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ENERGY-EFFICIENT DETECTION OF RAILWAY WHEEL DEFECTS USING HILBERT TRANSFORM-BASED VIBRATION ANALYSIS AND HISTOGRAM CLUSTERING

ENERGOOSZCZĘDNE WYKRYWANIE USZKODZEŃ KÓŁ KOLEJOWYCH PRZY UŻYCIU ANALIZY DRGAŃ OPARTEJ NA TRANSFORMACIE HILBERTA I KLASTERYZACJI HISTOGRAMÓW

***Summary**: Ensuring the safety and reliability of railway transport systems depends heavily on the early detection and monitoring of wheelset defects. If left unchecked, imperfections such as flat spots on wheels can increase vibration levels, accelerate component fatigue, and lead to serious safety incidents Traditional approaches to diagnosing wheel condition often depend on manual inspections or resource-intensive equipment, which can be challenging to deploy across large fleets or remote networks. This paper presents an energy-efficient, computationally lean method for detecting characteristic vibration patterns associated with common wheelset defects. The proposed approach employs the Hilbert transform to extract specific dynamic responses in time domain of vibration signals of vibration signals and then utilizes histogram-based clustering to identify deviations in peak distribution that indicate mechanical defects. Unlike more complex machine learning approaches that demand significant power and computational resources, our method is designed to operate autonomously on low-power, self-contained devices with limited external support. It achieves robust performance in a vehicle speed range of 10–40 km/h and track conditions, detecting subtle anomalies after accumulating modest amounts of data from short measurement windows.*

The results show that by focusing on the specific and exploiting simple but effective statistical analyses, the system can reliably differentiate healthy from defective wheels. This contributes to cost-effective maintenance strategies, reduces downtime, and enhances railway safety. Finally, we discuss future improvements, including integration with predictive maintenance frameworks, adaptive thresholding techniques, and potentially incorporating more advanced processing methods if energy budgets allow.

***Keywords**: railway wheel defect detection, Hilbert transform, vibration analysis*

Streszczenie: Zapewnienie bezpieczeństwa i niezawodności systemów transportu kolejowego w dużym stopniu zależy od wczesnego wykrywania i monitorowania usterek zestawów kołowych. Jeśli nie zostaną sprawdzone, niedoskonałości, takie jak płaskie miejsca na kołach, mogą zwiększyć poziom drgań, przyspieszyć zmęczenie podzespołów i doprowadzić do poważnych incydentów bezpieczeństwa. Tradycyjne podejścia do diagnozowania stanu kół często opierają się na ręcznych inspekcjach lub sprzęcie wymagającym dużych zasobów, co może być trudne do wdrożenia w dużych flotach lub sieciach zdalnych.

Artykuł prezentuje energooszczędną metodę wykrywania defektów kół kolejowych przy użyciu analizy wibracji. Wykorzystano transformację Hilberta do przetwarzania sygnałów oraz klasteryzację histogramową w celu identyfikacji nieprawidłowości. Rozwiązanie to jest bardziej efektywne energetycznie i precyzyjne w porównaniu z tradycyjnymi metodami. Skupiono się na analizie drgań jako wskaźnika stanu technicznego kół, co ma istotne znaczenie dla bezpieczeństwa i utrzymania infrastruktury kolejowej.

Wyniki pokazują, że poprzez skupienie się na konkretach i wykorzystanie prostych, ale skutecznych analiz statystycznych, system może niezawodnie odróżniać sprawne koła od wadliwych. Przyczynia się to do opłacalnych strategii konserwacji, skraca przestoje i zwiększa bezpieczeństwo kolei. Na koniec omawiamy przyszłe ulepszenia, w tym integrację z ramami konserwacji predykcyjnej, adaptacyjne techniki progowe i potencjalne włączenie bardziej zaawansowanych metod przetwarzania, jeśli pozwolą na to budżety energetyczne.

Słowa kluczowe: wykrywanie defektów kół kolejowych, transformata Hilberta, analiza wibracji

Introduction

The condition of railway wheelsets is a cornerstone of train safety and efficiency [1, 3, 5, 8, 9]. Undetected defects such as wheel flats, cracks, or uneven wear can increase vibration, noise, and dynamic loads transmitted through the vehicle structure and track [16, 19]. Over time, these issues may escalate into severe mechanical failures, risking derailments or causing expensive damage to rolling stock and infrastructure. Early identification of such problems is a high priority for railway operators aiming to minimize maintenance costs, reduce downtime, and enhance the safety and comfort of passengers and freight [8, 17].

Traditionally, wheelset diagnostics relied on periodic manual inspections, leveraging maintenance personnel's experience correlating acoustic cues or vibration signatures with known fault patterns. [3, 5, 8, 13]. While effective to a degree, these methods are inherently subjective, labor-intensive, and insufficiently scalable. Large railway networks, high traffic volumes, and diverse environmental conditions demand more automated and continuous monitoring solutions. Modern sensing technologies, data acquisition systems, and advanced signal processing methods offer an opportunity to move beyond manual checks toward continuous condition-based maintenance. [2, 7, 18, 22].

However, the demand for automated, data-driven diagnostics introduces new challenges. Many advanced signal processing and machine learning algorithms are computationally expensive, require continuous high-bandwidth data streams, or rely on external power sources. Such requirements can be impractical for onboard systems operating autonomously, often in remote areas [2, 5, 7] without easy access to maintenance facilities or stable power supplies. Minimizing energy consumption and computational overhead becomes critical if the diagnostic device is to run for extended periods, gather data incrementally, and provide actionable insights without frequent intervention.

This paper outlines the complete solution: from the theoretical underpinnings of using the Hilbert transform for non-stationary vibration signals to the practical details of experimental setup and sensor placement, the data processing pipeline, and the final interpretation of histogram-based clusters. We then present results obtained under various speeds and conditions, demonstrating robust performance in differentiating healthy wheels from defective ones. The discussion section explores the trade-offs between simplicity and performance and opportunities for refining and extending the proposed method. In the conclusion, we summarize our findings and propose directions for future improvements, potentially integrating these diagnostics into broader predictive maintenance frameworks.

In response, this paper focuses on developing an energy-efficient approach that balances diagnostic fidelity with the constraints of limited onboard resources. We propose a methodology that employs the Hilbert transform to extract repeating dynamic responses due to wheel flat spots of the vibration signals, followed by a histogram-based clustering analysis that identifies patterns indicative of wheel defects. The chosen techniques deliberately avoid large-scale model training or complex classification frameworks, thus limiting memory consumption, computational cycles, and power draw.

Background and Motivation

The railway wheel-rail interface is a complex environment where multiple dynamic phenomena converge. Factors such as wheel profile wear, track irregularities, speed variations, and load distributions produce inherently non-stationary vibration signals. [3, 10, 11, 16, 19, 23, 28]. Conventional frequency-domain techniques, such as Fourier-based analyses, often assume stationarity and linearity, making them less effective in capturing transient events or subtle nonlinear effects associated with wheel defects. [25–29].

Track joints create periodic impacts on the wheelsets. For instance, Figure 1 shows a typical rail joint that produces characteristic vibrations. As the wheelset rolls, these impulses

Fig. 1. Example of a joint – rail track weld on a railway route

Fig. 2. Flat spot defect on a railway rolling stock wheel

form a baseline pattern. A wheel flat Figure 2 disrupts this pattern, introducing irregularities detectable through the Hilbert transform-based envelope extraction and subsequent histogram analysis.

In contrast, the Hilbert transform offers a time-domain approach that can reveal instantaneous amplitude and frequency variations [8]. By treating the vibration signal as a complex analytic function, the Hilbert transform provides an envelope representation highlighting local changes and modulations. These can correspond to the periodic impacts caused by wheel flats or the changes in vibration patterns induced by cracks or out-of-round wheels.

Beyond the signal processing aspect, practical considerations heavily influence our choice of methods. Many railway operators are reluctant to invest in extensive data transmission infrastructures or rely on cloud-based analytics for continuous monitoring. They prefer devices that can function in a „deploy-and-forget" manner, requiring minimal human intervention and capable of running reliably on limited power reserves. These constraints shift the focus from computationally heavy machine learning models demanding substantial onboard computational resources and frequent data offloads.

Histogram-based clustering represents a simple yet powerful statistical tool. By focusing on the distribution of peak events – those that stand out in the Hilbert-transformed envelope – we gain insights into how the signal's most significant components are spaced in time. Healthy wheels might produce relatively regular patterns due to uniform rack joints and stable rolling conditions, whereas a defective wheel would alter these patterns, introducing irregular intervals or distinct statistical features that deviate from the assumed threshold. This concise approach reduces the data to a manageable set of straightforward features to compute and interpret, thereby conserving processing power.

Moreover, as rail infrastructure and vehicle operators strive to enhance safety and efficiency, there is growing interest in integrating such diagnostic systems into predictive maintenance frameworks. [22, 24]. The presented method can serve as a building block: operators can schedule targeted inspections or maintenance tasks once it reliably flags potential defects. This strategic approach prevents unnecessary downtime, ensures safer operations, and aligns with modern maintenance philosophies that emphasize data-driven decision-making, and supports planned maintenance adopted in railways.

Experimental Setup and Data Acquisition

The validation of the proposed method required data that represents realistic operational conditions. Tests were conducted on a 600 m track segment featuring straight sections, large radius curves, and typical track joints that produce periodic mechanical impulses. Speeds ranged from 10 to 40 km/h, encompassing scenarios from low-speed shunting operations to moderate-speed line travel. By spanning this range, we aimed to confirm that the diagnostic method remains reliable under different dynamic regimes.

Sensors were mounted on the wagon axle boxes and the wagon body. Figure 3 depicts an accelerometer mounted on the axle box, recording vibration signals in the vicinity of the wheel-rail contact point, providing more direct sensitivity to defects. [8, 9, 16, 19], Body-mounted sensors, while more shielded and influenced by many structural resonances, add robustness by indicating whether the defect signatures propagating through the vehicle's structure. Durable, high-quality vibration sensors from a reputable manufacturer ensured stable, low-noise measurements. Their magnetic mounts allowed secure yet

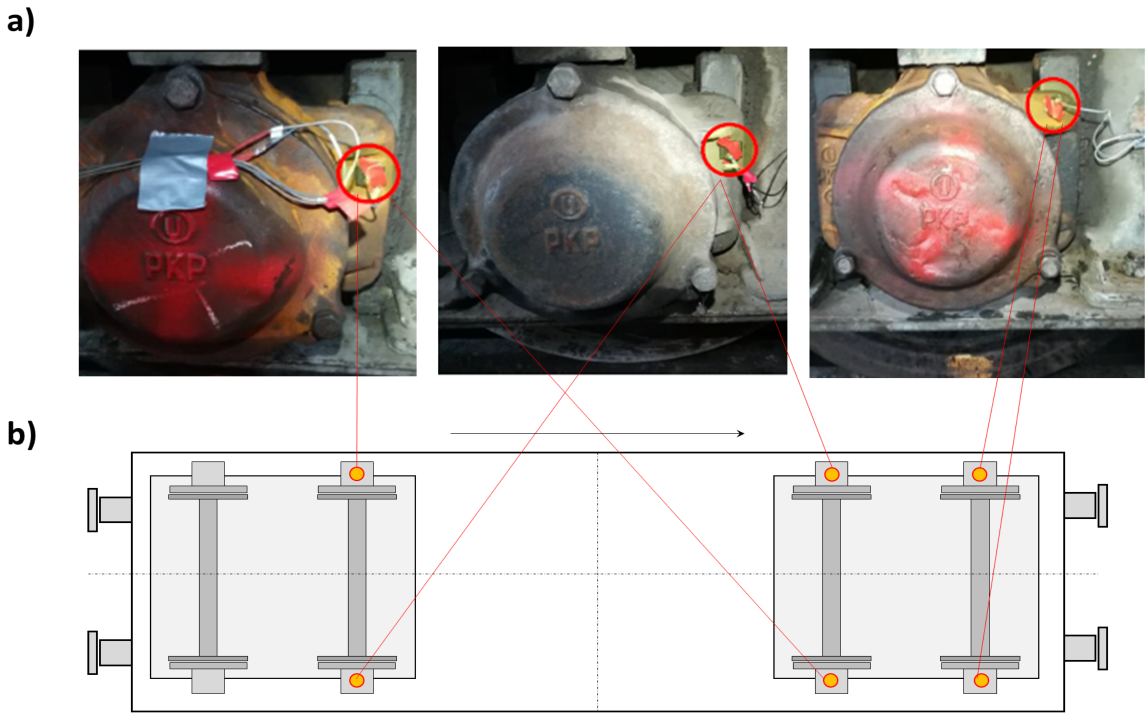

Fig. 3. Placement of vibration acceleration transducers on the examined components of a railway wagon using dedicated pads with magnets, where: a) transducer on the wagon wheel, b) location of measurement points on the bearing of the wheelset

easily adjustable placements, enabling us to compare different measurement points and refine the configuration.

Data collection does not relay on continuous data acquisition, the system can sample intermittently – recording short bursts of data periodically – then process and aggregate results over time. This cumulative strategy allows the device to run off a modest battery supply for weeks or months, gradually increasing its confidence in the detected condition of each wheelset. Once a defect signature is reliably identified, an alert can be transmitted to maintenance crews, enabling proactive interventions before problems worsen [22, 24].

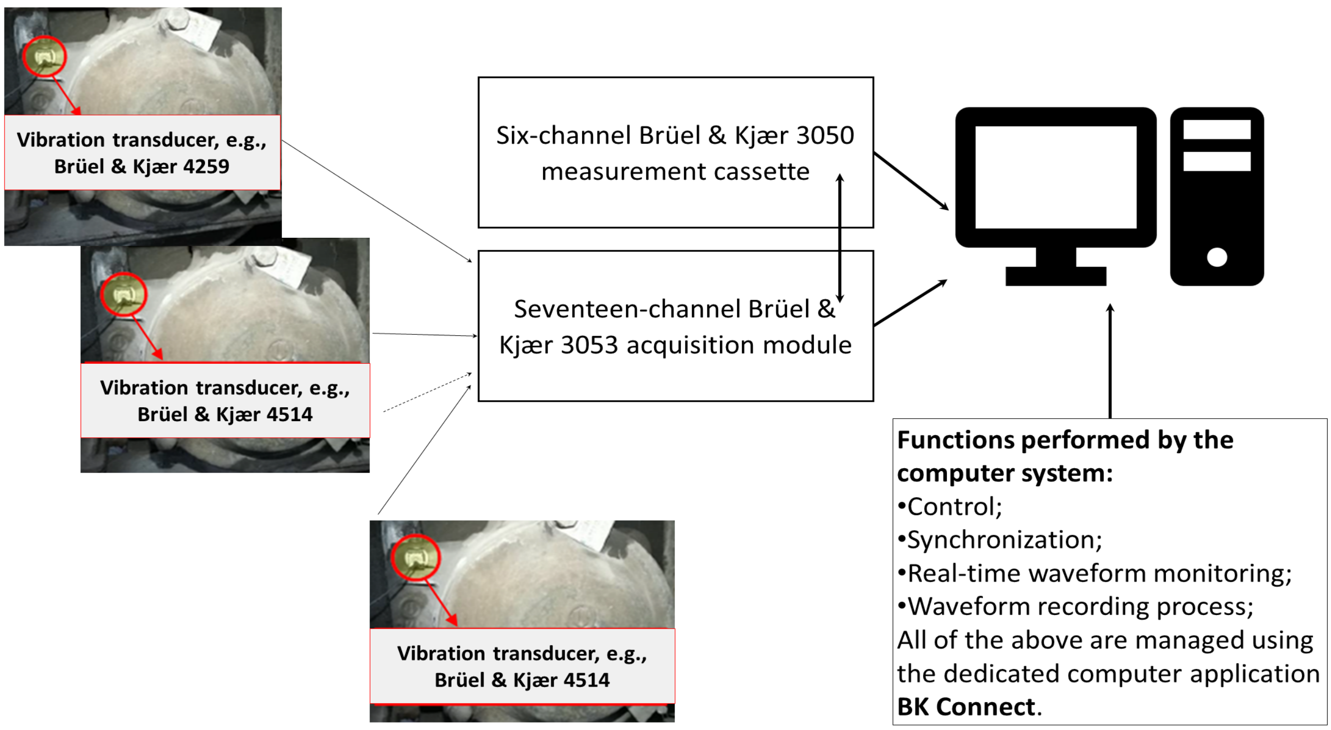

Fig. 4. Measurement setup for vibration signal analysis for the flat wheel defect or rail joint

Data was acquired using a portable instrument to log acceleration signals at high sampling rates (250–1000 Hz). Data acquisition instrumentation (Brüel & Kjær) and its setup are shown in Figure 4 Accessory sensors and geolocation devices recorded speed, position, and environmental conditions. Notably, the architecture was designed with future onboard integration in mind: the final target system should be smaller, more energy-efficient, and fully autonomous, possibly powered by batteries or energy-harvesting devices. Data were periodically offloaded throughout testing to a laboratory environment for offline analysis. This offline step allowed the refinement of algorithms and parameter selection, aiming to embed a final version directly into the onboard diagnostic unit.

Signal Processing Method: Hilbert Transform

The Hilbert transform converts a real-valued time signal x(t) into an analytic signal z(t) = x(t) + i y(t), where y(t) is the Hilbert transform of x(t) [25–29]. This enables the extraction of instantaneous amplitude (the envelope) and frequency. Figure 5 and Figure 6 illustrate fundamental examples: Figure 5 shows the real and imaginary parts of an analytic signal sin(2πt), while Figure 6 presents the envelope of an under critically damped vibration signal. Such visualizations clarify how the Hilbert transform highlights subtle modulations that might indicate wheelset defects.

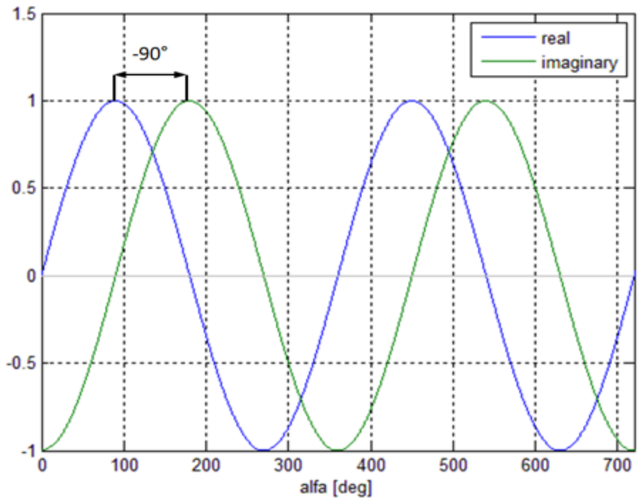

*Fig. 5. Real and imaginary parts of the analytic signal z = sin(2*pi()*t)*

To handle large data sets efficiently, preprocessing steps focus on reducing complexity while preserving diagnostic content. One key step is thresholding the envelope to isolate only the most significant peaks – often the top 5% of amplitude values. This approach filters out minor fluctuations, sensor noise, and low-level resonance effects that do not contribute meaningful diagnostic information. [1, 5, 8, 14, 15, 17, 30]. By discarding most data points and focusing only on the peaks, we

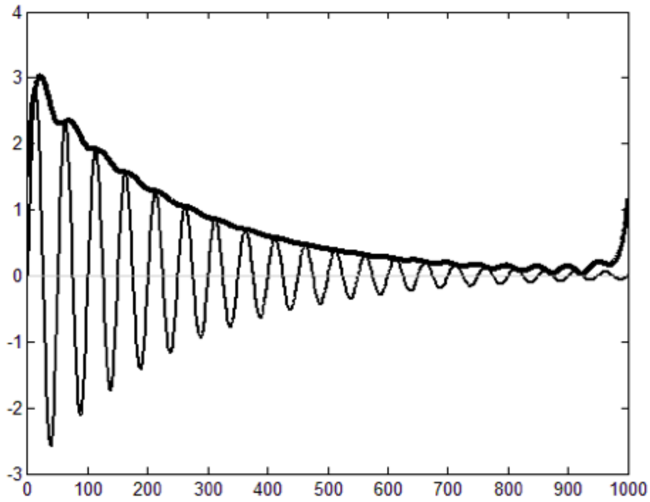

Fig. 6. Envelope of the acceleration signal for underdamped vibrations

dramatically reduce the computational burden for subsequent analyses.

Windowing strategies further enhance manageability. Instead of analyzing continuous data streams, the system can record short bursts – ranging from a few seconds to tens of seconds – at predefined intervals. This intermittent sampling conserves energy: the sensor and processor remain idle most of the time, waking up only periodically to capture and process data. Over days or weeks of operation, multiple short windows collectively form a statistical portrait of the wheel's condition. If the histogram patterns remain stable, the wheelset is likely healthy. If they drift or new patterns emerge, this could indicate the onset of a defect.

Selecting the window length and threshold levels requires experimentation. Longer windows provide more data but consume more energy, while shorter windows might need more repetitions to achieve the same confidence level. Similarly, the chosen percentile for peak selection can influence sensitivity: too strict and we might miss subtle defects; too lenient and we might incorporate noise. The trade-off is necessary for the intended operational profile and resource constraints by tuning these parameters with real-world data.

Histogram-Based Analysis and Clustering

Having extracted a sparse set of peak events from the Hilbert-transformed signal, we now seek to interpret their statistical distribution. Histograms come into play as a simple yet effective visualization and analysis technique. We can construct histograms of peak intervals, examining how these high-amplitude events are spaced in time. In a healthy wheel, periodic impulses – such as those from regular track joints – create distinctive interval distributions. Conversely, a defective wheel might introduce irregular spacing or additional peaks triggered by the sudden impact of a flat spot hitting the rail.

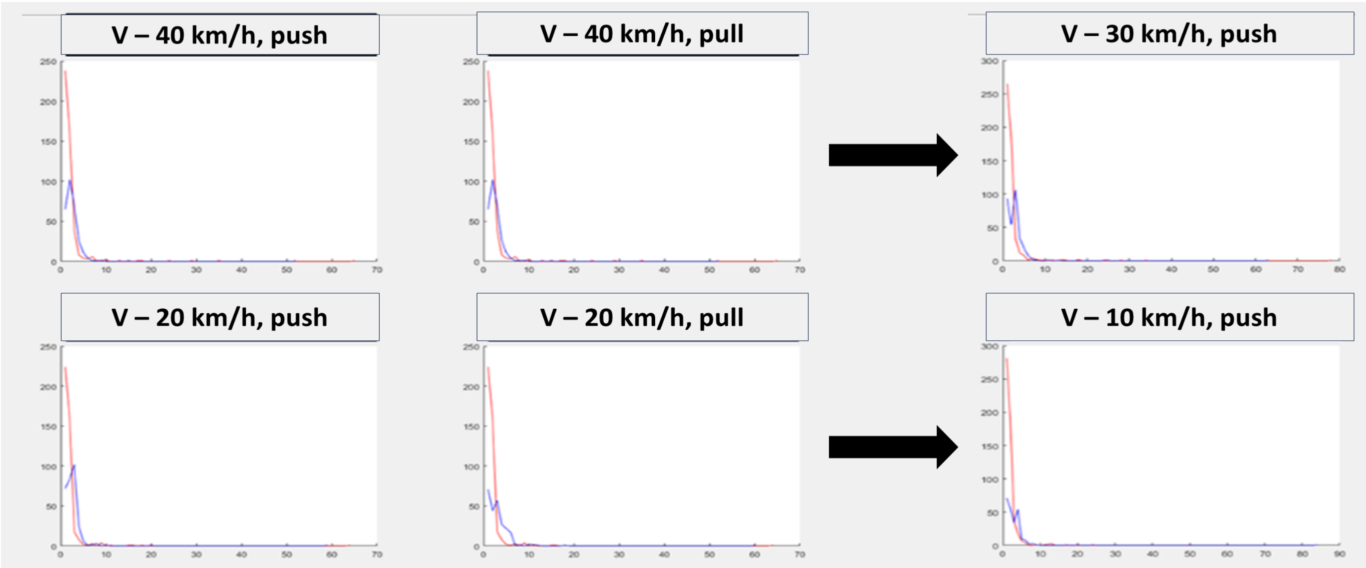

Fig. 7. Comparison of histograms of distances between clusters of peaks, data from the axlebox; Red line – result of the analysis of measurement readings from wagons with a functional wheelset Blue line – result of the analysis of measurement readings from wagons with a damaged wheelset

To enhance discrimination, we apply a basic clustering algorithm. The clustering groups together peaks that occur within a specified „range" of readings. We can emphasize features relevant to defect detection by selecting an appropriate range. For example, if a wheel flat leads to a repetitive pattern every rotation of the wheel, peaks influenced by that flat spot might cluster in a particular segment of the histogram. Figure 7 and Figure 8. Adjusting the range parameter can make these patterns more pronounced, revealing defect signatures that would be lost in a uniform distribution.

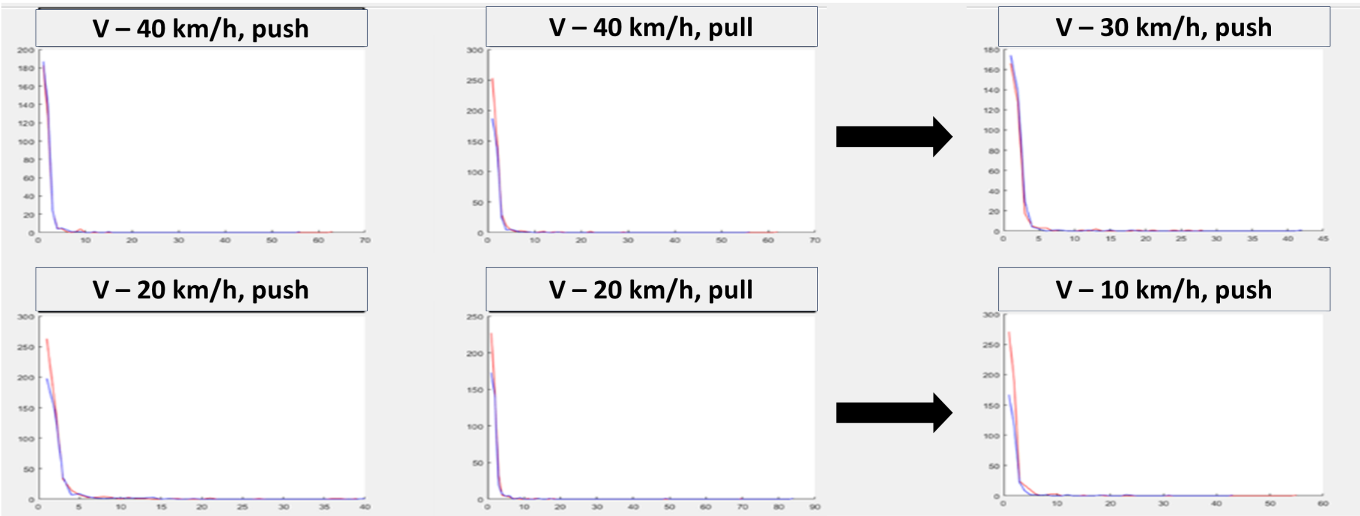

Fig. 8. Comparison of histograms of distances between clusters of peaks, data from the wagon body; Red line – result of the analysis of measurement readings from wagons with a functional wheelset; Blue line – result of the analysis of measurement readings from

This histogram-based clustering has several advantages. First, it is computationally light: counting events and sorting them into bins is far simpler than running iterative optimization or training procedures associated with advanced machine-learning techniques. Second, it provides interpretable results. Figure 9 and Figure 10 show how changing the range parameter influences histogram shapes, while Figure 11 illustrates characteristic histogram shapes for a given dataset. Maintenance personnel can interpret these histograms directly, linking emerging patterns to specific mechanical issues without requiring advanced signal processing expertise [17, 19, 23, 24, 28, 30]. Over time, this facilitates building intuitive links between histogram patterns and specific mechanical issues.

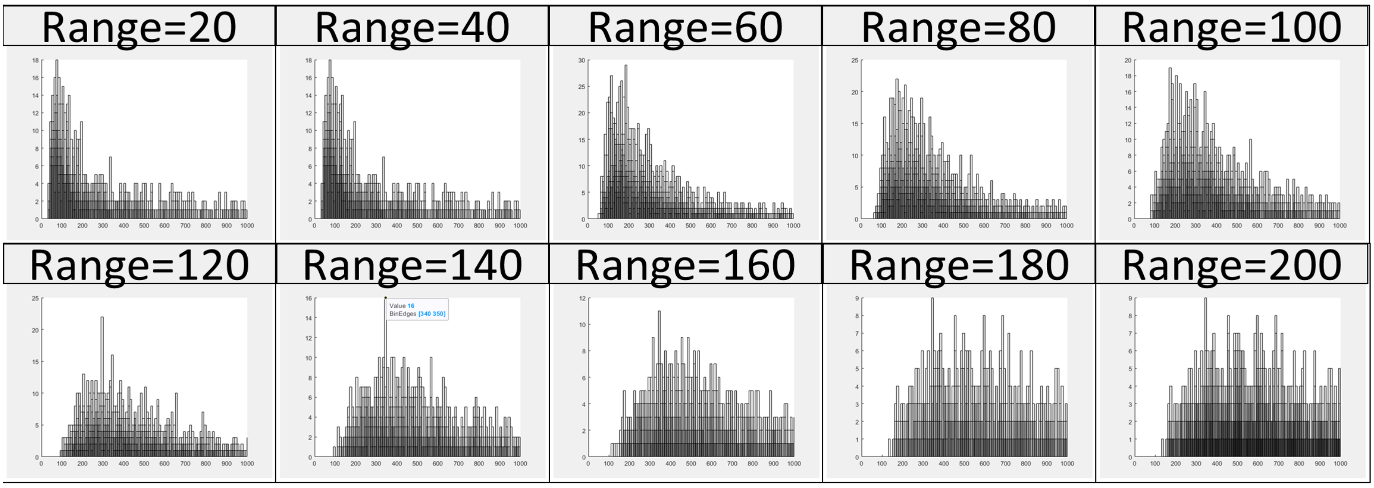

Fig. 9. Analysis of the impact of the range value on the shape of histograms of distances between peaks. Results from the wagon body, analysis of measurement readings from wagons with a damaged wheelset

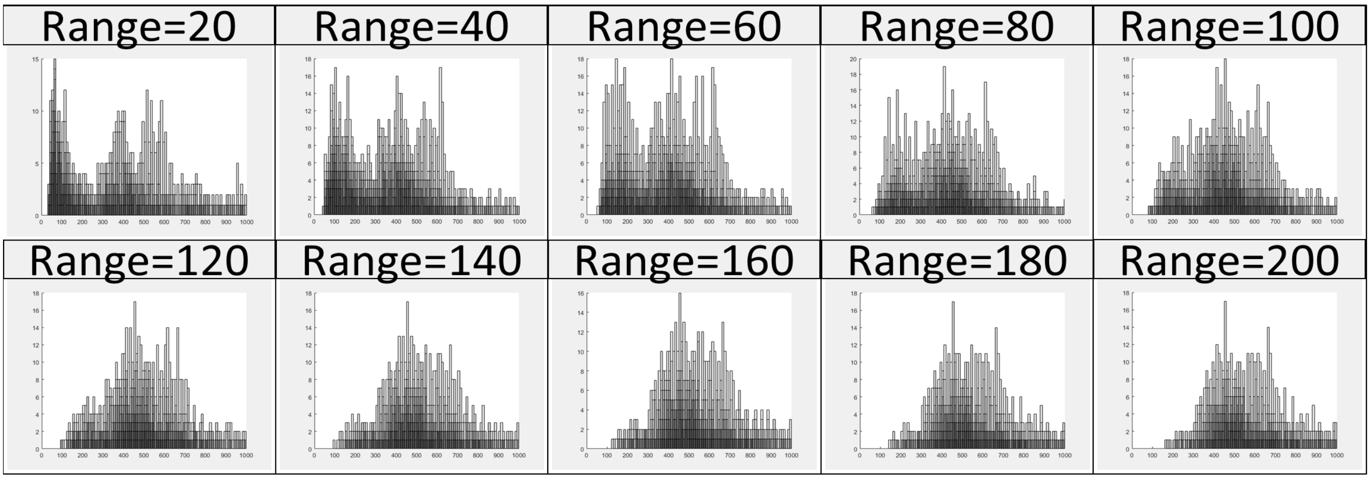

Fig. 10. Analysis of the impact of the range value on the shape of histograms of distances between peaks. Results from the wagon body, analysis of measurement readings taken from wagons with a damaged wheelset

Lastly, because histograms summarize distributions rather than focusing on individual data points, they can smooth out momentary anomalies. A single outlier event caused by a transient environmental factor might not significantly alter the histogram. However, a recurring pattern of unusual intervals, persisting over multiple time windows, signals that something is genuinely amiss.

Results

Our experiments confirmed that the described methodology delivers robust performance that distinguishes healthy wheelsets from those with defects. At lower speeds, around 10 km/h, defects such as wheel flats manifested clearly in the histograms. The distributions and clusters derived from axle box data were especially sensitive, reflecting the immediate mechanical responses near the point of wheel-rail contact. (Figure 7and Figure 8) Changes in histogram shape, such as a shift from a narrow distribution to a broader one or the emergence of secondary peaks, indicated the presence of irregularities associated with wheel defects.

The vibration environment became more complex as speed increased toward 40 km/h. Noise levels rose, aerodynamic and structural resonances contributed additional components, and the baseline patterns from track joints sometimes blended with other excitation sources. Figure 11: However, the Hilbert transform envelope extraction, peak thresholding, and histogram-based clustering still differentiated healthy from unhealthy states. Figure 2: The fundamental approach remained valid, while the patterns could be more subtle and require longer cumulative observation.

Crucially, the cumulative nature of the analysis enhanced reliability. A single short measurement might not guarantee a definitive classification, especially under variable conditions. However, as the device recorded multiple short windows over several operational cycles, it gained statistical confidence. If a wheel defect persisted or worsened, the corresponding histogram patterns became increasingly prominent across consecutive windows. Figure 12 compares results for smaller analysis windows (3, 5, 10 seconds), showing that even brief snapshots can contribute to a reliable diagnosis if aggregated.

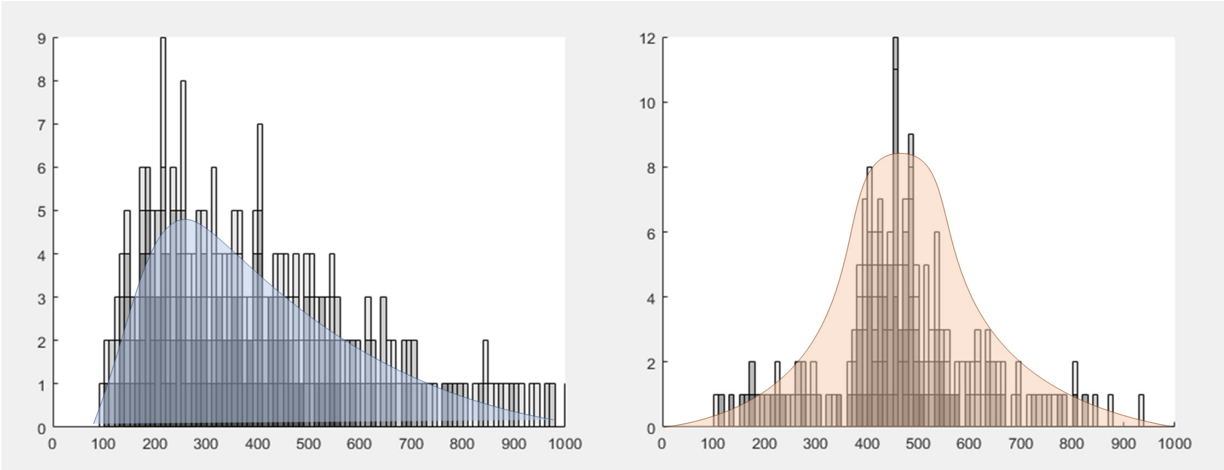

Fig. 11. Visualization of peak distance histogram shapes for a sample dataset.; Right: Results from the wagon body, analysis of measurement readings taken from wagons with a functional wheelset; Left: Results from the wagon body, analysis of measurement readings taken from wagons with a damaged wheelset

This incremental evidence-based approach matches the operational reality of railway systems, where immediate diagnostic certainty is less important than long-term reliability and early warning.

Figure 13 and Figure 14 present classification results as a function of n – the number of data segments – for 10-second and 3-second windows, respectively. While shorter windows yield more uncertainty per segment, accumulating data improves confidence. Figure 15 shows that after about 180 seconds of cumulative data, the algorithm surpasses 90% classification accuracy.

Finally, Figure 16 compares reference curves derived from healthy and defective datasets, illustrating how a consistent divergence emerges with sufficient data accumulation and appropriate parameter choices [18, 20, 22, 24].

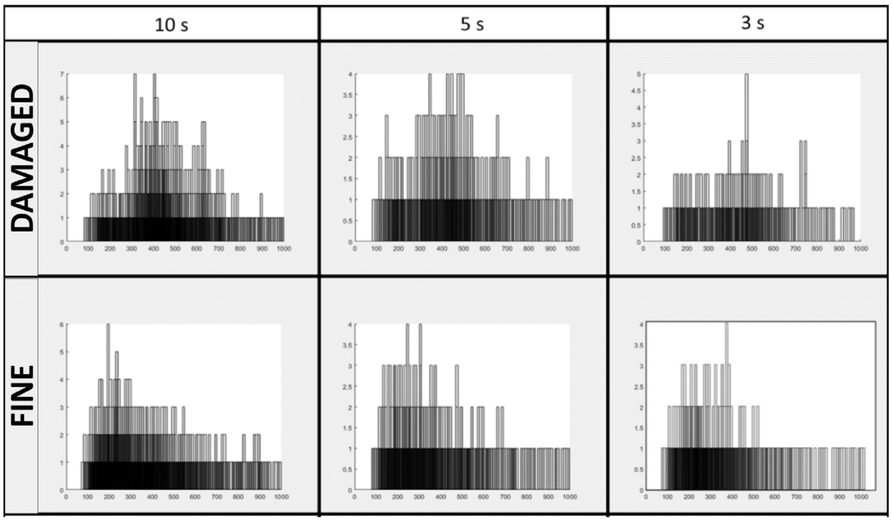

Fig. 12. Comparison of the results of the signal processing algorithm with a reduced analysis window

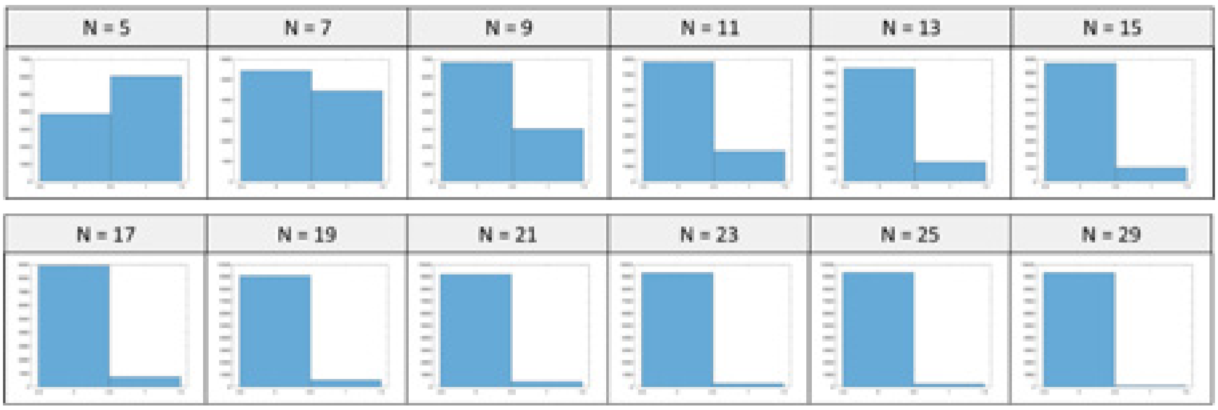

Fig. 13. Classification results depending on n, where n is the number of data packets used with a 10-second analysis window

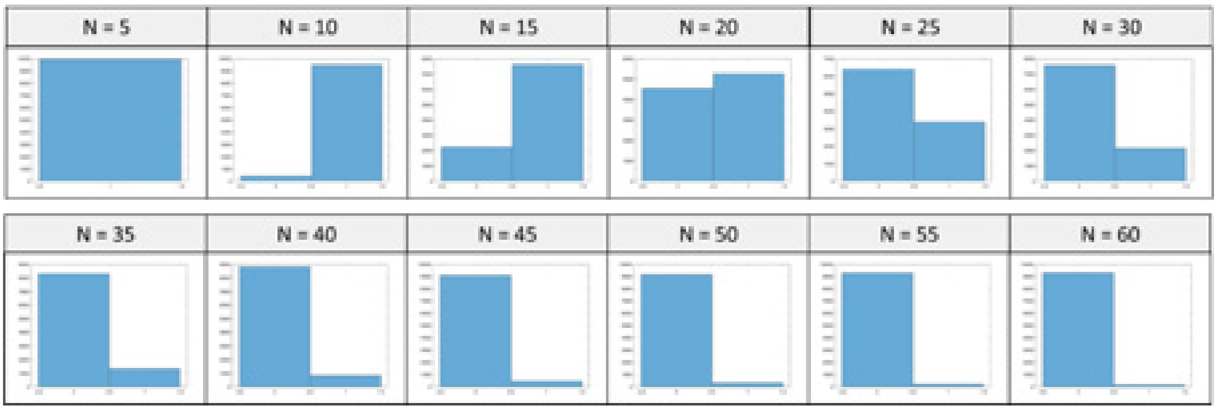

Fig. 14. Classification results depending on n, where n is the number of data packets used with a 3-second analysis window

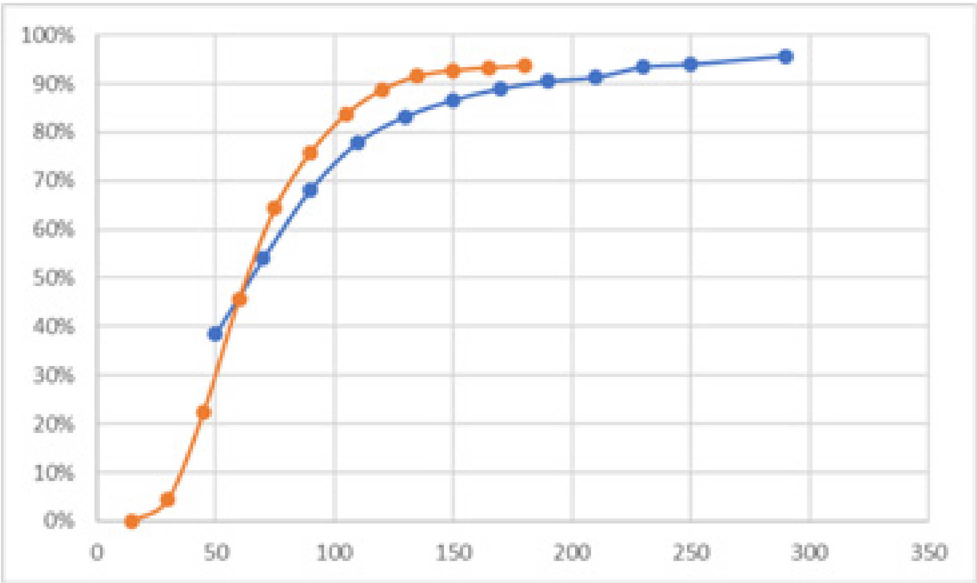

Fig. 15. Relationship between the classification accuracy of the algorithm and the total length of data packets; Blue line: Analysis window of 10 seconds; Orange line: Analysis window of 3 seconds

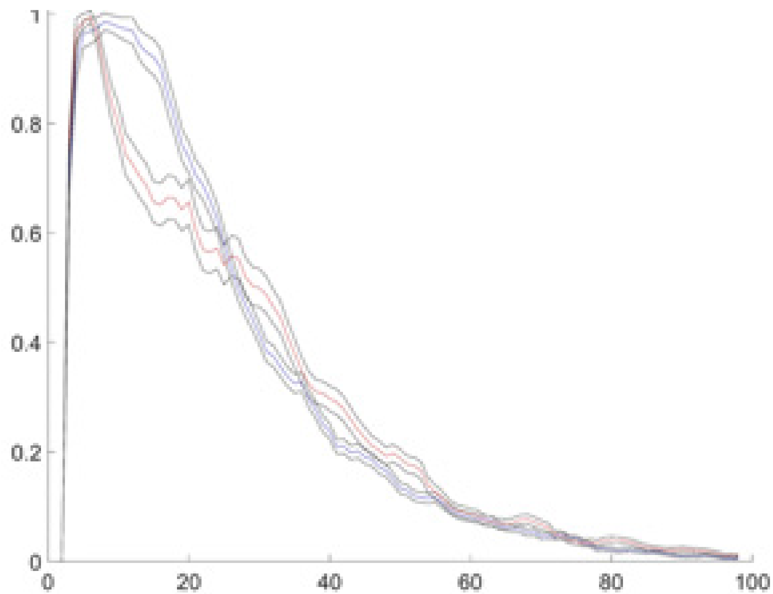

Fig. 16.Comparison of individual comparative curves with deviations from the mean; Blue line: Curve generated from signals originating from wagons with a functional wheelset; Red line: Curve generated from signals originating from wagons with a damaged wheelset

Discussion

The proposed approach highlights the trade-offs inherent in designing onboard diagnostic systems for railway applications. While more advanced algorithms, such as neural networks or Bayesian classifiers, might promise higher accuracy or more nuanced fault classification, they do so at the expense of increased computational complexity, memory consumption, and energy usage. These costs can be prohibitive for a battery-powered device operating autonomously in a harsh environment.

Our method's simplicity is a virtue. We achieve a robust detection mechanism that demands minimal resources by focusing on high-amplitude peak events, using the Hilbert transform to reveal intrinsic signal features, and employing histogram-based clustering for pattern recognition. This choice aligns with a design philosophy prioritizing reliability, interpretability, and longevity. Instead of perfection in fault classification, we aim for a practical solution that can run for extended periods, gather incremental evidence, and offer timely warnings.

That said, opportunities exist to refine and extend this method. One avenue involves adaptive thresholding. Instead of a fixed 95th percentile for peak selection, an adaptive scheme could consider the historical baseline and environmental trends. For example, if the device notices a gradual increase in baseline vibration over weeks – perhaps due to seasonal temperature changes or cumulative track wear – it could adjust thresholds to maintain stable sensitivity. Such adaptivity would reduce false alarms and maintain meaningful comparisons over long timescales.

Integrating this system into a broader predictive maintenance framework could enhance its value. By correlating onboard diagnostic findings with historical maintenance records, tracking geometry data, and even weather information, operators could identify systemic issues. Specific track segments or rolling stock configurations may be more prone to defects. Over time, fleet or network-level pattern recognition might reduce overall maintenance costs by guiding targeted infrastructure improvements or rolling stock design changes.

Environmental considerations also merit attention. The current solution has been tested on a specific track length, conditions, and limited speed ranges. Broader validation efforts could include varying track types, loading conditions (e.g., heavy freight trains), and extreme environmental factors (e.g., very low temperatures or heavy precipitation). The method's robustness under diverse conditions must be confirmed to scale well. The method could become a standard component of wheel health monitoring protocols if consistently reliable results are obtained.

Finally, there is room to consider complementary sensing modalities. For example, integrating acoustic emission sensors or using infrared thermography might provide orthogonal information about wheel conditions. [4,12, 21] If energy budgets improve over time, these additional data streams could be fused with vibration-based diagnostics to achieve more comprehensive fault detection. However, any such addition should be carefully weighed against the complexity and power implications, ensuring that the original goal of a low-energy, autonomous device remains achievable.

Conclusions

This paper presented an energy-efficient, low-complexity method for detecting wheelset defects in railway vehicles, combining the Hilbert transform for nonlinear, non-stationary signal analysis [25–29] with histogram-based clustering. guided the reader through each stage: from fundamental signal representations (Figure 5, Figure 6), track conditions Figure 1, defect illustrations Figure 2, measurement setups (Figure 3, Figure 4), histogram comparisons (Figure 7, Figure 8, Figure 9, Figure 10, Figure 11), time-window analyses (Figure 12, Figure 13, Figure 14, Figure 15), and final reference curve comparisons Figure 16.

The approach detects subtle defects under varying speeds and track conditions while operating on limited power and computational resources. By focusing on significant vibration events, discarding extraneous data, and translating complex signals into simple histograms, the method delivers actionable insights. Its simplicity and adaptability align with the practical needs of railway operations, supporting condition-based maintenance, reducing downtime, and enhancing safety.

Future refinements could involve adaptive thresholding, selective invocation of more advanced algorithms on demand, broader environmental testing, and integration with predictive maintenance frameworks. As sensor technologies and low-power processing capabilities evolve, it may become feasible to introduce slightly more complexity without sacrificing energy autonomy. In any case, the work presented here sets a foundation for practical, resource-conscious diagnostics that align with the evolving needs of the railway industry.

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