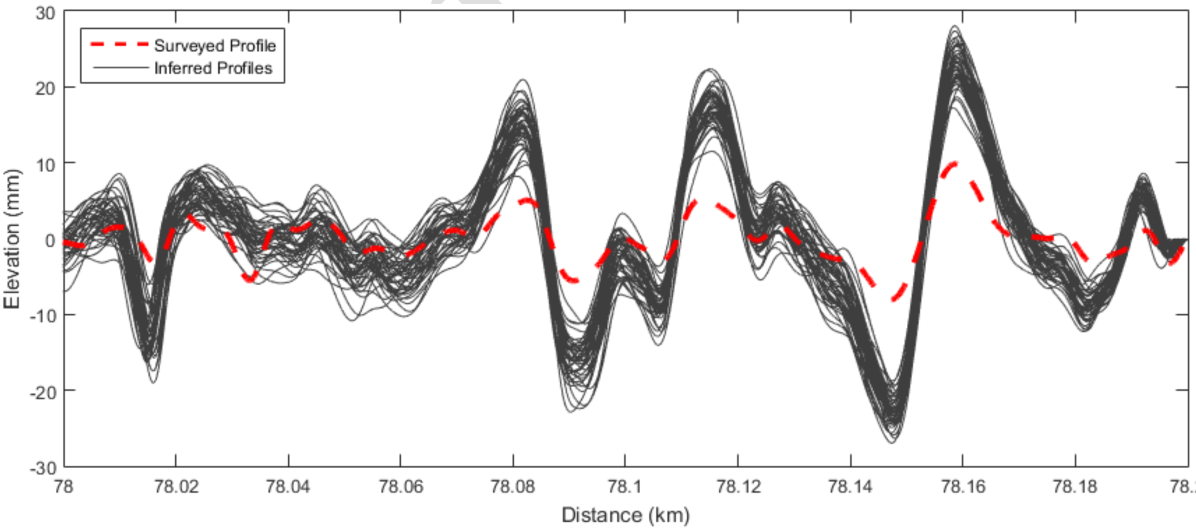

Figure 13. Filtered inferred profiles, $r(x)$, for 46 runs, and filtered surveyed profile (3 – 25 m)

A sample of the match between the measured signals achieved through optimisation for one dataset (‘27th January 2016 – Evening’) is presented in Figure 14. Tolerance bands between the upper and lower tolerance limits are shown for both signals. In Figure 14(a) it is observed that the match between the measured and modelled vertical acceleration for this example is generally quite good. In certain sections, for example 78.059 km and 78.067 km, the match between the signals is less good but within the tolerance limits specified. The algorithm ‘recovers’ to find a good match in the following phases. The sudden changes in the inferred signal are due to poor continuity between the phase boundaries.

Figure 14(b) shows the match between measured and modelled angular velocity. An excellent match between signals is achieved, likely as a result of the weighting given to this term. Minor differences are observed at 78.042 km and 78.057 km. This is most likely due to the inability of the 2D model to adequately characterise the actual response of the vehicle.

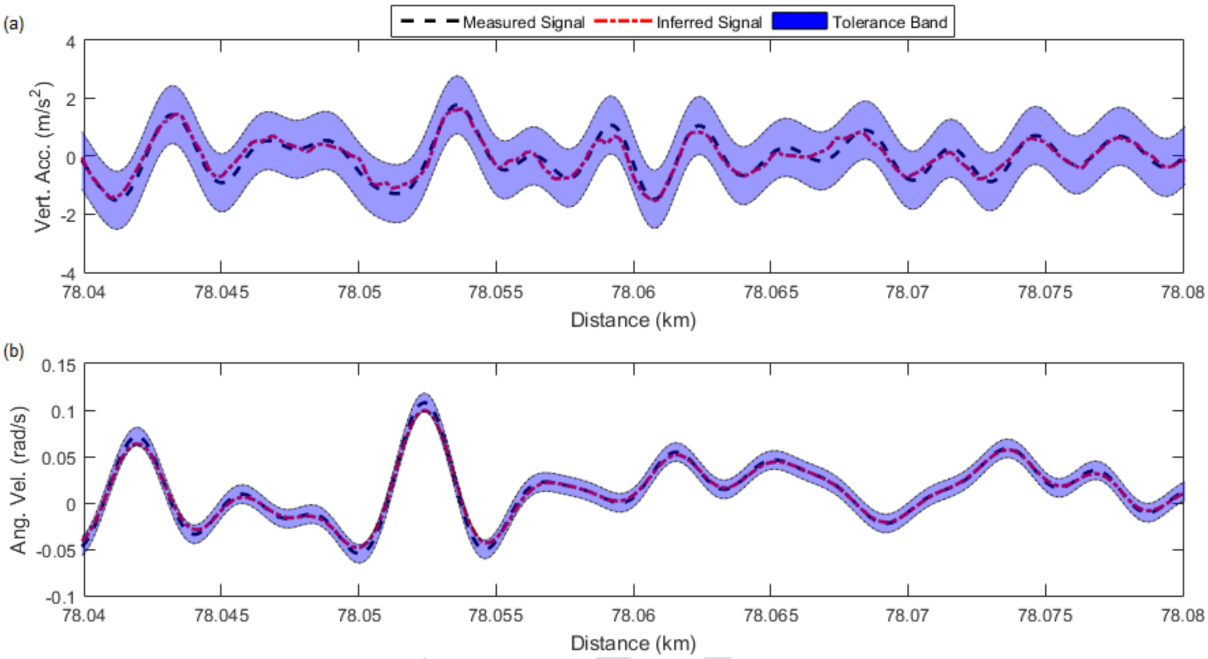

Figure 14. Quality of match to measured signals (‘27th January 2016 – Evening’); a) match of inferred to measured bogie vertical acceleration. b) Match of inferred to measured angular velocity.

Generally, the changes in elevation observed in the level survey are found in all datasets. The track geometry measurement standard, EN 13848 [3], defines repeatability as ‘the degree of agreement between the values of successive measurements of the same parameter made under the same conditions’ (e.g. same vehicle forward velocity, same environmental conditions, etc.). Reproducibility is defined as ‘the degree of agreement between the values of successive measurements of the same parameter made under varying conditions’. It is not possible to assess the repeatability of the method as defined in the standard due to differences in vehicle forward velocity and car body loads. However the reproducibility of the method is assessed here.

Figure 15(a) shows the mean of the 46 inferred profiles found through the case study section. The mean is used to calculate the 95th percentile value along the profile shown in Figure 15(b). An average 95th percentile value of about ±4 mm is found through the profile. This is significantly greater than the value of 0.8 mm required by EN 13848.

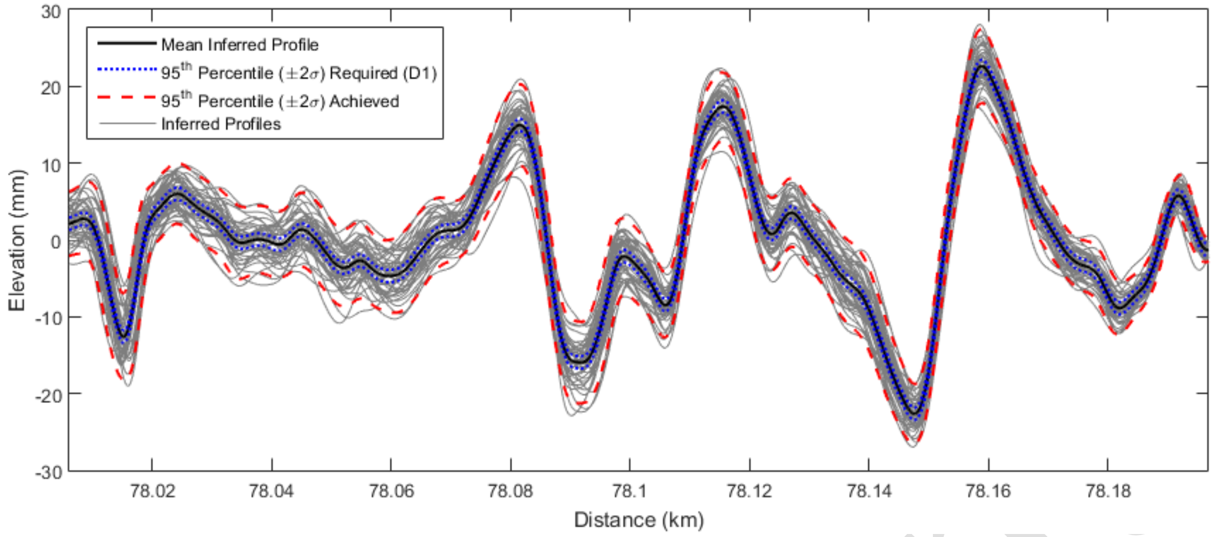

Figure 15. Reproducibility of inferred track longitudinal profiles through case study area.

6.0 SUMMARY AND CONCLUSIONS

An Irish Rail intercity train was instrumented for a period of 1 month to test a novel method for inferring railway track longitudinal profile through optimisation. Inertial sensors were placed on a non-powered trailer bogie of a coach at the front of the train. The measurements were correlated to particular sections of track using associated GPS data.

Bogie vertical acceleration and angular velocity are extracted through an area of known track settlement which was surveyed during the measuring period. Cross Entropy optimisation is used to find the track longitudinal profile that generates vehicle model responses that best match the measured signals. A novel approach of using tolerance limits combined with suitable weighting of the optimisation objective function to inject variance where required. This forces the algorithm to improve the match to the measured signals and, by extension, the inferred profile.

A good match is achieved between the inferred longitudinal profiles and the surveyed track profile, albeit with an overestimation of the profile elevations. Most profile features are detected. However the reproducibility of the method is some way off that required in current standards. Issues such as algorithm efficiency, accuracy of vehicle properties, improved representation of non-linear suspension in the vehicle model and knowledge of fuel and passenger loading may all help improve the accuracy and reproducibility of the method.

Aside from reproducibility and scaling issues, the method presented in this paper can be readily implemented using low-cost inertial sensors and simple numerical modelling. The method can give frequent updates of the track profile allowing the identification of differences in profiles produced suddenly or during prolonged periods of time.

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