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SURVEY PAPER

Big data acquisition for underground infrastructure condition assessment

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Abstract

The condition assessment of underground infrastructure (UI) is critical for maintaining the safety, functionality, and longevity of subsurface assets like tunnels and pipelines. This article reviews various data acquisition techniques, comparing their strengths and limitations in UI condition assessment. In collecting structured data, traditional methods like strain gauge can only obtain relatively low volumes of data due to low sampling frequency, manual data collection, and transmission, whereas more advanced and automatic methods like distributed fiber optic sensing can gather relatively larger volumes of data due to automatic data collection, continuous sampling, or comprehensive monitoring. Upon comparison, unstructured data acquisition methods can provide more detailed visual information that complements structured data. Methods like closed-circuit television and unmanned aerial vehicle produce large volumes of data due to their continuous video recording and high-resolution imaging, posing great challenges to data storage, transmission, and processing, while ground penetration radar and infrared thermography produce smaller volumes of image data that are more manageable. The acquisition of large volumes of UI data is the first step in its condition assessment. To enable more efficient, accurate, and reliable assessment, it is recommended to (1) integrate data analytics like artificial intelligence to automate the analysis and interpretation of collected data, (2) to develop robust big data management platforms capable of handling large volumes of data storage, processing and analysis, (3) to couple different data acquisition technologies to leverage the strengths of each technique, and (4) to continuously improve data acquisition methods to ensure efficient and reliable data acquisition.

Impact Statement

The condition assessment of underground infrastructures (UIs) is crucial for maintaining their functionality, longevity, and safety. The article synthesizes existing literature through comprehensively comparing both structured and unstructured data acquisition techniques for UI condition assessment qualitatively and quantitatively, and evaluating their strengths and limitations. The comparisons highlight that advanced data acquisition methods feature better data accuracy, data reliability, and operational efficiency than traditional ones. While previous works have focused on individual methods, our review is the one of the first to comprehensively compare and analyze these methods within a unified framework, offering new insights into UI condition assessment. A more efficient, accurate, and reliable condition assessment could benefit from the integration of data analytics, data management tools, method integration, and improvement in acquisition methods.

1. Introduction

Underground infrastructure (UI) plays a critical role in supporting urban development, transportation networks, and utilities. The condition assessment of UI is crucial for maintaining the functionality, longevity, efficiency, and safety of subsurface assets such as tunnels, pipelines, and mine shafts. To achieve such an assessment, the acquisition of various data and measurements from UI is essential. Traditional methods of data acquisition often rely on manual inspection and point-based measuring, which are time-consuming, labor-intensive, and prone to human error, and the data volume is rather limited (Jiang et al., 2019), failing to produce higher levels of data quality and accuracy, and larger amounts of data for more efficient, objective, accurate, and reliable UI condition assessment (Wang et al., 2023b). With increasing complexity and scale of UIs, and ever increasingly stringent and rigorous requirements in UI operation and maintenance, the need for a comprehensive understanding of UI structural health and performance grows. This is based on the collection of large amounts of comprehensive and continuous data, which are essential for effective monitoring, maintenance, and management of UI, enabling the application of more advanced techniques to ensure the reliability and longevity of these critical assets.

To conduct a condition assessment of UI like tunnels, it is necessary to understand the type of data that is needed. Generally, the data that are collected from UI can be broadly categorized into structured and unstructured data (Hu et al., 2019). Structured data acquisition involves the collection of organized, quantitative data such as stress, strain, and displacement measurements from UI. Traditionally, there are many techniques that have been used for successful data acquisition, such as precise leveling, total station, strain gauge, tape extensometer, and so forth (Bennett et al., 2010; Cheung et al., 2010; Di Murro, 2019; Ganguly and Paddington, 2019; Jiang et al., 2021). With technological advancement and development, methodologies based on Internet of Things, fiber optics, laser scanning, robotics, and so forth have emerged as advanced and innovative solutions, enabling the collection of bigger amounts of accurate and reliable structured datasets for UI condition assessment (Di Murro, 2019; Farahani et al., 2019; Montero et al., 2017; Wang et al., 2021). Unstructured data acquisition, on the other hand, includes a diverse range of formats such as images, videos, sensor logs, and so forth. Such type of data provides rich, detailed information that structured data might miss. Typically, the collection of unstructured data, like images and videos, relies on camera-based technologies, such as closed-circuit television and unmanned aerial vehicles, which facilitates the generation of new insights into the condition of UIs (Kumar et al., 2018; Liu et al., 2023; Zhang et al., 2024). These methods, if integrated with artificial intelligence and machine learning algorithms, can help automate the analysis and assessment of UIs and thus improve the decision-making process for assets management and maintenance (Liu et al., 2020b; Spandonidis et al., 2022).

However, despite the growing body of research in the field of UI condition assessment, significant gaps remain in the literature. Previous studies have primarily focused on individual data acquisition methods, often in isolation, without considering how these methods can be effectively integrated (Afshani et al., 2019; Bednarz et al., 2021; Hou et al., 2024; Kumar et al., 2018; Zhang et al., 2024). There is a lack of comprehensive comparisons between structured and unstructured data acquisition methods within the context of UI, which limits our understanding of their relative strengths and weaknesses. In addition, the potential for integrating data analytics with advanced methods to enhance the accuracy, reliability, and efficiency of condition assessments has not been fully explored.

This article aims to address these gaps by providing a comprehensive synthesis and analysis of existing literature on both structured and unstructured data acquisition methods for UI condition assessment. This review offers a unique perspective by comparing these methods side by side, evaluating their effectiveness and limitations, which contrasts with prior reviews that typically focus on individual methods in isolation. Furthermore, we critically discuss the role of advanced data management and analytical tools in processing the large volumes of data generated by some methods and in automating the analysis and interpretation of these data, which is an aspect that is often overlooked in earlier works, offering new insights into the future of UI condition assessment. The organization of the article is as follows: Section 2 reviews the acquisition of structured data by various methods, together with a comparison of their

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advantages, disadvantages, data amount, data quality, and level of automation; Section 3 reviews the acquisition techniques for unstructured data, analyses their pros and cons, and systematically compares their difference in data size, sampling interval, data management, transmission, and processing; and Section 4 presents the discussion, conclusion, and recommendations of this article.

2. Structured data acquisition

2.1. Definition of structured data

Data science commonly defines structured data as tabular-form quantitative data that are highly organized, easily decipherable, and straightforward-to-analyze (Mishra and Misra, 2017). For condition assessment of UI, structured data encompass organized and standardized information on understanding the performance of such subsurface assets, identifying areas of concern or potential risk, and facilitating the evaluation of their structural health, such as strain, stress, and settlement, serving as the backbone of efficient asset assessment practices and informed maintenance decision-making (Du et al., 2018). Such structured data of UI, despite its significance in providing essential information, can exhibit uncertainty (due to measuring errors), discreteness (arising from non-continuous monitoring), and poor quality (coming from subjective readings), contributing to inaccurate and inefficient condition assessment. One solution is to use big data analytics (e.g., machine learning) to automatically and accurately analyze and investigate or even predict underground structures' behavior, whereas the acquisition of big amounts of structured data for such purpose remains challenging because currently most data are obtained through manual site investigations, expensive laboratory tests, time-consuming field monitoring, and so forth (Cremona and Santos, 2018; Du et al., 2018). Recent advances in information and communication technologies have enabled the application of some innovative and emerging structured data acquisition methods such as wireless sensor network (WSN), distributed fiber optic sensing (DFOS), terrestrial laser scanning (TLS), and so forth, to acquire larger amounts of structured data at a lower cost of labor and time than previously available (Bennett et al., 2010; De Battista et al., 2015; Jia et al., 2021). The following subsection focuses on the main methods that are available to acquire structured data in the field of UI condition assessment.

2.2. Acquisition of structured data

Manual acquisition of structured data in UI was and is still commonly adopted for its condition assessment despite being subjective, inaccurate, unreliable, time, and labor-consuming (Loupos et al., 2018a; Zhou et al., 2020). In recent decades, emerging technologies with *automatic* data collection capability, WSN as an example, have seen increasing applications in underground structures to gather big amounts of structured data such as displacement (Sui et al., 2021; Wang et al., 2020; Xie and Lu, 2017). In this section, a comprehensive review of the acquisition of structured data through certain manual and *automatic* techniques is presented.

2.2.1. Data acquisition by traditional methods

Traditional methods, such as precise leveling, traditional total station, strain gauge, tape extensometer, and so forth, as in Figure 1, have been utilized to gather large amounts of structured information on UI for decades with great success (Bennett et al., 2010; Cheung et al., 2010; Di Murro, 2019; Ganguly and Paddington, 2019; Jiang et al., 2021). Table 1 lists some representative traditional methods, with their applications in gathering structured data for UI condition assessment.

To understand tunnel performance due to influences such as ground heave and tidal changes, precise levels were adopted to measure its deformation and movement (Burford, 1988; Nuttens et al., 2014; Webber, 1972). Other methods to acquire structured deformation data of underground structures, such as tunnels, include tape extensometers for 2D deformation monitoring (Bernardo-Sánchez and Arlandi-Rodríguez, 2014; Goh and Mair, 2012; Mohamad et al., 2012), displacement transducer for convergence

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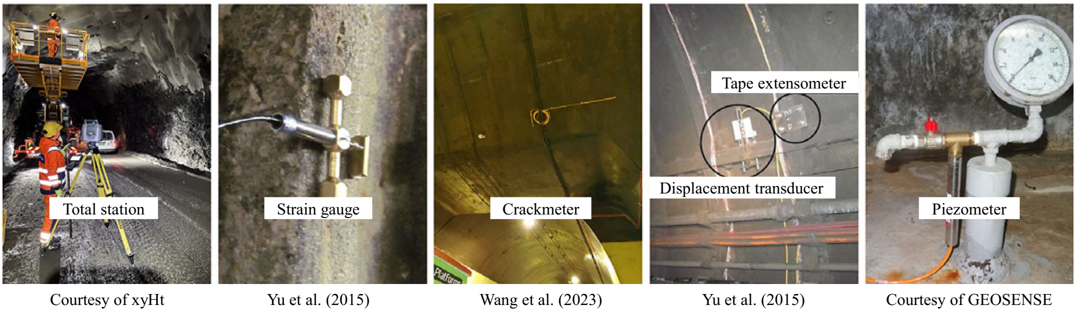

Figure 1. *Examples of traditional structured data collection methods.*

Table 1. *Traditional methods for structured data collection*

Method	Application	References
Precise leveling	Tunnel deformation due to tidal influences	Nuttens et al. (2014)
Total station	Tunnel settlement, dislocation, and convergence	Xie and Lu (2017)
Strain gauge	Tunnel deformation due to tidal influences	Nuttens et al. (2014)
Tape extensometer	Existing tunnel response induced by a new tunnel	Mohamad et al. (2011)
Tiltmeter	Tilt monitoring of a drainage tunnel in a landslide area	Chen et al. (2020)
Crack meter	Crack evolution of a tunnel intersecting a landslide	Bossi et al. (2017)
Piezometer	Water level evolution in landsides around tunnels	Bandini et al. (2015)
Stress cell	Measure soil stress state during tunnel excavation	Tian et al. (2023)
Displacement transducer	Deformation monitoring of tunnel cross-sections	Xu et al. (2017)

measuring (Shibayama et al., 2010; Xu et al., 2017), and traditional total stations for 3D liner convergence profiling (Kontogianni and Stiros, 2005; Luo et al., 2017; Xie and Lu, 2017). In addition, strain gauges, pressure cells, and crack meters are another three traditional methods widely used in UIs to measure strain development (Bennett et al., 2010; Nuttens et al., 2014), keep track of crack variation (Bennett et al., 2010; Bossi et al., 2017), monitor stress/pressure evolvement (Clayton et al., 2002; Tian et al., 2023) in ground and structures with time. To understand ground behavior, manual methods such as single- or multipoint borehole rod extensometers, magnetic extensometers, precise levels, sliding micrometers, inclinometers, piezometers, pressure cells, and so forth, are also commonly adopted to understand water table change, groundwater pressure evolution, ground displacement, and so forth (Bandini et al., 2015; Bossi et al., 2017; Chen et al., 2020; Pujades et al., 2015; Tian et al., 2023; Zhang et al., 2022).

The advantages of these traditional methods, such as being reliable and versatile in different conditions, accessible, and cost-effective to different practitioners, have made them very popular and successful in acquiring structured data in UI previously. However, increasingly stringent and rigorous project requirements, for example, less labor involvement, higher accuracy, and real-time and continuous monitoring, have made traditional data acquisition methods unsuitable. Additionally, the point-based nature and heavy reliance on human operators of these traditional methods can no longer satisfy modern data requirements such as higher levels of data quality and accuracy, greater volumes of data, and more comprehensive data types for obtaining a comprehensive picture of UI performance. With technological development and advancement, recent decades have witnessed a wider application of more advanced structured data acquisition systems such as WSN and DFOS in acquiring a larger amount of structured data from underground structures, which is detailed in the following sections.

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2.2.2. Data acquisition by automatic methods

Automatic methods typically refer to the ability of technologies or systems to perform monitoring tasks and/or data acquisition processes relatively independently of human intervention. Automatic structured data acquisition systems, based on sensor types, can be broadly categorized into microelectromechanical system sensing (e.g., WSN) (Bennett et al., 2010; Li et al., 2020a; Wang et al., 2021), fiber optic sensing (e.g., DFOS) (Cheung et al., 2010; Di Murro, 2019; Li et al., 2018b; Mohamad et al., 2011; Monsberger et al., 2017), laser sensing (e.g., TLS) (Farahani et al., 2019; Li et al., 2020b; Wang et al., 2014), and robotics-associated integrated sensing (e.g., robotic total station [RTS]) (Loupos et al., 2018b; Montero et al., 2017; Xu and Yang, 2020; Zhou et al., 2020), as demonstrated in Figure 2. This section presents a comprehensive review on those advanced monitoring approaches featuring automatic structured data acquisition that have seen increasing applications and installations in various UIs for their condition assessment (Bennett et al., 2010; Ganguly and Paddington, 2019; Kim et al., 2008; Wang et al., 2020).

2.2.2.1. MEMS-based data acquisition. MEMS sensors have been extensively and successfully deployed in various underground structures to acquire a huge amount of structured data, such as inclination, strain, pressure, and temperature (Tariq et al., 2022; Wang et al., 2020). MEMS-based automatic-sensing systems typically involve the integration of MEMS sensors with automated data collection, processing, and transmission system, enabling real-time acquisition of various structured data from UI for condition assessment without the need for human intervention. One representative example of MEMS-based automatic monitoring method is WSN where a network of multifunctional MEMS sensor nodes collects various structured data from UIs or their surroundings and the data collected are then transmitted wirelessly to cloud for processing, as illustrated in Figure 3 for its working principles. Having gained significant popularity in collecting structured data from bridges, such as vibration and displacement, WSN is being gradually applied in various subsurface assets to assess their conditions, exemplified by tunnels (Bennett et al., 2010; Wang et al., 2021), mines (Li and Liu, 2007; Muduli et al., 2018b), and caves (Wang et al., 2022a). Table 2 presents some representative studies on acquiring structured data from UIs using WSN.

In tunnels, WSNs were deployed mainly to gather extensive data on structural deformation. For example, WSN sensors were used to acquire the deformation and deterioration data of the Prague metro tunnel such as convergence, joint opening, crack propagation, inclination, and strain due to concerns over postflood tunnel safety (Vaníček et al., 2012). In London, structured data on cast-iron tunnels including inclination, strain, and joint opening were collected by the WSN system to investigate their aging performance (Bennett et al., 2010) and the response induced by adjacent tunnel excavation (Alhaddad et al., 2014). Similarly, Shanghai shield tunnel data were collected by WSN systems from aspects of aging deformation (Xie and Feng, 2012), inclination caused by adjacent construction (Wang et al., 2021), and tunnel longitudinal settlement/differential settlement (Xie and Feng, 2012; Yin and Huang, 2015). Figure 4 presents the range of deformation development rates recorded in previous studies on tunnels

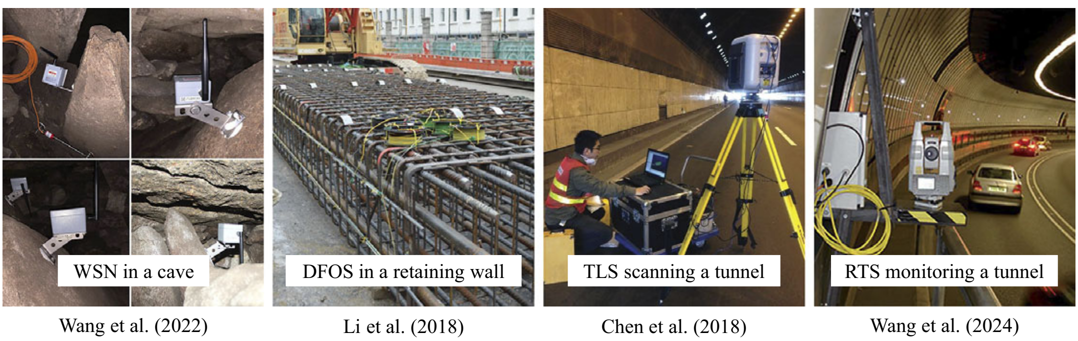

Figure 2. *Examples of automatic structured data collection methods.*

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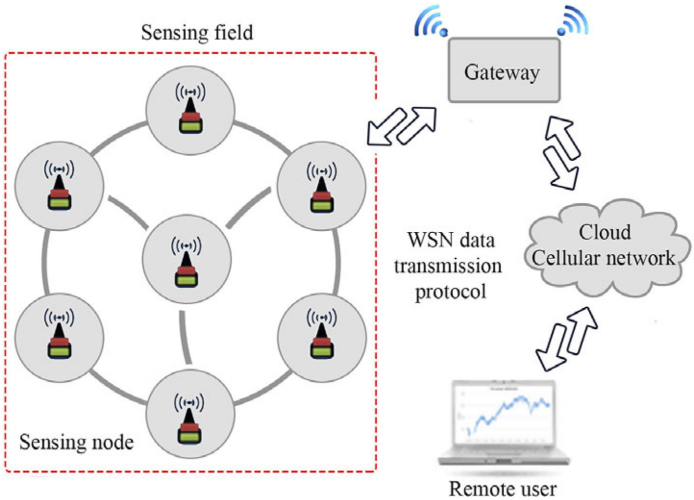

Figure 3. *Working principle of WSN (Wang et al. (2022a)).*

using WSN (Wang et al., 2023a). In addition, coal mines have also seen applications of WSN sensors to get information on structural variations caused by underground collapses (Li and Liu, 2009), under environmental conditions (Muduli et al., 2018b), on gas concentration and liner position (Wang et al., 2007), and on fire and safety hazards (Muduli et al., 2018a). For the assessment of underground caves, WSN sensors have been used to gather structured data mainly on microclimatic conditions, for example, temperature, humidity, CO_2 concentration, air speed, and direction (Ming et al., 2008; Novas et al., 2017) and structure inclination (Wang et al., 2022a). Other areas of UIs that have seen deployments of WSN systems to acquire structured data include pipeline pressure measuring (Sadeghioon et al., 2014), pipeline leakage detection (Lin et al., 2019; Spandonidis et al., 2022), and foundation pit displacement monitoring (Hong et al., 2022).

Compared to traditional structured data acquisition techniques in Section 2.2.1, MEMS-based wireless sensor networks excel in automatic data collection, wireless data communication, flexible deployment, cable elimination, self-organization, scalability, and real-time data acquisition, saving labor, time and monetary resources. However, its drawbacks such as network signal reliance and network vulnerability, data loss, and point-based measurements somewhat restrict it from obtaining spatially continuous data. In addition, WSNs typically are battery-powered, and replacing or recharging batteries in underground environments can be challenging. Studies have reported that the lifespan of WSN batteries depends on various factors (e.g., type of sensor, frequency of data transmission, and environmental conditions), and generally WSN sensor node batteries can last from several months to a maximum of 2 years when the sampling rate is high (e.g., every few minutes to an hour) and it can last even longer (e.g., up to 5 years) for low-power sensors that sense the environment or structure infrequently (e.g., on a weekly or monthly basis) (Rodenas Herráiz et al., 2016). For example, wireless inclinometers in the WSN system reported in Wang et al. (2023a) can last up to about 3 years in a single hop network with a sampling rate of every 1 hour in relatively good underground environments, while its matching gateway's battery can last for around a year. Regarding the communication range of WSNs, it is also influenced by various factors, such as signal frequency, antenna type, environmental conditions, and tunnel configurations, depending on the type of specific wireless technique, the typical communication range of WSNs varies between several meters and several hundred meters. For instance, a maximum of 200 m communication distance in a ZigBee-based WSN was reported in Soga et al. (2017) when monitoring an underground tunnel section. Section 2.3 summarizes the characteristics of WSN in data acquisition.

2.2.2.2. Distributed fiber optic-based data acquisition. The distributed fiber optic-based data acquisition method features change detection of parameters such as temperature and strain caused by light

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Table 2. *Structured data collection using WSN*

Infrastructure	Application	Reference
Tunnel	Deformation data collection on the performance of aging tunnels	Bennett et al. (2010)
Tunnel	Convergence data acquisition on shield tunnel with straight joints	Wang et al. (2021)
Tunnel	Vibration data of an existing tunnel due to new tunnel construction	Lai et al. (2015)
Tunnel	Tilt data collection on the behavior of a cross-passage twin tunnel	Wang et al. (2023b)
Tunnel	Data collection including convergence, joint, crack, tilt, and strain	Vaníček et al. (2012)
Tunnel	Horizontal convergence of tunnels induced by unexpected leakage	Liu et al. (2020a)
Coal mine	Structural variation data caused by underground collapses in mines	Li and Liu (2009)
Coal mine	Abnormal gas centration data and miner position data in coal mines	Wang et al. (2007)
Coal mine	Collect temperature, humidity, and gas concentration data in coal mines	Muduli et al. (2018b)
Heritage cave	Tilt, temperature, humidity, and CO_2 data collection in a heritage cave	Wang et al. (2022a)
Heritage cave	Temperature, humidity, CO_2, air speed, and direction in a cave	Novas et al. (2017)
Heritage cave	Temperature, humidity, and CO_2 concentration in Mogao Grottoes	Ming et al. (2008)
Pipeline	Data collection on relative indirect pressure change in plastic pipes	Sadeghioon et al. (2014)
Pipeline	Monitor pipeline joint leakage induced by large ground movements	Lin et al. (2019)
Pipeline	Immediate detection of leaks in metallic oil and gas piping systems	Spandonidis et al. (2022)
Foundation pit	Collect data on the horizontal displacement of foundation pit support	Hong et al. (2022)

traveling along a single fiber. The single fiber acts as a sensor with thousands of sensing points, enabling continuous acquisition of structured data in UIs along the entire length of a fiber that may span over tens of kilometers (Sui et al., 2021). By realizing spatially and temporally continuous structured data acquisition, the DFOS method has gained increasing applications in acquiring extensive structured data from various UIs for their condition assessment, such as tunnels, pipelines, piles, and diaphragm walls (D-wall). Figure 5 illustrates the DFOS working principle for applications in UI condition assessment.

DFOS systems have been used to acquire several types of primary structured data, including strain, temperature, vibration, and acoustic events. Each data type leverages different scattering phenomena and interrogation techniques, which allows DFOS to provide comprehensive structured data acquisition solutions across various UIs. Table 3 lists some representative studies regarding DFOS-based data

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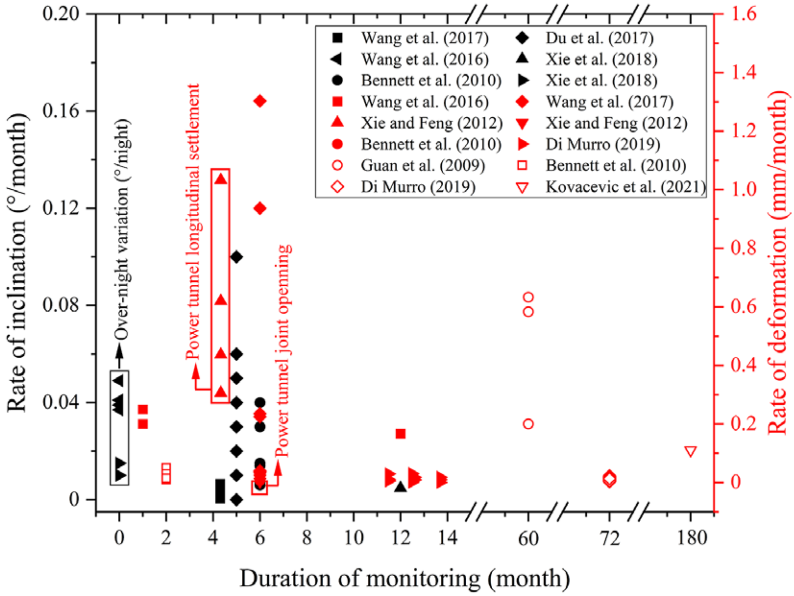

Figure 4. *Rate of recorded tunnel deformation acquired by WSN (Wang et al., 2023a).*

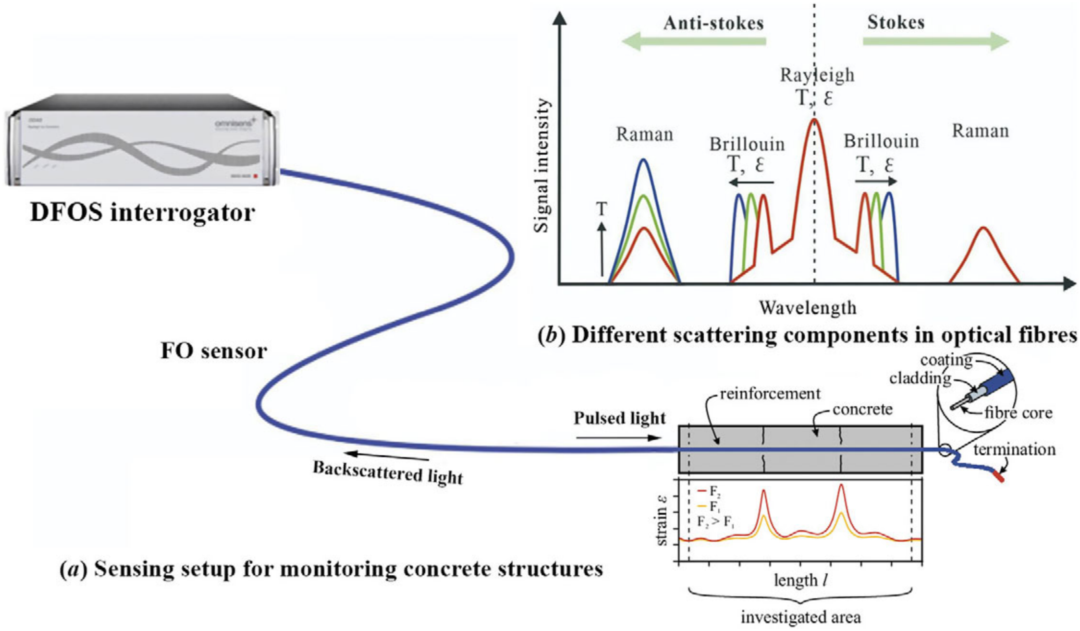

Figure 5. *Working principle of DFOS (modified from Monsberger and Lienhart (2021)).*

acquisition in different underground structures, and Figure 6 presents some examples of strain measurements of a CERN tunnel acquired by DFOS (Wang et al., 2024).

It can be seen that DFOS has been widely used for monitoring UI's strain and temperature. In tunnels, DFOS structured data acquisition mainly concentrates on gathering information on the tunnels during the construction and operation stages. For instance, during construction, structured strains are monitored (1) to analyze the deformation and stress of tunnels during excavation to ensure structural stability, (2) to

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Table 3. *DFOS-based data acquisition in different underground structures*

Asset type	Data type	Scattering	Application	References
Tunnel	Strain	Brillouin	Study the behavior of a London Crossrail tunnel induced by adjacent excavation	De Battista et al. (2015)
Tunnel	Temperature	Raman	Obtain information about concrete curing and construction during tunnel excavation	Buchmayer et al. (2021)
Tunnel	Strain	Brillouin	Analyze tunnel performance caused by cracking and crushing-induced deterioration	Sui et al. (2021)
Tunnel	Strain	Brillouin	Assess the performance of an inclined CERN tunnel due to observed deteriorations	Di Murro (2019)
Tunnel	Strain	Brillouin	Evaluate the working face safety of an Austrian tunnel shotcrete lining	Monsberger et al. (2017)
Tunnel	Strain	Brillouin	Assess the health condition of a CERN tunnel due to cracks, leakage, etc.	Wang et al. (2024)
Pipeline	Temperature	Raman	Locate the leakage area of an LNG pipeline and an ethylene pipeline in the UK	Tanimola and Hill (2009)
Pipeline	Strain	Brillouin	Calculate the cross-sectional deformation/displacement of a composite tubular pipe	Bednarz et al. (2021)
Pipeline	Acoustic	Rayleigh	Prevent third-party damage to buried high-pressure gas pipelines	Tanimola and Hill (2009)
Mine	Temperature	Raman	Examine the applicability of DFOS temperature monitoring in an underground mine	Aminossadati et al. (2010)
Pile	Temperature	Raman	Derive temperature profiles along a pile during concrete curing to infer pile integrity	Rui et al. (2017)
Pile	Strain	Brillouin	Understand the cast-in-situ test pile performance and integrity under axial loading	Kechavarzi et al. (2019)
D-wall	Strain	Brillouin	Investigate the behavior of diaphragm walls due to deep excavation in London Clay	Li et al. (2018b)
D-wall	Temperature	Raman	Monitor the leakage of D-walls under different testing conditions using the model test	Liu et al. (2019)

assess the impact of nearby construction on the tunnel structure, (3) to detect early signs of structural issues like cracking, and (4) to analyze the load distribution in the linings and prevent failures. In some cases, DFOS temperature data are collected to track temperature profiles during concrete curing to ensure their proper setting and prevent thermal cracking. In comparison, during the operation stage, the acquisition of structured strain data dominates due to the concerns over tunnel deterioration, tunnel

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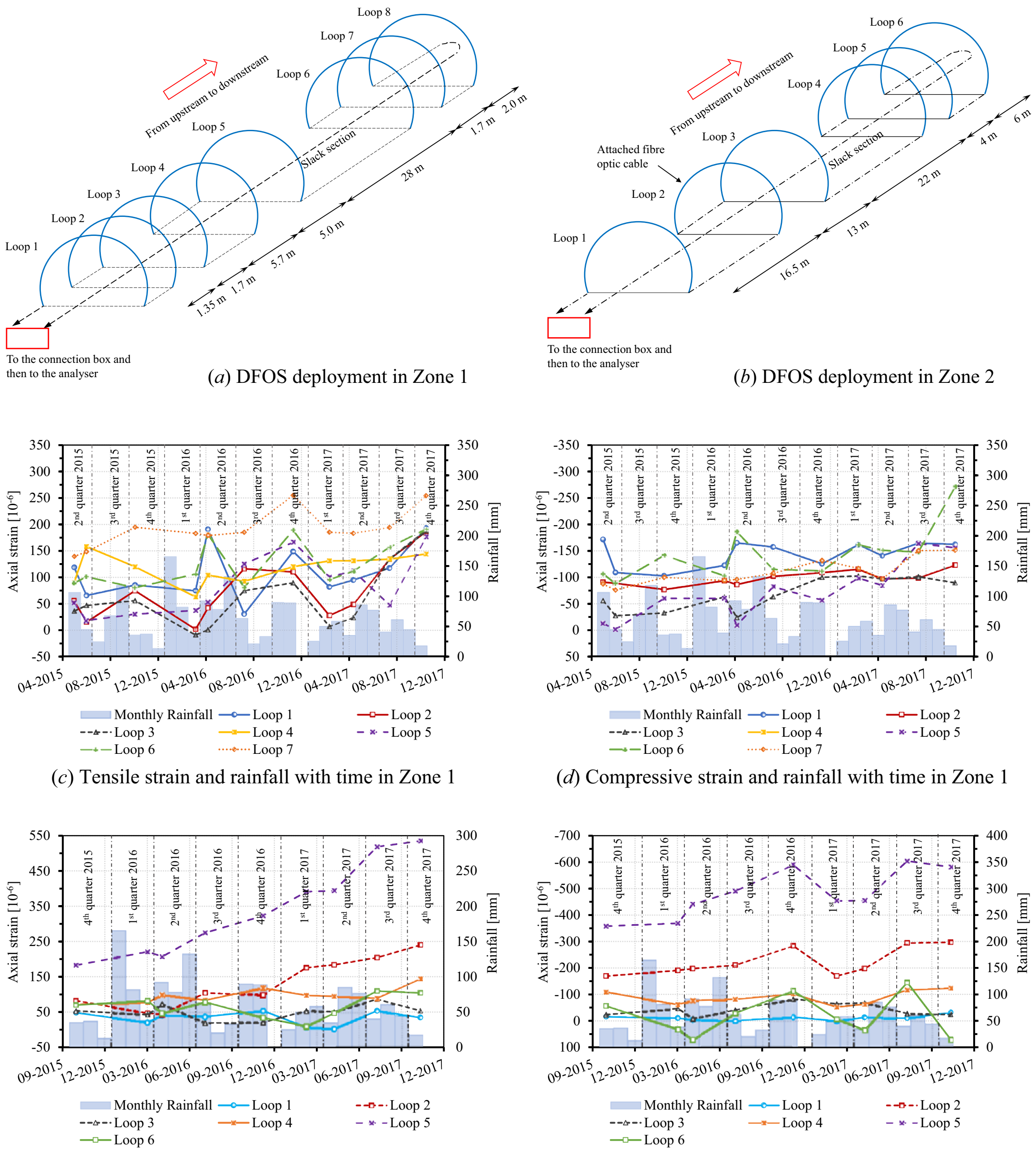

(*a*) DFOS deployment in Zone 1

(*b*) DFOS deployment in Zone 2

(*c*) Tensile strain and rainfall with time in Zone 1

(*d*) Compressive strain and rainfall with time in Zone 1

(*e*) Tensile strain and rainfall with time in Zone 2

(*f*) Compressive strain and rainfall with time in Zone 2

Figure 6. *DFOS strain measurements in a CERN tunnel (Wang et al., 2024).*

structural health, maintenance, and repair. Strains are monitored to detect and assess deterioration over time, to identify the development of cracks and other defects that could compromise tunnel safety, and to plan maintenance activities before significant damage occurs. For pipelines, depending on the specific types and purposes, the application scenarios of DFOS in acquiring structured data vary from leak detection and prevention to structural health and ground movement, temperature profiling, third-party interference detection, and corrosion monitoring. Strains are gathered to assess the deformation of pipelines during installation to ensure that they are not overstressed and to detect any changes caused by ground movements like earthquakes that might threaten pipeline integrity. Temperature data are collected to enable leakage detection and localization in pipelines such as LNG and ethylene ones.

Acoustic measurements are mainly acquired to facilitate the detection of leaks, third-party interference, and flow monitoring. For foundations and their supporting structures, such as piles and diaphragm walls, both strain and temperature datasets are important parameters for understanding their structural performance and integrity. Temperature profiling ensures the proper setting of pile concrete to avoid integrity problems, while strain data enables the assessment of pile's long-term structural health. Similarly, D-wall strain data help understand its structural behavior in both the short and long term, while temperature measurements facilitate the detection of leakage of water through the wall.

Like WSN, DFOS enables real-time and automatic structured data acquisition without direct access to underground structures. However, DFOS stands out by not relying on discrete sensors at specific points. Instead, it uses the optic fiber cable itself to measure parameters such as strain, temperature, and acoustic events along extensive sections of UIs like tunnels. Typically, the DFOS system can have a cable length that can be effectively read by an interrogator from several to tens of kilometers, depending on various factors, such as scattering type, fiber signal attenuation, spatial resolution, tunnel curvatures, interrogator power, and sensitivity. For example, the distance range of distributed Brillouin sensing can reach 150 km with 2-m spatial resolution and 1 °C temperature resolution under optimal conditions (Bao and Chen, 2012). Regarding DFOS accuracy, based on the parameter being measured and the scattering type employed, DFOS systems may have different accuracies. For instance, the Brillouin-based DFOS system, commonly used for temperature and strain monitoring, can achieve an accuracy of ±20 με for strain measurement and ±1 °C for temperature. Raman-based systems, primarily used for temperature sensing, typically offer an accuracy of ±0.1 °C. This DFOS approach allows for continuous spatial and temporal structured data collection, providing a higher volume of information for a more comprehensive assessment and evaluation of UI (Buchmayer et al., 2021).

2.2.2.3. Laser sensor-based data acquisition. LiDAR-based TLS is one representative laser sensor-based structured data acquisition technique. The advantages of acquiring high-accuracy and high-precision 3D point density, spatial resolution from a single setup in a short time, remote and noncontact operation, adaptability to various underground environments such as tunnels and mines, have gained increasing attention in structured data acquisition from UIs (Mukupa et al., 2017; Wang et al., 2014), exemplified by the increasing applications of TLS in geometry detection, deformation monitoring, and feature extraction of UIs (Wang et al., 2014). The following Figure 7 illustrates the general working procedures of data acquisition using TLS in UIs.

To gather information on UI geometrical dimensions, previous studies mainly focused on utilizing TLS to obtain tunnels' geometry profile data to ensure tunnel construction quality control (Wang et al., 2014), to assess tunnel conditions (Farahani et al., 2019), and to monitor the progress of works and supervise tunnel deformations during construction (Argüelles-Fraga et al., 2013). In addition, TLS has also been used to gather UI's deformation data, such as tunnel excavation face displacement (Lemy et al., 2006), aging deformation of operation tunnels (Farahani et al., 2019; Jia et al., 2021; Xie and Lu, 2017), underground pipeline deformation (Vezočnik et al., 2009), and so forth Figure 8 shows an example of tunnel convergence deformation at different construction stages of a Shanghai metro tunnel acquired by TLS. In terms of feature extraction, TLS has mainly been used to collect measurements of tunnel invasion detection (Yang et al., 2021), underground mine rock mass discontinuities (Chen et al., 2018), and rock bolt position (Gallwey et al., 2021).

LiDAR-based TLS complements discrete point-based monitoring techniques (e.g., traditional methods and WSN) by obtaining structured data from numerous points on various UIs, and spatially continuous methods (e.g., DFOS) by gathering bigger amounts of structured data in continuous 3D spaces of certain length via a single reading. Additionally, TLS provides highly accurate and precise 3D measurements of comprehensive UI areas promptly. However, it cannot replace these approaches as all techniques do not compete but support each other (Mukupa et al., 2017). For example, TLS may not achieve real-time measurements as WSN does, while DFOS may not gather as much data as TLS can do in one scan.

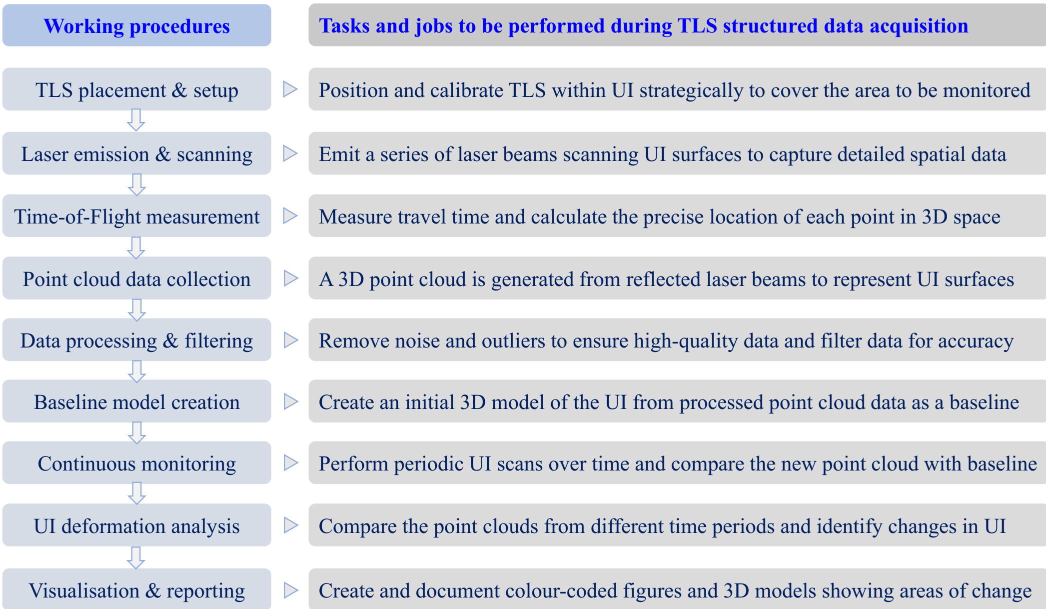

Figure 7. *TLS working procedures for UI structured data acquisition.*

2.2.2.4. Robotics-involved integrated data acquisition. The automatic structured data acquisition methods presented in previous subsections still have a certain level of reliance on human intervention, prompting the pursuit of even higher levels of automation in the data acquisition process and postmonitoring data processing. One potentially emerging solution is the integration of robotics, computer/machine vision, and artificial intelligence into those widely applied structured data acquisition techniques. Recent years have witnessed some examples/proposals of such robotics-involved integrated methods (Loupos et al., 2018a; Xu and Yang, 2020; Zhou et al., 2020), but they are still in their infancy with no practical and realistic applications in the wider UI industry. This subsection reviews some of these autonomous methods for potential applications in future big data acquisition in UIs. Figure 9 presents the robotics-involved integrated systems for structured data acquisition from previous studies.

Zhou et al. (2020) reported the use of an RTS with capabilities such as automatic target recognition, power search, and automatic and remote wireless data collection in a metro tunnel to gather tunnel lining deformation. However, a large number of RTSs may be needed to establish a complete deformation profile of a tunnel due to its short range. Xu and Yang (2020) proposed the use of artificial intelligence (AI)-assisted TLS to gather geometric information about tunnel structures to obtain tunnel deformation. Another robotics-involved integrated system to gather structured data is the autonomous robotic tunnel monitoring system ROBO-SPECT (Montero et al., 2017). It has multiple capabilities such as autonomous navigation of the equipment, automatic identification of tunnel defects, autonomous crack measurement taking and transverse deformation monitoring, autonomous data processing, and decision-making (Loupos et al., 2018b; Menendez et al., 2018; Montero et al., 2017). The ROBO-SPECT system enables automation in not only data acquisition but also the work before, during, and after the acquisition of structured data. Similarly, another two studies on inspection of CERN tunnel structures demonstrated the autonomous capabilities in conducting monitoring, acquiring both structured data and unstructured data, transmitting data and postprocessing data: (1) a remote and automated tunnel crack monitoring system, characterized by remote and automatic data acquisition, storage, and transmission by CERNbot and deep-learning-based automatic crack segmentation and density and distribution prediction, was used to identify tunnel areas with severe crack damage (Ouyang et al., 2023); (2) a train inspection monorail (TIM) was installed in the large hadron collider (LHC) tunnel at CERN, together with an automatic computer vision

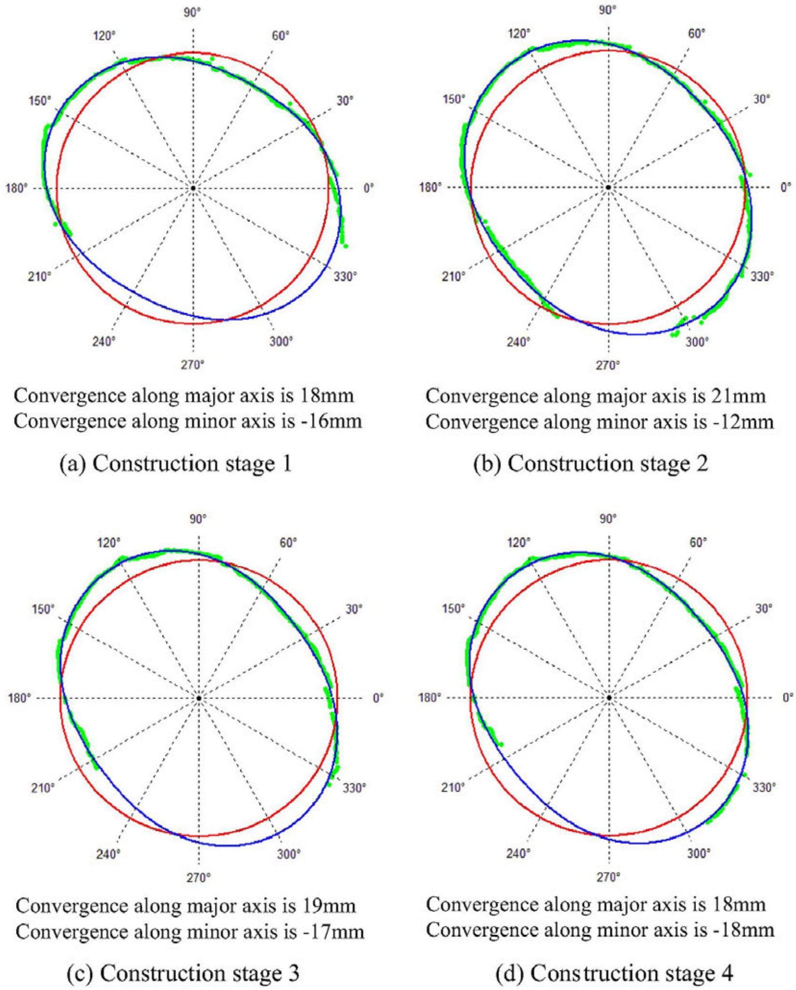

Figure 8. *TLS convergence at different construction stages of a tunnel (Xie and Lu, 2017).*

system (TInspect), to acquire various structured and unstructured data with mounted sensors and cameras without manual intervention, aiming to monitor changes on tunnel linings such as cracks, leakage, and so forth (Attard et al., 2018b).

Such robotic data acquisition systems provide an even higher level of automation compared to previous techniques, although their development incurs additional costs in terms of labor, time, and monetary resources. Additionally, many robotics-involved integrated data acquisition systems laid more focus on image data acquisition for UI surface inspection, followed by AI-enabled image processing for further data analyses/UI condition assessment. These systems offer a feasible and promising direction for future research and development in the field of data acquisition in UI.

2.3. Comparison of structured data acquisition

In Section 2.2, a comprehensive review on the widely used techniques for acquiring structured data in UI is presented. It is necessary to understand their similarities and differences in data acquisition for the reference of engineers, researchers, and so forth, in terms of infrastructure condition assessment. Table 4 gives a detailed comparison among the listed data acquisition methods from three aspects of structured data: data acquisition, data amount, and data quality. It is noted that traditional structured data acquisition

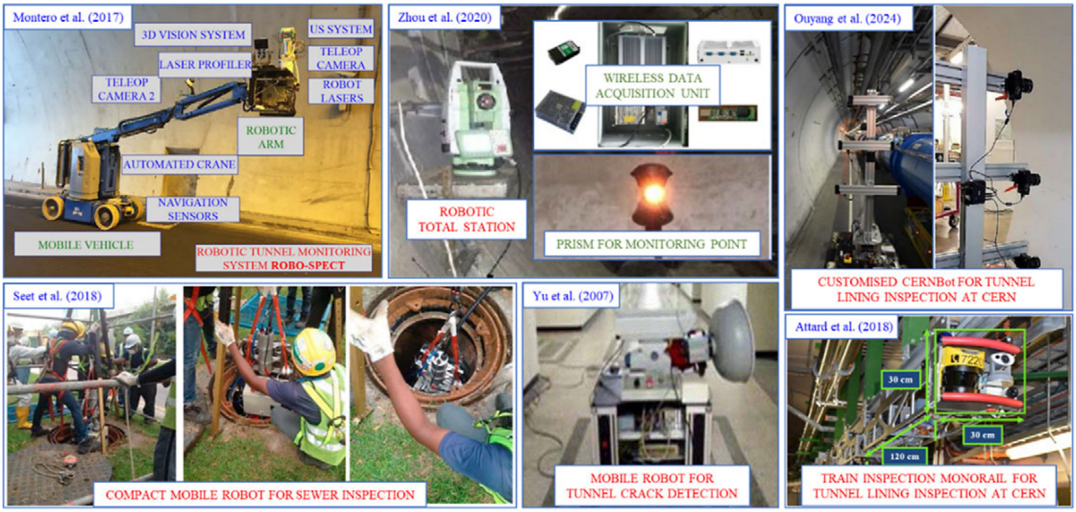

Figure 9. *Robotics-involved integrated systems for structured data acquisition.*

methods can only obtain relatively low volumes of data due to low sampling frequency, manual collection and transmission, whereas more advanced and automatic methods can gather relatively larger volumes of data due to automatic data collection and high and/or continuous sampling frequency or comprehensive monitoring. For example, traditional total stations, typically with a sampling frequency in the range of 0.01 to 0.1 Hz (once every 10s–100 s) depending on the manual operation and the specific type of instrument used, can produce a data volume from a few megabytes to tens of megabytes per day, depending on the number of sensors and measurement frequency. Upon comparison, more advanced methods such as DFOS (e.g., with a sampling interval as frequent as 1 second) is able to generate gigabytes of data per day and TLS can produce tens of hundreds of millions of points per scan, resulting in data volumes that can exceed gigabytes per session. The quality of structured data obtained by traditional methods remains largely low to medium due to factors such as subjectivity in data reading, environmental effects such as temperature, signal interference, human error, instrument sensitivity, and so forth, compared to the relatively higher data quality by advanced methods. Regarding the level of automation, it is commonly accepted that traditional methods are characterized by heavy reliance on human involvement, including manual installation and calibration, manual operation and data collection, while the more advanced techniques for structured data acquisition in UIs minimize human intervention, thus enabling a medium-high level of automation and the subsequent improvement in data acquisition efficiency, accuracy, quality, and comprehensiveness.

Table 5 compares the advantages and disadvantages of traditional and automatic methods in general in various aspects, from installation and calibration to environmental scalability and system applicability. It can be seen that traditional methods such as total stations, strain gauges, crack meters, and so forth require manual installation, calibration, and data collection, making them labor-intensive, time-consuming, and prone to human error. These methods also involve higher risks for workers and frequent maintenance. While they are often lower in initial cost and well-suited for straightforward monitoring tasks, they often lack real-time capabilities and scalability. On the other hand, advanced methods such as WSN-, DFOS-, and LiDAR-based scanning offer automated data collection, real-time monitoring, and higher accuracy with reduced human intervention. These systems are more efficient, scalable, and safer, although they require a higher initial investment and specialized technical expertise. Those advanced methods are ideal for comprehensive, large-scale monitoring and facilitate predictive maintenance, but their complexity and maintenance needs may be a disadvantage in some scenarios.

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Table 4. Comparison of structured data acquisition

Acquisition methods		Data acquisition		Data amount		Data quality			
		Data collection	Data transmission	Frequency	Data volume	Data loss	Data accuracy	Data reliability	Level of automation
Traditional	Total station	Manual	Manually download from total station	Low (every several minutes to hours)	Low (within tens of megabytes)	Medium	Medium-high	Medium-high	Low
	Strain gauge	Manual	Manually download from the data logger	Low-medium (can be continuous or every several minutes to hours)	Low (within tens of megabytes)	Medium-high	Medium	Medium	Low
	Various meters	Manual	Manually download from readout unit	Low (every several minutes to hours)	Low (within tens of megabytes)	Medium	Medium	Medium	Low
Advanced	WSN	Automatic	Wireless and real-time transmission	High (can be up to every 1 second)	High (in the range of gigabytes)	Low	High	High	High
	DFOS	Automatic	Wired transmission but remote download	High (can be continuous or be up to every 1 second)	High (in the range of gigabytes)	Low	High	High	High
	TLS	Automatic	Manually download from the laser scanner	Low (each scan takes time due to millions of points)	High (in the range of tens of gigabytes)	Low	High	High	Medium
	RIS	Automatic	Depends on the integrated sensor system	High (integration with techniques like WSN)	High (in the range of tens of gigabytes)	Low	High	High	High

Note: 1. Only three representative methods (e.g., total station, strain gauge, and various meters) in the traditional category are listed for comparison.
2. WSN—Wireless Sensor Network; DFOS—Distributed Fiber Optic Sensing; TLS—Terrestrial Laser Scanning; RIS—Robotic Integrated System.

Table 5. *Advantages and disadvantages of traditional and automatic methods*

Comparison	Feature subcategory	Traditional	Automatic
Installation	Manual installation	×	×
	Time and labor-intensive	×	
	Physical access to UI	×	
Calibration	Manual calibration	×	
	Automated calibration		×
	Frequent calibration	×	
Data collection	Manual data collection	×	
	Automated data collection		×
	Prone to human error	×	
	Periodic data collection	×	
Accuracy	High accuracy if properly installed	×	×
	Reduced human error		×
Efficiency	Labor-intensive data collection	×	
	High-speed data collection		×
Maintenance	Frequent manual maintenance required	×	
	Prone to wear and tear under harsh conditions	×	
Data integration	High integration with digital platforms		×
	Advanced data management and processing		×
Cost	Low initial device and system setup cost	×	
	Higher long-term labor and maintenance cost	×	
Safety	Remote operation reduces exposure to hazards		×
	High risks for workers in hazardous environments	×	
Scalability	Easily scalable for wider coverage of UIs		×
	Additional labor and equipment if scaling up	×	
Data quality	High and consistent		×
	Affected by human error and external conditions	×	
Real-time monitoring	Real-time monitoring and alerts		×
	Immediate data availability		×
Data processing	Manual data processing	×	
	Automated data processing		×
Comprehensiveness	Limited to specific types of data (e.g., strain)	×	
	Multimodal and comprehensive data collection		×
Remote accessibility	Remote access		×
	Off-site monitoring and management		×
Environmental resilience	Less affected by harsh conditions	×	
	Regular maintenance to ensure functionality	×	
Applicability	Well-established principle for UI monitoring	×	
	Suitable for complex, large-scale monitoring		×

3. Unstructured data acquisition

3.1. Definition of unstructured data

Unstructured data usually refers to information that does not possess a predefined format or organization, commonly originating from diverse sources. This type of data is particularly challenging to process and analyze due to its lack of structure, and unlike easy-to-use structured data, it can manifest in forms such as text files (e.g., documents, emails, and webpages), multimedia files (e.g., images, videos, and audios), sensor data (e.g., logs, signals, and data streams), and social media data (e.g., tweets and comments)

(Gandomi and Haider, 2015). Within the context of UI, this typically involves the acquisition of data from sources such as geospatial surveying, maintenance logs and reports, historical records, images, and videos. For the condition assessment of UIs, multimedia data such as images and videos taken during inspection or construction are particularly important to enhance a comprehensive understanding of UI's structural health and behavior, as they may contain richer information than that of structured data and capture details that structured data may miss. However, the large volumes of unstructured data acquired from UIs pose challenges for data management, analysis, and interpretation, meaning that robust data management solutions, advanced tools, and/or techniques such as high-quality cameras, image recognition, and machine learning algorithms are needed for efficient, effective, and accurate UI condition assessment. The acquisition of unstructured data in the context of UI condition assessment (i.e., with a focus on images and videos in this article) involves the use of approaches such as ground-penetrating radar (GPR), closed-circuit television (CCTV), unmanned aerial vehicle (UAV), and infrared thermography (IRT). The integration of these methods with artificial intelligence and autonomous platforms has gained increased attention in recent years, positioning unstructured data acquisition and analysis as a prominent area of UI condition assessment research (Hsieh and Tsai, 2020; Koch et al., 2015; Menendez et al., 2018). However, the reliance of these technologies on environmental conditions (e.g., light, moisture), UI accessibility, and mobility (e.g., confined space) also poses some challenges to the acquisition and analyses of unstructured data. The following subsections review the main methods that are available to acquire big amounts of unstructured data in the field of UI condition assessment and then compare their advantages and disadvantages in acquiring unstructured image and video data.

3.2. Acquisition of unstructured data

Acquiring unstructured data relies on monitoring methods/techniques that extract feature information pertinent to structural health by analyzing images and/or videos to identify and evaluate changes. These methods predominantly utilize computer vision technology and image or video processing algorithms, offering the benefits of noninvasive and remote monitoring capabilities. The following subsections review some representative technologies that have been utilized to acquire unstructured data.

3.2.1. Ground-penetrating radar

GPR is a nondestructive testing method that employs radar signals to visualize subsurface structures. It is effective for detecting UI, assessing its condition, and identifying potential issues like voids or structural damages. Due to the varying dielectric properties of different materials, the captured signals of reflected waves are processed to construct an image or profile of the subsurface, which enables the identification of the location, depth, and size of any anomalies or structures beneath the surface, such as tunnel, voids, or other structural features. Figure 10 illustrates the working principle of GPR in detecting utility pipes as an example.

GPR has been successfully and extensively employed in various UI scenarios with different purposes, including estimating the thickness of concrete liners and grouting layers (Guo et al., 2020; Li et al., 2011; Liu et al., 2023; Prego et al., 2016; Zeng et al., 2023; Zhang et al., 2010), identifying defects in tunnel lining such as voids and cracks (Hou et al., 2024; Kravitz et al., 2019; Qin et al., 2020; Wu et al., 2022). In addition, GPR has also been applied to detect and identify geological features such as water seepage (Li et al., 2010), to check rebar cover and location (Wang et al., 2020; Xiang et al., 2019a; Xiang et al., 2019b), to detect leakage, voids, thickness of pipelines, and to analyze their integrity (Ékes et al., 2014; Li et al., 2022; Wang et al., 2022b). Table 6 presents some representative studies on the acquisition of image data for UI condition assessment.

Acquiring GPR images serves as the first significant step toward successful UI condition assessment and analyses. Following that, the interpretation of GPR image information is a crucial step in utilizing the data effectively, and it can be difficult owing to the complex reflection patterns (ringing noise and diffractions) and the interactions with different subsurface materials. Traditional GPR interpretation

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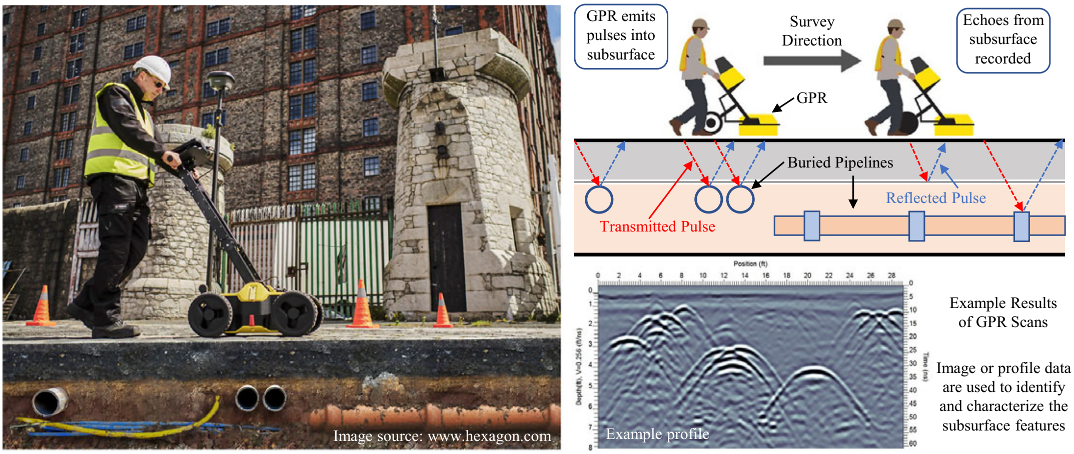

Figure 10. *Working principle of GPR in underground utility pipes.*

Table 6. *GPR-based image data acquisition for different UI condition assessments*

UI	Application	References
Mineshaft	Determine the distribution range of anomalies behind a mine shaft	Guo et al. (2020)
Tunnel	Automatically recognize lining layer and estimate lining thickness	Li et al. (2011)
Tunnel	Identify the shape, type, and depth of lining defects and thickness	Liu et al. (2023)
Tunnel	Acquire data on granite layer thickness, liner voids, and delamination	Prego et al. (2016)
Tunnel	Automatic detection of backfill grout thickness behind shield tunnel	Zeng et al. (2023)
Tunnel	Estimate the width and buried depth of hidden cracks in the tunnel lining	Hou et al. (2024)
Tunnel	Detect voids in annular grout behind a precast segmental tunnel	Kravitz et al. (2019)
Tunnel	Detection of voids inside and behind a physical tunnel lining model	Qin et al. (2020)
Tunnel	Detection of air-filled and water-filled voids in concrete tunnel liner	Wu et al. (2022)
Tunnel	Prediction of geological hazards such as groundwater and faults	Li et al. (2010)
Tunnel	Semi-automatic detection of buried rebar in underground tunnels	Wang et al. (2020)
Tunnel	Locate rebar, estimate liner thickness, and determine lining defects	Xiang et al. (2019b)
Tunnel	Automatically recognize rebar in underground concrete structures	Xiang et al. (2019a)
Pipeline	High-efficiency and high-quality detection of leakage in oil pipeline	Li et al. (2022)
Pipeline	Detection and characterization of erosion voids near buried pipelines	Wang et al. (2022b)
Pipeline	Detect voids outside pipes, pipe thickness, and analyze pipe integrity	Ékes et al. (2014)

primarily depends on experienced professional technicians, which is time-intensive and subjective (Liu et al., 2023; Yue et al., 2024). In recent years, machine learning and deep learning, with their powerful self-learning and data mining capabilities, have gradually been applied to the intelligent recognition of GPR profiles of various UIs like tunnel lining. For example, Liu et al. (2023) proposed a new method for simultaneously identifying tunnel defects as well as lining thicknesses from GPR images based on a multitask deep neural network and curve-fitting postprocessing operation. Liu et al. (2020b) proposed an automatic detection and localization method using deep learning and migration for lining defects. The machine learning-based methodologies have demonstrated effectiveness in automatically classifying and identifying lining defects from GPR images.

GPR is a highly valuable technology that provides essential unstructured information across different fields. The nondestructive nature of GPR and its capability to deliver real-time, high-resolution data

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renders it indispensable for numerous applications. Despite GPR's widespread success in acquiring unstructured data for UI condition assessment, some challenges and limitations still exist, including (1) limited penetration depth (which is typically within several centimeters to tens of meters) caused by electromagnetic wave signal attenuation with increasing detection depth, (2) high sensitivity to ground conditions where high moisture content attenuates radar signal and rough surfaces scatter radar waves, (3) difficulty in data interpretation as GPR data can be prone to noise in complex environments and thus is highly dependent on the operator's proficiency, and (4) resolution and depth tradeoff where higher resolution is typically achieved with higher frequencies and limited depths, and vice versa. Additionally, other challenges like cost considerations, equipment operation, electromagnetic interference, and so on require meticulous management when using GPR to acquire unstructured data for UI assessment.

3.2.2. Closed-circuit television

Unstructured data acquisition by CCTV in UI refers to the process of utilizing CCTV cameras, sometimes mounted on robotic crawlers or remotely operated vehicles, to collect visual data in the form of video recordings or images to visualize the interior of underground conduits, tunnels, and so forth, aiding in the identification of defects such as blockages, corrosion, leakage, dislocation, and so on. The CCTV technique was first applied to pipeline corrosion detection in the mid-1960s and has been widely used for pipeline inspection globally since the 1980s (Wang et al., 2022b). It has become an economical and appropriate tool for acquiring unstructured data from pipelines, especially from those that are too confined or dangerous for human entry. With its application scenarios becoming increasingly diverse, this method is gradually becoming a crucial tool for monitoring, inspecting, and assessing the condition of not only pipes but also tunnels, and other subsurface structures. Figure 11 illustrates the general process of unstructured data acquisition by CCTV for UI condition assessment.

For unstructured data acquisition on pipelines, CCTV has been used mainly to achieve the following purposes: identify structural defects such as cracks and joint offset, deformation in pipeline cross-section, and corrosion (Kumar et al., 2018; Yin et al., 2020), locate blockages and obstructions within pipelines to plan cleaning and maintenance operations (Hawari et al., 2018; Myrans et al., 2018; Romanova et al., 2013), and also identify leaks and points of water infiltration in water supply and sewage systems (Jo and Boon, 2012). In addition to pipes, tunnels, and conduits are also common UIs where CCTV has seen some applications in their structural assessment (including the identification of cracks, spalling, and other structural issues) (Khan et al., 2020). However, CCTVs in such UIs mainly perform vital functions related

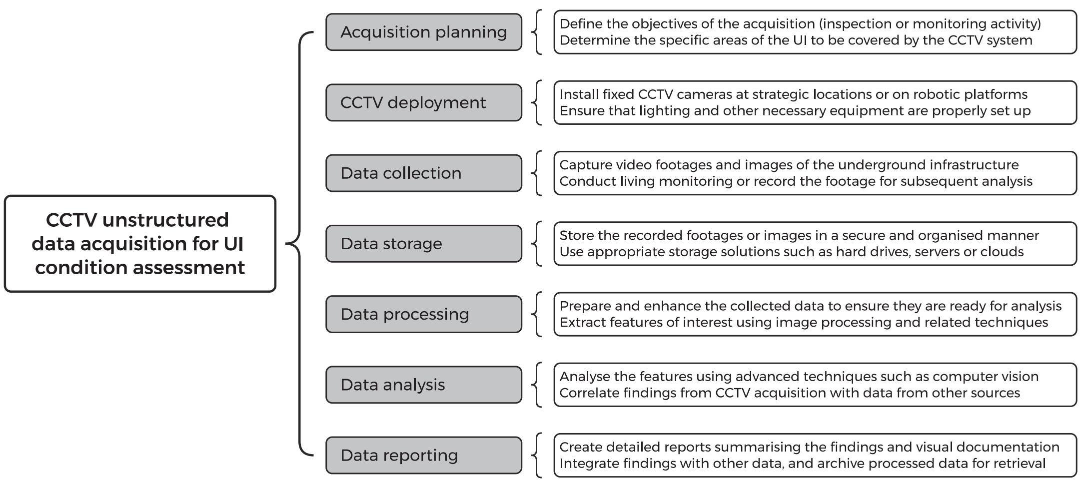

Figure 11. *General process of CCTV-based unstructured data acquisition for UI condition assessment.*

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to security surveillance, traffic management, and incident documentation, instead of structural health monitoring and condition assessment.

After acquiring unstructured images or videos from CCTVs, the next main steps include the processing and analysis of these data to gain a good understanding of the UI conditions. Traditionally, the postassessment of structural conditions from CCTV inspection needs to be performed manually by trained operators, which is time-consuming and highly relies on the operators' experience and skills (Yin et al., 2020; Zhou et al., 2021). The large volumes of unstructured data collected indicate that (1) significant storage capacity and efficient data management solutions are required and (2) reviewing and processing of the data can be complex, time-consuming, and labor-intensive. Recently, automated defect detection and classification methods based on machine learning algorithms have emerging and rapidly developing (Hawari et al., 2018; Kumar et al., 2018; Zhou et al., 2021), facilitating a significant improvement in accuracy, efficiency, and cost-effectiveness in UI condition assessment based on unstructured image data.

3.2.3. Unmanned aerial vehicles

Unstructured data acquisition by UAVs in UI involves using drones equipped with various cameras or sensors to collect high-resolution images, videos, and other data (Colomina and Molina, 2014). Similar to CCTV data acquisition, UAV data acquisition could provide information on critical UIs' conditions, like tunnel defects including leakage, cracks, spalling, and void, from images and/or videos, which could further reveal tunnel deformation and other health issues based on image processing. Figure 12 briefly illustrates the UAV inspection on tunnel surface for image data acquisition, Table 7 lists some representative studies on UAV applications for UI unstructured data acquisition, and Figure 13 presents an example of tunnel geometrical reconstruction based on UAV-acquired image data.

It is noted the applications of UAV in acquiring image data from UIs like tunnels have been relatively limited (Feng et al., 2021; Mansouri et al., 2020; Özaslan et al., 2017; Pahwa et al., 2019; Tan et al., 2018; Zhang et al., 2024). This is primarily due to several significant challenges inherent to the underground environment, including (1) environmental interference to the sensors exemplified by the presence of airborne dusts and particles obscuring sensors, (2) insufficient visible light such as uneven lighting that affects visual sensors/cameras, contributing to poor image quality (for example, a minimum of 4 lux of luminance in a tunnel reported in (Zhang et al., 2024) is not enough for UAV inspection which requires a

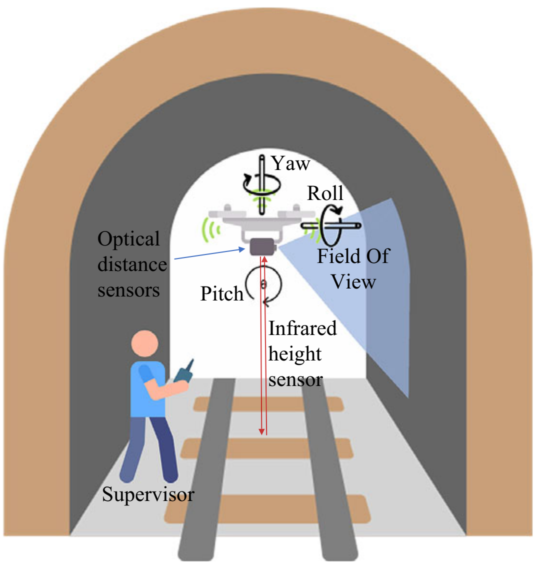
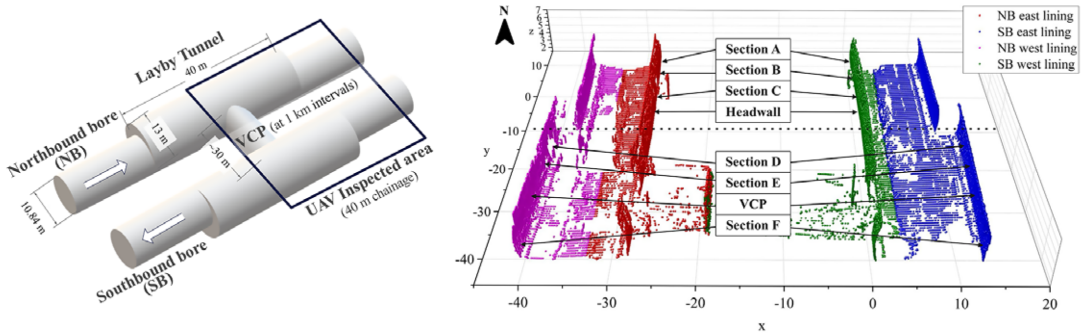


Figure 12. *Illustration of UAV image data acquisition on tunnel surface (Zhang et al., 2024).*

Table 7. *UAV-based image data acquisition for different UI condition assessments*

UI	Application	References
Tunnel	Identify defects and potential problems related to tunnel safety	Pahwa et al. (2019)
Tunnel	Capture high-resolution images for defect detection and classification	Tan et al. (2018)
Tunnel	Automatic image data acquisition for tunnel defect identification	Zhang et al. (2024)
Penstock	Inspect the structure to detect features that might indicate failures	Özaslan et al. (2017)
Mine	Present a framework to enable the deployment of micro UAVs in mines	Mansouri et al. (2020)
Spillway	Efficiently detect spillway tunnel defects based on UAV images	Feng et al. (2021)



(a) Illustration of the inspected twin tunnel section (b) Reconstructed inspection section using UAV image data

Figure 13. *Reconstructed inspection area of Dublin Port Tunnel (Zhang et al., 2024).*

light intensity of at least 15 lux), (3) lack of global positioning system (GPS) signal that may lead to inaccurate UAV positioning, challenging autonomous flight and increasing collision risks, (4) complex navigation environment in confined space like narrow passages and tunnels with cables, pipes and other obstructions that may interfere with UAV's flight path, (5) limited battery life (within a space of tens of minutes, e.g., 20–40 mins on a single battery) owing to constant maneuvering, and frequent battery change in long tunnels leading to data acquisition interruption, (6) coverage range that is influenced by multiple factors, including battery life, tunnel geometry, inspection requirements, tunnel conditions, and so on, leading to a disperse range of coverage from tens of meters to several kilometers in a single UAV flight, and (7) dependence of accuracy on onboard sensors and environmental conditions where positional accuracy can vary from several to tens of centimeters when GPS is available and measuring accuracy relies on lighting, dust, smoke, and so on. Despite these challenges and limitations, compared with other image/video acquisition techniques, such as camera-mounted vehicle inspection, the use of UAVs offers several advantages, including increased safety, lower costs, more efficient deployment and inspection processes, and greater accessibility and flexibility. UAVs can provide consistent photography and operate at various heights and angles, making them ideal for capturing images/videos in irregular and inaccessible environments (Toriumi et al., 2022; Zhang et al., 2023).

As recent technology innovations on UAVs are continuously being introduced to the field (Attard et al., 2018a), some problems such as navigation and localization, and autonomous path planning, have made great progress and improvement. Investigations have demonstrated the possibility of using LiDAR and laser sensors for autonomous path planning, collision avoidance, and navigation in both indoor and underground environments (Bi et al., 2017; Li et al., 2018a; Mansouri et al., 2020; Suzuki, 2018; Tripicchio et al., 2018; Vong et al., 2017). Nowadays, active research on crack detection for tunnel inspections based on UAVs has gained

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increasing attention, and more and more custom-built UAVs for tunnel inspection are proposed. The limited previous efforts on UAV image data acquisition in UI, like tunnels, demonstrated the positive potential for automatic UAV inspections but it should be highlighted their focus was mainly on the development of the acquisition methodology instead of on UI condition assessment. With the maturing of UAV inspections in unfavorable underground conditions, attention should be laid on automatic processing and analysis of the collected unstructured data for an enhanced and improved understanding of UIs, in the context of emerging digital image processing techniques based on machine learning and deep learning.

3.2.4. Infrared thermography

Acquisition of unstructured data from UIs by IRT features the use of thermal imaging cameras to capture thermal images to detect temperature changes that indicate potential issues. It can be applied to identify leaks (indicating the presence of water, gas, or other fluid leaks in pipelines), thermal anomalies (that indicate structural weaknesses such as cracks and voids), or areas of excessive heat in underground facilities, which are indicative of potential insulation issues, corrosion, or equipment malfunctions (Maldague, 2001). IRT includes both passive and active techniques. Figure 14 briefly illustrates its working principle. The former refers to the detection of natural temperature differences, while the latter refers to the detection of temperature differences after active heating, mainly for detecting deep subsurface defects (Jiang et al., 2023). In UI condition assessment, passive IRT is more commonly utilized for identifying water leakage, cracks, voids, moisture infiltration, and corrosion in transport tunnels (Afshani et al., 2019; Huh, 2024; Jiang et al., 2023; Lu et al., 2019; Yu et al., 2018), diagnosing pipe crown conditions (invisible liner defect) of utility tunnels (Sham et al., 2019), detecting leaks in buried water pipelines (Bach and Kodikara, 2017; Yahia et al., 2021), and so forth Table 8 summarizes these representative IRT studies on acquiring thermal images for UI condition assessment.

Acquiring unstructured thermal image data from various UIs by using IRT brings advantages like noninvasive inspection of critical UIs, early detection of structural problems like water leakage, cracks, and voids, real-time collection of thermal images, etc., as well as challenges, including influential factors like high humidity, dust and poor light that may affect the accuracy of thermal imaging, heavy reliance on specialized expertise on data interpretation, dependence of high-quality data on high-quality camera, and so forth. Figure 15 gives a summary of these pros and cons.

The challenges faced by the IRT technique in thermal image acquisition necessitate the further development of more accurate and reliable algorithms for UI condition assessment. This points out some promising future directions for IRT, including integration with other technologies exemplified by GPR to provide a more comprehensive assessment of various UIs, the development of advanced algorithms and machine learning techniques to improve automated analysis and interpretation of thermal images, and the use of robotic systems such as UAVs mounted with infrared cameras for remote and autonomous inspections.

3.3. Discussion and comparison of unstructured data acquisition

In Section 3.2, a comprehensive review of the commonly used techniques for acquiring unstructured image and/or video data in UI is presented. It is necessary to understand their similarities and differences

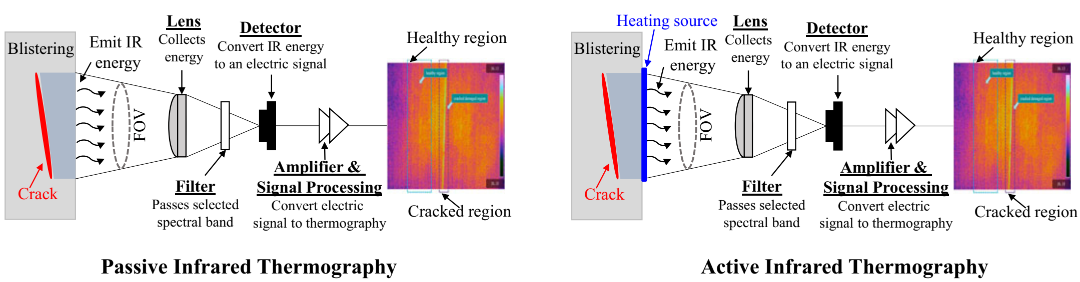

Figure 14. *Working principle of passive and active IRT.*

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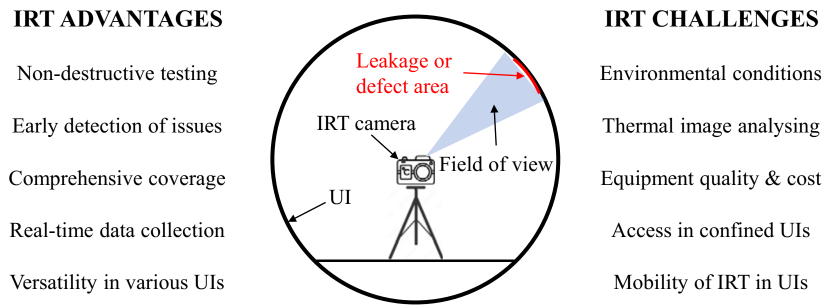

Figure 15. *Advantages and challenges of IRT in acquiring thermal image of UIs.*

Table 8. *IRT-based thermal image data acquisition for different UI condition assessments*

UI	Application	References
Tunnel	Identify defects in an aging reinforced concrete tunnel lining	Afshani et al. (2019)
Tunnel	Detect delamination and moisture penetration in rock tunnels	Huh (2024)
Tunnel	Detection of tunnel leakage based on IRT thermal images	Jiang et al. (2023)
Tunnel	Automatic detection of water seepage into cable tunnels	Lu et al. (2019)
Tunnel	Diagnose geometry and attribute of water leakage in metro tunnels	Yu et al. (2018)
Utility tunnel	Imaging and diagnosis of underground sewer pipe crown conditions	Sham et al. (2019)
Water pipeline	Identify onsite water leaks using IRT-based passive leak detection	Bach et al. (2017)
Water pipeline	Water leakage detection and localization in water distribution pipes	Yahia et al. (2021)

in unstructured data acquisition for the reference of engineers, researchers, etc., in terms of infrastructure condition assessment. Table 9 gives a detailed comparison among the listed data acquisition methods from various aspects of unstructured data, including data type, data size, sampling interval, data management, and transmission and processing. It is clear that CCTV and UAV methods produce the largest data volumes due to their continuous video recording and high-resolution imaging, posing greater challenges to data storage, transmission, and processing, while GPR and IRT produce smaller volumes of image data that are more manageable. Despite the differences in the above aspects of unstructured data acquisition, these methods follow a similar general workflow, including image acquisition, image enhancement, image processing, and defect analysis, as shown in Figure 16. The common steps for the above-mentioned techniques are image processing and defects analysis, while the differences lie in image acquisition which is based on various physical mechanisms and principles. Different inspection methods have their advantages, disadvantages, and scope of applications, which means relying solely on one technique typically leads to limited performance in UI condition assessment.

4. Discussion, conclusion, and recommendation

4.1. Discussion

The acquisition of both structured and unstructured data is essential for the comprehensive condition assessment of UIs. This study highlights the evolution of data acquisition methods from traditional techniques to more advanced automatic systems, focusing on both structured data (e.g., stress, strain,

Table 9. *Comparison of unstructured data acquisition*

Method	Data type	Typical data size	Sampling interval	Data management	Transmission and processing
GPR	**Radar images/profiles**	**Tens of MB to several hundred MB per scan**	**Can be as frequent as every several minutes depending on the requirements**	**High due to large raw data in frequent sampling**	**GPR data are often stored locally and its processing requires specialized software**
CCTV	**Video footage/images**	**Several hundred MB to several GB per hour**	**Can be continuous or every several hours depending on the requirements**	**High for intermittent recording and very high for continuous recording**	**High bandwidth required for real-time data transmission and data postprocessing is time-consuming**
UAV	**High-resolution images/videos**	**Several GB to tens of GB per flight**	**Continuous during each flight and intermittent during different flights**	**Extremely high especially for long flights**	**UAV data are typically stored onboard and significant postprocessing is needed**
IRT	**Thermal images**	**Several MB to Several GB per session**	**Can be as frequent as every several minutes depending on the requirements**	**Moderate to high, dependent on resolution and frequency**	**Data transmission and processing may require real-time capabilities**

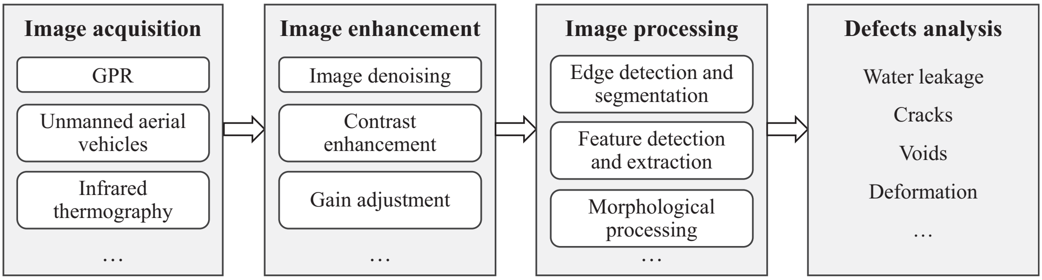

Figure 16. *Flowchart of acquiring unstructured image/video data.*

displacement) and unstructured data (e.g., images and videos). Traditional structured data acquisition methods, such as total stations and strain gauges, have been reliable but are labor-intensive and prone to human error. The advent of technologies such as WSN, DFOS, and TLS has revolutionized data acquisition, offering higher accuracy, real-time monitoring, and reduced human intervention. These advanced methods facilitate large-scale, continuous data collection, essential for modern UIs' maintenance and management. Unstructured data acquisition in UIs, mainly involving images and videos, leverages techniques such as GPR, closed-circuit television, and unmanned aerial vehicles. These methods provide detailed visual information, capturing aspects that structured data may miss. The integration of data analytics, like machine learning algorithms, with these methods enhances the analysis and interpretation of vast volumes of datasets, improving defect detection and condition assessment. For example, Lin et al. (2024) employed machine learning algorithms such as random forest and support vector machine to classify strain profiles acquired from DFOS in identifying structural cracks and cavities in underground structures. Hou et al. (2021) adopted neural network to enhance the accuracy and efficiency of tunnel deformation monitoring by DFOS, aiming to automatically map strain measurements from DFOS to the actual deformation shape of tunnel cross-sections. To address the challenges related to manually interpreting the vast amount of DFOS data during monitoring of structural cracks, Liu and Bao (2023) integrated the data with deep learning algorithms to automate the detection and localization of cracks in real time. These case studies showcase such an integration can help enhance the accuracy, efficiency, and reliability of UI condition assessment. This combination enables more precise defect detection, predictive maintenance, and so on, while reducing human subjectivity and error in data analysis, ultimately leading to safer and more reliable infrastructure management. Despite the significant advancements, there are some challenges, including high initial cost, need for specialized technical expertise, and dependence on environmental conditions, and they affect the widespread deployment of these advanced data acquisition systems. Moreover, managing and analyzing large volumes of data necessitate robust data management solutions and sophisticated analytical tools. To quantitatively compare traditional methods and advanced methods in acquisition of both structured and unstructured data, Table 10 lists some quantitative measures of their costs, accuracy, and reliability. It is easy to notice (1) in structured data acquisition, traditional methods such as total stations and strain gauges are relatively low-cost, while advanced methods such as DFOS and TLS can be quite expensive, (2) generally, structured data acquisition methods such as DFOS, TLS, and WSN offer high accuracy, while unstructured data acquisition methods such as GPR and UAV tend to have medium-high accuracy due to the influence of environmental conditions, equipment quality, and manual operation, and (3) structured data acquisition methods typically offer high reliability, due to the well-established techniques such as strain gauges and continuous and precise monitoring techniques such as DFOS. In contrast, the reliability of unstructured data acquisition methods such as GPR and CCTV is considered to be medium owing to their sensitivity to ground and environmental conditions. The comprehensive comparison allows for a better understanding of the tradeoffs between various data acquisition methods, helping to choose the most suitable and efficient approach based on the specific needs of UI projects.

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Table 10. Quantitative comparison of cost, accuracy, and reliability of data acquisition methods

Category	Method	Data type	Cost	Accuracy	Reliability
Structured	TS	Deformation settlement	Low to moderate depending on precision and supplier (e.g., €3 k-€10 k per total station)	Medium (e.g., ±1–5 mm)	High (well-established method but depends on manual operation)
	SG	Strain measurement	Low to moderate depending on the number of SGs and supplier (e.g., €50–€200 per gauge)	High (e.g., ±1–5 με)	High (well-established principle but sensitive to installation quality)
	WSN	Inclination displacement	Moderate to high depending on the network scale and supplier (e.g., €1 k-€5 k per WSN tiltmeter)	High (e.g., ±0.1–1 mm)	High (real-time, continuous, and wireless monitoring)
	DFOS	Strain temperature	High (e.g., ≥€50 k per Brillouin interrogator and €5–€50 per meter for DFOS strain cables)	High (e.g., ±20–50 με)	High (continuous, long-range sensing, immune to electromagnetic influence)
	TLS	Point cloud coordinates	High (e.g., €20 k-€150 k each depending on the scanner's range, accuracy, speed, etc)	High (e.g., ±1–2 mm)	High (precise and comprehensive data, sensitive to the environment)
	RIS	Relies on the integrated system	High due to the integration of e.g. TS with robotics (e.g., €3 k–€10 k per total station, plus robotics cost)	High (depending on the type of integrated system)	High (autonomous and continuous monitoring and repeatable inspections)
Unstructured	GPR	GPR profiles	Low to moderate depending on antenna frequency, penetration depth, etc. (e.g., €5 k–10 k for a basic one)	Medium to high depending on material and depth	Medium (sensitive to ground conditions, limited penetration depth)
	CCTV	Video footage images	Low to moderate depending on camera quality (e.g., €2 k–€10 k for a complete system with 10 cameras)	Medium to high depending on image quality	Medium (subject to lighting and environmental conditions)
	UAV	Video footage images	Moderate to high depending on the type and quality of UAV (e.g., €5 k–€50 k from basic to high-end one)	Medium to high depending on sensor quality	Medium to high (subject to flight stability, environment, etc.)
	IRT	Thermal images	Low to moderate depending on resolution, sensitivity, etc (e.g., 1 k to 30 k from entry level to high end)	Medium depending on cameras (e.g., ±1–3 °C)	Medium (affected by environmental factors such as humidity)

4.2. Conclusion

This article reviewed various representative methods for acquiring structured and unstructured data for UI condition assessment, highlighting their advantages, limitations, and potential integration. The shift toward advanced and automated, real-time, and continuous data acquisition methods from traditional ones represents an improvement in monitoring the health and performance of UIs. The main research findings are summarized as follows:

With regard to structured data acquisition for UI condition assessment, (1) traditional structured data acquisition methods usually obtain a relatively low volume of data due to low sampling frequency, manual data collection and transmission, whereas more advanced and automatic methods can gather a relatively larger volume of data due to automatic data collection, high, continuous sampling frequency and comprehensive monitoring; (2) the quality of structured data gathered by conventional methods remains largely low to medium due to factors such as subjectivity in data reading, environmental conditions, signal interference, human error, instrument sensitivity, and so forth, compared to relatively higher data quality by advanced methods; (3) traditional methods are characterized by heavy reliance on human involvement, including manual installation and calibration, manual operation and data collection, while the more advanced techniques minimize human intervention, thus enabling a medium to a high level of automation and subsequent improvement in data acquisition efficiency, data accuracy, data quality, and data comprehensiveness. In terms of unstructured data acquisition, (1) the techniques reviewed typically require low-moderate initial cost in comparison to the relatively high initial investment in advanced structured data acquisition methods; (2) methods such as CCTV and UAV often produce large volumes of image/video data that have medium-high accuracy due to the influence of environmental conditions, equipment and sensor quality, compared to the high accuracy offered by WSN, DFOS, and TLS; (3) the reliability of unstructured data acquisition methods such as GPR and IRT is considered to be medium owing to their sensitivity to ground and environmental conditions, when compared with structured data acquisition techniques like DFOS that typically offer high reliability due to its continuous and precise monitoring capabilities; (4) the methods reviewed are only responsible for collecting raw unstructured images or videos, and they do not inherently possess the capability for automated postprocessing and analysis, necessitating the integration of data analytics to enable automated unstructured data processing and analysis and therefore more efficient, effective, and accurate UI condition assessment.

4.3. Recommendation

To assess the condition of UIs, acquiring large volumes of both structured and unstructured data is the first step. To enable efficient, accurate, and reliable UI condition assessment, it is recommended (1) to integrate advanced artificial intelligence and machine learning algorithms to automate the analysis and interpretation of the collected big data, which can help enhance the accuracy and reliability of UI condition assessment, enable effective decision-making, and predict potential failures and maintenance needs, facilitating proactive rather than reactive maintenance strategies; (2) to develop robust big data management platforms capable of handling large volumes of data and supporting cloud integration for scalable storage, processing, and real-time analysis; (3) to couple different data acquisition technologies to leverage the strengths of each method, aiming to provide a more comprehensive understanding of UI conditions; (4) to continuously improve data acquisition techniques by investing in sensor development and algorithm enhancement to ensure efficient data acquisition in harsh underground conditions, such as GPS-denied deep tunnels.

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