A Physics-Guided Hybrid Digital Twin for Early Warning of Ground-Related Hazards in Railway Corridors

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***Abstract*—In this paper, we introduce a multi-scale, multi-temporal digital twin dedicated to detecting geotechnical hazards and managing alerts along railway corridors. Indeed, infrastructure managers are increasingly relying on dense LiDAR acquisitions, very high-resolution optical imagery, and satellite InSAR series, but these data streams are still mostly exploited separately, with limited multi-sensor fusion and incomplete integration into operational alert systems. The proposed digital twin aggregates these different sources within a unified spatio-temporal infrastructure, discretized into corridor segments that constitute the basic units of risk analysis. Within this infrastructure, two advanced detection approaches are deployed: the first performs centimeter-resolution 3D change detection on multi-epoch LiDAR series, while the second implements 3D semantic segmentation based on a point transformer trained on physics-guided synthetic data, in order to characterize subsidence/uplift and sinkholes, respectively. The outputs of these modules are cross-referenced with indicators derived from InSAR time series and optical imagery to produce segment-level risk scores. We describe the twin's architecture, the data processing pipeline, and the associated alert logic, and we illustrate the feasibility and operational relevance of the proposed approach using real data.**

Keywords—Digital twin; Railway infrastructure; Multi-sensor data fusion; 3D LiDAR change detection; Ground-instability early warning

I. INTRODUCTION

Linear railway infrastructure is particularly sensitive to geotechnical hazards such as landslides, subsidence/heaving, and sinkholes. These ground movements can alter the stability of earthworks, degrade track geometry, and, in extreme cases, lead to derailments or prolonged traffic interruptions. The length of the networks, the variability of geological and climatic conditions, and the sometimes gradual and inconspicuous nature of these phenomena mean that monitoring based solely on spot inspections is insufficient. In this context, the implementation of proactive, continuous, and spatially extensive monitoring systems is a key challenge for railway infrastructure managers. Traditionally, monitoring has relied on field inspections (track and surrounding area inspections, targeted auscultations), track geometry measurement equipment, and information provided by remote monitoring and operating staff. While these approaches have proven effective for several decades, they have structural limitations: partial spatial coverage, acquisition frequency constrained by available resources, mostly retrospective detection of damage, and difficulty in characterizing soil processes upstream of defects observed on the track. At the same time, managers now have access to much richer observation datasets: dense LiDAR acquisitions along lines, regional-scale InSAR deformation products, very high-resolution optical imagery, measurements from in situ IoT sensors, and geological and hydrological contextual layers. Taken individually, these sensors have proven their relevance for detecting ground movements, but they are still rarely analyzed jointly and remain poorly integrated into operational alert chains. The main challenges relate to (i) the heterogeneity of spatial and temporal resolutions of different sources (from centimeters to kilometers, from weekly to annual surveys), (ii) the variability in metric quality and referencing, particularly for multi-epoch LiDAR data, and (iii) the difficulty in defining robust, interpretable, and actionable risk indicators at the line segment level. In this context, the concept of digital twins applied to linear infrastructure provides a unifying framework for organizing the fusion of multi-source data, encapsulating advanced detection algorithms, and structuring the production of risk scores and alerts for monitoring earthworks and their environment.

In this paper, we propose a multi-scale and multi-temporal digital twin dedicated to the detection of geotechnical hazards and the management of alerts along railway corridors. The twin aggregates centimeter-level mobile LiDAR acquisitions, InSAR time series, and high-resolution optical imagery within a unified spatiotemporal infrastructure, discretized into corridor segments that constitute the basic units of risk assessment. Within this framework, we encapsulate advanced detection approaches in the form of modular services: (i) a centimeter-resolution 3D change detection engine on multi-epoch LiDAR series, enabling the extraction of morphometric indicators of subsidence and uplift, and (ii) a 3D semantic segmentation engine based on a point transformer, trained on physics-guided synthetic data, dedicated to the automated detection of sinkholes. The outputs of these engines are cross-referenced with indicators derived from InSAR series and optical imagery to generate segment-level risk scores. The contributions of this work are as follows. First, we define a corridor-oriented digital twin architecture designed to integrate and harmonize heterogeneous LiDAR, InSAR, and optical data into a common spatiotemporal reference frame suitable for monitoring railway surroundings. Second, we show how state-of-the-art detection algorithms for 3D change and 3D point cloud segmentation can be integrated as services within this twin and enhanced by physically plausible synthetic data. Third, we propose a scheme for generating segmental risk scores and an associated alert logic, and we illustrate the feasibility and operational relevance of the digital twin for the early detection of landslides, subsidence, and sinkholes using real data.

II. Related work

Soil-related risks along linear infrastructure are now systematically monitored using multi-temporal remote sensing. Time-series InSAR methods (PS-InSAR, SBAS) are widely used to map slow subsidence and landslides in urban, mining, and linear infrastructure contexts, with millimeter sensitivity over large areas [1], [2]. Several studies demonstrate their relevance for railway monitoring, for example to analyze subsidence along operational lines and newly constructed corridors [3]. Advantages include wide geographic coverage and long histories; limitations include loss of consistency in vegetated or rural areas, atmospheric artifacts, and limited spatial resolution for narrow infrastructure such as railways [1], [3]. Airborne and mobile LiDAR provide complementary centimeter-accurate 3D information. Indeed, multi-temporal airborne LiDAR has been used to LiDAR study of an active landslide at Montaguto [4]. The combination of LiDAR-derived DTMs with InSAR has also proven effective in improving the quantification of subsidence patterns in coastal environments and infrastructure [5]. In situ systems (GPR, fiber optics, dense IoT networks) add high-frequency local measurements on ballast, platform, and structures, but their deployment at the network scale remains costly and they are rarely integrated into a continuous view at the corridor scale. Deep learning has become a key approach for the automatic detection of geological hazards from DTMs, optical imagery, and InSAR products. For sinkholes, machine learning models trained on images derived from DTMs (slope, gradient, shaded relief) or high-resolution satellite data have been used to delineate tens to hundreds of thousands of karst depressions over large areas [6][7]. This works show strong spatial generalization, but also highlights sensitivity to DTM artifacts, vegetation, and significant imbalance between classes. For landslides, various architectures (U-Net, encoder-decoder, Siamese networks, GAN) have been trained on pre/post-event optical or SAR images and merged DTMs, demonstrating that multi-temporal and multi-source inputs significantly improve large-scale mapping performance [8][9]. In the 3D domain, recent research exploits point-based networks and 3D transformers to detect small-scale changes and relief features in multi-temporal LiDAR point clouds, including railway-related sinkholes and micro-geomorphological features [10][11]. These approaches improve sensitivity to fine 3D patterns, but public annotated datasets for railway applications remain scarce, and the generalizability of models across sites has not yet been fully established. Deep learning-based multisensory fusion is a third major area of work. Several studies propose pixel-, feature-, or decision-level fusion architectures that jointly exploit optical imaging, SAR (InSAR, coherence, interferograms), and LiDAR for landslide and subsidence detection [12] [13]. They show that the explicit combination of spectral-textural indices, deformation, and 3D structure can improve the detection of weak signals and partially vegetated failures. However, these models are costly to train, require carefully harmonized multisensory datasets, and typically produce maps that are not directly structured as risk indicators aligned with operational alert procedures. Bridging the gap between these powerful fusion models and the needs of infrastructure managers (stable, interpretable, segment-level indicators) remains a challenge.

Furthermore digital twin (DT) concepts are increasingly being explored in the railway sector. Recent research identifies several DT-related studies for rolling stock, tracks, structures, and stations, and uses IoT sensors, cloud platforms, and AI as for predictive maintenance and decision support [14][15]. This often involves combining digital models and monitoring data to track asset condition, simulate scenarios, and optimize response plans [16]. These works focus primarily on structural or operational performance (fatigue, vibrations, passenger flows), rather than geotechnical risks affecting the surrounding soil. Work explicitly targeting platform defects, settlement, or slope instability generally combines a limited set of sensors (e.g., InSAR plus leveling, or GPR plus track diagnostics) without formalizing a spatio-temporal risk model at the corridor level or dedicated alert logic. In this context, our work lies at the intersection of remote sensing, deep learning, and digital twins. We propose a corridor-oriented digital twin that (i) unifies mobile LiDAR, InSAR, and high-resolution optical imagery in a segmented spatio-temporal representation adapted to railway lines; (ii) encapsulates advanced detection engines (centimeter-level 3D LiDAR change detection and 3D sinkhole segmentation trained on physics-guided synthetic data) as modular services within the twin; and (iii) translates their results into segment-level risk scores and alert logic explicitly aligned with the workflows of a national railway infrastructure manager.

III. Digital Twin Architecture

The proposed digital twin is a service-based, data-flow-oriented architecture that is aligned with the way railway infrastructure managers acquire, store, process, and use monitoring data. The system is broken down into five functional layers (Fig. 1):

- Measurement layer, responsible for multi-source data acquisition;
- Data Storage layer, which provides persistent, queryable repositories;
- Data Management layer, which coordinates access to data and controls the execution of services;
- Service layer, where domain-specific analytics are implemented, including an Environment Fault Detection service dedicated to ground-related hazards;
- Model Output, Alert Dissemination and Feedback layer, which exposes alerts and collects operational feedback.

A. Measurement layer

This layer allow acquiring the data needed to monitor the railway environment at multiple spatial and temporal scales. Three types of data are considered: First, systems mounted on a measurement locomotive provide multi-temporal mobile LiDAR point clouds and images taken from the track throughout the network.

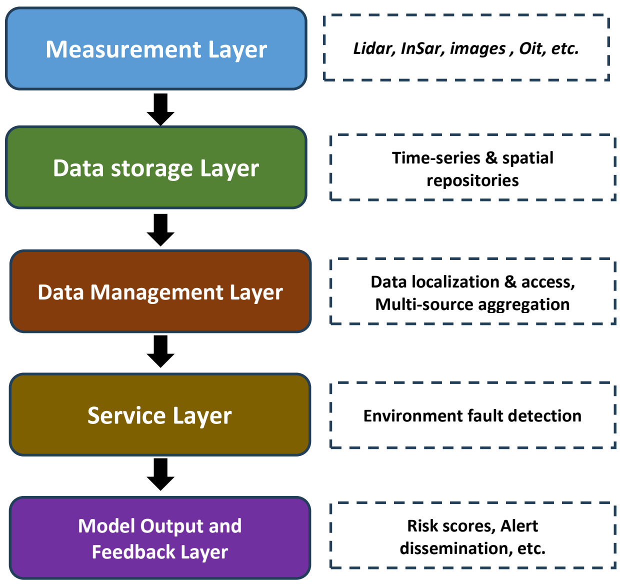

Fig. 1. Digital Twin architecture

Railway LiDAR provides dense 3D sampling of the track, earthworks, and immediate environment, with typical relative accuracy in the order of centimeters, a density of several thousand points per square meter, and revisit intervals of between approximately 8 and 18 weeks. Co-recorded RGB images, acquired every few meters along the line, provide a detailed visual record of ballast, platforms, vegetation, and built structures. Second, satellite systems provide InSAR deformation products and very high-resolution optical imagery. Multi-date InSAR datasets provide millimeter-level information on displacements and velocities at the corridor and regional scales, while sub-meter optical imagery characterizes land cover, geomorphological context, and major surface changes in the vicinity of the railway. Third, in situ and operational measurements include geotechnical and topographic surveys, time series of IoT sensors at selected sites, track geometry data, and structured inspection or maintenance records, which document local conditions and historical events that are not fully captured by remote sensing. Each acquisition subsystem is encapsulated as a measurement service. These services interface with the corresponding operational platforms or providers, collect data according to their native acquisition schedules, attach essential metadata (timestamps, spatial reference, acquisition parameters), and expose the resulting streams in a uniform and well-documented manner to the upper layers of the digital twin. Harmonization and semantic interpretation are deliberately deferred to the data storage and management layers.

B. Data storage layer

The aim of this layer is to archive the collected data, organizing it into a unified geodetic reference system and providing standardized metadata documentation, so that it can be directly queried by the upper layers. Spatio-temporal data is thus represented in a single reference coordinate system (RGF93/ETRS89) with a complete description of the projection and spatial resolution parameters. This layer also stores complete metadata, compliant with ISO standards (origin, sensor, campaign, processing level, accuracy, resolution, quality), as well as data traceability via provenance and versioning mechanisms (data and processing lineage).

C. Data mangement layer

This layer provides the interface between the storage layer and the services. Its main function is to gather, via targeted queries, the data necessary to execute a given service. Based on the service requirements (data types, period, spatial coverage), it formulates spatio-temporal queries to the storage databases, selects the relevant LiDAR, InSAR, onboard RGB imagery, and IoT datasets, applies the appropriate spatial and temporal filters, and then assembles a coherent multi-source data set, accompanied by consolidated metadata. This layer ensures that each service accesses exactly the data it requires, under controlled, traceable, and reproducible conditions.

D. Service layer

This layer brings together the processing carried out by the digital twin. It uses the data prepared by the management layer and implements algorithms for detecting and characterizing changes in the railway environment, particularly the ground near the rails. The services are designed as loosely coupled business modules: they do not manage data acquisition or persistence, but only their transformation into anomaly maps, indicators, and alerts. In this paper, we present two key services for detecting anomalies in the ground near the rails. The first is a module for detecting centimeter-scale 3D changes using high-density mobile LiDAR series. It is based on a corridor-aware chain comprising (i) a two-step multi-epoch registration by ICP, whose hyperparameters are optimized using Bayesian methods to ensure stable accuracy and robustness across all sites, and (ii) adaptive cloud-to-cloud vertical change calculation, where altitude residuals are evaluated in local neighborhoods and aggregated into patches. Each patch is then classified as subsidence, uplift, stable, or inconsistent, and characterized by morphometric indicators (amplitude, extent, support). The second is a module for automatic detection of sinkholes in LiDAR clouds. It is based on physics-guided synthetic data generation, where two families of artificial sinkholes are simulated: parametric models based on inverted elliptical Gaussians and more varied geometries from a flow matching generative model. These deformations are injected into DEMs derived from LiDAR to produce a rich training corpus covering a wide spectrum of plausible morphologies. The enriched DEMs are reprojected into point clouds and processed by a SuperPoint Transformer-type 3D segmentation pipeline. Geometric post-processing then filters the detections according to criteria of depth, volume, compactness, and proximity to the road, in order to eliminate artifacts and prioritize critical anomalies. The outputs of these two services (change maps, sinkhole probability maps, synthetic indicators) constitute the main input to the output layer for calculating risk scores and generating alerts.

E. Model output and feedback layer

The output layer translates the results of the services into risk indicators and alerts that can be used directly by infrastructure managers. For each section of track and each type of hazard, it combines descriptors from different services—LiDAR change measurements, sinkhole probabilities, InSAR deformation indicators, abnormal signals from IoT sensors, contextual information—to produce continuous risk scores with confidence indices reflecting the level of corroboration between sources. These scores are then projected into discrete alert levels using fusion rules and thresholds defined with business experts, while retaining, for each alert, the indicators used and the associated decisions in order to ensure traceability and auditability. At the same time, the output layer provides the visualization and integration tools needed for operational use: map representations of scores and detected anomalies, access to underlying LiDAR/InSAR/RGB/IoT evidence, and interfaces to maintenance supervision and planning systems. Finally, it sets up a feedback loop, where field inspections, geotechnical expertise, and work undertaken in response to alerts are recorded, linked to the initial events, and then fed back into the digital twin..

IV. IMPLEMENTATION AND PRELIMINARY RESULTS

A. Railway Dataset

Several types of data are used in this study, it include : multi-epoch LiDAR point clouds acquired by SNCF Réseau survey vehicles (ESV, WIM-SV, EMI) and stored in LAZ/EPT formats. These clouds have a relative accuracy of approximately 1 cm, a point density greater than 3,000 pts/m², and a volume of less than 20 GB per kilometer of track (Fig. 2). Onboard RGB images (Imajing) acquired approximately every 10 m along the track (Fig. 3). Track geometry data (FMB) provides acceleration, rail positioning, and XYZ coordinates, and is used to accurately position LiDAR point clouds and images along the line.

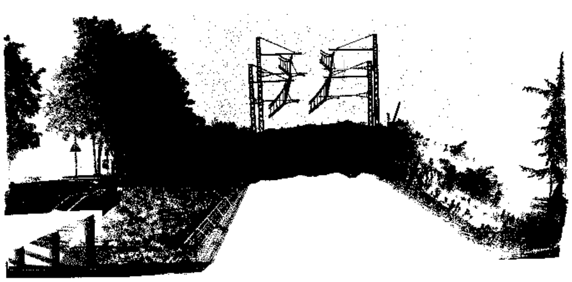

Fig. 2. Raw LIDAR Data

In addition, we use InSAR satellite radar data providing, on several dates, estimates of line-of-sight displacement and average speed over large areas covering rail corridors. The principle is based on the highly accurate measurement of the distance traveled by the radar signal between transmission and reception: by comparing the change in this distance over time, radar interferometry can detect ground deformations with millimeter sensitivity. An initial series of InSAR datasets has been produced from freely accessible missions (Copernicus program and Sentinel satellites) and is used to characterize long-term deformation trends along the tracks and in their immediate environment (Fig. 4).

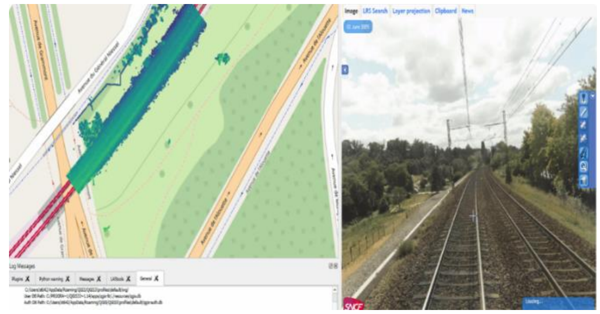

Fig. 3. Example of an acquired RGB image

For certain areas of interest, higher-resolution interferometric products can then be ordered to refine the local analysis in the vicinity of the tracks.

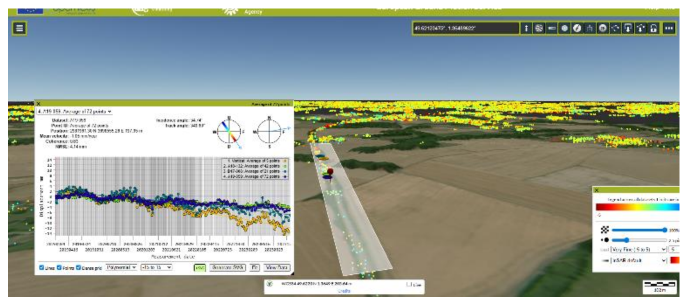

Fig. 4. Example of InSAR time-series image showing line-of-sight displacements along a railway corridor.

Finally, local in situ and IoT measurements, such as geotechnical and topographic surveys, displacement or pore pressure sensors, and weather stations, are also taken into account when available in the study areas. In this work, mobile LiDAR is the main source of quantitative information for both detection algorithms, while RGB imagery, InSAR data, and IoT are mainly used as complementary modalities to interpret and cross-check LiDAR-based detections, and will be exploited more systematically for data fusion in future stages.

B. LiDAR-based 3D change detection

This detection module operates on pairs of multi-epoch mobile LiDAR point clouds covering the same sections of track. Rigid 3D registration is applied to each pair using the ICP algorithm on the points of stable objects (rails, catenary poles). Thanks to a processing pipeline that allows the extraction of the ground, only the terrain component is retained, while vegetation, rolling stock, and other transient objects are eliminated. A digital terrain model (DTM) is then generated for each epoch by interpolating the points on the ground. To assess the sensitivity of the approach and mimic realistic failure scenarios, synthetic deformations are injected into these DTMs using parameterized landslide-type displacement models with controlled amplitude, spatial footprint, and orientation.

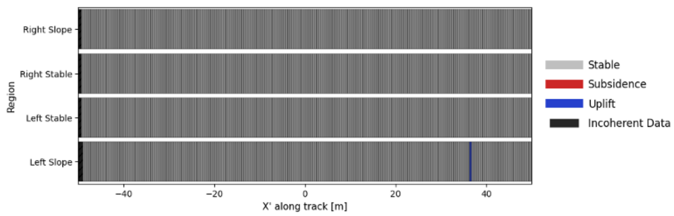

Fig. 5. Patch level diagnostic map

The deformed DTMs are resampled into point clouds, and “reference vs. deformed” pairs are constructed to emulate the subsidence or uplift affecting the railway embankments. Change detection is performed on longitudinal slices and cross-sectional regions extracted from these ground-only point clouds. For each slice, the vertical differences between time periods are estimated in local neighborhoods and summarized at the patch level using robust statistics (median vertical change, dispersion, support).

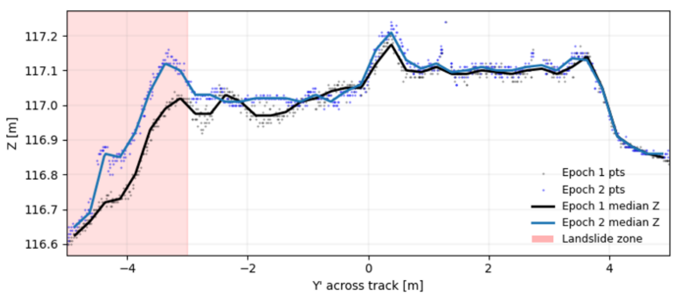

Fig. 6. Vertical enbankement profile

The patches are then assigned to simple diagnostic classes (subsidence, uplift, stable, unreliable) based on amplitude and support thresholds. An example of a vertical change map and corresponding profile, obtained on an embankment, with patches classified according to the dominant vertical trend, is shown in Figure 5 and 6, respectively. In the other hand, when the approach is applied on real datasets, the obtained qualitative results indicate that the detected vertical change patterns follow the expected geomorphology of embankments and cuttings and are consistent with available contextual information. These experiments confirm that the “ground-based DTM only + synthetic deformation + slice detection” pipeline provides a robust and interpretable LiDAR-based component for integration into the digital twin.

C. LiDAR-based sinkhole detection

The second module implemented aims to detect sinkholes in the ballast and soil near the tracks using mobile LiDAR point clouds. The approach combines physics-guided synthetic data and 3D semantic segmentation. From DEMs derived from LiDAR point clouds, two families of synthetic sinkholes are generated: (i) compact depressions defined by parametric models with controllable depth, lateral extent, and orientation, and (ii) more irregular shapes produced by a generative flow matching model trained on a small set of real potholes. These artificial deformations are integrated into real DTMs and resampled as point clouds, resulting in augmented training and validation datasets that cover a wide range of plausible geometries while preserving a realistic railway context.

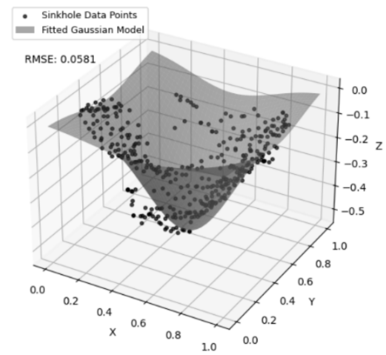

Fig. 7. Fitted Gaussian model for a sample sinkhole

The detection phase relies on a SuperPoint-Transformer-based segmentation pipeline applied to these point clouds. The scene is first partitioned into geometrically homogeneous superpoints; local geometric descriptors (e.g., dispersion, flatness, elevation, verticality, normal information) are calculated and integrated, and a basic transformer structure propagates contextual information on the resulting superpoint graph.

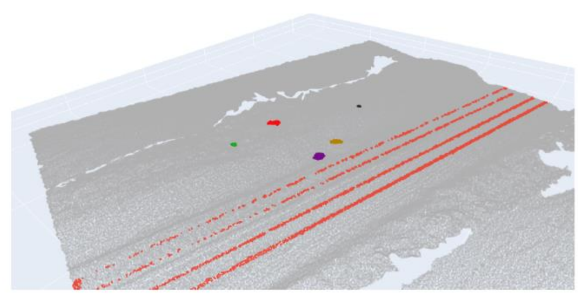

Fig. 8. Fitted Gaussian model for a sample sinkhole

The network is trained in a binary segmentation framework to distinguish sinkhole areas from other areas, using labels provided during DTM deformation. At inference time, the predicted superpoints are projected onto the original clouds, producing dense probability maps of sinkhole presence in the vicinity of the track. An example of the detections obtained on a real railway scene is shown in Figure 8. Since DTM construction and vegetation filtering can introduce spurious depressions, a dedicated post-processing step is applied to the raw predictions. Connected components are extracted in raster space, and each candidate region is characterized by morphometric attributes such as depth, footprint length, volume, and shape compactness. Only regions that meet the thresholds calibrated on the observed depressions are retained, which significantly reduces false positives related to artifacts. A second validation step assigns each retained detection a score based on its distance from the rails, allowing operational priorities to be established without discarding distant anomalies.

D. Cross-sensor analysis and confidence indices

In this section, we show how InSAR and onboard RGB imaging can be used to verify detections and define confidence indicators for future fusion within the digital twin. InSAR data provide a large-scale view of ground movements along and around railway corridors: time series of displacements and average velocity maps are used to identify areas with long-term deformation trends on a decametric or hectometric scale. In contrast, LiDAR-based change and collapse detection modules provide small-scale diagnostics focused on the immediate vicinity of the tracks. A natural strategy is therefore to use InSAR to flag potentially unstable corridors or areas, and to interpret the bands of subsidence or local depressions detected by LiDAR in this broader kinematic context. For onboard RGB imaging, the acquisition geometry and camera calibration allow 3D LiDAR detections to be projected onto the image plane and compared with image-based change indicators [17][18]. We implemented a preliminary change detection pipeline based on a transformer on sequences of images taken along the tracks, producing 2D maps of visually detected changes.

V. CONCLUSION

In this paper, we proposed a physics-driven hybrid digital twin for early warning of ground-related risks along railway corridors. The digital twin organizes heterogeneous monitoring flows (mobile LiDAR, InSAR, onboard RGB imaging, and IoT measurements) within a service-oriented and stratified architecture that separates data acquisition, storage, management, analysis, and alert dissemination. Within this framework, we have instantiated two basic LiDAR-based services: a module for detecting centimeter-scale 3D changes on a multi-epoch mobile LiDAR and a module for detecting 3D sinkholes trained on physics-guided synthetic data and transformer-based 3D segmentation. On representative railway datasets, these modules produce interpretable indicators such as subsidence/elevation diagnostics at the patch level and morphometrically filtered sinkhole candidates. We also presented preliminary experiments on multi-sensor cross-validation, where LiDAR-based detections are qualitatively compared to RGB-based change maps, highlighting how multimodal confidence indices can be defined. Future work will focus on scaling these components to larger parts of the network, formalizing fusion schemes combining LiDAR, InSAR, RGB, and IoT indicators into segment-level risk scores with explicit uncertainty estimates, and integrating alert logic and visualization tools into existing supervision and maintenance workflows.

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