Automatic Rail Track Surface Anomaly Detection with Smartphone Based Monitoring System

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Abstract. Railroad companies spend a significant portion of their revenue on track inspections to maintain safety and maximize operational efficiency. Deviations from the designed track geometry over time could lead to poor ride quality and possible derailments. The existing approaches to track inspections are expensive and laborious. The use of low-cost sensors aboard revenue service trains to screen the infrastructure for track irregularities could improve the cost-efficiency of track inspections by targeting the available resources to high-risk locations. Unevenness of rail track running surfaces cause dynamic forces generated at the wheel/rail contacts which in return results the vibration of the car. This study focuses on detecting track unevenness by associating its influence on vibration with it. A comparative analysis is carried out on unevenness response prediction and the accuracy of detecting such track surface unevenness is analyzed with the ground truth location collected by the railroad track inspectors. The main finding of the study were 1) the unevenness event estimation error are within 15 matters with one run for one phone based system and 2) the three-phone based track surface anomaly detection system can improve its forecasting accuracy to 5 meters and to 3 meters with two traversals.

Introduction

Condition monitoring of railroad tracks is essential for ensuring operational safety and efficiency¹,². Railroads periodically inspect tracks by manual means, but they often supplement those by using special inspection vehicles, such as automated track geometry equipment. However, railroads cannot afford to run automated inspection systems frequently because they are expensive, require specially trained personnel, and may require track closures or slow orders. Railroads can also monitor track geometry by using commercial in-service vehicles equipped with sensors such as accelerometers, gyroscopes, and geospatial position sensors³–⁶. The emergence of smartphones that embed similar types of sensors have prompted research to investigate their potential as a lower-cost alternative⁷. Such sensors on board revenue service trains could screen automatically and continuously for inertial events produced from traversing irregular track geometry at different speeds. The approach can enhance the efficiency of track inspectors, especially for short-lines, by focusing their limited resources on high-risk locations. High-intensity inertial event clusters likely expose locations with irregularities that can potentially lead to derailments.

Smartphone Based Detection System

The authors developed a smartphone application (app), railroad infrastructure and vehicle evaluation technology (RIVET) to collect the following data with accelerometers, gyrometer, and global position system embedded in Pixel phone: 1) sample collection time 2) GPS latitude (Lat) and longitude (Lon) 3) ground speed reported by the GPS receiver in meters per second 4) accelerometer values Ax, Ay, and Az, which are in the x, y, and z directions, respectively, with
units in meters-per-second-squared 5) angular rotations Rx, Ry, and Rz in the x, y, and z directions, respectively, with unit in radians-per-second 6) magnetic field strength Mx, My, and Mz in the x, y, and z directions, respectively, with unit in micro-Tesla 7) pitch, roll and yaw (Azimuth) in degree angles.

The accelerometers produce samples at an average rate of 400 measurements per second whereas the GPS positions update approximately every second. The analysis did not use the magnetic field data.

### Smartphone Location Setup

A hi-rail vehicle is typically a modified road truck that can operate on both rail tracks and roadways. Short-line railroads typically use such hi-rail vehicles are for daily manual inspections. The smartphone location setup considered the different kinetic energy responses, power supply resources, and the GPS signal strength. Figure 1 shows the hi-rail vehicle used and the three locations of smartphone installations.

![Figure 1. a) Hi-rail vehicle used b) Phone 1 installed on dashboard c) Phone 2 installed under driver seat d) Phone 3 installed under passenger seat.](image)

### Methodology

Rail track surface unevenness and irregularities such as damaged rail, flattened rail, track alignment, profile, and warp result in roughness when the train load traverses them at some speed. The smartphone embedded three-dimensional accelerometers sense the induced roughness. A first step in data preparation is the conversion of each accelerometer value in meters/second to g-force. A second step is to remove any signal offset between GPS updates by subtracting the mean signal. A third step is to produce the resultant g-force, Gt by computing:

\[
G_t = \sqrt{A_{xg}^2 + A_{yg}^2 + A_{zg}^2}
\]

(1)

Subsequently, the Road Impact Factor (RIF) transform extracts a feature such that:

\[
RIF = \sqrt{\frac{1}{L} \sum_{n=0}^{N-1} |Gt[n] \times v[n]|^2 \delta t[n]}
\]

(2)

where \(v[n]\) is the instantaneous speed at inertial sample n, \(\delta t[n]\) is time changes between two inertial samples, and L is the distance between GPS updates.
Results

The purpose of the data analysis is to detect irregular track geometry and align its corresponding geospatial position on the track. The proposed method identified a track surface irregularity that a railroad track inspector frequents with a hi-rail vehicle. The identified irregularity is a crushed head with some shelling. The identified irregularity served as the ground truth data.

The data used for this study is from two traversals collected from the three smartphones installed at three different locations on the Hi-rail vehicle. ArcGIS plots the intensity of the RIF features at the corresponding longitude and latitude position of each GPS position update (GPS blocks) as small circles with a color-coded level. Figure 2 shows the RIF features from the data collected by one smartphone on the dashboard. One can tell there is one location based on our peak RIF value that corresponds to the inertial signals indicating really high probability of surface abnormality at that location shown as a red triangle while all the rest reported peak RIF values are coded as other colors.

To validate the forecasting surface anomaly and its location, the authors checked with the railroad maintenance engineer and based on engineer report, at location coded as big green circle in Figure 2, there is an irregularity where a crushed head with some shelling issue is reported. The actual reported location will serve as ground truth location for our method validation comparison.

Table 1. Identified surface irregularity from three phones and two traversals compared to ground truth.

| Data Resource ID | 1    | 2    | 3    | 4    | 5    | 6    |
|------------------|------|------|------|------|------|------|
| RIF Peak Values  | 0.268| 0.290| 0.292| 0.397| 0.451| 0.488|
| Distance to Ground Truth Location (M) | 9.59 | 12.38| 9.87 | 10.07| 13.59| 4.89 |

Table 2 summarized the location estimation errors in meters for each traversals and all traversals. Figure 3 indicate an example for one traversal from three phones.
Table 2. Identified surface irregularity from three phones and two traversals compared to ground truth.

| Centroids | 1st traversal, three-phone | 2nd traversal, three-phone | All data |
|-----------|----------------------------|----------------------------|----------|
| Distance to Ground Truth Location (M) | 4.45 | 1.54 | 2.73 |

Figure 3 indicates a centroid using data from three phones at different locations for the same traversal. The distance between the centroid and the ground truth data is measured. An error based on all data collected by having a centroid calculated all available data from both traversals is also measured. Table 2 summarized forecasting accuracy for each traversal and both traversals with three-phone based system. The distance between the centroid from all the data to the ground truth data is 2.7 meters.

Figure 3. Estimated anomaly location from three smart phones with one traversal data.

Conclusions

This paper introduced a road impact factor based g-force transformation algorithm to estimate the position of peak inertial events in order to identify the positions of possible rail surface irregularities. The study indicates that the extract features from the inertial sensor signaling data can accurately estimate the event of rail track surface unevenness and its location. Each traversal data from one smartphone will provide reasonable location estimation. With our test data, the errors are within 15 meters which is within sight distance. This finding is critical because each single run with one phone will narrow down the potential surface anomaly within sight distance. Such a solution would free up more track time and capacity previously reserved for manual inspections while improving safety for railroad workers on duty. The three-smartphone based data collection system will significantly improve the location estimation errors, with one traversal, the offset can be improved to within 5 meters and with two traversals, and it can be improved to within 3 meters.

Future work will focus on sensitivity analysis to evaluate the optimal number of traversals needed to provide perfect location estimation and further algorithms development to transfer the detected inertial events into the actual measures of track geometries.

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