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UNDERSTANDING THE CHALLENGE OF DIGITALLY TWINNING THE GEOMETRY OF EXISTING RAIL INFRASTRUCTURE

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Abstract
The exploitation of the concept of Digital Twins, i.e. virtual copies of physical assets, for existing rail infrastructure has the potential to revolutionise asset management in this sector. However, such exploitation is only possible if methods exist can cost effectively generate the Digital Twins of rail assets. The first step in this "twinning" process is the capture of the asset's raw geometry and its conversion to high level geometry suitable for further enrichment with design, construction, operation and maintenance data. This paper investigates the state of the art in the first twinning step, i.e. generating geometrically accurate models of existing rail infrastructure, focusing on the track assets. The paper starts off by defining the digital twin, then explaining the benefits of real-virtual synchronisation and challenges to exploit the digital twin in its full potential. The subsequent sections provide a longitudinal literature indicate that current studies are sensitive to varying railway geometries, neighbourhood structures, scanning geometry and intensity of input data. These factors render methods designed for digital twinning ineffective for any track structure which contains varying horizontal and vertical elevations. Such variance is quite common; hence, we conclude that the problem of automatically generating geometric digital twins of track structure is yet to be solved.

Keywords: *Geometric Digital Twin (GDT); Point Cloud (PCD); Rail Infrastructure.*

1. Introduction

Digital Twin (DT) is the digital representation which links the physical and virtual model. It was initially defined by the National Aeronautics and Space Administration (NASA) as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin" (Shafto *et al.*, 2010). The Geometric Digital Twin (GDT) contains the core dataset of a DT; which is the geometry; on top of which all other structured data can be linked. The GDT is static throughout the infrastructure life cycle. Its first iteration is as-designed model (AD-GDT) during the design phase; as-built iteration (AB-GDT) during the construction phase; and as-is iteration (AI-GDT) during the operation phase (Koch et al., 2014). However, few assets today have a usable digital twin, because the perceived cost of creating and maintaining the DT counteracts the perceived benefits of the twin. This happens in part due to the labour cost required to manually build/maintain the digital model, which is roughly 10 times greater than laser scanning it (Fumarola and Poelman, 2011). This explains the need to automate the process of creating digital twins of rail infrastructure.

In this article, we provide a longitudinal view of current practice and the state of research of the geometric modelling process. We discuss the current state of digital twin in Section 2 and 3, and then outline the current practice of digital twin generation in Section 4. We identify the knowledge gaps in the DT generation of rail infrastructure in section 6 by thoroughly reviewing in two parts the past studies on the state-of-the-art DT technologies given on section 5. Finally, we elaborate potential research directions in section 7. The contributions made by this paper to knowledge highlight the knowledge gaps derived by the review.

2. Benefits of real-virtual synchronisation

Over the last five years, an estimated £770 billion worth of global investment has been expended to maintain and upgrade railway networks (Leenen and Wolf, 2018). The top industry challenges are capacity, operational efficiency and reliability, structural and component issues, safety and security (Love *et al.*, 2017). Among those, cost overspend, delays and shortcomings in scope and quality are

endemic features of rail projects. 48% of the rail projects failed to achieve the required baseline time, cost and quality objectives (Love, Ahiaga-Dagbui and Irani, 2016) while the Edinburgh Tram System being the latest to experience a cost overrun of over 100% (Love *et al.*, 2017). Hence, the need to maintain better documentation of the existing and under construction railways has been established.
UK is undertaking the biggest rail system modernisation programme for the 21st century with £48 billion for maintaining and improving the network (Crossrail, 2017). The majority of these railways were built before the advent of Computer-Aided Design (CAD) in 1977 and dates to 1830 therefore, working models are not available to assist any regenerating operations (NAO, 2014). Hence, these recent developments have resulted in an increased demand for digitised railway environments since it provides an opportunity to visualise, explore and plan railway scenes indoors (Bower, 2014; Love *et al.*, 2017; Bensalah and Elouadi, 2018). Research evidence highlighted that the DT can deliver 80% reduction in time, 10% saving through clash detection, 40% elimination of unbudgeted change (Eastman *et al.*, 2008; Furneaux and Kivvits., 2008), especially to address current hurdles in rail projects.

3. Challenges to exploit the digital twin

The creation of GDT is a complex process, starting with the acquisition of the Point Clouds (PCD)s, followed by the accurate creation of surfaces and the inclusion of information regarding the objects, such as materials and costs. While other applications of DT use automated sensor technology for this process, the construction industry still relies on manual processes. For instance, a recent laser scanning process was only 4 hours, whereas Three-dimensional (3D) semi-automated modelling of scanned 2,602 objects took 15 days (Fumarola and Poelman, 2011). Thus, despite its potential; its time, cost and knowledge-intensive nature, make GDT a laborious manual task. The total cost of DT generation can be broken down to fixed and variable costs. Fixed costs refer to fees for DT modelling software licenses, hardware required for the software, and training for inexperienced modellers. Variable costs spent on each individual modelling project, which are usually represented by the total modelling hours of and the corresponding hourly labour cost. Assuming the fixed costs and the hourly labour cost are constant, the total cost GDT generation is then determined by the total modelling hours. This means cost savings will be achieved if we can reduce the total modelling time by automated solutions. Hence, geometric modelling remains the "bottleneck" during the creation of DT of any rail element given how costly and time consuming it is.

4. Current Practice of Digital Twin Generation

The current practice of digital twin generation known as "Scan-to-BIM process" (Tang *et al.*, 2010) consists of 4 main steps (1) raw image and/or PCD capture; (2) data preparation; (3) geometric modelling; and (4) semantic enrichment of the model with additional information, such as topological relationships and material specifications. The final DT can be continuously updated using data collected from the sensors. As 3D data become popular nowadays, the advantage that PCDs can avoid problems such as illumination and background confusion, which are common issues in images and videos, has been realised. Airborne Laser Scanning (ALS) and Mobile Laser Scanning (MLS) are two LiDAR systems for acquiring accurate PCDs over large areas. According to the comparison given on Amos et al. (2018), ALS is the most robust method to scan over large areas, hence the ideal scanning technology for rail infrastructure.

Major software vendors such as Autodesk, Bentley, Trimble, AVEVA and ClearEdge3D, etc. provide the most advanced PCD-to-DT modelling solutions. Agapaki and Brilakis (2018) provided the pros and cons of current DT modelling commercial software. These software packages can automate to a large extent the DT generation process; however, they are still far from being fully automatic. For example, existing software packages can automatically extract the maximum number of planar features, up to 90% pipes in a plant PCD, and specific standard shapes like valves and flanges from industry catalogues (ClearEdge3D, 2017) followed by fitting built-in models to them, though a few clicks and manual adjustment. However, ClearEdge3D is tailored for building and industrial environments. In the following table 1, we elaborate the entire workflow of the DT generation of a typical double track railway from its PCD using CloudCompare 2.8.1 (2018) and Autodesk Revit 2018. According to the table 1 modellers must first manually segment a PCD into subparts, and then manually fit 3D shapes to the subparts. This demands a significant amount of attention when extracting the target objects and the fitting accurate 3D shapes to the segmented sub-point-clusters is quite challenging.

Table 1: Workflow of the manual rail infrastructure GDT generation from PCDs

Step 1: After registering the raw scans, the registered raw PCD of a railway is imported into CloudCompare.
Step 2: The PCD is sub-sampled using the Cloud Sub Sampling functionality in CloudCompare and then the sub-sampled result is saved. The reason for down-sampling the original PCD is that current modelling software such as Revit is an in-memory system which slows down significantly or even collapses when working with large PCD.
Step 3: The sub-sampled data is cropped, which aims to remove irrelevant points such as trees, vegetation, etc. Modeller needs to repeatedly select regions of interest to delete by creating polygons through CloudCompare's clipping functionality.
Step 4: The clipping functionality is again repeatedly used in order to segment the cropped PCD into individual sub-point-clusters, such as masts, rails, sleepers, and cables etc. which correspond to the components making up a railway. Each segmented sub-point-cluster is saved into an .e57 file.
Step 5: A Revit project is opened and a point cluster in .e57 file is imported by clicking the Insert Point Cloud tab. The .e57 file needs to be first converted into an .rcp file by an indexing process, and then positioned by shared coordinates. This procedure is repeated until all .e57 files are indexed and a set of .rcs and .rcp files are created.
Step 6: The sub-point-clusters are modelled one by one. Based on the geometric nature of the current point cluster, a modeller uses his or her engineering knowledge and modelling experience to decide the object's type and to fit the point cluster with (1) a generic shape from the built-in shape library, or (2) a manually created customized shape using Revit Family editor. For complicated point cluster like the cantilever, a modeller needs to fit it using multiple customized shapes by manually generating Family objects so that its overall topology can be approximated.
Step 7: Finally, the Revit modelling project can be exported into an .ifc file after a manual semantic enrichment process. To do so, a modeller can label each component with its real-world taxonomy and then choose a specific IFC setup (IFC2x3 or IFC4) to create an .ifc file. The final IFC file can be visualized in Solibri Model Viewer or any other IFC viewer

Next, modellers need to enrich other explicit and implicit information such as the component's taxonomy, the connectivity and aggregation and the defects. Finally, all detected shapes need to be exported in a common format such as Industry Foundation Class (IFC) format (table 1).

As explained, a modeller can only manually produce a railway GDT with components' labels using current software. However, this GDT modelling process is laborious, containing many repetitive processes. Step 6 is the most time-consuming step, with 95% of the total modelling time spent on customizing shapes and fitting them to the sub-point-clusters especially for rail infrastructure which generally lengths over kilometers. The results of this process summarize the "bottlenecks" of current software packages in modelling an actual railway DT. Firstly, existing software packages cannot automatically extract non-canonical shapes, which are frequently present in railways. Manual shape customisation is laborious. Secondly, the presence of occlusions and sparse data add hours of adjustments. Thirdly, the generated 3D models from existing software packages do not carry any implicit information. This information is necessary to produce a "meaningful" DT, which can be used to support the condition rating, including but not limited to the semantic meaning of elements, element materials, relationship, defects, schedule, cost, and maintenance history. Finally, there is no single software that can offer a one-stop DT generation solution. Modellers have to shuttle intermediate results in different formats back and forth between different software packages during the modelling process, giving rise to the possibility of information loss.

5. State of Research of Digital Twin Generation

The use of existing software packages in the DT modelling process is still human dependent to a great extent. Hence, much research effort has been devoted to automating the modelling process using PCDs and/or images.

5.1 METHODS EMPLOYING A BOTTOM-UP STRATEGY FOR RAIL ASSET TYPES

In bottom-up strategy, the individual base elements of the whole system are initially defined in fine detail, and arranging those elements together to provide a more complex system at the end (Borenstein and Ullman, 2008).

Arastounia (2015) proposed a sequential algorithm in which the recognition of objects is carried out separately and highly dependent on each other. First, track bed is extracted identifying points with uniform-height neighbourhood. However, this method recognises rail track points as track bed points hence needed a further segmentation process. Thus, considering their three primary properties such as height variation on the track bed; continuity; and smooth curvature gradient, tracks were separated from track bed points. Overhead cable structure points were then identified based on the track bed points by first considering the 3D vector connecting each non-track bed point to its closest point on the track bed. Cable points were then filtered using their linearity and the rest of the points considered as mast and cantilever points. The sequential identification implies that a failure in recognition of an object leads to failure in detection of the remaining objects which was a major limitation of the study. Also, the performance of the algorithm deteriorates for poorly sampled data includes more diverse features such as humans, cars, and buildings in a much denser configuration. This issue emerges due to its low sampling rate and complicated configuration. Furthermore, the neighbourhood analysis imposes a significant computational load (taking roughly 3 hours). Addressing limitations of this method, another algorithm has later improved the computational efficiency of the rail track extraction by coarsely classifying all of the data based on height of points into three clusters from which the rail tracks, contact, and catenary cables are identified (Arastounia and Elberink, 2016). The rough classification assumes that the vertical spatial offsets among the railroad assets are constant throughout the entire dataset. This assumption holds for most parts of the urban rail corridors, but it may not be the case in rural rail corridors such as mountainous areas whose track bed may experience a large slope.

Yang and Fang (2014) used the geometry and intensity data to detect objects belong to the track structure. Initially, the track bed was identified using spatial patterns of the scanning lines. Rail points were then located using shape features such as height and slope and intensity data such as incidence angle, and the material features of the surface. However, this method only focused on the extraction of rail tracks and other objects are not recognised and highly depend on the scanning geometry. Also, the method is less accurate in extracting forking junctions. This is due to the complexity of track geometry, the existence of side tracks, and constructive measure.

Jwa, Sohn and Kim (2009) used Voxel-based Piece-wise Line Detector (VPLD) to automatically reconstruct 3D powerline models using PCDs. The method uses voxels to detect powerline candidate points from the unclassified raw laser scanning data; line compass filtering to determine powerline orientation; outlier testing and segmentation to extract powerline primitives and finally VPLD for 3D powerline reconstruction. This method assumes that the transmission line is continuous within one span and the direction of the powerline is not changing abruptly within a span. Furthermore, partial detected powerlines occur in case that powerline passes through vegetation and powerline points are sparsely distributed at the lower height. In case of un-detected part, as powerline points with low point density can be grouped as other object, the powerline cannot be extracted in the VPLD process. Hence, the assumptions decrease the performance of the method, and the accuracy of the results obtained was limited due to its' under and over segmentations. To avoid under- and over-segmentations, later they improved the method with a multi-level span analysis (Sohn, Jwa and Kim, 2012). They proposed a piecewise catenary curve model-growing algorithm to identify the points, which achieved clustering by iterative catenary curve fitting and cubic growing. Power cables in Jwa, Sohn and Kim, (2009) and Sohn, Jwa and Kim (2012) were recognised using polynomial functions to fit models to catenaries. The piecewise model growing (Sohn, Jwa and Kim, 2012) precisely modelled power-line spans with catenary curve models in 3D, once the pylon localization is accomplished. Yet, these methods assumed that the powerlines were parallel. In practical applications, cables are not always parallel.

A similar approach has been used in Cheng *et al.* (2014), where a voxel-based hierarchical method is developed for extracting power line points from PCDs. For the power line point's extraction, two hierarchical layers were used namely; single voxel filtering and neighbouring voxel filtering. This method only considered the point distance, and it ignored breakage points, which may have detrimental effects. Finally, a polynomial function is used to fit the power line points to obtain the 3D power lines. The Hough Transform and Euclidean Distance clustering were used to extract power-line points in the identified non-road points in Guan *et al.* (2014). However, previously mentioned algorithms cannot fit to a complex railway point data very well as there are a lot of lines in railway traffic circumstances, yet only part of them is power lines. Those methods cannot distinguish a power line from a vertical suspension wire and a horizontal suspension wire in the wire net and cannot find the joint region of the power line either.

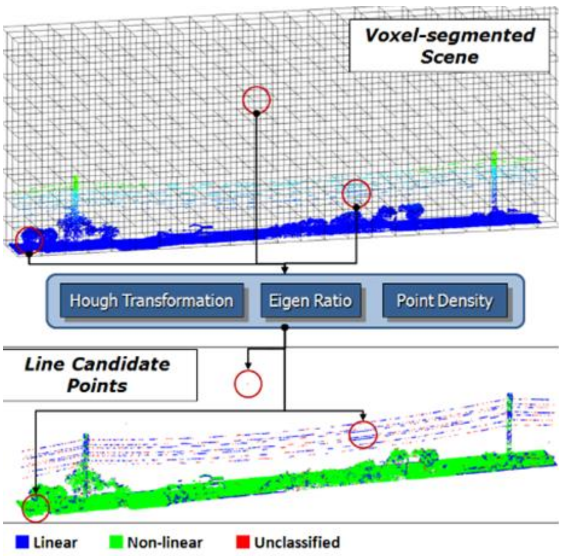

Figure 1: Voxel-based Piece-wise Line Detector (Jwa, Sohn and Kim, 2009)

RANdom Sample Consensus (RANSAC) line detection was used in Guo *et al.* (2016) to detect powerline points. Prior to the reconstruction of power lines, they classified points into five categories (power line, vegetation, building, ground and pylon). Due to the detection rate of power-line points and data gaps, there are still several defaults of the performance of their reconstruction method. Furthermore, they have circumvented the sag of power-line span; which changes with the time according to the ambient conditions such as the temperature and the ageing of span.

5.2 METHODS EMPLOYING A TOP-DOWN STRATEGY FOR RAIL ASSET TYPES

The top-down strategy begins with a broad-picture view, breaks it down for gaining an insight into a few major compositional sub-systems followed by individual solutions for each sub-system (Kokkinos and Yuille, 2006).

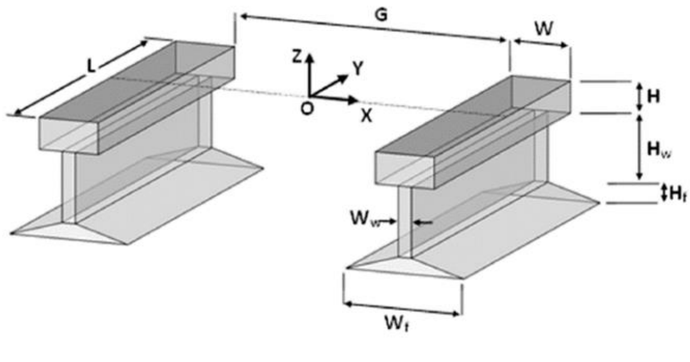

Figure 2: Parametric model of a pair of two rail pieces (Elberink and Khoshelham, 2015)

The method proposed in Elberink and Khoshelham (2015) used top down strategy to detect the rail track centrelines using piecewise model fitting. Firstly, they coarsely extract the rail tracks by using local properties of rails such as height and parallelism; using grid wise height histogram analyses. The fine extraction of the rail track was done using a 3D rail model, which was generated by fitting parametric pieces to point segments along the rail followed by interpolating a smooth and continuous rail model between the pieces. This method was computationally intense due to; (a) the least squares adjustment applied to every piece of rail track; (b) the employed mathematical model has too many unknown parameters; (c) the utilised least squares adjustment is a non-linear model, which needs to be linearised and run in many iterations in order to deliver acceptable results; and (d) the Fourier series is applied (after modelling) to enforce the smoothness in the rail tracks' shape, which imposes even more computational load. Addressing the limitations of this method, Arastounia and Elberink (2016) proposed a method which identified points belonging to rail tracks by fitting a Two-Dimensional (2D) grid to the track bed and investigating the height variation within each grid cell. This method significantly decreases the computational load. Local neighbourhood distribution of PCDs in 3D space (including the height information) was analysed for the initial classification of rail tracks. This is followed by a customised template matching algorithm for the elimination of rail track false positives by considering the topological relationship among rail tracks and cables. The template matching used a simple equation which obviously is computationally very much less intense than previous methods (Elberink and Khoshelham, 2015) presented.

6. Gaps in knowledge

The existing methods in bottom-up strategies are computationally less intensive than top-down strategies however, the latter is likely to produce better results when the dataset point sampling is poor. Furthermore, 'top-down' methods are very useful in recognising parameterised-shape objects that are composed of geometric primitives such as planes and cylinders. The dominant approach used by the researchers is bottom-up process, since the physical shape of the railroad elements are more complicated than those of geometric primitives. The current practice and the state of research summarises the following research gaps, which remain as challenges in digitally twinning the geometry of existing rail infrastructure.

The existing methods for rail track detection cannot be applied for sloped rail tracks, as well as short radius track curvatures. In practice, these remain as major limitations for digital twin generation, as tracks contain varying horizontal and vertical elevations as they are (a) not always flat-sloped and (b) along the track, short radius curvatures are a frequent occurrence. Current methods have provided promising results for overhead cable system, yet most of these methods lack precision and accuracy. For instance, their assumption that the contact and catenary cables are parallel and straight is debatable for railroad environments (Jwa, Sohn and Kim, 2009; Sohn, Jwa and Kim, 2012; Guo *et al.*, 2016). In addition, many methods have dependencies over scanning geometry and neighbourhood structures

(Arastounia, 2015). Furthermore, no attempt was made to automatically detect sleepers and droppers in both state of research and the state of practice to our best knowledge, despite the substantial cost incurred for manually modelling them.

7. Summary and discussions

The use of DTs for existing rail infrastructure is limited as the perceived benefits outweigh the cost of and the effort required for DT modelling. The average time required to manually create an infrastructure GDT from a PCD using cutting edge modelling software (e.g. Autodesk Revit 2016) is about 10 times more than the time required to obtain the PCD, as the current software packages are not fully automatic. This stresses the need for automating the PCDs-to-GDT process.

The knowledge gaps in the DT generation of rail infrastructure were identified by thoroughly reviewing in two parts the past studies on the state-of-the-art DT technologies. The approaches presently available cannot effectively tackle the detection of sloped rail tracks, as well as short radius track curvatures. In addition, none of them can address the challenges of complex geometry and topology of overhead cable system where the sag and the unparalleled structures are frequent. Moreover, the existing methods cannot automatically detect and reconstruct sleepers and droppers despite of the cost and time incurred to manually model those assets. The contributions made by this paper to knowledge highlight the knowledge gaps mentioned in Section 6. These gaps lead to potential research directions such as;

(a) Investigating a method to automatically detect rail infrastructure assets in PCDs – These assets include rails, sleepers, track bed, cables, masts and cantilevers. The approach will differ with the non-idealised shape of the particular asset type. In addition, this approach can combine the strengths of the data-driven strategy scenarios with very high point densities and model-based strategy in scenarios with very low point densities. For instance, on a railway track PCD the vast majority of points are concentrated on the elements sitting on the ground, with a lot fewer points on the overhanging cable structure. This leads us to safely hypothesize that the number of points per asset type on the wire-like assets is substantially less than the rest, and likely inadequate for traditional 'data-driven methods searching for local features. On the other hand, no such restriction applies to the rest of the assets.
(b) Investigating a method to automatically fit 3D solid models to the detected point clusters – To tackle the need of the common format, the output 3D model shall compatible with many software available, such as Industry Foundation Class (IFC) format.

(c) Leveraging a reasonable 3D model assessment metrics to assess the generated GDTs of rail infrastructure – This is necessary as the problem of evaluating the quality and degree of automation of a generated GDT compared to its PCD has yet to be studied in depth. This assessment must compatible with the end user requirements and the level of the detail expected from the resulting model.

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