MUHAFIZ: IoT-Based Track Recording Vehicle for the Damage Analysis of the Railway Track

Ali Akbar Shah, *Member, IEEE*, Naveed Anwar Bhatti, Kapal Dev, *Member IEEE*, and Bhawani Shankar Chowdhry, *Senior Member, IEEE*

***Abstract*—Fault diagnosis plays a major role in railway condition monitoring, as early diagnosis of the emerging faults can save valuable time, reduce maintenance costs and, most significantly, help save people's lives. However, the conventional data-driven methods used to diagnose track faults, especially in underdeveloped countries, use push trolley/train-based track recording vehicles (TRV) that rely heavily on manual extraction of track data. It is a very demanding process and significantly affects the final results due to its reliance on human judgment in assessing track conditions and its suboptimal performance. In contrast, with the advent of IoT-based smart inertial measurement units, the data-driven fault diagnosis became a core component in the smart industrial automation safety system. We proposed, Muhafiz, a prototype that is an automated and portable TRV with a novel design based on axle-based acceleration methodology for rail track fault diagnosis. Our contribution concluded, based on site-specific experimentation, that Muhafiz is 87% more efficient than the traditional push trolley-based TRV mechanism.**

***Index Terms*—Axle-based acceleration (ABA), condition monitoring, fault diagnosis, IoT-based smart inertial measurement units (IMUs), track recording vehicle, wavelet transform.**

I. Introduction

RAIL transport is the most efficient, cost effective, and convenient means of transport. It has lower fuel costs, is capable of transporting large loads, environmentally friendly and, most importantly, is also very reliable, as it is not hindered by weather in the same way as road and air transport do. Rail transport has, therefore, become the backbone of every emerging economy. However, effective management of the rail infrastructure is very essential for continuous and smooth operation of rail transport. A key part of the management is railway condition monitoring, which detects the deterioration and deformation of rail tracks, due to various factors, including the load of rail vehicle on rail tracks, terrain where rail track is deployed, materials used in rail track construction, and environmental conditions. The purpose of railway condition monitoring is to detect the track deterioration before it causes any failure or prevents rail operations.

Rail tracks, the most important rail transport infrastructure, have a direct impact on passenger safety and comfort. The deterioration and degradation of the rail track will have an impact on the health of the track resulting in a track irregularity, which will be detrimental to the safety of the rail riders [1], [2] as there is a direct relationship between the rail track and rail vehicle [3]. Late in the degradation stage, maintenance becomes expensive and time consuming, as the rail tracks usually have to be replaced. Rail condition monitoring is, therefore, required to be carried out on in-service rail lines several times a month by the railway management. For this purpose, track inspection vehicles [or track recording vehicle (TRV)] are used to measure several track diagnostic parameters. Among them, vibration and acceleration are considered to be the two most important parameters. Variations in vibration and acceleration are caused by the contact forces of the rail wheel and rail track. Amplitude variations of vibrations and accelerations may vary mainly due to surface rails, imperfections, such as rail roughness, corrugation, or defects on a rolling contact surface of the rail track. These variations in vibration and acceleration reveal a great deal of information about the deterioration of the rail tracks.

Our Work: In this article, we developed, Muhafiz[1] a low-cost, low-power, wireless, and real-time IoT-based sensing system along with a customized TRV replacing the manual production of features with an automated process for rail condition monitoring and damage diagnosis. Our novelty stems from the unique design of TRV, as compared to traditional trolley-based TRV, to detect minor fluctuations in vibrations that plays a key role in the early detection of track damage. TRV is designed with the goal to make it portable and easy to operate. The IoT-based sensing system on TRV uses the axle-based acceleration (ABA) technique and is equipped with an inertial measurement unit (IMU) for the precise extraction of instantaneous irregular amplitudes of the acceleration signals in all three axes, which identify the faults of the track and determine its severity. The accelerometer data of the track dynamics are measured and transmitted using NodeMCU [4] to an online cloud network service "Thingspeak" [5] in real time through which the irregularity of the track is detected. Our results have shown that the proposed novel design of

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Ali Akbar Shah and Bhawani Shankar Chowdhry are with the National Center of Robotics and Automation, Rawalpindi 71000, Pakistan.

Naveed Anwar Bhatti is with the Department of Computer Science, Air University, Islamabad 44000, Pakistan (e-mail: naveed.bhatti@mail.au.edu.pk).

Kapal Dev is with CONNECT Centre, Trinity College Dublin, D02 PD91 Dublin, Ireland (e-mail: kapal.dev@ieee.org).

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[1] Muhafiz is an Urdu word, meaning "preserver".

TABLE I
MAIN TRACK PARAMETERS FOR MONITORING PURPOSES

Monitoring Purpose	Example	Literature
Track Profile	Stiffness and Elevation Profile	[1], [11]–[14]
Track Component	Joints, crossings, frogs and squats	[15]–[18]
Others	Irregularities in the rail surface, track replacement, welding, tamping and rail bump	[19]–[21]

TABLE II
ABA METHODOLOGIES

Researcher(s)	Work	Literature
Wei et al.	Identification of the railway crossing degradation.	[22]
Oregui et al.	Rail joint monitoring (e.g., bolt tightness)	[16]
Salvador et al.	For determining faults in turnout frogs, welded joints and squats	[11]

TRV can determine the damage to the track(s) with remarkable measurement accuracy.

The remainder of this article is structured as follows. Section II gives the overview of the state of the art for railway condition monitoring while defining basic terminology and challenges faced by them. Sections III and IV explain the overall design and working of the Muhafiz. In Section V, we describe our acceleration fault detection system. Section VI discusses the results before we end this article with brief concluding remarks in Section VII.

II. RELATED WORKS

To date, various types of sensors have been employed to serve the purpose of TRV-based railway condition monitoring, such as laser displacement sensors (LDS), infrared thermography (IRT) cameras, and IMU [6]–[9]. These technologies can be merged together or play a pivotal role even as a stand-alone technology. There are, however, certain drawbacks associated with the first two technologies, such as: 1) LDS are expensive and their maintenance is also costly and 2) IRT camera-based techniques are cheaper in contrast to LDS but require expensive image processing devices to overlap irregular delays, while IMUs, such as accelerometer and gyroscope, are cheaper in comparison with LDS and IRT cameras [10], [11]. They are widely used in the literature due to their low price, simplicity, and efficiency. These IMUs can be easily installed in the rail vehicle's carriage or axle box, and their response can also be easily measured. The main track parameters for TRV-based rail monitoring using IMUs are summarized in Table I.

Whereas, for the analysis of track damage using ABA methodology, mentioned in Table II, the most commonly used IMU component is accelerometer, among other components, such as gyroscope and magnetometer as illustrated in Table II. Several researchers, as shown in Table III, have proposed a track condition monitoring using accelerometer mounted on TRV. A rich body of literature also exists on deploying IoT-based systems, covering various applications of rail transport (not necessarily rail monitoring), mentioned in Table IV.

TABLE III
ACCELERATION-BASED STUDIES

Researcher(s)	Work	Literature
Le Pen et al.	Identification of the track stiffness using TRV.	[14]
Real et al.	Measurement of the rail profile by vertical acceleration using TRV.	[12]
OBrien et al.	Measurement of the longitudinal track profile.	[11]
Tsunashima et al.	Development of the portable track health monitoring system.	[23]
Paixao et al.	Analysis of the geometrical structural degradation.	[23]

TABLE IV
IOT-BASED RAILWAY TRACK MONITORING

Researcher(s)	Work	Literature
C. Chellaswamy et al.	Remote IoT based measurement of track parameters using Particle Swarm Optimization Algorithm	[24]
O. Jo et al.	Optimizing the smart railway applications by the variation of IoT architecture.	[25]
M. Saki et al.	Enhancing Access Points efficiency using train-to-wayside (T2W) communications along a rail network	[26]
I. Rajkumar et al., B. Mishra et al.	Using IoT for Train Collision Avoidance.	[27] [28]
B.S. Chowdhry et al.	Real time railway structure monitoring.	[29]

In Table V, various research works are mentioned regarding condition monitoring of the railway track using IMUs. Amongst them, Paixão *et al.* [30] have used the built-in accelerometer of the smartphone as a sensing device for analyzing the track-related damages. Smartphone as a sensor has various sensitivity-related issues. Therefore, there are high chances of dubious readings. In another study, David Milne *et al.* [31] performed the track analysis by mounting accelerometer ADXL335 and ADXL326 on the track itself. As a result of this, the system developed by David Milne cannot identify track surface-related defects, such as squats and turn out frogs. Whereas, Weston *et al.* [32] conducted a survey based on the techniques that are implemented on the traditional service vehicles such as track recording couches. Similar to David Milne, King [34] discussed the Trackline system that is mounted on the U.K.'s railway network for observing the U.K.'s fastest track. The Trackline system analyzes various track parameters and is fixed on the railway

TABLE V
STUDIES ON IMUs

Researcher(s)	Work	Literature
Andre Paixao et al.	Used smartphone sensing capabilities for analyzing the track degradation and performance by mentioning that track data can be sent wirelessly (WiFi) for further analysis.	[30]
David Milne et al.	Used a merge of geophone and accelerometer by installing them on the railway track. And it was noted that the geophone had less variation and standard deviation in analyzing the track health.	[31]
Weston et al.	Smart IMU can be used for analyzing the track faults by assigning them with a fixed threshold	[32]
Ackroyd et al.	The train ride quality is monitored by installing inertial sensor of Acela train set.	[33]
King et al.	Simulation softwares like Delta Rail are used for analyzing the track health condition, remotely.	[34]

track for observing the track's dynamic properties. Both these systems developed by Weston *et al.* and King *et al.* are either installed on the tracks or use train for the identification of the track damage. Likewise to the study conducted by Paixao, Ackroyd *et al.* [33] have applied vibration detection system on the train instead of a smartphone, which uses three accelerometers for the determination of the train's ride comfort of the train.

Table VI summarizes the existing techniques and the rail faults that can be detected using those techniques. Techniques, such as image processing, laser displacement sensing, and ultrasonic testing are mostly 1-D and fail to identify 3-D track defects such as the dip angle [35]. In order to make them work in three dimensions, it is recommended that more such sensors be used that increase the processing power making the whole system less cost effective. One the other hand, the IMU technique is a cost-effective alternative for the determination of various track faults but with the exception of squats and turn out frogs. It fails to detect these two track faults since the mass/weight of the rail track and the instrumented train act as a vibration damper that suppresses its nonlinear frequency response making it hard for the IMU sensor to identify the negligible variation in the frequency response of these sensors.

In this article, we introduce Muhafiz and its novel design of TRV make IMU's resourceful enough to identify all the track surface faults, including squats, frogs, and dip angles.

III. Design of Muhafiz

We split the Muhafizinto two high-level modules: 1) *TRV Controller* and 2) *Diagnosis* modules, as shown in Fig. 1. Both these modules were powered by rechargable battery pack.

A. TRV Controller Module

The purpose of the TRV Controller module is to control the movement of the TRV on rail tracks. It consists of three

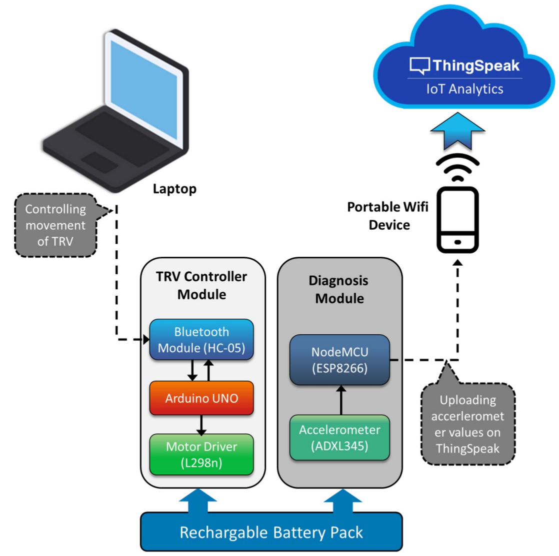


Fig. 1. High-level architecture of Muhafiz.

components: 1) Bluetooth module; 2) Arduino; and 3) Motor Driver. Both the Bluetooth module and motor driver interfaced with Arduino. The Bluetooth module connects the TRV controller with the user laptop to give commands to Arduino. Arduino, after receiving commands, drives the motors through the motor driver.

The initial prototype of TRV operated only on the NodeMCU for both, diagnosis and controlling of the DC motors, via WiFi connectivity but it caused delays in the transmission of the sensory data to the cloud platform. We believe it is because of the NodeMCU performing multiple tasks, such as controlling the DC motor, location tracking, and accelerometer data transmission at the same time. To avoid lag in the track damage detection, which can lead to false and faulty readings, we resort to separate Arduino UNO module.

Furthermore, when motors of TRV were initially controlled using Internet connectivity, it caused a visible delay in the operation of the DC motors. For example, when the user gave a command for turning TRV at the rail junction, the TRV due to delay in the transmission performed the task at approximately 37 s later.

B. Diagnosis Module

On the other hand, the main responsibility of the diagnosis module is to collect accelerometer readings and upload them to ThingSpeak for further analysis. The diagnosis module consists of two components: 1) NodeMCU and 2) accelerometer. The IMU-based accelerometers are interfaced with NodeMCU, which is connected with the Internet through portable 4G equipped WiFi device. These inertial sensors are installed on the basis of ABA technique and are as close as possible to the center of mass of the portable TRV.

C. Track Recording Vehicle

Most of the existing TRVs are trains with some instrumentation [1], [12], [14]. The problems with these implementations of TRV is their cost, maintenance, and portability. Due to the

TABLE VI
COMPARISON OF MUHAFIZ WITH STATE-OF-THE-ART TECHNIQUES FOR DETECTING RAIL TRACK FAULTS

		Faults					
		Squat	Turn Out Frogs	Dip Angles	Drainage	Broken Rail	Corrugation
Techniques	Image Processing	✓	✓			✓	✓
	Laser Displacement Sensor	✓	✓			✓	
	Inertial Measurement Unit (IMU)			✓	✓	✓	✓
	Infrared Thermography (IRT)					✓	
	Microphone					✓	✓
	Fiber Bragg Grating			✓	✓	✓	
	MUHAFIZ	✓	✓	✓	✓	✓	✓

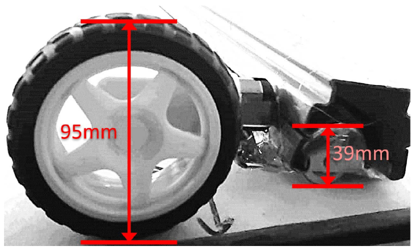


Fig. 2. TRV front and back wheels comparison.

size of these TRVs, the maintenance of their rail tracks can not be scheduled in a timely manner and is not accessible to engineers for the analysis of the problems associated with the damage to the rail tracks faced by the maintenance department on a daily basis.

We designed our TRV while keeping portability in our minds. It has two front wheels of less than half the diameter of the rear two wheels as shown in Fig. 2. Since the two sets of wheels are not of the same size, the lateral motion due to track damage will be higher than if we have the wheels sets having the same size. The large wheels act as driving wheel and connected with motors. The accelerometers are interfaced on the axle of the smaller wheels to detect minor fluctuation in vibrations. This plays a key role in the early damage diagnosis of minor squats and frogs (track damage caused by sudden braking or dips). These minor squats and frogs cannot be determined if accelerometers are installed on the existing train-based TRV. The main highlight of our TRV is its size, which makes it possible to port anywhere quickly and easily. The entire structure of TRV is constructed using a 185-m long aluminum beam as shown in Fig. 3. The wheels are separated by a length of 1676 m (i.e., the actual width of the rail broad gauge) and are positioned at the extreme ends of the aluminum beam. Whereas, the accelerometer sensors are installed in the middle and two ends of TRV.

D. Mathematical Modeling of TRV

Considering the fact that propulsive force Fp (t) and acceleration of the instrumented TRV tends move in the forward direction while the disturbance force or frictional force Fd (t) tends to resist the movement of the vehicle. Considering all these parameters, the mathematical model of the instrumented track recording vehicle is

$$m\frac{dv}{dt} + Bv = F_p(t) + F_d(t) \tag{1}$$

$$m\frac{dv}{dt} + Bv = K_e(t) + F_d(t) \tag{2}$$

where $K_e(t)$ is the controller that drives the instrumented TRV into the forward direction.

IV. WORKING OF MUHAFIZ

The fully instrumented TRV is shown in Fig. 3 with all the components interfaced together. The motors we used for drive TRV operate at a voltage range between 6 and 12 V and have an rpm of 180. The total number of motors used is two and they are mounted behind the driving wheels as shown in Fig. 2. As the output pins of Arduino are not capable of supplying enough current to motors, we interface them with L298n motor driver. A rechargeable power bank of 18-W output is used for supplying the power to the Arduino and motor driver. Digital output pins of the Arduino from D6 to D12 were connected to the L298n motor driver. Whereas, the D0 and D1 transmission pins of the Arduino were connected with the Bluetooth module HC-05 to control the locomotion of TRV wirelessly.

The built prototype is proposed to replace a push trolley-based TRV, shown in Fig. 4. As compared to push trolley, our portable system works mostly in autonomous mode with more precision and reliability. The developed system is a cost-effective alternative to push trolleys. The portable instrumented TRV included three triaxial accelerometers (ADXL345) mounted near the axle of the vehicle, connected by hardwiring to NodeMCU that transmitted data to a cloud service (Thingspeak) for the further data analysis purpose. The efficacy of the use of accelerometers for damage diagnosis of in-service railway tracks is mentioned in earlier studies [11], [12], [14], [23], [36]. The ADXL345 is 3 mm × 5 mm × 1 mm in dimension and has a high resolution of (4 mg/LSB) that enables the sensor to detect variation in the inclination as low as 1°. The accuracy and measurement precision of ADXL345 were validated on the actual in-service rail track and it was highly responsive on the squats and turnout frogs, when installed on the designed instrumented TRV. Malekjafarian *et al.* [1], in his study, also validated the application of the accelerometer for analyzing the track damage from the data acquitted by a similar sensor.

In order to diagnose damage to the track, the TRV is moved across the track at a constant speed of 3.2 km/h (measured from laser tachometer). The amplitude of the acceleration varies at multiple peaks with the locomotion of the TRV. The amplitude variation of the acceleration reveals very minute details of the track structural behavior. To improve the accuracy of the data, an additional accelerometer is placed at the middle of the TRV, while the other two are near the wheels

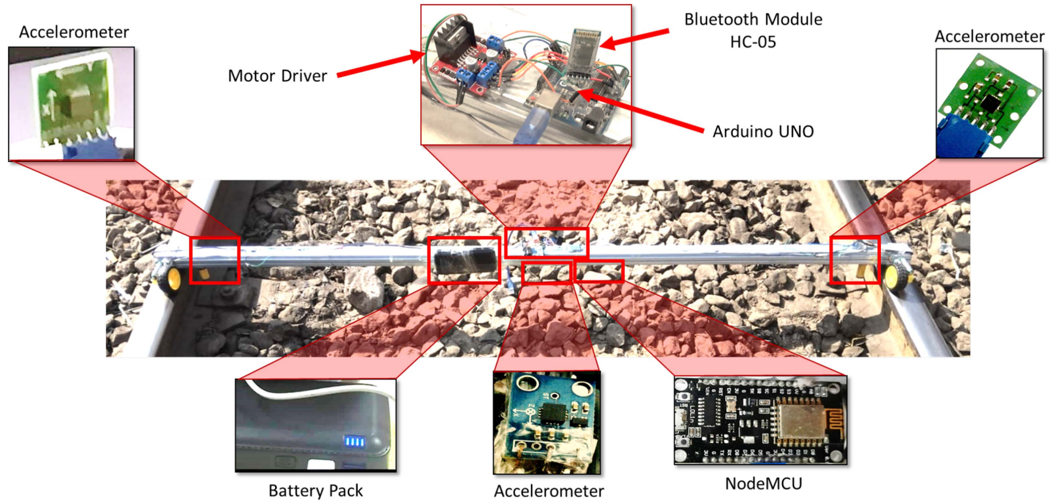


Fig. 3. Instrumented TRV.

Fig. 4. Working of the Push trolley.

of the TRV. This approach is known as the ABA methodology. Different research work [11], [12], [14], [23], [36] had validated ABA by acquiring the data for calculating and measuring parameters like, track stiffness, vertical acceleration of the track, rail profile and various track irregularity parameters that are vastly used in the track condition monitoring. To visualize and process the accelerometer readings, they are transmitted wirelessly using Node MCU to Thingspeak.

In addition, the location of the instrumented TRV is also transmitted by using Google Map Developer API as shown in Fig. 5, where the place of the track can be traced using Google Maps. For this, we used IP-based location instead of interfacing GPS module which will further consumes the battery power. The location will be triggered and send to Google Map Developer API only when the damage will be determined based on accelerometer value.

V. Acceleration-Based Detection Algorithm

The technique applied by Lederman *et al.* [21] used data acquired from the *y*-axis of the accelerometer, which contains valuable information regarding the structural condition of the railway track, by passing the track recording vehicle on it. Such that if the data acquired from the accelerometer have nonlinear transient values, then that region of the track is said to be defected. These transient values denote the frequency of the acceleration signal present at that particular defected region

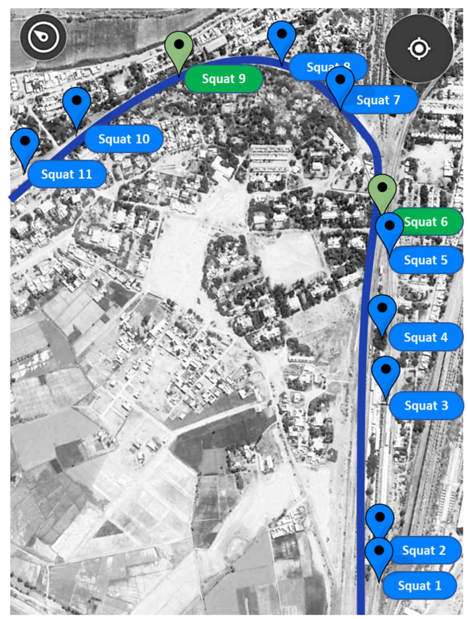
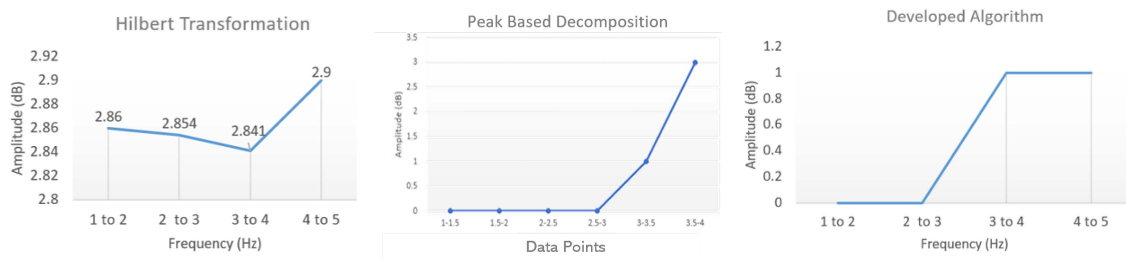


Fig. 5. 2-km long track near Hyderabad. Blue pins show the locations where only Muhafiz identified faulty rail. Green pins show the locations where both Muhafiz and train-based TRV detected the faults.

of the track. Thus, the Lederman *et al.* [21] technique further proposes the use of those average amplitude of the acceleration signals that are acquitted from a moving window alongside the track itself. This technique is complicated as it requires summing of the amplitudes (dB) of the *y*-axis obtained from the accelerometer, which represents the signal intensity. Therefore, the data acquired from the proposed instrumented TRV are initially tested through Hilbert's transform and then peak-based decomposition (PBD). On the basis of these algorithms, a new threshold normalized-oriented algorithm is developed for fast real-time processing of the track damage.

A. Hilbert Transform

Hilbert transform is applied for the extraction of the acceleration amplitude and frequency. The frequency (Hz) of the



(a) (b) (c)

Fig. 6. Comparison of Hilbert transformation, PBD, and our developed threshold algorithm. (a) Hilbert transformation. (b) PBD. (c) Developed threshold algorithm.

acceleration is denoted by the y-axis data of accelerometer that determines the track faults. The mathematical form of the Hilbert transform [37] is mentioned as follows:

$$\alpha(t) = \frac{1}{\pi} p \int \frac{a_z(\tau)}{(t-\tau)} d_\tau. \tag{3}$$

In 3, p is the representation of the Cauchy principle value, which is obtained from the single integral function, where analytic signal of the y-axis acceleration amplitude is defined as follows:

$$\beta(t) = a_z(t) + j\alpha(t) \tag{4}$$

where j represents the iota that has the value of $\sqrt{-1}$. Thus, $\beta(t)$ that expresses the polar form is mentioned as follows:

$$\beta(t) = \mathrm{amp}_{\mathrm{inst}}(t)e^{(in(t))}. \tag{5}$$

While the transient amplitude of the nonlinear acceleration is computed using the following equation:

$$\mathrm{amp}_{\mathrm{inst}}(t) = \sqrt{a_z^2(t) + \alpha^2(t)}. \tag{6}$$

The Hilbert amplitude of the y-axis acceleration is measured over 200 m of various junctions of Pakistan using the accelerometer (ADXL345) as shown in Fig. 6(a). Fig. 6(a) represents the extraction of the transient response of the nonlinear acceleration signal due to the presence of the track surface fault.

B. Peak-Based Decomposition

To get the precise and accurate measured readings, it is recommended to sample the instantaneous transient amplitude of the acceleration with the same sample rate as that of the original. However, during the processing of the signal, the size of the entire track length amplitude single is too large and it requires compression in order to avoid time-consuming computations and memory-related issues. Whereas, the signal intensity must be retained at the same frequency. For representing the signal intensity in a much compressed form, a technique known as PBD is employed. The PBD approach in this research works as high bandpass filter. It considers the maxima values of the Hilbert transform, while eradicating the smaller peaks of the original signal. As the maximum peak values represent the track faults by using PBD, the size of the entire signal is reduced, making the computation process simpler and less time consuming. The output of the first step signal after PBD is called as peak function 1, the second peak signal is known as peak function 2, and so on.

The above mentioned Fig. 6(b) represents PBD of the acquired Acceleration from the accelerometer. It is clearly evident that PBD considers the peak values of the signal amplitude values of the acceleration while removing the smaller peaks when comparing it with Fig. 6(a). Finding the maximum peak values of the acceleration amplitude is the main objective in this research because through this the track fault and the severity of the faults can be known using the developed instrumented TRV.

C. Detection Algorithm Using Axle-Based Acceleration

After the data are processed through PBD, the data are being compressed and any uneven noises are eradicated from it. These uneven noises could have put confusion in the selection of specific threshold amplitude. The detection steps implemented are stated as follows.

Step 1: The identification of the uneven track surface fault by examining the highest frequency peaks of the acceleration data, when the track recording vehicle is moving at a speed of 5 km/h.

1) The highest peaks, that is, 1, trigger the latitude and longitude of the track location by using Google Map Developer API. In this way, the damaged tracks are been marked on the Google Maps.
2) If the frequency amplitude exceeds 3 dB, then it is most likely that the track is damaged.
3) In graphical form, a unit graph is computed based on PBD graph. It rises to 1 when the frequency threshold exceeds 3 dB whereas, 0 indicates no track surface damage detected as shown in Fig. 6(c).

Step 2: The location traced along with peak amplitude (after being marked on the track) using Google Map Developer API is then revisited using another handheld track recording vehicle for validation of the damage and determining the severity of the track damage using Wavelet transformation.

VI. Results

In order to validate the damage to the track, another specially designed handheld track recording vehicle is used manually to determine the severity of the damage using the image processing technique. The image processing technique used to

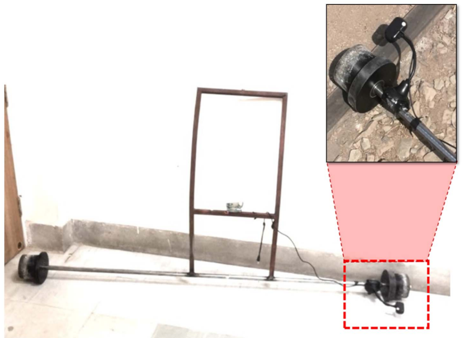


Fig. 7. Handheld track recording vehicle with camera mechanism.

identify track damage is 2-D discrete wavelet transformation by OpenCV API.

The image processing technique that is mentioned while comparing it with the recorded results is wavelet transformation. The wavelet transformation requires high processing speed, therefore, it is hard to process in real time on an embedded platform. Moreover, while attaching the camera with the track recording vehicle produces noise and most of the captured rail images due to that are blurred and unclear.

If we compare other low processing computer vision algorithms such as morphological operation, then the possibility of acquiring faulty data increases as those techniques is less reliable than wavelet transformation. Moreover, to quantify those morphological images into 2-D graphs, certain processing power is used.

A. Wavelet Transformation

The severity of the track surface damage as determined by ABA methodology is processed with 2-D discrete wavelet transformation, which splits the track image into two subbands, namely: 1) low frequency subband and 2) high frequency subband. The edges containing the damage to the track are classified in a high-frequency subband. Whereas, noise and other unnecessary details are classified in a low-frequency subband. The wavelet expansion is mathematically represented as shown in the following equation:

$$f(t) = \sum_{k} c_{(j,k)}\phi_{(j,k)}(t) + \sum_{j}\sum_{k} d_{(j,k)}\phi_{(j,k)}(t) \tag{7}$$

where $f(t)$ is basically the standardized image that will be processed using Wavelet transformation and the decomposition of the image into two frequency subbands is represented in the equations stated as follows:

$$c_{(j,k)} == (f(x), \phi_{(j,k)}(x)) = \int f(x)\phi_{(j,k)}(x)dx \tag{8}$$

$$d_{(j,k)} == (f(x), \varphi_{(j,k)}(x)) = \int f(x)\varphi_{(j,k)}(x)dx \tag{9}$$

where $c_{(j,k)}$ is the constant approximation and $d_{(j,k)}$ is the detail coefficient

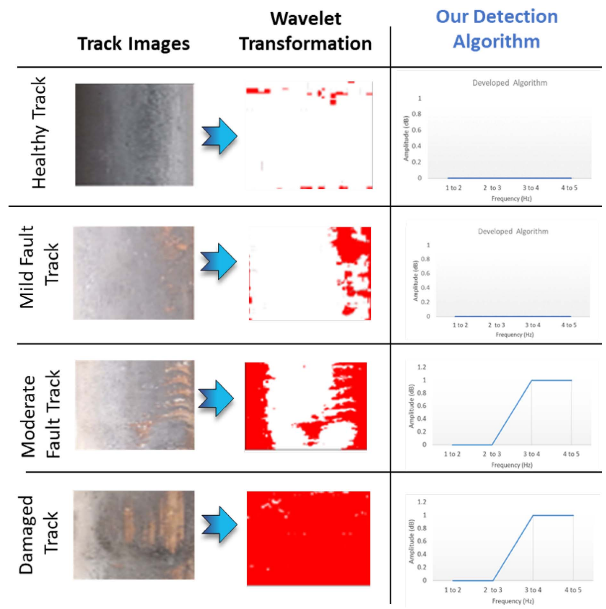


Fig. 8. Validation of the fault detection algorithm using Wavelet transformation.

B. Handheld Track Recording Vehicle

The handheld TRV is used to validate the damages that have been identified by iur detection algorithm and the locations of those damages have been stored by the instrumented TRV using the Google Map Developer API. Handheld TRV is specially designed to analyze the severity of the damage to the track using image processing. The Logitech 5MP Web camera module was mounted on the handheld TRV wheel as shown in Fig. 7. The handheld TRV has the same mathematical modeling as prescribed in (8).

C. Validation of Detection Algorithm by Using Wavelet Transformation

To validate the damages recognized by the developed threshold algorithm, the 2-D discrete wavelet transformation is used. By validation, we mean to check whether any dubious reading is formed by the algorithm. The readings were logged when the threshold of the acceleration amplitude reached 1 dB in the amplitude graph as shown in Fig. 6(c). The measurements were taken at the rail junction on a 2-km long operational track near Hyderabad city. These damages acquired from the readings were tested using wavelet transformation.

Track defects analyzed by the developed algorithm are classified as mild, moderate, and damaged after manual inspection. The images were captured manually after the damage was recognized by the automated TRV and were validated with the wavelet transformation as shown in Fig. 8. The results of the damage analysis were found in agreement with the damage identification. A total of 11 moderate faults and 1 mild fault were identified using this algorithm within 2 km of track surveillance. However, mild fault do not impose any immediate danger to the track and can be ignored. The wavelet transformation evidently proves the efficiency of the developed threshold algorithm for damage recognition using

Fig. 9. Comparing results of train-based TRV (using trolley) and Muhafiz. Train-based TRV failed to detect any of the faults on track. In contrast, Muhafiz detected all the faults correctly.

Fig. 10. Paper author sitting on four wheel trolley with accelerometers installed on it to replicate train-based TRV.

the automated TRV. The difference of the healthy track from rest of the faulty tracks is clearly visible as shown in Fig. 8.

D. Comparison With Train-Based TRV's Using IMU and Vision-Based Algorithms

1) *Comparison With the Push Trolley:* Most of the existing TRVs are either push trolley-based or in some cases trains with some instrumentation [1], [12], [14]. To replicate the train-based TRV, we used a four-wheel trolley with accelerometers installed on it as shown in Fig. 10. Fig. 9 shows the results of both trolley-based TRV and Muhafiz. In total, we have detected 11 faults on the stretch of 2-km track but due to limited space, we are showing results of only the first four faults. The first column of Fig. 9 shows the picture of the fault on the track. The second column shows the raw accelerometer value at that fault in the frequency domain using the trolley. The third column shows the raw accelerometer value at that fault in the frequency domain using Muhafiz. In the fourth column, we apply our detection algorithm on accelerometer values measured by trolley. In the last column, we apply our detection algorithm on accelerometer values measured by Muhafiz. By comparing the second and third column, we can clearly see that trolley-based TRV failed to generate any vibrations on all four faults. Due to this, the detection algorithm also failed to detect faults in column four. In contrast, Muhafiz correctly detects all four faults because of its novel TRV design. In total, out of 11 faults on 2-km track, trolley-based TRV managed to detect only two faults, as shown in Fig. 5, which makes Muhafiz87% efficient than trolley-based TRV.

2) *Comparison With the Morphological Image Processing Techniques (Dip Angle):* Morphological operations are efficient in processing the data in real time but they have limited fault detection capability, as mentioned earlier in Section II. To validate the superiority of the Muhafiz, it was compared with the data processed in the Morphological operation. In morphological operations, the gradient filter had optimal results in processing the data. In morphological operation, the Canny Edge detector was implemented. To process the image faster, 3-D (red, green, and blue) image is transformed into 2-D (grayscale) image by applying

$$\text{Gray} = 0.299(R) + 0.587(G) + 0.114(B). \tag{10}$$

For the noise cancellation, a 2-D Gaussian filter is implemented that transforms each pixel of the image into normal distribution using

$$h(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{11}$$

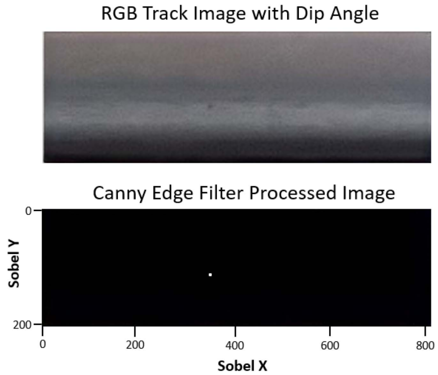


Fig. 11. Canny edge detector response on dip angles.

(a) (b) (c)

Fig. 12. Track with and without dip angle. (a) Dip angle. (b) W/o dip angle. (c) With dip angle.

where h represents the standard deviation of the image, which is used in the calculation of the normal distribution. Sobel filter masks (X and Y) are applied to each of the pixels of the processed image using the following:

$$h_x = \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix} \tag{12}$$

$$h_y = \begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 0 \\ -1 & 0 & 1. \end{matrix} \tag{13}$$

The processed image is mentioned in Fig. 11. Dip angles appear on the railway track when the track encounters excessive loading condition that cause the track to bend. The dip angle also may occur due to a lack of ballast material. This result in the track to ultimately break due to exceeding plastic limits. The figure mentioned in Fig. 12(a) is of the dip angle. The topmost view of the track is similar to the healthy track as shown in Fig. 12. The major drawback of using image processing is that it is not able to analyze the dip angle efficiently. Because in some scenarios, there is no surface mount damage found in those tracks that are having joint angles. By applying the image processing techniques such as Canny Edge detector, there are no traces of the dip angle found in the processed image and is just like that of the healthy track as illustrated in Fig. 11. In addition, deep-learning image processing algorithms found in studies [35], [38], [39] similar to gradient filters use camera(s) at the top view of the track that can monitor only surface-based track defects, such as squats and frogs, but cannot detect 3-D-based faults such as a dipped angle on the rail surface. To mitigate this issue, two to four cameras can be used to detect the dipped angle [40] in all three dimensions of the track. This dramatically increases the overall processing of the algorithm, making the product more expensive.

VII. Conclusion

In this article, we proposed an IoT-based portable TRV design that can track critical faults such as squats, turn out frogs using our novel mechanism based on the ABA approach. The distinctive aspect of the developed IoT-based instrumented TRV is its wheel design and contributes in the portability of the entire device. The wheels of this TRV were designed in such a way that the minimal marginal railway faults that can result in the train derailment could be analyzed. Muhafiz was tested over the range of 2 km near Hyderabad city on an operational rail track where 11 squats were diagnosed whereas typical trolley-based TRV mechanism identified only 2 squats on the same track. Therefore, the results proved that Muhafiz is 87% more efficient than traditional approaches adopted by the railway authorities. For the future work, we believe that testing on different tracks over longer routes will help in making our proposed mechanism more generalized.

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Ali Akbar Shah (Member, IEEE) received the M.E. and B.E degree from the Mehran University of Engineering and Technology, Jamshoro.

He is currently serving as a Design Engineer with the National Center of Robotics and Automation (Condition Monitoring Systems Lab-MUET), Rawalpindi, Pakistan. Formerly, he has served as Sr. Lab Engineer, Datacenter Engineer and Safety Engineer in various organizations.

Naveed Anwar Bhatti received the Ph.D. degree from the Department of Electronics, Information and Bioengineering, Politecnico di Milano, Milan, Italy, in 2017.

He was a Senior Researcher with the Research Institute of Sweden (RISE), Gothenburg, Sweden. He is currently an Assistant Professor with the Department of Computer Science, Air University, Islamabad, Pakistan. He has published research articles in reputed transactions/journals/conferences including TOSN, TECS, SenSys, IPSN, EWSN, and ICC. His primary research area is cyber–physical systems with a focus on transiently powered embedded systems.

Kapal Dev (Member, IEEE) received the Ph.D. degree from Politecnico di Milano, Milan, Italy, in 2019, under the prestigious fellowship of Erasmus Mundus funded by European Commission.

He was a Postdoctoral Research Fellow with the CONNECT Centre, School of Computer Science and Statistics, Trinity College Dublin, Dublin, Ireland. He is a Senior Researcher with Munster Technological University, Cork, Ireland. He worked as 5G Junior Consultant and Engineer with Altran Italia S.p.A, Milan, Italy, on 5G use cases. He worked as a Lecturer with Indus university, Karachi, Pakistan, back in 2014. He is also working for OCEANS Network as Head of Projects funded by European Commission. He is very active in leading (as Principle Investigator) Erasmus + International Credit Mobility, Capacity Building for Higher Education, and H2020 Co-Fund projects. His research interests include Blockchain, 6G networks, and artificial intelligence.

Dr. Dev is serving as an Associate Editor in *Wireless Networks* (Springer), *IET Quantum Communication*, *IET Networks*, a Topic Editor in MDPI Network, and a Review Editor in *Frontiers in Communications and Networks*. He is also serving as a Guest Editor in several Q1 journals; IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, Elsevier COMCOM and COMNET, and Tech press CMC. He served as Lead chair in one of CCNC 2021 workshops, and the TPC member of IEEE BCA 2020 in conjunction with AICCSA 2020, ICBC 2021, SSCt 2021, DICG Co-located with Middleware 2020, and FTNCT 2020. He is expert evaluator of MSCA Co-Fund schemes, Elsevier Book proposals, and top scientific journals and conferences, including IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, IEEE TRANSACTIONS ON NETWORK SCIENCE AND ENGINEERING, IEEE INTERNET OF THINGS, IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, and *Future Generation Computer Systems* (Elsevier) and COMNET.

Bhawani Shankar Chowdhry (Senior Member, IEEE) received the Ph.D. degree from the School of Electronics and Computer Science, University of Southampton, Southampton, U.K., in 1990.

He is the Lead Co- Principal Investigator with National Center of Robotics and Automation-Condition Monitoring Systems Lab, Jamshoro, and also the Distinguished National Professor and the former Dean Faculty of Electrical Electronics and Computer Engineering with the Mehran University of Engineering and Technology (MUET), Jamshoro, Pakistan. He is having teaching, research and administration experience of more than 35 years. Also, he has Chaired Technical Sessions in the USA, U.K., China, UAE, Italy, Sweden, Finland, Switzerland, Pakistan, Denmark, Spain, and Belgium. He is the lead CO-PI with NCRA “Haptics, Human Robotics, and Condition Monitoring Lab,” MUET. His list of research publications crosses to over 60 in national and international journals, IEEE, and ACM proceedings.

Dr. Chowdhry holds the position of Chair IEEE Karachi Section and the member of various professional bodies, including Fellow IEP, Fellow IEEEP, and Senior Member of ACM, Inc., USA.