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IDENTIFYING ISOLATED DEFECTS IN THE BALLAST BED USING A FRACTAL ANALYSIS APPROACH WITH REDUCED WINDOW LENGTH

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Abstract

Due to increasing demands on the availability of railway infrastructure, accurate estimates of safety-critical track condition as well as breakdowns of individual track components are crucial. This task can be supported by analysing track measurement data. Ballast breakdown can be determined by analysing the longitudinal level using fractal analysis. Typically, a window of 150 meters is drawn over the signal and an approximation of a fractal dimension of the signal is calculated for each position of the window. While a large window length can be used to describe the condition of ballast and substructure simultaneously, it fails to precisely localize isolated defects in the track (short-section ballast breakdown). To describe local effects in the ballast bed, this work analyses a set of 114 known weak ballast spots. By reducing the window length, the position of short-section ballast breakdowns can be reliably depicted. Using a smaller window size in modified fractal analysis allows for targeted maintenance of specific components. Ultimately, fractal analysis with reduced window sizes facilitates allocating maintenance resources and helps reducing unexpected downtime and saving on costs.

Keywords: data analysis, targeted maintenance, track quality, fractal analysis

1 Introduction

Efficient maintenance planning is essential for ensuring the safety and optimal condition of railway tracks, particularly as demand increases [1]. To achieve this, vehicles equipped with specialized measurement tools are used to assess the condition of the track by measuring the longitudinal level, alignment, cross level, gauge, and twist according to the European standard EN 13848-5 [2]. Assessment of track quality typically involves analysing the longitudinal level. The standard deviation of the longitudinal level is used as the primary indicator of track geometry quality and deterioration [2–4]. Maintenance decisions such as tamping are based on this metric [5, 6]. However, tamping may not always be the best solution if the ballast is contaminated and loses elasticity, as this can lead to faster deterioration [7]. This study focuses in particular on using fractal analysis of the longitudinal level to determine short-section ballast breakdowns. The longitudinal level of our research is provided by the Austrian Federal Railways. Ballast breakdowns in the investigated sections are manually identified by the responsible track engineers. Other methods of investigating the ballast bed, such as ground penetrating radar or direct excavation, are not included. Ground penetrating radar data is rarely available, while investigations through excavation require considerable time and only provide information on the condition of track components at the exact location where the investigation took place.

A fractal analysis approach is used to detect geometric irregularities and match patterns to specific damage types [8]. The purpose is to identify underlying causes of track geometry errors and optimise track maintenance through targeted interventions based on identified ballast problems. This data-driven approach aims to identify the root cause of defects, enabling more precise maintenance that can improve track quality over time, extend maintenance intervals, and ultimately prolong the service life of the track [9].

2 Methodology

Fractal analysis is a mathematical technique that examines a signal by jointly analysing its wavelengths and amplitudes together and quantifies the roughness of the signal [8, 10]. It is particularly useful for assessing the condition of tracks by assigning track geometry irregularities to specific components. To calculate fractal dimensions, we use methods such as the box-counting, yardstick, or divider method, depending on the structure being analysed [11, 12]. Hansmann and Landgraf use a 150-meter window to perform a fractal analysis. The approach follows an iterative procedure outlined in the following steps [13]:

1. Determining the location to be evaluated.
2. Spanning a window (150 m) around the specified location.
3. Dividing the window into sub-segments with a length of .
4. Identifying the intersection points between the longitudinal level signal and the sub-segment boundaries.
5. Computing the length of the connecting line between each pair of intersection points (segment length).
6. Calculating the polygonal length as the sum of the segment lengths.
7. Plotting the polygon length and the corresponding segment length in a log-log diagram (Richardson plot [8, 13]).
8. Applying a linear regression in the Richardson plot and determining the fractal dimension.

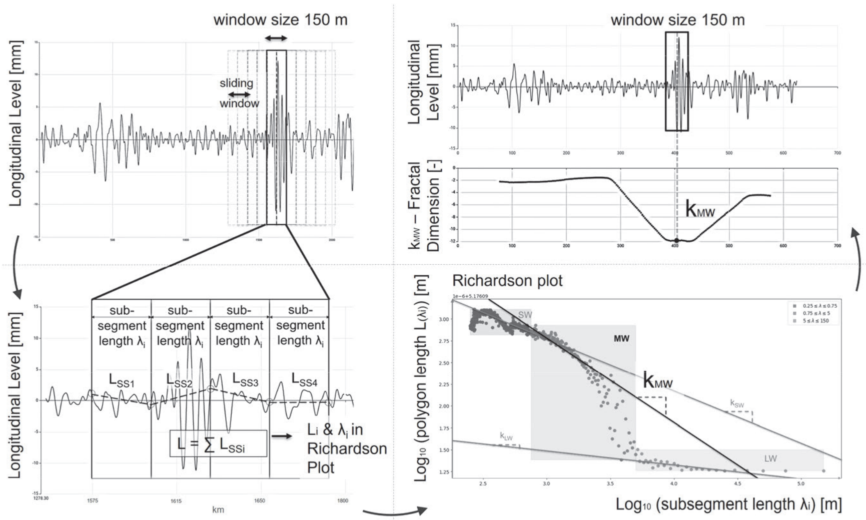

Figure 1 Iterative procedure for estimating fractal dimension using the Hansmann and Landgraf method. Upper left: steps 1 and 2; lower left: steps 3 through 6; lower right: steps 7 and 8; Upper right: the first plot reveals a measurement of the longitudinal level, the plot below displays the corresponding estimated fractal dimensions, indicating poor ballast bed condition at the marked position

The fractal dimension is calculated using a modified version of the yardstick method. However, rather than circling the signal as in the conventional yardstick technique, the data segment is divided into constant sub-segments () as described above. Assuming that the points plotted in the Richardson plot are best approximated by a power function, the following approach is applied [14]:

$$L(\lambda) = c \cdot \lambda^{a} \tag{1}$$

With b = ln(c) it follows that

$$\ln(L(\lambda)) = b + a \cdot \ln(\lambda) \tag{2}$$

$$\alpha = \frac{\ln\left(L(\lambda)\right) - b}{\ln\left(\lambda\right)} \tag{3}$$

It can be shown that the fractal dimension can be approximated with d = 1-α [15]

$$d = 1 - \frac{\ln\left(L(\lambda)\right) - b}{\ln\left(\lambda\right)} \tag{4}$$

As with the yardstick method, the following limit value must now be determined:

$$\lim_{\lambda \to 0} 1 - \frac{\ln\left(L(\lambda)\right) - b}{\ln\left(\lambda\right)} = 1 - \lim_{\lambda \to 0} \frac{\ln\left(L(\lambda)\right)}{\ln\left(\lambda\right)} \tag{5}$$

The fractal analysis algorithm presented here uses linear regression in the Richardson plot to estimate the size

$$k \approx \lim_{\lambda \to 0} \frac{\ln\left(L(\lambda)\right)}{\ln\left(\lambda\right)} \tag{6}$$

Thus, the fractal dimension of the analysed signal is estimated as . Given that |k|‹‹1, using -k+1 in calculations can cause issues with floating-point arithmetic. Therefore, in all experiments, the constant 1 is excluded. Additionally, in this study, is scaled by a factor of to align with previous research findings and facilitate comparisons with them, as well as with the standard deviation of the longitudinal level.

2.1 Modified fractal analysis with REDuced window size (FRED)

In the presented study, the fractal analysis algorithm has been modified to introduce a reduced window size that improves error detection in the longitudinal level of the track. This modification targets defects that have predominantly local effects, often in areas smaller than 150 meters. Hansmann and Landgraf's method of fractal analysis focuses on three elements of track composition: the sleeper, the ballast bed, and the subgrade. This technique includes data segments that detect wavelengths ranging from 3 to 70 meters. By narrowing the data segment length, the algorithm aims for more accurate fault location. However, this limits the range of analysed wavelengths with a focus on the ballast bed.

This study evaluates the effectiveness of smaller data segments, ranging from 6.25 to 50 meters, in assessing ballast bed condition. Eight different segment sizes were considered because ballast contamination typically affects the 3-to-25-meter wavelength range.
The FRED approach uses smaller window sizes than Hansmann and Landgraf. It also automates the linear regression of the Richardson plot using the RANSAC algorithm. This incorporation of RANSAC reduces the computational time required by the algorithm. An explanation of how the RANSAC algorithm functions is also included for clear understanding.
The RANSAC algorithm [16] efficiently estimates model parameters in data with significant outliers, making it ideal for linear regression on the Richardson plot. It distinguishes between fitting (inliers) and non-fitting (outliers) data points through an iterative process of random selection, model estimation, and inlier counting, continually refining the best model. This technique is particularly useful for datasets that contain noise or anomalies, such as railway track data, as it reduces the need for manual removal of outliers and improves model accuracy by being resilient to outliers.

Table 1 Investigated data segment sizes

Input	Hansmann Landgraf	FRED approach							
	Longitudinal level (3 - 70 m)	Longitudinal level (3 - 25 m)							
Window size W [m]	150	50	25	20	15	12.5	10	8	6.25
λ_{min} [m]	0.75								
λ_{max} [m]	5	50	25	20	15	12.5	10	8	6.25
Delta Gliding [m]	2.5	1							
No. sub-segments	59	66	33	26	20	16	13	10	8

Table 1 compares fractal analysis parameters of different window sizes. The 'Hansmann and Landgraf approach' column serves as the baseline, using a 150-meter window. This standard setup analyses the longitudinal level of the left rail for wavelengths ranging from 3 to 70 meters. For smaller windows between 6.25 and 50 meters, the analysis is limited to wavelengths ranging from 3 to 25 meters, targeting the ballast bed specifically. Data points are taken every 25 centimetres on the track. The segment length minimum remains constant at = 0.75 meters, but the maximum length (λ_{max} = W) varies depending on the window size. The scanning interval for 'Delta Gliding' has been reduced from 2.5 to 1 meter. The efficiency of our implementation allows for tighter intervals, requiring a balance between analysis detail and computational costs when selecting the window size.
In order to determine the optimal window size for the detection of short-section contamination in the ballast bed, we developed models with different input data sets, as described in the experimental results section. The effectiveness of these models was evaluated using the F_1-Score, a critical measure for model assessment. The F_1-Score is the harmonic mean of precision (the accuracy of positive predictions) and recall (the model's ability to detect all actual positives), and serves as a key indicator of model performance. The F_1-Score is a comprehensive metric that takes into account both false positives and false negatives and ranges from 0 to 1. This metric is especially valuable for comparing the performance across different datasets, including those with uneven class distributions, by providing a balanced evaluation of essential factors for accurate model assessment.

3 Empirical results

To determine the optimal window size for detecting short-section ballast breakdowns using fractal analysis, we compared three types of models, each calculated for eight different window sizes. Thus, a total of 24 models is investigated. The three types are (1) the standard deviation of the longitudinal level, (2) the fractal dimension, and (3) fractal dimension combined with its variation over time. The investigation analyses whether fractal analysis provides more insights into the condition of the ballast bed compared to simply analysing the standard deviation of the longitudinal level. Each model was tailored to a specific window size and evaluated for its ability to accurately identify isolated ballast-bed issues. A detection threshold was established for each model by analysing 114 known short-section ballast breakdowns. A precise identification of a short-section ballast breakdown occurs when its location is pinpointed within a margin of plus or minus 7.5 meters. The thresholds were adjusted to maximize the F_1-Score on the validation dataset for each window size.
During our data analysis, we observed a significant increase in fractal dimensions over time at sites with existing short-section ballast breakdowns. Our research methodology extends beyond the identification of short-section ballast breakdowns by fractal dimensions to include an analysis of how these dimensions change over time. The method involves computing changes between successive fractal dimensions, aggregating their absolute values, and dividing by the total number of data series. Models were designed based on this method, which require setting two threshold values to optimize the F_1-Score. Table 2 provides details on the thresholds determined for each window size and their respective model performances.

Table 2 F_1-Score - Performance of all models

	Fractal dimension		**Standard deviation**		**Fractal dimensions + temporal changes**		
Window size [m]	THR	F_1	THR	F_1	THR Frac.	THR Temp.	F_1
6.25	33	0.7547	4.5	0.6538	33	0	0.7547
8	32	0.7692	5.25	0.6818	32	0	0.7692
10	25	0.7843	5.25	0.6667	5	2.5	0.7170
12.5	25	0.7917	5	0.6667	25	1.5	0.7917
15	25	0.7660	4.75	0.6977	7	1.75	0.7170
20	20	0.7451	4	0.7111	18	2	0.6939
25	17	0.7925	4.25	0.6818	16	1.75	0.7234
50	13	0.7917	3.5	0.6383	6	0.75	0.7119

Table 2 depicts how the F_1-Score varies across different window sizes and methodologies. For instance, window sizes of 12.5 and 25 meters show relatively high F_1-Scores when using fractal dimensions alone or in combination with temporal changes, indicating a strong performance in anomaly detection. The inclusion of temporal changes does not always improve the F_1-Score, as seen in the 10-, 15-, 25- and 50-meter window sizes, suggesting that the effectiveness of incorporating temporal changes depends on the specific window size and the thresholds applied.

4 Discussion and future work

Table 2 presents the performance of various anomaly detection models across different window sizes. The models use fractal dimension, standard deviation, and a combination of fractal dimensions with temporal changes.

The models that performed best in terms of analysing fractal dimensions alone were those with window sizes of 12.5 meters and 25 meters. The model with a window size of 25 meters achieved the highest F_1-Score of 0.7925. This makes it the best model for this criterion. Similarly, the model with a window size of 12.5 meters also showed a strong performance, yielding an F_1-Score of 0.7917. This indicates that both window sizes are highly effective for detecting anomalies in the ballast bed based solely on fractal dimensions, with a slight advantage for the 25-meter window size in terms of raw F_1-Score.

However, when considering the integration of temporal changes alongside fractal dimensions, the 12.5-meter model not only maintains its high F_1-Score but also demonstrates the feasibility of incorporating temporal dynamics without compromising accuracy. This is important for practical applications where both detection accuracy and the ability to track changes over time are valued.

Furthermore, the models that utilized fractal dimensions systematically outperformed those based on standard deviation in achieving higher F_1-Scores. This suggests that fractal dimensions, particularly when combined with temporal variations, provide a more reliable measure for identifying anomalies caused by short-section ballast breakdown.

In conclusion, the analysis suggests that the 12.5-meter window size model, whether using fractal dimensions alone or in conjunction with temporal changes, offers the best combination of high detection accuracy and practical applicability. This model is notable not only for its performance in anomaly detection but also for its potential in capturing temporal variations, making it an optimal choice for real-world implementations intended to detecting local ballast issues.

Future research could further optimize this model, especially in environments where detecting subtle changes over time is critical. Therefore, investigating short-section ballast breakdowns is important to solidify the findings of this study. Additionally, reducing the window size to 12.5 meters could provide new applications, such as using fractal analysis to evaluate ballast beds in turnouts. Previously, this was hindered by the need for a larger window size of 150 meters. This advancement could facilitate root cause-based maintenance and evaluation practices in these critical rail asset areas.

References

[1] Landgraf, M.: Smart data for sustainable Railway Asset Management, Verlag der Technischen Universität Graz, 2018.

[2] EN 13848-5: Railway Applications-Track-Track Geometry Quality-Part 5: Geometric Quality Levels, Brussels, Belgium: European Committee for Standardization, 2008.

[3] Vale, C., Simões, M.L.: Prediction of Railway Track Condition for Preventive Maintenance by Using a Data-Driven Approach, Infrastructures, 7 (2022) 3, DOI: 10.3390/infrastructures7030034

[4] Elkhoury, N., Hitihamillage, L., Moridpour, S., Robert, D.: Degradation Prediction of Rail Tracks: A Review of the Existing Literature, The Open Transportation Journal, 12 (2018) 1, pp. 88–104, DOI: 10.2174/1874447801812010088

[5] Caetano, L.F., Teixeira, P.F.: Predictive Maintenance Model for Ballast Tamping, J. Transp. Eng., 142 (2016) 4, DOI: 10.1061/(ASCE)TE.1943-5436.0000825

[6] Bakhtiary, A., Zakeri, J.A., Mohammadzadeh, S.: An opportunistic preventive maintenance policy for tamping scheduling of railway tracks, International Journal of Rail Transportation, 9 (2021) 1, pp. 1–22, DOI: 10.1080/23248378.2020.1737256

[7] Offenbacher, S., Antony, B., Barbir, O., Auer, F., Landgraf, M.: Evaluating the applicability of multi-sensor equipped tamping machines for ballast condition monitoring, Measurement, 172 (2020) 80, DOI: 10.1016/j.measurement.2020.108881

[8] Hyslip, J.P.: Fractal Analysis of Track Geometry Data, Transportation Research Record, 1785 (2002) 1, pp. 50–57, DOI: 10.3141/1785-07

[9] Nielsen, J.C.O., Berggren, E.G., Hammar, A., Jansson, F., Bolmsvik, R.: Degradation of railway track geometry – Correlation between track stiffness gradient and differential settlement, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 234 (2020) 1, pp. 108–119, DOI: 10.1177/0954409718819581

[10] Hyslip, J.: Fractal Analysis of Geometry Data for RailwayTrack Condition Assessment. Dissertation, Department of Civil and Environmental Engineering, University of Massachusetts Amherst, May 2002.

[11] Klinkenberg, B.: A Review of Methods Used to Determine the Fractal Dimension of Linear Features, Mathematical Geology, 26 (1994) 1, pp. 23-46

[12] Liang, Z., Feng, Z., Guangxiang, X.: Comparison of Fractal Dimension Calculation Methods for Channel Bed Profiles, Procedia Engineering, 28 (2012), pp. 252–257, DOI: 10.1016/j.proeng.2012.01.715

[13] Landgraf, M., Hansmann, F.: Fractal analysis as an innovative approach for evaluating the condition of railway tracks, Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit, 233 (2019) 6, pp. 596–605, DOI: 10.1177/0954409718795763

[14] Mandelbrot, B.: How long is the coast of britain? Statistical self-similarity and fractional dimension, Science, 156 (1967) 3775, pp. 636–638, DOI: 10.1126/science.156.3775.636

[15] Filler, A.: Fraktale, Humboldt-Universität zu Berlin 2019.

[16] Dusmez, S., Heydarzadeh, M., Nourani, M., Akin, B.: Remaining Useful Lifetime Estimation for Power MOSFETs Under Thermal Stress With RANSAC Outlier Removal, IEEE Trans. Ind. Inf., 13 (2017) 3, pp. 1271–1279, DOI: 10.1109/TII.2017.2665668