

3D Reconstruction of Rail Tracks based on Fusion of RGB and Infrared Sensors

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Abstract— Rail tracks, an essential part of the rail system, have remarkably demanded thorough inspections amid rising passenger volumes and high-speed rail development. Non-destructive testing (NDT), without disrupting train operations, aims to mitigate risks by employing safe physical properties like sound, electromagnetic, and light. However, each NDT technique is sensitive to specific damage types, offering limited diagnostic perspectives and placing considerable requirements on operators, resulting in a high cognitive load. To improve the above situation, this study proposes an innovative approach for rail inspection by developing a 3D RGB-T model that combines Visual Testing (VT) and Thermal Inspection (TI) through image registration, 3D reconstruction, sensor fusion, and non-destructive testing (NDT). Their fusion facilities a complementary assessment of rail tracks by capturing both surface texture and thermal radiation to identify damages effectively. The introduction of a novel RGB and IR registration method enables the spatial alignment of images from both, reconstructing the 3D RGB-T model. This model broadens the detection scope beyond the limitations of singular NDT methods, utilizing complementary data to locate and assess the damage extent effectively and accurately. This integrated approach reduces training requirements, minimizes human errors, and provides a clear and interpretable visualization of track conditions.

Keywords— multi-sensor information fusion, rail inspection, 3D reconstruction, non-destructive testing, pulsed thermography.

I. INTRODUCTION

Rail tracks are critical for safe train operations, as they are in direct contact with trains and thus a primary focus of safety inspections [1]. The demand for thorough inspections has grown significantly because of the increased passenger traffic and the development of high-speed rails [2]. Regular inspection and maintenance can mitigate the risk of typical damages (illustrated in Fig. 1), extending the lifespan of rail tracks, ensuring the safe operation of trains, and reducing the costs associated with accidents. Network Rail reported they spent nearly 2 billion pounds on rail track maintenance during 2021 [3]. Ideally, these expenses should be made without interrupting normal service because of the high cost associated with operational disruption, while it does not. The non-destructive testing (NDT) method brings remarkable research value because it is possible to achieve rail inspection without damaging tracks or interrupting train operations on in-service rail tracks.

NDT detects damages in rail tracks by employing physical excitation sources such as sound, electromagnetic, and light instead of using approaches that could potentially cause damage in tracks [4]. Regular inspections use a variety of NDT methods, including ultrasonic testing (UT) [5], [6], eddy current testing (ECT) [7], [8], thermographic inspection (TI) [9], [10], and visual testing (VT) [11], [12]. UT uses ultrasound waves to assess the internal state of rail tracks, requiring slow sensor movement for precise damage detection. ECT can detect rail surface and subsurface damages by capturing eddy currents, which places high technological demands on inspectors. VT not only reveals the surface texture and geometric details of tracks but also has considerable potential in damage localisation. Without treating rails, TI can detect surface and subsurface damages, offering significant prospects for rail inspection. In comparison to other NDTs, VT and TI provide intuitive rail track information more swiftly through standard RGB and infrared (IR) cameras, respectively.



Fig. 1. Railway rail damages are mainly divided into four categories: transverse damages, longitudinal damages, web damages, miscellaneous damages.

An intuitive visualisation of NDT outputs provides detailed and easily understandable information, improving the accuracy of damage identification, localisation, and personnel work efficiency. The common visualisation data format is 1D signals or 2D images in current NDT solutions [5], [13], [14]. Engineers need to calibrate and analyse signals or images based on experience, resulting in large training time, additional cognitive load, and inevitable human errors. In contrast, 3D models offer clearer and more interpretable

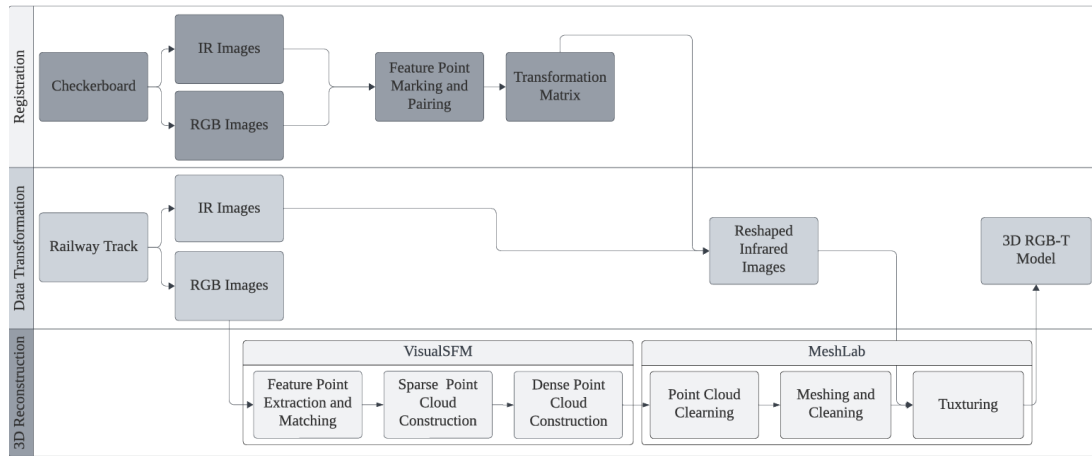


Fig. 2. The experiment flowchart. It consists of three parts: registration, data transformation, and 3D reconstruction. The vertical arrangement of the blocks represents the approximate sequence of experimental steps. The direction of the arrow marks the direction of the data flow.

visualisations, highlighting geometric features and the extent of the damage. Chen *et al.* used 3D eddy current pulsed thermography (3D ECPT) to perform tomographic reconstruction of rolling contact fatigue (RCF) in the short rail track [15]. Wang *et al.* proposed a camera array for building a VT 3D model of rail tracks and studied the effects of the camera number, layout, working distance, and scanning step interval on model quality [16]. While these models offer a user-friendly visual interface and effectively display information about rail tracks, their capability to represent damage is constrained by reliance on a single NDT method. Consequently, such models are restricted in their ability to capture various types of damage. Introducing multi-NDT 3D modelling will extend the scope of damage detection, offering multiple sources of evidence for assessing the damage. This approach ensures that 3D rail inspection is thorough and reliable, enhancing overall trustworthiness.

This study aims to improve the readability of rail inspection data and working efficiency by developing a 3D RGB-T model combining images from both VT and TI using a novel 3D reconstruction technique. VT captures rich texture and colour information, providing geometric information required for reconstruction, while it is not sensitive to damages other than surface ones. TI collects thermal radiation reflected from the target surface after the heat excitation, reflecting both surface and subsurface damages. However, the feature points in IR images are cluttered because IR images represent the temperature distribution, as opposed to the geometric distribution making them unsuitable for the 3D reconstruction of rail tracks. These two technologies can complement and support each other. We propose to use RGB images from VT for reconstructing and displaying the track surface in 3D, while IR images from TI are utilised to identify and quantify the damage extent, particularly subsurface damages. Leveraging their comparable imaging principles, RGB and IR images can establish spatial correlation through image registration, enabling simultaneous integration into a model. By presenting diverse rail track damages within a unified 3D model, this research will reduce requirements of worker training, enhance rail data interpretability, and mitigate human errors.

The contributions of this article are as follows:

- 1) We present a novel framework for multi-dimensional rail track modelling, designed specifically for integrating data from multiple NDTs. It merges a range of data types including surface texture, geometric details, damage extent, and thermal profiles, thereby providing a holistic approach to assessing railway tracks.

- 2) We propose a method for registering 2D-to-3D information that facilitates the integration and mapping of 2D RGB and IR pixel data into a cohesive 3D model. This method relies on the spatial correlation between RGB and IR imaging systems to accurately depict the real world, enabling precise localisation and analysis of anomalies of rail tracks.

- 3) This study develops an integrated data acquisition system that enables the simultaneous acquisition of both RGB and IR images with a fixed relative pose. The system will provide a richer data source for rail damage inspection, ensuring consistency and accuracy in data collection.

II. METHODOLOGY

This paper proposed a novel solution, illustrated by Fig. 2, for projecting both RGB and IR information of rail tracks onto a 3D model constructed from RGB images via a process involving calibration, registration, and reconstruction. Initially, Section 2.1 details the data collection process, where rail track images, alongside a calibration checkerboard, are captured using an integrated data acquisition system equipped with RGB and IR imaging sensors. Subsequently, in Section 2.2, the checkerboard images are used as input to calculate the transformation matrix between two types of images by extracting and matching feature points. This matrix facilitates the alignment of IR images with the coordinate system of RGB images. Then, Section 2.3 describes the creation of the meshed 3D model using the RGB images, employing tools including VisualSFM [17] and MeshLab. Finally, the 3D RGB-T model containing surface texture, geometric information, and thermal distribution (potentially leading to subsurface damage information) is generated by projecting both RGB and adjusted IR images onto the model.

A. Data Collection

In this study, we designed and implemented an integrated data acquisition system comprising both RGB and IR cameras for capturing images, as depicted in Fig. 3(a). The two cameras are assembled tightly to capture images from different heights and angles. It employs an 8.0 Megapixel

USB RGB camera, operating at a voltage of DC 5V, with a spatial resolution of $1,600 \times 1,200$ pixels and a sample rate of 30Hz. The IR camera is FLIR A35 with a 45-degree field of view and operates at a sample rate of 60 Hz. The working distance for the setup is set at 40 cm, ensuring that the objects are well-focused in both cameras. To improve the clarity of thermal data, pulsed thermography is applied with a flash lamp serving as the thermal excitation source in this experiment, as illustrated in Fig. 3(b). This experiment utilises a BW-3935 lamp, working at a voltage of 230 V, set to its maximum illuminance to heat the target with a flash duration of $1/2400$ second. The number of RGB and IR image pairs collected from the checkerboard and the rail track is 8 and 251 respectively. The distance between two consecutive shots is less than 20 cm to ensure sufficient overlapping between images, thereby providing enough feature match. The target rail track, featuring five segments of the CEN56E1 type with artificial damage illustrated in Fig. 3(c), represents a model extensively utilised across roughly 70% of the rail systems in the UK [16].

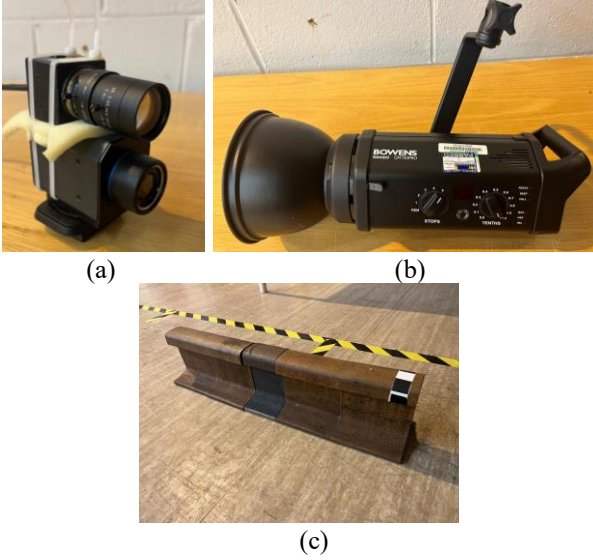


Fig. 3. A snapshot of equipment. (a) The integrated data acquisition system, where the top one is the RGB camera, and the bottom one is the IR camera. (b) The flash for the thermal excitation. (c) is the target long rail track composed of five CEN56E1 tracks.

B. RGB and IR Registration

Extracting feature points from thermal images reveals the thermal distribution but lacks the geometric information needed for 3D reconstruction. The image registration is achieved through a matrix derived from matching feature points across various RGB and IR image pairs, facilitated by the fixed relative positioning of both cameras. This allows IR images to leverage the spatial relationship between RGB images and the 3D model, generating an RGB-T model.

The essence of RGB and IR registration lies in calculating the transformation matrix through the corresponding feature points in RGB and IR images, facilitating image transformation on pixel coordinates. The operational principle behind both cameras involves transforming the world coordinate of a point (X, Y, Z) into a coordinate in the imaging plane. This is achieved through rotation and translation (using extrinsic parameters K_{P1}) and then scaling into pixel coordinates (using intrinsic parameters K_{P2}). Equation (1) refers to the projection process from real-world 3D coordinates to image pixel 2D coordinates, where $P_p(x, y)$

stands for the position of (x, y) in the pixel coordination, $P_w(X, Y, Z)$ stands for the position of (X, Y, Z) in the world coordination. P stands for pixel coordinates. The selection of P dictates whether the system utilises RGB or IR camera parameters, thereby adjusting the camera settings (K_{P1} and K_{P2}) and coordinate the system accordingly.

The points in real-world 3D coordinates can be projected into RGB and IR image planes via RGB and IR camera models, and the projection process can be expressed using Eqs. (2) and (3), respectively. The transformation matrix (T) (Eq. (4)), describing the relationship of the two cameras, is fixed in this experimental setup because the intrinsic parameters (K_{IR2} and K_{RGB2}) are determined.

The pose (locations and orientations) of IR images can then be estimated according to the pose RGB images in this integrated camera system through the transformation matrix. The fixed relative position of the two cameras can numerically transform K_{IR1}^{-1} into K_{RGB1}^{-1} through T . Hence, the transformation matrix T can achieve mutual conversion between RGB and IR images.

$$P_p(x, y) = K_{P1} K_{P2} \cdot P_w(X, Y, Z) \quad (1)$$

$$P_w(X, Y, Z) = K_{IR1}^{-1} K_{IR2}^{-1} \cdot P_{IR}(x, y) \quad (2)$$

$$P_w(X, Y, Z) = K_{RGB1}^{-1} K_{RGB2}^{-1} \cdot P_{RGB}(x, y) \quad (3)$$

$$P_{RGB}(x, y) = T \cdot P_{IR}(x, y) \quad (4)$$

In this study, the accurate registration of RGB and IR images, fundamental for the 3D RGB-T model reconstruction, is facilitated by the distinct visual boundaries presented by the checkerboard. The distance of around 40 cm between the integrated data acquisition system and both the checkerboard and target rail track ensures uniform focus. In both RGB and IR images, the checkerboard's black and white squares exhibit stark contrasts, as demonstrated in Fig. 4. The feature point connections between the RGB and IR images of the checkerboard are established through manual annotation.

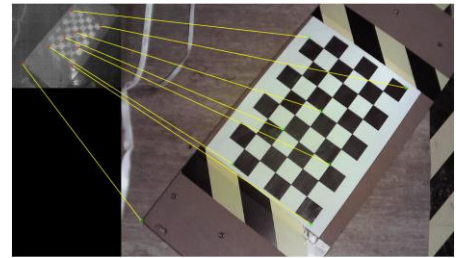


Fig. 4. One schematic diagram of the feature point connection between RGB and IR image of the checkerboard. The IR image is displayed on the top left, while the RGB image is on the right. Red points are the feature points in the IR image. Green points are the feature points in the RGB image. The corresponding point pairs are connected using yellow lines.

Although the checkerboard corners are clear, manual annotation introduces potential inaccuracies between the RGB and IR images' correspondence. To reduce the error, the transformation matrix used is the optimal global average, incorporating multiple checkerboard images and extensive global feature points. This approach aims to enhance the overall accuracy of the feature point annotation and subsequent transformation matrix estimation.

C. 3D Reconstruction

In this research, 2D images from both cameras are transformed into a 3D RGB-T model by extracting feature points and image projection. Initially, the scale-invariant feature transform (SIFT) algorithm extracts the feature points from the RGB images. Its robustness to changes in brightness, scale, and rotation makes it suitable for rail track inspection [18]. These feature points are then matched based on vector distance calculations to form feature pairs. Simultaneously, the camera's intrinsic and extrinsic parameters are estimated using singular value decomposition (SVD), a mathematical method to calculate the camera pose.

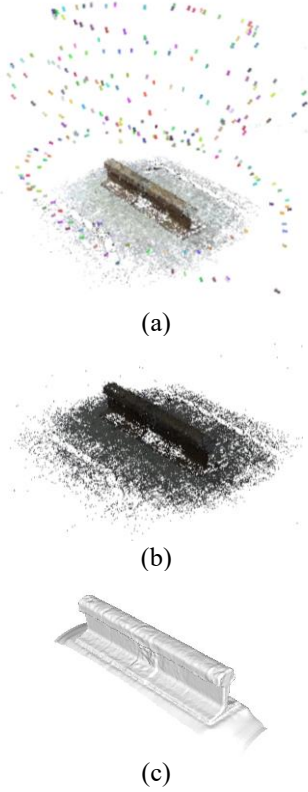


Fig. 5. An illustration of the proposed 3D reconstruction process. (a) the sparse point cloud with camera positions, (b) the dense point cloud, and (c) the meshed 3D surface. In (a), colour points surrounding the model represent the cameras positions.

The connections between feature pairs allow the mapping of the 3D coordinates of these feature points through triangulation, a process by which 2D images are used to establish depth and spatial relationships. This initial step results in a sparse point cloud model, optimised through the bundle adjustment method to refine the parameters and coordinates, as illustrated in Fig. 5(a). However, this sparse point cloud lacks the density required for meshing or texturing.

We employ Clustering Views for Multi-View Stereo (CVMS) and Patch-based Multi-view Stereo (PMVS) techniques to achieve a dense point cloud [19]. CVMS clusters images to streamline the data needed for dense reconstruction, while PMVS enhances the sparse cloud into a dense one by ensuring local photometric consistency and global visibility, processing through initialisation, feature point matching, patch diffusion, and patch filtering. This comprehensive

approach culminates in a detailed and dense point cloud, shown in Fig. 5(b).

This dense point cloud obtained from the previous steps requires manual denoising to remove the background noise unrelated to the rail track. Once denoised, the point cloud undergoes Screened Poisson surface reconstruction, a method creating watertight surfaces ideal for 3D modelling. To define the direction of the surface, a vector field is constructed from the point cloud and its normal vector. By solving Poisson's equation, a scalar function is found, whose gradient scalar field is the closest to the vector field of the point cloud. This is visualised as an isosurface, effectively representing the model's exterior, as depicted in Fig. 5(c).

The next step involves UV mapping, where the 3D mesh is unfolded into a 2D plane (with U and V axes) to allow for accurate texture application. In this 2D coordinate system, each mesh vertex is precisely aligned with its corresponding point on the 2D images. The consistency between the poses of RGB and IR images ensures their respective UV coordinates match, allowing colour information to be accurately mapped on the mesh. Smooth interpolation processing fills in any gaps, ensuring a seamless surface texture. Finally, a 3D RGB-T model is generated based on the RGB images and the adjusted IR images through UV mapping. This model combines detailed geometry with realistic texturing, showcasing a seamless integration of both datasets.

III. RESULTS AND DISCUSSIONS

The proposed RGB-T modelling offers an effective and precise approach for rail track inspection. The RGB-T model incorporates shape, structure, and NDT data, providing comprehensive and multi-modality information for further diagnosis. As demonstrated in Fig. 6 (a), (b), and (c), the RGB-T model is equipped with RGB, thermal, and geometric layers. The RGB-T model effectively reflects the damage location and geometric shape, offering a more intuitive sense of the track's physical condition than the traditional RGB 3D models or thermal 2D images. Conversely, the thermal layer represents NDT information, benefiting an in-depth analysis of the track's internal status without real colour distraction. This combined approach enables a thorough assessment of the rail track's health, highlighting areas of concern and assisting in the prioritisation of repair actions.

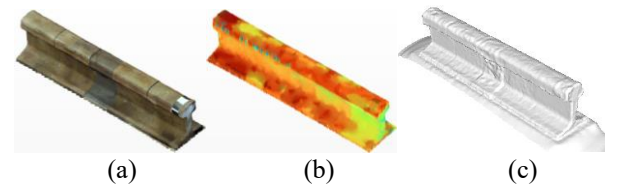


Fig. 6. Reconstruction results of the railway track. (a) 3D RGB layer; (b) 3D thermal layer, (c) 3D geometric layer.

A. RGB Texture Layer

The RGB layer effectively illustrates the geometry and wear status of the rail tracks, highlighting damage locations and shapes across five distinct sections, as depicted in Fig. 7. Area 1 exhibits a white fracture at the junction, visible upon magnification. In Area 2, the oxidation is more serious than that on the side, in addition to black spots on side B. The sensitivity of the RGB layer enables the identification of even minor damages, including the crescent-shaped and elongated damages in Area 4. This visual representation allows for an

assessment of the track, revealing signs of long-term use and significant surface oxidation.

The information displayed in the RGB layer helps operators initially determine damage information on rail

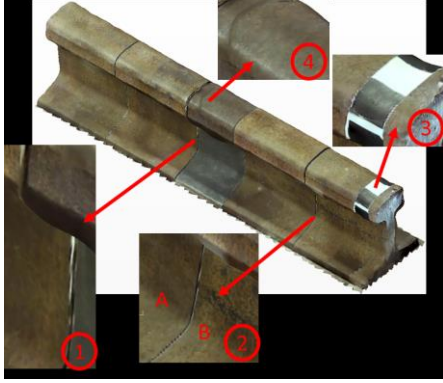


Fig. 7. The generated RGB Layer of the rail track.

tracks. The layer intuitively presents a simulated fracture in Area 1 and highlights textural and colour differences indicative of oxidation in Area 2, guiding regular maintenance efforts. However, the RGB layer fails to show the specific area of the oxidation area in detail, making it difficult to localise the specific area for maintenance. In addition, operators may not be able to identify the damages in Area 3 and Area 4, which pose a risk of misidentification.

B. Thermal Layer

The thermal layer reveals the rail track thermal distribution after the flash excitation, as illuminated in Fig. 8. In Area 5,

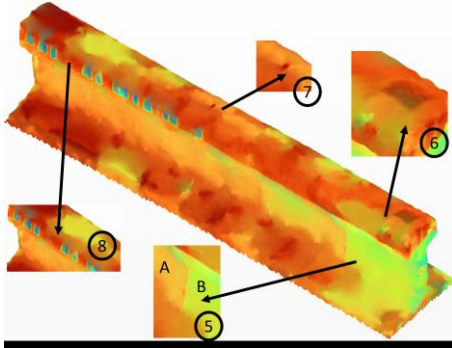


Fig. 9. Thermal Layer of Rail Track. In order not to confuse Areas, the numbers in this image follow Fig. 6, starting from Area 5.

the temperature difference between sides A and B indicates large-area damage on the track surface. Area 6 appears an abnormal dark square, suggesting a potential area of concern for rail inspection. Meanwhile, the dark red dot in Area 7 suggests an anomaly of thermal concentration, hinting speculating that there may be spots, or cracks on the surface or subsurface. Compared with the RGB layer, the thermal layer has eye-catching features that make the detection highly directional, thereby improving operators' working efficiency and reducing their cognitive pressure.

Although the thermal layer is adept at detecting abnormal thermal zones and directing detection strategies, it cannot provide detailed information, such as identifying the specific type of damage. Without additional data, the thermal layer alone cannot accurately distinguish between actual damage and interference information in Areas 5, 6, and 7.

C. RGB-T Model

Combining the RGB and IR layers, the qualitative analysis of the RGB-T model includes three corresponding areas. The white Area 6 in Fig. 8 matches the mark in Area 3 in Fig. 7, which is the additional evidence improving the identification of the damages with high confidence. The oxidized extent is further confirmed in the thermal layer (Area 5 in Fig. 8), which is identified in the RGB layer (Area 2 in Fig. 7). The presence of the red dot in Area 7 enhances the visibility of damage within Area 4. The RGB-T model reflects rail track damage information in multi-dimension, highlighting the damage details, thereby improving the accuracy and reliability of inspection results. The RGB-T model improves the efficiency and accuracy of rail track damage diagnosis by providing extra damage information, including damage extent and oxidation conditions. Within the RGB-T model, the RGB and thermal layers complement each other by providing mutual evidence, jointly expanding the area for damage identification, and enhancing the accuracy of detection. When engineers cannot judge the damage impact or do not have the detection focus, the thermal layer highlights the damage area to define damages and guide engineers. Conversely, if there is abnormal temperature distribution in the thermal layer, the RGB layer provides texture support to identify and supplement the

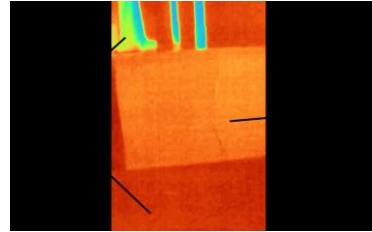


Fig. 8. One of IR Images of Railway Track. It includes rail track and background information. The background information is mapped in the thermal layer.

damage information.

While the RGB-T model proficiently represents the condition of the rail track, there are some imperfections in its display. For instance, despite the uniform temperature at the head of the rail track, its representation in the thermal layer does not reflect this uniformity. One of the reasons for this phenomenon may be the instability of flash heating. Another possible result is the complex background temperature captured by the IR camera, resulting in inaccurate temperature readings in the IR images. In addition, the background temperature in Fig. 9 is mapped onto Area 8, which means there is an error in the registration between the RGB images and IR images. Thus, our future work will focus on reducing environmental noise, evenly heating the rail track, and improving the accuracy of image registration.

Although there remain areas for improvement in technical specifics and practical implementations, this technology demonstrates a high fidelity in reproducing the features and properties of rail structures. It significantly aids in the identification and understanding of rail damage with a reduced cognitive load compared to other NDT technologies. Notably, the rail track model accurately delineates the spatial geometric position of damages within the rails and provides an intuitive visualization of damage severity. This stands in stark contrast to numerical results [20], [21], [22], [23], as our fusion models align more closely with human visual perception, enabling engineers to comprehend the actual damage scenarios more

effectively. This improved understanding enhances diagnostic efficiency, uncovers trends in damage progression, and supports informed decision-making. Furthermore, compared to traditional VI and TI technologies, our model integrates multi-dimensional information, providing a robust foundation for enhancing detection capability and improving the probability of detection. This comprehensive and reliable diagnostic approach ensures a more thorough and accurate assessment of rail integrity.

IV. CONCLUSION

This study presents an innovative NDT visualisation approach to reconstruct a 3D RGB-T model for rail inspection by fusing data from VT and TI. A novel RGB and IR registration method is proposed to establish the precise correspondence between RGB and IR cameras, enabling the spatial transformation from IR coordinates to RGB coordinates. For data collection, an integrated data acquisition system comprising both RGB and IR cameras is developed to ensure the accuracy and consistency of data from rail tracks. The RGB layer exhibits texture details and geometric specifics, while it is difficult to confirm the damage extent. The thermal layer could highlight the suspected damage area but cannot define the detailed information. By fusing these two layers and geometric layer, this RGB-T model can display surface texture, geometric specifics, the scope of damage, and thermal distribution to guide the inspection and offer adequate damage evidence, thereby improving the reliability and accuracy of track inspection. Through the RGB-T model, operators can detect rail conditions in a targeted manner under low cognitive pressure, thereby reducing working time and improving work efficiency.

The current exploration of the RGB-T model faces distinct operational challenges, especially the influence of environmental temperature, inconsistent heating across the subject, and intricacies involved in aligning images accurately. These issues underline the necessity of precise environmental control and advanced image processing techniques to ensure data integrity. Consequently, future research will aim to establish a more robust connection between these operational challenges and their solutions, leveraging sophisticated methodologies such as data fusion to enhance accuracy in RGB and IR data integration, and point cloud technologies for more precise damage inspection. This strategic focus on employing advanced computational techniques and environmental management will significantly refine the quality and applicability of the RGB-T model (quantitative evaluation, integration with actual maintenance processes, and multi-type track handling issues), making it a powerful tool for detailed and accurate analysis.

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