A Conceptual Framework for Updating Urban Infrastructure in City Digital Twins

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Abstract

This work presents a conceptual framework for updating urban infrastructure by separating the update process into two loops, the data loop and the application loop. The key aspect of the data loop is intelligent change detection followed by validation strategies to maintain an up-to-date catalogue of city infrastructure. The updated catalogue can subsequently utilised to create user-centric digital twins. The advantages of using such a framework are presented, in addition to discussing the challenges and their possible solutions. Further, the scope of integrating advanced change detection approaches, new data structures such as Knowledge Graphs and Voxels, and AI methods such as the recent Large Language Models (LLM) and Continual Learning are discussed.

1. Introduction

Building digital twins usually involves capturing the appearance and structural details of the city infrastructure using photogrammetry, aerial LiDAR (including DEM), mobile laser scanners and terrestrial laser scanners. While photogrammetry models (photomesh) are commonly used to create digital twins, terrestrial and mobile laser scanners provide accurate structural information that is crucial for accurate 3D modelling. Vector data such as CityGML, BIM and Shapefiles have also been used. The real-time data from the IoT sensors represent the current state of the digital twins' dynamic objects (or systems such as transportation). However, changes to the appearance, structures and other city infrastructure happen continuously, which need to be incorporated into the digital twin.

Updating digital twins, particularly in urban environments, presents significant challenges due to several interconnected factors. One of the primary difficulties is the dynamic nature of urban landscapes (Lei et al., 2023), where features such as vegetation, infrastructure, and land use are constantly evolving. These changes can be rapid and occur at varying scales, making it difficult to capture and integrate updates in real time. Additionally, urban environments are often complex, with dense and heterogeneous data that include both spatial (e.g., 3D point clouds, GIS data, etc.) and temporal data (e.g., construction changes) (Jeddoub et al., 2023). Ensuring that these updates are accurate, consistent, and timely requires sophisticated data collection and processing technologies.

The usual trend for updating the digital twin involves creating a new one from scratch (Lei et al., 2023). While this is a straightforward process, it might present additional challenges. For instance, significant changes can occur during the update interval, which is largely dependent on the available budget and infrastructure, and could occur once in several years. Moreover, the knowledge of the change detection which is useful to model in several scenarios has to be generated separately and comes at an additional computational overhead. Furthermore, several challenges arise due to the dynamic nature of the urban environments and due to the use of diverse data sources to create digital twins. These challenges include data quality, interoperability and data integration. Therefore, subsequent to updating the digital twin, validation is required to ensure the updated digital twin accurately represents the real world. Without validation, there is also a risk that the digital twin may diverge from reality (Lehtola et al., 2022), leading to flawed insights that could impact urban planning, policy-making, climate resilience, infrastructure management and other critical applications.

This work proposes a conceptual framework for updating urban digital twins. The update is performed in two separate loops: Data Loop and Application Loop. The data loop runs continuously and keeps an updated catalogue of city infrastructure as more data becomes available. The application loop uses the updated infrastructure catalogue to create a city digital twin based on the application area defined by the user. Several aspects of the framework can be automated, and the two-step validation will ensure the correctness of the created city digital twin for the application.

The advantage of integrating change detection into the data loop is that it can be used to update *only* parts of the digital twin that have changed, instead of updating the whole digital twin. This way, if no change is detected, then the digital twin can operate as is. Additionally, the update interval (latency) of the framework is low as the changes are frequently incorporated compared to updating the whole digital twin at once. Further, the framework allows the integration of data that has not been specifically captured for updating the digital twin, thereby reducing the cost of update. Finally, the addition of change detection will enable the end users to understand their physical environment better, enabling better visualisation of changes in 3D data. Motivated by the recent success in 3D change detection approaches (Stilla and Xu, 2023; Xiao et al., 2023) that are robust to dynamic and changing environments, this study proposes the integration of such approaches in the data poop.

Section 2 presents the background, Section 3 introduces the different phases of the conceptual framework, and Section 4 discusses a case study, followed by conclusions and recommendations.

2. Background and Relevance

Key principles of complex systems are vital for understanding urban environments, particularly through digital twins that model dynamic city interactions. Interconnectedness, a central principle, refers to the interdependence of urban subsystems such as transportation, housing, and the environment (Batty, 2024). Digital twins effectively represent these links, showing how changes in one area, such as transportation, can impact others, like air quality (Wang et al., 2023). Digital twins can also simulate non-linear effects, where small perturbations can trigger disproportionate impacts across the system, thus providing insights into potential cascading consequences (Jiang et al., 2024). Further, digital twins enable data integration across multiple scales and multiple contexts, from modelling individual buildings to modelling entire city infrastructures supporting a holistic analysis of urban systems (Jia et al., 2022). Adaptability, another key principle, emphasises a city’s capacity to respond to both internal and external *changes*. Digital twins enhance this adaptability by integrating real-time data and simulating various scenarios, including policy changes or environmental disruptions (Xia et al., 2022). Together, these principles equip digital twins to capture the complexity of urban environments and support informed, adaptive decision-making.

Recent research has recognised the value of integrating complex systems theory into the development and application of city digital twins, and several frameworks have been proposed. Deng et al. (2021) propose a Digital Twin City framework which consists of Infrastructure construction, Urban Brain Platforms and new Applications, and propose several research directions including the Data Center, the City Information Model (CIM), the urban smart brain and the security guarantee mechanism. Raes et al. (2021) propose an additional framework containing models and data in a common environment which can be used for dynamic simulations to help city decision-making. Further, Supianto et al. (2024) propose another digital twin for urban digital twins for sustainable digital transformation which consists of six main components, mainly Physical entity, Data, Virtual Entity, Services, Users and Connections between these components. Additionally, some frameworks are application-specific, e.g., integrating federated learning (Ramu et al., 2022), improving city logistics (Belfadel et al., 2023) and urban heat island mitigation (Omrany and Al-Obaidi, 2024). Differently, Caldarelli et al. (2023) propose a framework where cities are not merely as considered as large machines or logistical systems but as self-organising phenomena that evolve similarly to living systems. Lei et al. (2023) discuss the lifecycle framework consisting of six phases, v.i.z. Collecting, Processing, Generating, Managing, Simulating and Updating. The authors highlight the importance of *updating* changes and *versioning* city digital twins and the involved challenges.

The literature review reveals that there is a lack of a unified framework that can integrate change detection to frequently update the digital twin. Further, many of the digital twins are application-specific and there is a requirement for a framework that is independent of user applications.

3. Conceptual Framework

As shown in Figure 1, we propose a two-phase framework designed to address the inherent complexity and dynamism of urban systems containing two loops: Data Loop and Application Loop. The data loop is integral to ensuring the creation of an updated and accurate catalogue of the city’s infrastructure enabled by validation strategies. This loop consists of a data collection step which holds the existing data and a placeholder for new data as it is available. Multi-source data fusion is performed to detect changes in the infrastructure. The detected changes are validated to ensure their correctness (more discussion in Section 3.5). When a change is detected, it can be passed to the application loop to keep the digital twin updated.

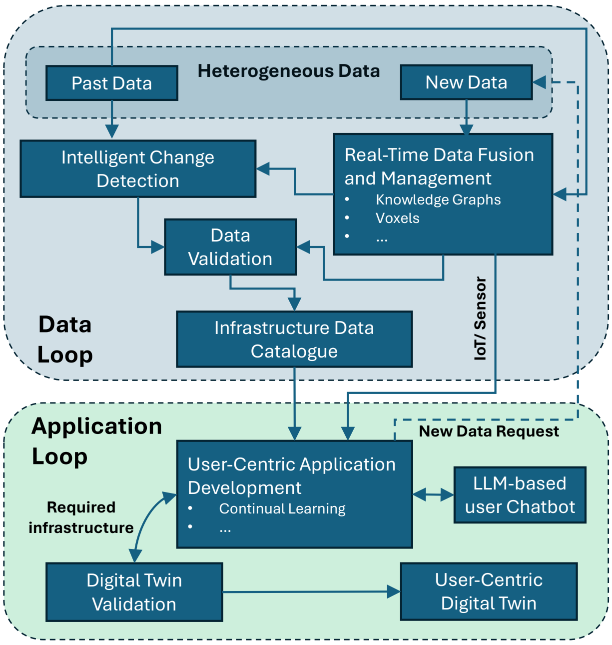

Figure 1. Overview of the main phases of the framework.

Application Loop aligns the framework with the user needs, where the generated digital twin will facilitate specific decision-making and support the development of sustainable urban environments. This loop consists of a User-Centric Application Development component that identifies the required city infrastructure, including the real-time sensors for integration into the digital twin. The created digital twin can be validated using experts or citizens using the Human-in-loop validation strategy or rule-based strategies. The output digital twin can then be used for simulating different scenarios, which will provide real-time insights for planning and management, thus providing feedback to the physical twin. In the following paragraphs, the individual components of the framework are described in detail.

3.1 Heterogeneous Data

Creating city digital twins involves using a broad range of data to model the 3D geometry of the cities (including terrain and the buildings), other auxiliary or system information like road networks or metadata, and the real-time state of the city’s infrastructure and the residents (Jeddoub et al., 2023). For geometrical and structural details, photogrammetry, laser scanning (including mobile, terrestrial and aerial), remote sensing and survey data are used, whereas GIS databases and other vector data forms are used to provide the additional auxiliary information. The real-time state of the city’s infrastructure and the residents are collected by a network of IoT sensors.

The two loops: We break two components of the framework into two parts; past and new data. Past data refers to the collection of existing heterogeneous data (excluding the sensor/IoT data), whereas the new data refers to new data scans, the availability of new databases and the real-time sensor/IoT data. The past data is *only* used as a reference to perform Intelligent Change Detection, whereas, in addition to performing the change detection. The new data is used to update the city's Infrastructure Data Catalogue and subsequently in the next loop to create digital twins.

Alternative data sources can be used to update the city's infrastructure, for instance by mounting cameras or laser scanners to council garbage trucks that traverse the whole city every week (Anjomshoaa et al., 2018). Similarly, the laser data from self-driving cars can be used integrated for more frequent data collection of the city landscape. That way any additional data that does not exist in the city's Infrastructure Data Catalogue can be requested through this pipeline. However, this data collection method will be limited largely to public roads, and we need to rely on crowdsourcing by crowdsourcing by citizens in other areas. In addition to 3D point clouds and 3D models (that can be sourced from Building Information Modelling IFC format or large-scale CityGML files), alternative sources of data include reports, images, maps and GIS shapefiles (2D vector data). However, significant challenges exist for the interoperability of such diverse datasets (see the paragraph on integrating heterogeneous data in Section 3.2).

Integrating scheduled activities of the city, such as new constructions, demolitions, or renovations as a part of the data acquisition process will capture the known changes with certainty. The city's construction projects often have intermediate survey results of progress and generate final as-built models at completion. A central platform or an API can be created, where the information about these changes can be integrated automatically. Further, in the case of missing data, open datasets can be utilised to gather additional information (discussed more in Section 3.4).

3.2 Data Fusion and Management

The task of this component is to combine and harmonise multidimensional data from diverse sources operating at different spatial, temporal, and thematic scales. This phase ensures the integration of slower-changing datasets like 3D point clouds, satellite imagery, census data, infrastructure layouts, and environmental conditions, ensuring the model consistently reflects the evolving urban landscape. However, such a data integration component will be limited by the type of sensor used for data collection, scalability, data standards and accuracy (Lei et al., 2023). To handle the vast and continuously growing volume of urban data, automated and scalable processing, in addition to validation is essential.

Integrating heterogeneous data: is the first step that is achieved within the data fusion and management component of the data loop, and deals with the interoperability of multi-source datasets. Spatial Database Management Systems (SDBMS), such as one proposed by Li et al. (2020) can be used to tackle the challenges. The authors develop semantic precinct information modelling based on multi-source heterogeneous data and present a case study. Further, solutions such as those proposed by Diakite and Zlatanova (2020) for the integration of BIM with GIS can be utilised.

Voxels: Datasets are flawed by errors, contain data gaps, and the same data type can contain large variances. For instance, depending on the type of laser scanner (aerial, mobile or terrestrial) used for data acquisition, the point density can largely vary. Approaches such as the use of *Voxels* (Stilla and Xu, 2023) are used to tackle the challenge of such data integration and can allow the modelling of city-wide phenomena, thus making it scalable (Gorte et al., 2024). Also, Voxels can be optimised for parallel computation to speed up the processing times. On the other hand, they come with the limitation of information loss and high requirement of computer resources (such as RAM). Voxel-based modelling is an active research area, and several well-established approaches exist that can offer a high level of autonomy thereby facilitating the continuous integration of new data.

Semantics and Knowledge Graphs: Semantic information plays an important role in decision-making. The data used for creating digital twins often contain additional semantic information and metadata that can be used to create *Knowledge Graphs* (Ramonell et al., 2023) which can be used for creating APIs for advanced queries, data traversals and complex data retrievals. One advantage of using such a data structure will be the ability to perform *context-based change detection* and to create different *versions* of city infrastructure.

Handling real-time data derived from IoT devices, sensors and other sources is required to ensure the digital twin reflects the current state of the physical world. This aspect requires reliable and robust data pipelines capable of handling high-frequency and time-series data updates while minimising latency, and synchronising different data formats while preserving the quality. Addressing these challenges requires advanced data processing platforms, standardised communication protocols, and robust architecture design. Key technologies include edge computing for localised processing, APIs for standardised data input, and streaming platforms. Prominent platforms include Apache Kafka for high-throughput and low-latency streaming, Apache Flink for advanced event-driven processing, and cloud-based solutions like Microsoft Azure Stream Analytics or Google Cloud Dataflow for performing real-time sensor integration and predictive analytics. These platforms allow digital twins to reflect real-time changes which occur in the physical world and support advanced applications and adaptive control, such as predictive analytics, scenario modelling, and emergency response planning. Alternatively, open-sourced tools for real-time IoT sensor data integration can be used to improve accessibility and repeatability, for instance, the study by Diakite et al. (2022). The authors develop a demonstration project by integrating standardised 3D data from CityGML and integrating urban infrastructure such as buildings, roads, vegetation, water bodies, etc., and store city features in a 3D city database called 3DCityDB.

3.3 Intelligent Change Detection

Intelligent change detection focuses on identifying the deviations or transformations in the urban environment resulting from changes in the city's infrastructure, such as structural changes of the buildings or new constructions, infrastructure deterioration, land use changes or anomalies that are not so obvious. Using the past data as a reference, changes can be detected using time-series analysis of 3D models, point clouds, remote sensing data or other slow-changing datasets.

Challenges lie in the selection of the approach for performing change detection, as well as the selection of the reference data (Jeddoub et al., 2024). For instance, let us consider a new point cloud data captured using a mobile laser scanner in a city's public park. For change detection:

- We first need to identify the existence of previous datasets covering the area. The existing data could be point clouds collected from aerial LiDAR or UAV having significantly different properties, or it could be sourced from a photogrammetry model created using drones. Alternatively, the past data could be in the form of vectors, 2D shapefiles or 3D models.
- Change detection of 2 point clouds can be performed directly using several robust and established methods (Stilla and Xu, 2023). For the point cloud-to-vector change detection, two approaches can be used; performing change detection directly (point cloud-vector) or converting the point clouds to a 3D/2D model first and doing model-model change detection.

The decision will largely depend on whether the changes are required in a point cloud format, vector format, or other required data formats which is dependent on the Infrastructure Data Catalogue.

Dynamic objects such as people, cars, etc., pose challenges during data collection, which can result in erroneous change detection, especially for point-based change detection algorithms that do not consider semantics. Recent advancements in semantic-based (also known as object-based) change detection algorithms, which apply to both image and 3D data, can be used to segment those dynamic objects for robust mapping of the physical world (Stilla and Xu, 2023). An additional advantage of using these approaches is the classification of infrastructure or objects into known categories (e.g. people, cars, buildings, vegetation, roads, etc.) which provides additional context for *thematic analysis* and can be used to update relevant categories to the updated Infrastructure Data Catalogue. Further, the identification of the dynamic objects over a longer period might enable further analysis of the trends without explicitly collecting that information, e.g., which areas pedestrians take often while walking on the footpaths (Pomerleau et al., 2014). Alternatively, voxel-based (also known as occupancy-grid-based) difference approaches are also a popular way of performing change detection, especially under varying point densities and occlusions. Moreover, voxel-based approaches present some additional benefits for large-scale volumetric calculations and data visualisation (Crassin et al., 2009).

Versioning: Another relevant question will be whether to keep the most updated 'snapshot' of the city infrastructure at a particular time or to keep all the spatio-temporal links between the snapshots in time by keeping different 'versions' of the infrastructure (Eriksson et al., 2021). Keeping different versions will allow us to make small, but incremental changes to the infrastructure, thus reducing the latency of synchronisation, which will result in a more accurate representation of city digital twins. Lei et al. (2023) points out that the main setback of implementing different versions of the model is to know the changes between the versions, and this is the major setback for practical implementation. The Intelligent Change Detection component of the framework will facilitate the versioning of the city digital twins.

Supporting analysis and visualisation: The knowledge of the change itself can be utilised later in the framework for analysis and visualisation. For example, in vegetation monitoring, changes can be detected over canopy cover, plant health, or deforestation by using temporal analysis of aerial LiDAR and remote sensing data. Early identification of such changes will allow for proactive interventions, such as scheduling plantations, addressing environmental stressors, or optimising greening policies. Furthermore, anomaly detection approaches can be integrated into this component of the framework to identify changes that are not obvious (Lu et al., 2020). By capturing these shifts, Intelligent Change Detection enhances the adaptability and effectiveness of digital twins in supporting sustainable management and planning efforts.

3.4 User-Centric Application Development

The component of the User-Centric Application focuses on *tailoring* digital twin applications to meet the needs of the end-users, ensuring their usability, relevance, and engagement. These goals are achieved by prioritising and aligning the digital twin's functionalities with the users who interact with it, including city planners, heritage conservators, ecologists, citizens, or utility managers. A comprehensive list of applications can be found in Lei et al. (2023) and Ramu et al. (2022), and Jeddoub et al. (2023) present several case studies. Additionally, this phase serves as a guiding principle for all subsequent components because it ensures that data collection, modelling, and decision-making processes are rooted in real-world concerns and practical applications. Without this user-focused objective, the digital twin might become an abstract tool disconnected from the needs it is meant to serve, leading to inefficiency and low adoption.

New data request: Using such a user-centric component will allow the utilisation of the Infrastructure Data Catalogue to create a digital twin for monitoring the environmental impacts on the structures of a heritage site or it could be used to create a flood resilience digital twin for the proactive mitigation of emergencies. If during the creation of a digital twin, some critical data is missing, it can be requested from the Data Loop (shown in the dotted line in Figure 1). For instance, open data that are easily accessible, such as a real-time public sensor API, historical flood records or crime rates can be incorporated automatically from the official government websites. Also, as mentioned in Section 3.1, new data can be acquired by the city garbage trucks or self-driving cars.

Use of Large Language Models (LLM): Another aspect to consider during the design of a framework is the domain knowledge of the users. Even a domain expert using such a framework might not be technically sound - an urban planner might not know about complex databases or advanced AI-based change detection algorithms. Therefore, there is a need to integrate tools to make the framework user-friendly for a wider range of users, including citizens. Recently, AI-powered LLMs have been widely popular for creating chatbots for answering complex domain-specific questions. LLMs are now being adapted into several geospatial frameworks to automate processes with minimal input from non-technical users (Li and Ning, 2023). For instance, Zhang et al. (2024) use an LLM that can interact with natural language and can serve as an assistant for GIS professionals by conducting geospatial data collection, processing, and analysis in an autonomous manner. Integrating such tools will create a wide range of applications and acceptability of digital twins across several industries. Imagine a future city planner's instructions to a chatbot: "*Simulate and visualise how many trees should be planted in Carlton Gardens along with* *their locations to cover at least 50% of the pedestrians who are walking in the park's trials with shadows during the summer months*."

Data selection for digital twins: The next question will be the identification of the relevant data for creating the user-centric digital twins. For instance, Omrany and Al-Obaidi (2024) propose a conceptual digital twin for urban heat island mitigation. The authors consult past studies to identify the key phenomenon and the data required to create such a digital twin. Similarly, for other application areas, these attributes can be selected based on the case studies. where decision trees can be used. However, in the case of novel user-centric digital twins, this strategy will fail. While some automation can be done by the use of the LLMs that can propose the possible data for integration by reading the previous works, expert validation must be performed before creating the twin.

Continuous learning: Lastly, keeping an updated model will mean it will change frequently. An important question here in the context of AI models is whether they need to be regularly updated. While this might not sound like a huge task, there is a significant computational and energy demand associated with training such models. AI models have also shown to *forget* tasks following a re-training with new data. A possible solution to tackle this challenge will be the integration of AI models that can learn continuously, by rapidly learning new knowledge by performing small but frequent changes, without forgetting what was learned before. This approach is called Continual Learning and has been applied to several areas including transportation, public health and safety and environmental monitoring (Yang et al., 2024).

3.5 Validation

Validation mechanisms ensure the accuracy, reliability, and trustworthiness of digital twins, and include benchmarking digital twin outputs against real-world observations, historical data, or established models. Validation can occur at multiple levels: data validation (ensuring raw inputs are accurate and free of errors), model validation (testing algorithms and simulations against known outcomes), and system validation (ensuring the twin's performance under various scenarios). Continuous validation, combined with stakeholder review and quality assurance protocols, maintains the integrity of digital twins.

Two-step validation: In the context of this work, the steps involved in validation differ between the two loops due to their distinct data and processing needs. In Data Loop, the validation phase ensures verifying the accuracy of data fusion and multi-source integration, ensuring that diverse data sources, such as laser scanning, photogrammetry, satellite imagery, traffic data, metadata and the relationship between them are correctly combined. For Application Loop, validation focuses on accurately reflecting the system's behaviour. This step involves real-time data integrity by checking for completeness and consistency, confirming that the updates like environmental monitoring or infrastructure status are accurate before analysis or decision-making.

Scope of automation: Both validation methods can be automated using rule-based techniques, where rules can be custom-made or can come from geometrical constraints, policies, or data standards. Most laser systems come with proprietary software that allows preliminary quality checks related to noise and potential data issues, and provide automatic tools for analysis, e.g. point classification. In addition, quality checks of the 3D point clouds can be performed by evaluating their accuracy, correctness and completeness (Khoshelham et al., 2017, 2018), or in the context of 3D cadastral data (Asghari et al., 2020) it can be performed by examining the 3D digital plans. Some studies have reported the use of open-source geometry validation software like Val3dity, or have used CityJSON Validator (Kharroubi et al., 2024). Another possibility of automated validation is to use alternate sources of information, for instance, visual information from Google Street View.

Human-in-loop: Despite the automatic methods of data validation, human validation is mandatory for the correct functioning of any of the two loops. In the Data Loop, the Infrastructure Data Catalogue must be visually reviewed by experts or citizens to check the correctness and consistency. This kind of human-in-loop validation can be performed using 3D game engines where the users can navigate freely in the virtual cities to point out errors or improvements. Computer-Aided Virtual Environment (CAVE), and Virtual Reality (VR) platforms can be used for viewing data, while Augmented Reality (AR) can be used for real-time data collection. A case study is presented in Ham and Kim (2020) where the authors propose a crowd-sourcing framework to integrate vulnerable objects (such as a broken electric pole) visually into the digital twin and use CAVE for interactive visualisation. Validation from citizens or experts can also be done by using crowdsourcing open web-based platforms like OpenStreetMap (OSM) where erroneous or outdated infrastructure can be reported, similar to the study conducted by White et al. (2021).

4. Case study: The Royal Exhibition Building and Carlton Gardens

Laser scanning was performed in 2024 using a backpack mobile mapping system developed by The Department of Land Surveying and Geo-Informatics, Hong Kong Polytechnic University (PolyU). The location was Carlton Gardens which consists of a complex layout of vegetation (trees with varying canopy densities, grass and shrubs), pedestrian pathways and the UNESCO World Heritage-listed site, the Royal Exhibition Building. We also collected aerial LiDAR data[1] from the Department of Transport and Planning, Victoria, which was captured during 2017-18 to perform change detection. Additionally, we gathered a photogrammetry mesh and a UAV-sourced laser scan of the Royal Exhibition Building (Khoshelham, 2018) which was collected in 2017. The backpack laser scanning data was geo-registered, subsequent to sub-sampling all the datasets to 10 cm resolution. Noise and outlier filtering was performed on all the datasets. Cloud-to-cloud distances are calculated using open-source software CloudCompare to visualise change detection. The preliminary results of change detection for the aerial LiDAR data and photogrammetry-derived point cloud data are shown in Figure 2 and Figure 3, respectively.

Comparing the mobile laser scanner data with aerial LiDAR data (Figure 2), we observe that most of the changes are observed in the large trees in the Carlton Gardens (bottom half of the scene). The changes observed in the structure of the Royal Exhibition Building are very small (top centre of the scene). We also observe a new construction, near the top right which is

[1] Data download available at: `https://www.land.vic.gov.au/maps-and-spatial/imagery/elevation-data/major-lidar-projects/greater-melbourne-lidar-2017-18`

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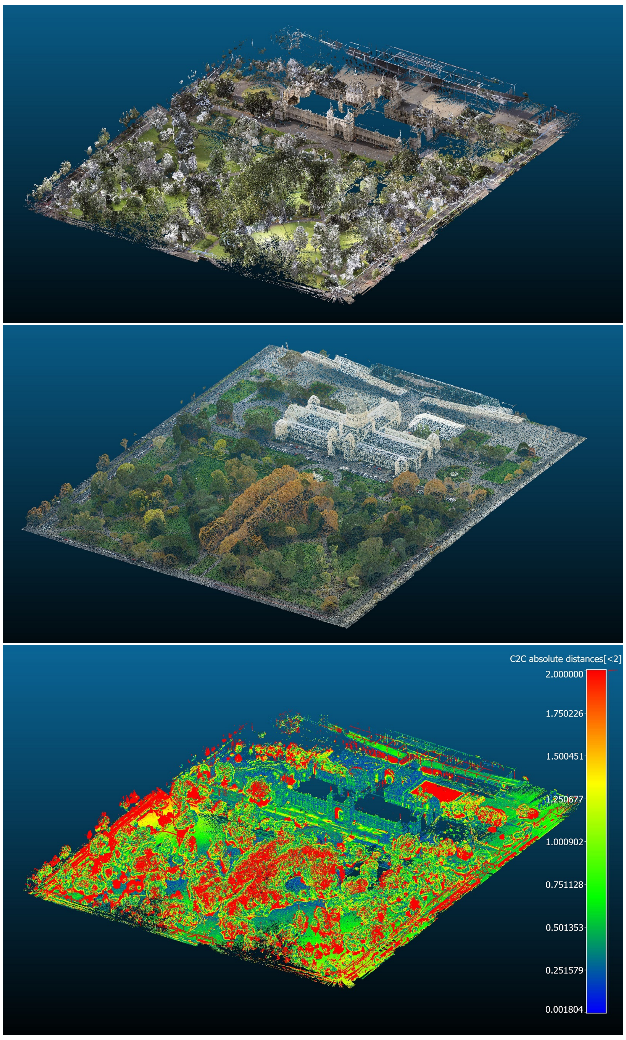

Figure 2. Visualisation of the changes using mobile laser scanner and aerial LiDAR data. Top: Backpack laser scanner data. Middle: Aerial LiDAR data. Bottom: Colour-coded detected changes.

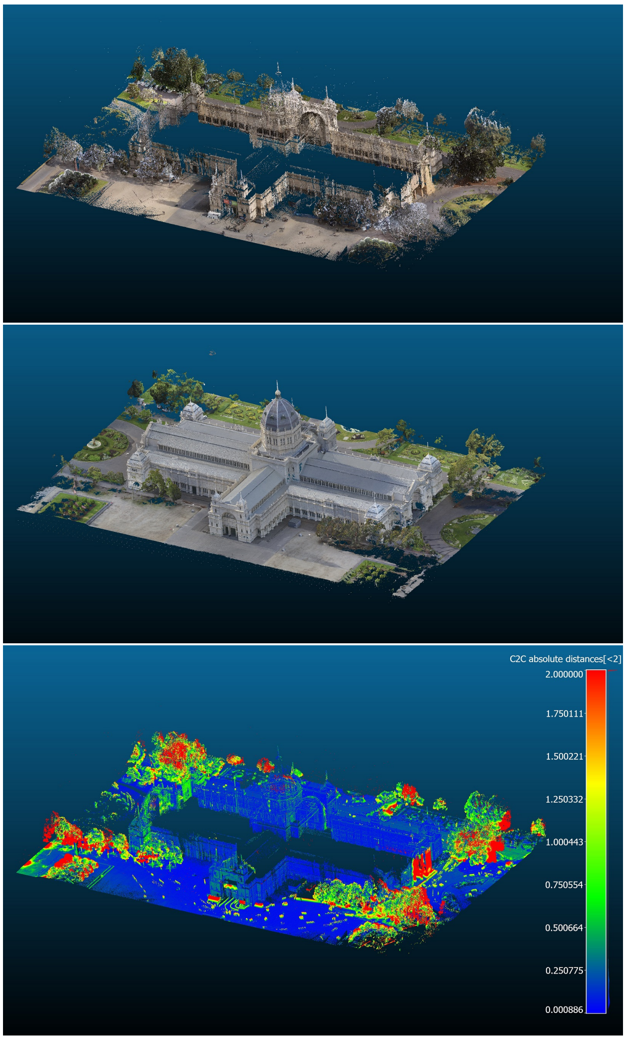

Figure 3. Visualisation of the changes using mobile laser scanner and aerial photogrammetry data. Top: Backpack laser scanner data. Middle: Photogrammetry-derived point cloud data. Bottom: Visualisation of the detected changes.

seen as a square block in the aerial data. Comparing the mobile laser scanner data with the photogrammetry-derived point cloud (Figure 3), we observe a similar trend, where most of the change is observed for the trees around the building, whereas there are no observable changes in the building. Although both the aerial LiDAR and the photogrammetry point cloud were taken in the same year, the construction is not observed in the photogrammetry point cloud, indicating it must be a temporary construction for an event (for instance an exhibition stall).

As a part of future research, we propose a change detection method integrating point clouds and photogrammetry mesh. The proposed methodology will employ semantic segmentation of point clouds with deep learning approaches, such as RandLA-Net (Hu et al., 2020), with particular emphasis on capturing significant updates in urban infrastructure. We will explore the applicability of voxels, knowledge graphs, decision trees and the M2C3 algorithm (Lague et al., 2013). This method will not only effectively avoid false alarms caused by noise but also will enable accurate identification of changes at various scales through semantic information. This approach will help us to achieve the goal of identifying different infrastructure changes within Digital Twin applications.

5. Conclusions and Recommendations

We presented a conceptual framework for creating user-centric digital twins by performing automated updates of the city’s infrastructure which is achieved by integrating intelligent change detection. The whole framework has two loops, the data loop and the application loop. The core idea of the framework is to independently maintain the data loop to keep the Infrastructure Data Catalogue updated all the time, which can then be used by the application loop to create user-centric digital twins. The following are the advantages:

1. **Low latency updates**: This framework allows small but frequent changes to happen continuously, thus decreasing the update interval or the latency of data updates.

2. **Knowledge of change detection**: This information will enable versioning of the digital twins, and can be used for further analysis and visualisation of the created digital twin.

3. **Reduced data capture costs**: The use of general-purpose vehicles and crowdsourcing for data collection and validation will reduce the cost of updating the digital twin.

Further, we propose several approaches, tools and techniques that can be integrated into the framework such as knowledge graphs, or highly scalable voxel structures supporting parallel computations, robust semantic-based change detection approaches, continual learning, and the recent LLMs for the applicability to a wide community. However, we identify some challenges and future directions:

1. **Data selection for novel user-centric digital twins**: Without expert knowledge and validation it might be hard to generate novel user-centric digital twins, however, for existing or closely related application cases, the use of LLM models can be explored.

2. **Digital Twin validation**: Automatic validation strategies of the created digital twin are required to check whether they are performing as expected. These approaches should focus on reduced manual involvement and should not be dependent on the collection of new data for validation.

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