The Development of an Integrated Computing Platform for Measuring, Predicting and Analyzing Profile-specific Fixity of Railway Tracks

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Introduction

What is "track fixity"?

Track fixity refers to the degree to which the position of a railway track remains unchanged over time; it is one of the key measures used to calculate clearances between rolling stock and structures.

Motivation

- The UK's current measurement of the track fixity remains at a low level of granularity.
- There is a lack of predictive tools that can provide more detailed information about the movement of tracks through a continuously updated, ongoing automated process.

Aims

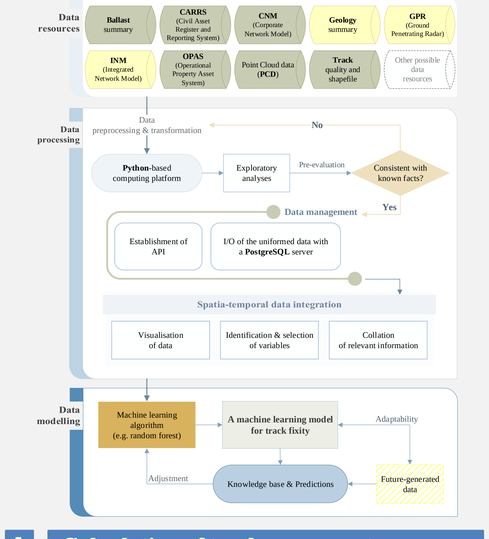
- Design a data pre-processing workflow, enabling smooth integration and management of a structured corpus of data for track fixity
- Create a data mining tool as a prototype, for predicting and analyzing the track fixity parameters for any given section of a railway track.

Objectives

1. Propose an effective metric and method of calculating track movements using LiDAR (**L**aser **i**maging, **D**etection, **A**nd **R**anging) data.
2. Create an integrated data model with a machine learning model (e.g., a random forest model), which is trained on the calculated track movements and the data of a selection of the factors influencing track movement.
3. Verify the key factors that can cause the track movements.

Methodology

Methodological framework



1 Calculation of track movement

Propose a new metric for calculating the displacement of rail heads in terms of both rate and direction.

2 Data integration

Cross-reference the track fixity measures with data of identified influencing factors, given the availability of the data resources.

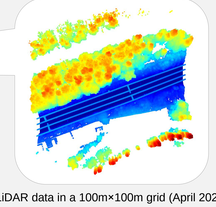
3 Predicting track movements

Create a comprehensive data set, with which a prototype machine learning model was developed and applied to predict and analyze track fixity.

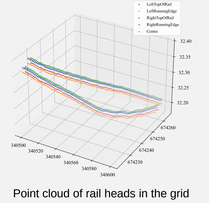
A Case Study Example

Track movements for the case-study region

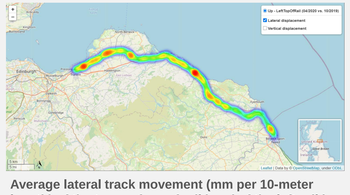
We demonstrate the feasibility of the prototype with data from an approximately 80-km section of the East Coast Main Line south of Edinburgh in Scotland.



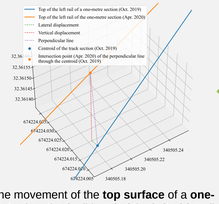
LiDAR data in a 100m×100m grid (April 2020)



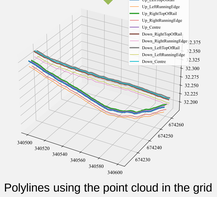
Point cloud of rail heads in the grid



Average lateral track movement (mm per 10-meter length) of the top surface of rail head of the left rail in the up direction (October 2019 vs. April 2020)

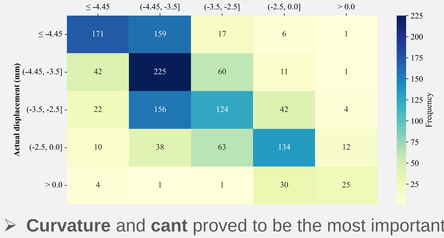


The movement of the **top surface** of a **one-meter** length of rail head of the **left-side** rail in the **up** direction



Polylines using the point cloud in the grid

Modelling results (based on a random forest model)



Factor	Relative importance
Curvature	0.3887
Cant	0.3725
Maximum speed	0.2016
Presence of underline bridges	0.0095
Presence of over-line bridges	0.0073
Maximum axle load	0.0067
Presence of retaining walls	0.0060
Presence of tunnels	0.0058
Presence of stations	0.0019

- **Curvature** and **cant** proved to be the most important among all that were considered in the model. **Axle load** and **train speed** would also be expected to significantly impact track fixity.
- In terms of the presence of structures,
  - track fixity of ballasted track can be more vulnerable to movement than fixed structures such as **retaining walls** and **tunnels**.
  - Track sections within **station** areas are much less likely to suffer from fixity issues given a much slower train speeds and lack of track curvature.

Conclusion

- We designed and tested the most comprehensive integrated computing framework (prototype) to date for track fixity in the context of the UK's railway system.
- With the established workflow, we propose a new metric for assigning track fixity values to a given track profile in terms of its movement relative to the plane of rail within a given period.

Further development of the framework

1. Improved quality reference data over the different location identifiers across different data sources.
2. The comprehensive data set should be extended to include additional line sections with differing reference curves and speed profiles.
3. Using data from additional measurement campaigns to enable the existing model to be further developed, leading to improved accuracy and greater confidence in the results produced by the model.
4. Would require a more harmonized and unified data codification system across the rail industry to accelerate the development and implementation of a full-fledged, automated computing platform to be integrated into the railway track system.

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