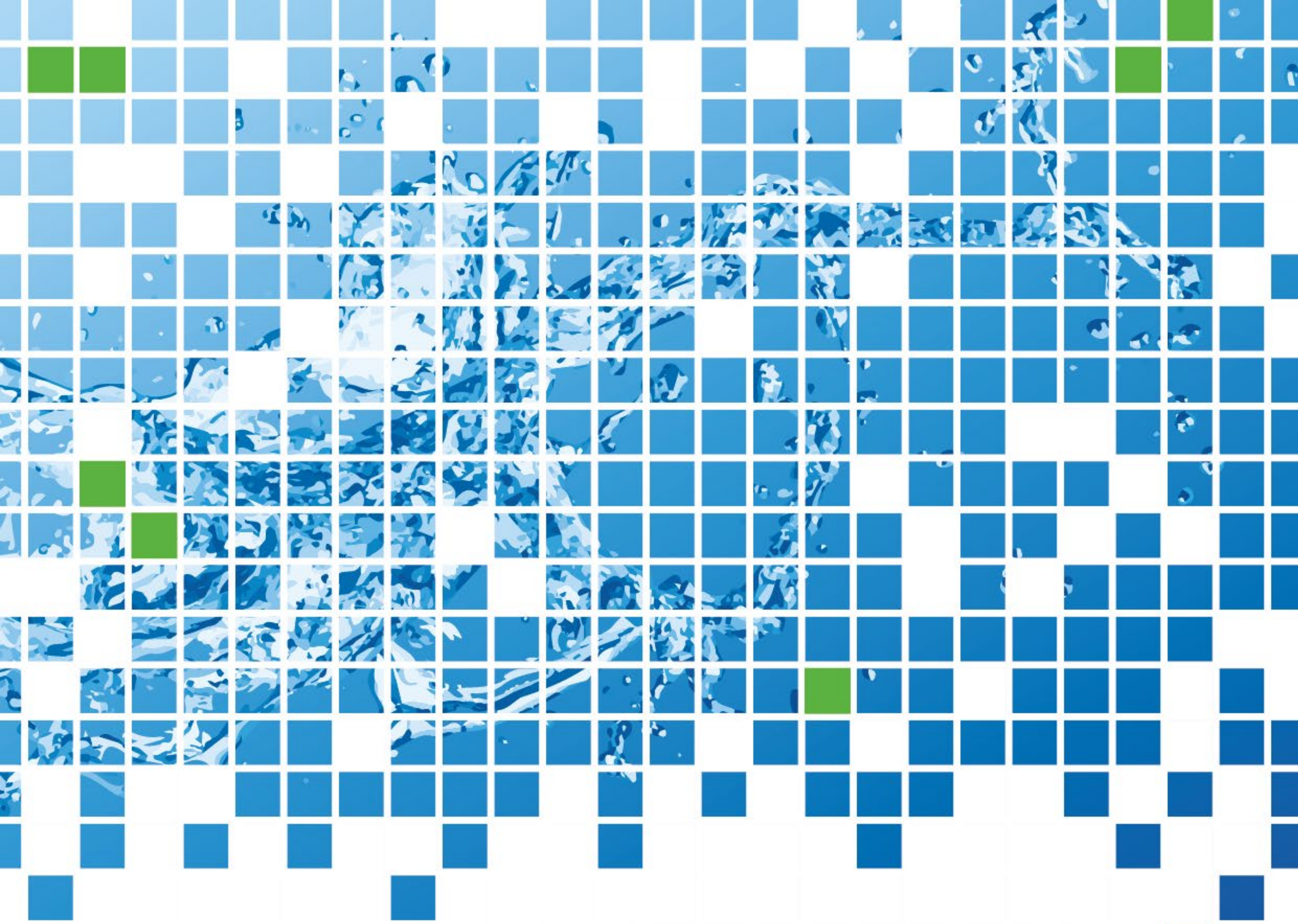

Co-UDlabs

Building Collaborative Urban Drainage research Labs communities

D07.1. Report on methodologies used to identify in-pipe defects

Date of delivery - 31/10/2022
Authors – Tait S., Kazemi E.
Institution: University of Sheffield

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement N°101008626

DOCUMENT TRACKS DETAILS

Project acronym	Co-UDlabs
Project title	Building Collaborative Urban Drainage research labs communities
Starting date	01.05.2021
Duration	48 months
Call identifier	H2020-INFRAIA-2020-1
Grant Agreement No	101008626

Deliverable Information	
Deliverable number	D07.1
Work package number	7
Deliverable title	Report on methodologies used to identify in-pipe defects
Lead beneficiary	University of Sheffield
Author	Simon Tait
Due date	31/10/2022
Actual submission date	31/10/2022
Type of deliverable	Report
Dissemination level	Public

VERSION MANAGEMENT

Revision history and quality check			
Version	Name	Date	Comment
V 0.1	Simon Tait, UFSD	16/10/22	First draft
V 0.2	Ehsan Kazemi, UFSD	21/10/22	Internal review
V 0.3	Francois Clemens, DEL	24/10/22	Partner review
V 0.4	José Anta Álvarez, UDC	26/10/22	Coordinating partner review
V 1.0	Simon Tait, UFSD	28/10/22	Final version for submission

Table of Contents

Background: about the Co-UDlabs Project

Co-UDlabs is an EU-funded project aiming to integrate research and innovation activities in the field of Urban Drainage Systems (UDS) to address pressing public health, flood risks and environmental challenges.

Bringing together 17 unique research facilities, Co-UDlabs offers training and free access to a wide range of high-level scientific instruments, smart monitoring technologies and digital water analysis tools for advancing knowledge and innovation in UDS.

Co-UDlabs aims to create a urban drainage large-scale facilities network to provide opportunities for monitoring water quality, UDS performance and smart and open data approaches.

The main objective of the project is to provide a transnational multidisciplinary collaborative research infrastructure that will allow stakeholders, academic researchers, and innovators in the urban drainage water sector to come together, share ideas, co-produce project concepts and then benefit from access to top-class research infrastructures to develop, improve and demonstrate those concepts, thereby building a collaborative European Urban Drainage research and innovation community.

The initiative will facilitate the uptake of innovation in traditional buried pipe systems and newer green-blue infrastructure, with a focus on increasing the understanding of asset deterioration and improving system resilience.

List of acronyms

Acronym / Abbreviation	Meaning / Full text
AI	Artificial Intelligence
CCTV	Close circuit television
DL	Deep Learning
DTS	Distributed temperature sensing
FELL	Focused electrode leak detection
FEM	Finite element modelling
FO	Fibre optic
IKT	Institute for Underground Infrastructure, Germany - www.ikt-online.org
ML	Machine Learning
MSCC	Manual for Sewer Condition Classification
NASSCO	National Association of Sewer Service Operators - www.nassco.org
PACP	Pipeline Assessment and Certification Program
R-CNN	region-based convolutional neural network (R-CNN)
RF	Random Forests
ROV	Remotely operated vehicle
RWA	Regional Water Authority
SRM	Sewerage Rehabilitation Manual - http://srm.wrcplc.co.uk/home.aspx
SSET	Sewer Scanning and Evaluation Technology
TA	Transnational access
UDS	Urban Drainage Systems
UFSD	University of Sheffield
USEPA	United States Environmental Protection Agency
WRc	Water Research Centre (UK) - https://www.wrcgroup.com/

Acknowledgments

The authors would like to acknowledge the assistance of Dr Seiji Hosaka, of Nihon University in the interpretation of the current Japanese sewer condition standard. The work of Guillaume Geoffroy of the Ecole des Ingeniures de la Ville that he undertook during an Internship at the University of Sheffield is also acknowledged. We would also like to thank Mr Iain Naismith for the provision of information on the inspection activities of IKT and Mr Robert Lee of subterra.ai for the provision of technical information.

1. Executive summary

This report is Deliverable 7.1 “Report on the methodologies used to identify in-pipe defects” of the Co-UDlabs project, which is funded under the European Union’s Horizon 2020 research and innovation programme via Grant Agreement No 101008626. The Deliverable is an output from Work Package 7, “Asset Deterioration”. The University of Sheffield (UFSD). UFSD is the author of this deliverable.

The report describes current defect inspection and classification methodologies and provides a review of their effectiveness. The report argues that historically there has been a strong linkage between the development of international and national defect classification systems and sewer inspection approaches. A state-of-the-art review of commonly used inspection technologies is provided. The potential for newer emerging inspection technologies is also described and discussed. These new approaches are being developed to (i) reduce cost so as to allow the wider use of sewer inspection and (ii) gather more physically relevant information about in-sewer defects so that more physically based pipe deterioration models can be developed, and (iii) to provide inspection data with less uncertainty. If improvements in inspection approaches could be achieved it would allow water utilities to better focus investment for sewer rehabilitation and renewal and also more rapidly identify operational issues that cause system failures such as flooding and the release of untreated wastewater via sewer overflows.

Different sources of information were considered: (i) a search of academic and governmental agency sources – peer reviewed outputs; (ii) search of documentation from other sources that had not been reviewed; and (iii) information from commercial sources, mainly companies providing in-pipe inspection services.

This review has shown that CCTV based inspection currently still dominates sewer inspection, despite the recognition that there is significant uncertainty and cost associated with human based analysis of CCTV images. Different technologies have been developed and deployed to identify defects that are difficult to identify using visual means and that also allow for larger proportions of sewer networks to be inspected. The review has also shown the benefits of multi-sensor approaches when identifying and characterising sewer pipe defects.

Emerging inspection technologies can be organised into 3 groups: new sensing technologies, autonomous, multi-sensor inspection platform and adaptation of AI based approaches to better identify and characterise in-pipe defects from CCTV images. It is also clear that new inspection techniques are being developed so that more physically relevant inspection data can be collected to inform the development and use of more physically based pipe/asset structural deterioration models.

2. Defect Classification

The first stage of any sewer rehabilitation program requires existing in-sewer defects to be identified and their character assessed against their likelihood to cause a failure in that pipe to provide the expected level of performance. In order to provide a logical structure to assessing defects within sewer pipes, structured systems of sewer defect coding have been developed. It is important that structured defect information is collected so that this knowledge can be exchanged between all those responsible for managing sewer networks, e.g. asset owners, operators, consultants and contractors responsible for rehabilitation. There has been a strong linkage between the development of defect classification/coding approaches and the use and development of particular in-sewer inspection technologies.

Initially a pragmatic approach was taken in that early developments of defect classification systems were constrained by the availability of particular inspection technologies. These were generally visual and relied on human interpretation of mainly CCTV images. As awareness of the key in-pipe failure mechanisms increased there has been a desire to develop more physically based deterioration models this has highlighted the additional need for much better characterisation of defects and the surrounding environment in which buried sewer pipes exist (Makana et al. 2022). This awareness has slowly encouraged the development of new approaches for in-pipe inspection so that better linkage between inspection and deterioration modelling can be achieved. This report will first highlight this historical development, the range of current in-sewer inspection technologies and approaches and how changing needs is driving the emergence of new inspection technologies that will provide more physically based defect data, that can be then implemented in improved pipe deterioration models.

3. Historical Development of Defect Classification

Early research in the 1970’s in the United Kingdom led to the development of the first structured system to code in-sewer defects. In 1973, ten separate Regional Water Authorities (RWA) were set up with the responsibility to supply water and wastewater services. The RWAs were organised based on river basin boundaries, but were public bodies with representatives from local authorities providing oversight and governance. One of the main reasons to create these large regional bodies was to raise the level of engineering expertise and so create more efficient delivery of water and wastewater services. The RWAs replaced a large number of local authority-based operators who ranged from large urban cities to small rural authorities so the range of the level of engineering competence within these utilities was very large.

In the larger RWAs it was identified that better management of wastewater collection infrastructure was needed. This increased awareness led to the creation of the Standing Committee on Sewers and Water Mains of the National Water Council. The Standing Committee's first report concluded that the UK’s piped water infrastructure was moving from an expansion phase, after the post-war development boom in the 1960’s to a state in which renewal would be the main engineering activity. This development timeline was similar to many advanced economies (e.g. Germany, France and Japan) in which rapid post-war development had led to significant lengths of new sewer infrastructure, followed by a reduction in economic growth rates in the 1970’s resulting in lower levels of development. This change in the rate of sewer infrastructure construction meant that the renewal of existing infrastructure slowly started to receive more attention.

In the UK, after the creation of the RWAs it was clear that for large parts of the country basic asset knowledge, including knowledge on asset condition was not available and information was needed to make decisions on where to focus investment in asset renewal. As regards sewer pipes and networks a project led by the Water Research Centre (WRc) and the Transport and Road Research Laboratory developed the first methodology for describing internal sewer pipe conditions (Lester et al., 1978). This project proposed the first set of logical and structured sewer defect coding this system was further developed in steps by the UK’s Water Research Centre. This enhanced coding system still provides the basis for the current WRc Manual of Sewer Condition Classification (MSSC). In the 1970’s sewer survey methods were still rudimentary, mainly visual based (from CCTV surveys) and did not delivery quantitative engineering measurements of in-pipe defects but observed descriptions from CCTV surveys. Given this limitation it became obvious that broad categories of defects needed to be defined, with a structured coding method to attempt to “measure” pipe defects to provide objectivity in decisions on renewal and replacement investment. The coding system was structured to identify (i) structural defects (16), (ii) descriptor and (iii) radial location. This structure and parameters have been retained in the later versions of WRc’s Manual for Sewer Condition Classification manual.

In the 1980’s it was recognised that even with better asset information that the UK’s sewer networks were still suffering increased failure rates. Further research by WRc resulted in the first version of the Sewerage Rehabilitation Manual (SRM) in 1983. This manual has also been revised and its latest version is now available electronically. The SRM impacted on the use by water utilities of the sewer defect codes. It recognized that 80 percent of the costs of dealing with sewer incidents were focused on around 10 percent of the sewer network; not all sewer defects were equally important and a national defect identification framework was needed as they claimed that the nature of in-pipe defects would be a critical factor in any successful renewal program. A scoring system for each defect and depending on the severity of defects a Condition Grade was assigned to individual sewer pipes from 1 to 5. The first manual for sewer condition classification (MSSC1) was published in 1980. The MSSC1 Structural Condition codes for sewer pipes were identical to the earlier codes, and retained the same modifiers. However, the number of features expanded considerably. This expansion in complexity was a common factor that was to be seen in many of the later versions of the defect classification system. In 1988, MSCC2 was published and this added new codes for in-pipe surface damage, with two new modifiers for spalling and wear and one new miscellaneous code.

At this point, the MSCC2 codes were adopted by water utilities in Australia. While some changes were made to accommodate local conditions, the MSCC2 coding structure and codes were largely adopted into the first Australian Conduit Evaluation Manual (ACCEM, 1991, Australia). The wider availability and application of computer coding programs for recoding and analyzing CCTV data in particular led to an expansion of all codes. In MSCC3 the most common code/modifier combinations were harmonized, and codes were re-ordered and presented alphabetically. At this time in the United States—the National Association of Sewer Service Companies NASSCO, the US's leading national trade organization for the underground asset rehabilitation, recognized that a standard for sewer pipeline assessment was needed. NASSCO entered into an agreement with WRc for support in the development of a national US standard for defect coding. The basis for the new standard (the Pipeline Assessment and Certification Program - PACP) was the MSCC3. NASSCO developed a simplified method of assigning severity to the various defects and grading each pipeline similar to the internal condition grade used by WRc. The NASSCO grading does not include consideration of environmental factors such as soil type, and groundwater conditions. Similarly to the Australian Code, PACP has some differences from the earlier MSCCs due to the nature of sewers and terminology in the U.S. However, given its development origins it had significantly similarities in coding structure to the earlier MSCCs. The incorporation of defect codes for manholes and chambers led to the production of the Manual of Sewer Classification Version 4 (MSCC4) in 2004.

In 2003, a new 'Euro Code'-EN13508: Part 2 was produced, knowledge from experience within the U.K. was used to provide a common structure for collating information on sewer defects. In essence, the well-established Manual of Sewer Condition Classification codes that had been adopted and applied in the U.K. were deemed to be the most mature coding methodology available. The fourth edition of MSCC4 in 2004 described and listed what became the National Equivalent coding system listed in BS EN 13508-2:2003. This British Standard was updated in 2007 and 2011. Other European countries created their sewer inspection standards and updated them periodically (e.g. AFNOR, 2011, NEN 2011) based on the structure of the earlier UK standard. However, they did not rationalise their defect codes – this resulted in standards with a larger number of defects codes. Considering the various standards across Europe the number of defect codes are now greater than 300. In Japan, a defect classification system was developed by the Japan Sewage Works Association, independently of the UK influenced standards found in the US and Europe. The Japanese standard has just 10 defect types, with each defect type assigned one of three severity scores. This classification system is considerably simpler to apply that the other defect coding systems currently used in Europe and the US. In each country a similar assessment process is followed in that CCTV images are commonly used to identify and code defects and then the number and severity of the defects are then used to assign a condition class that is then used to rank assets when decisions are made on refurbishment and replacement. There is growing evidence that the coding systems with larger number of defect codes leads to a reduction in the accuracy of defect identification and characterisation, van der Steen et al. (2014). Thus it is likely that using different defect coding systems as well as different inspection technologies will impact on the quality of the inspection of sewers.

4. Conventional In-Sewer Inspection Technologies

Sewer inspection technology has gradually evolved from the 1980's as defect coding systems became more widely used. A service industry developed with companies developing mainly CCTV based inspection systems, gradually improving the capability of their crawler platforms, their cameras (mainly visual and but some infrared) and illumination. However, non-image-based inspection systems have also developed some based on other underlying sensing technologies, such as radar, acoustic/ultrasonic, electrical impedance and other focussing on physical measurements of actual pipes to assess their current structural condition. Examples include laser-based scanning, focussed electrode leak detection, acoustic, and fibre optics. The sections below describe image-based systems and newer groups of non-visually based technologies. An assessment of deployment cost for many of the approaches described below is summarised in Selvakumar et al. (2014) which was based on data from a program of comparative testing carried out by the USEPA and reported in Martel et al. (2011).

4.1. Visual Inspection Techniques

Internal sewer inspection of pipe walls can be carried out either through physical man entry into the pipe or the use of closed-circuit television cameras (CCTV). Man-entry is now unfavoured because of the limited access to most pipes is sewer networks, its high costs and especially because of Health and Safety concerns as regards working in confined and hazardous spaces. Camera based inspection technologies can only be used in gravity sewers, the opaqueness of wastewater means that image-based technologies cannot be used in pressurized wastewater sewers. In gravity sewers the pipe wall cannot be inspected below the dry weather flow water surface. Even, with the development of new inspection and sensing technologies, after several decades the majority of internal sewer inspections of gravity sewers are still carried out using some type of CCTV based inspection system.

Makar (1999) carried out studies to examine the use of both stationary and mobile CCTV. They reported that the low cost of mobile CCTV, combined with the limited range of stationary CCTV (this was a static camera inserted at a manhole, now often termed a "zoom" camera) and the capability of operator controlled mobile CCTV to evaluate the whole length of sewer, and to examine defects in detail by stopping and for the operator to adjust the tilt and zoom of the camera when viewing a defect made mobile CCTV the more desirable of the two CCTV techniques. Data collected from mobile CCTV inspection includes location and descriptive detail of defects such as cracks, blockages/debris/roots and gross pipe deformations and deflections. Such defects are coded in most current classifications systems – see Section 3.1. Because the camera has to travel along the pipe located on some type of mechanical crawler, usually equipped with a wheel encoder, locating the position of in-pipe defects with high accuracy is often problematic. Although more sophisticated crawlers have been developed, accurate system location is still an issue with encoders on system tethers struggling to measure distance travelled to a defect although some more experimental systems do have a secondary odometer to address this issue (Kirkham et al., 2000).

Stationary CCTV has the same function as a mobile CCTV system, which is to collect images of in-pipe defects but involves the insertion of a camera often at a manhole, with a controllable focal length lens, so that the camera does not move through the pipe being inspected. These cameras are often referred to as "zoom" cameras. They can be used to inspect pipes and have advantages and disadvantages over mobile CCTV systems.

Using manhole "zoom" cameras means that sewer pipes do not need to be pre-cleaned before inspections and there is no risk that the inspection can be delayed by in-pipe obstructions as is the case with mobile CCTV. Operatives can inspect pipes more rapidly giving costs savings. However, their inspection range is limited is based on image quality mainly due to illumination constraints. Makar (1990) recommended that manhole-based camera systems should inspect sewer lengths no longer than 50 m from the manhole. A weakness of a manhole camera is if the inspected sewer pipe deviates strongly from a straight line, or there is a significant sag in the sewer line then the manhole located zoom camera will not be able to image the distant pipe wall and so defects may go undetected. The zoom camera does not provide the same flexibility, in terms of pan and tilt capabilities as a conventional CCTV system and so the image quality of defects is poorer leading to it being more difficult for an operator to code defects. However, the zoom camera has been promoted as a screening tool that can provided lower quality images whose analysis can be used to prioritize pipes for more detailed inspection using conventional CCTV inspection, or as a low-cost method to monitor developing defects (Joseph and Di Tullio, 2002).

Because of their low cost, flexibility and rapid deployment zoom camera systems have also been used to support pro-active condition-based maintenance strategies, In the INNOKANIS project (2011-14) manhole zoom cameras were used in over 300 pipes (diameters from 150 mm to 1300/1900 mm egg-shaped sections) to assess the amount of deposited material in each section of pipe, relative to the pipe diameter. A deposit threshold value of 15% was adopted, based on previous work, to trigger sewer cleansing operations. Rapid inspection of >300 pipes indicated that 1% in combined sewer pipe sections and 11% in foul sewer pipe sections did not achieve self-cleansing conditions that would prevent a deposit of 15% of the pipe diameter forming. This inspection information allowed selective cleansing strategies to be developed. Plihal et al. (2014) reported that In Salzburg, one of the case study cities that only 1% of the pipes had in-pipe deposit depths greater than 10% of the pipe diameter. This inspection information was used to create inspection informed cleaning schedules. This caused the amount of removed material to rise from 0.5 tonnes/km (before zoom camera inspections) to over 2 tonnes/km after inspection, with the total annual amount of removed material doubling. Even though the annual load increased the city was able to reduce its fleet of cleansing vehicles by just under 70% due to their more focussed deployment. Thus, highlighting simultaneous gains in cleansing effectiveness and reduction in costs derived from use of a zoom camera-based inspection scheme.

CCTV sewer inspection is the dominant technique used to assess sewer condition. Decisions on sewer rehabilitation and replacement are often based on the interpretation of inspection reports produced by inspectors viewing CCTV images. In practice, and even in some research studies (Baur and Herz, 2002), the quality of this type of defect data is not normally questioned. Wirahadikusumah et al. (2001) highlighted the need for accurate defect data when attempting to model asset deterioration. Dirksen et al. (2010) reports on the quality of visual sewer inspection data based on several European case studies. In this study two types of error were identified. The first when not all defects or all aspects of a defect were observed and recorded. This could be caused by insufficient light, fouled optics or too rapid a survey. The second type of error occurred when the inspector viewing the images did not record all defects accurately. Inspector can make a number of errors. Firstly, a defect is present and the inspector fails to register it or a defect is not present and an inspector unfortunately reports that it is present. Secondly, the inspector fails to recognise and record a defect correctly. This may be because the inspector is focused on one type of defect and as a consequence ignores other types of defects, this bias particular affects the recording of rarer defect types. Data from the case studies and training events in France, the Netherlands and Germany were used to quantify the performance of human inspection of CCTV images. It was found that the probability that an inspector fails to record the presence of a defect is significantly larger (around 25%) than the probability of a defect being reported and is not present (<5%). The likelihood of false positive identifications is inversely related to the likelihood of a particular defect. In terms of recognising a defect and assigning it an appropriate defect code, the analysis showed that the probability of an incorrect assignment was around 50%. Based on this analysis Dirksen et al. (2010) recommended that inspection coding systems should be simplified. This recommendation was strengthened by a later study in which it was clearly shown that the introduction of a more complex sewer defect classification standard in the Netherlands (NEN 2011) is likely to lead to higher levels of defect mis-identification and that more complex defect classification codes did not necessarily result in an increase in information for specific defects (van der Steen et al., 2014).

It has been seen that manually interpreted CCTV images do not provide reliable and accurate defect identification at a low cost. This has led to efforts to develop reliable automated sewer defect detection approaches. Methods used to deliver improved automated defect detection normally use conventional CCTV images and consist of two stages – i) object detection using classical computer vision methods such as colour thresholding and feature extraction, and ii) machine learning (ML) for classification of objects/defects. Moradi et al. (2019) provides a comprehensive summary of studies that have improved image quality and enhanced feature extraction for in-sewer defects. Recently, more advanced computer vision models are being developed using deep learning (DL) without a need for a separate phase of feature extraction since DL approaches can automatically learn an object's inherent features through analyzing images at a pixel level.

In this report, we will focus on current progress in the more advanced object recognition schemes. Object recognition studies have mostly used ML based techniques to develop trained algorithms to identify particular in-sewer defects. Myrans et al (2019) used a Random Forests based approach to identify defect types as specified in WRc's Manual for Sewer Condition Classification (MSCC). This approach classified the probability of a defect (type) in an image frame against all others listed in the MSCC, using a collection of RF algorithms trained on image data for specified defect types. The highest ranked defect was then assigned to that frame. Using case study data this approach was able to correctly identify different defect types from 86% for joints, to 20% for holes. It is clear that the approach's reliability varied strongly with defect type, and it did not return information on the severity of identified defects.

Unlike other ML algorithms, DL approaches train using the raw image pixel data so omits the feature extraction stage. Cheng and Wang (2018) report on a study that uses DL to identify defects from CCTV images. Defects are identified in Regions of Interest (ROI) and are used as a training data set. A region-based convolutional neural network (R-CNN) was used. One limitation of R-CNN is that it uses a multi-stage training process so computational times can be high, but it delivers precision and accuracy. In this study, 1260 images were used for training and validation, the images contained four defect types:

root intrusion, cracks, infiltration and cracks. The results indicated that there were clear trade-offs between the number of available labelled images and number of defect types in a ROI. In general, this approach seemed to trend to a rate of around 20% false positives for all defect types. In terms of defect type identification, there were precision values of 0.9 to 0.8 for roots and cracks. There was poorer performance for the two other defect types studied – infiltration and deposits. Thus, this study indicated a similar, or slightly better performance than other ML approaches, but the training data set was limited in size (around 3000 images) so there claimed that there is the potential for improvement with a larger training data set.

Detailed work by Meijer et al. (2019) also used a region-based convolutional neural network combined with a larger image data set and focussed on the approaches for validation of their and any other classifier. They had considerable concerns about bias in previous studies when examining their identification performance and carefully considered the sources of bias and how they can be reduced. Their R-CNN classifier performed reasonably well, and better than other reported in previous studies, for example Kumar et al. (2018), but their classifier did not perform well enough for fully automated operation. Using their defect classifier offered the potential for water utilities to significantly reduce, but not eliminate the number of images that would require manual intervention. They did suggest that combining automated image approaches with data from other sensors on an inspection vehicle may provide further improvements. This recommendation aligns with other studies (e.g. Plihal et al., 2016), that have encouraged a multi-sensor approach for in-sewer inspection.

Digital scanning is another optically based inspection method that uses high-definition cameras to provide a more detailed visual assessment of the internal pipe walls above the water surface (Iseley and Radcliffe, 2002). The cameras are transported along the sewer pipe using manually controlled crawlers, the cameras are typically high-resolution equipped with wide angle lenses at the front and rear of the crawler that collect synchronous time series of images (Knight et al. 2009). Digital scanning develops a distorted image of the internal surface of a pipe. As with conventional CCTV the image time series are analysed by a person post survey. The inner pipe wall image can be “unfolded” and the operator can tilt/pan/zoom to observe defects at a resolution that permits their identification and measurement. The ability of the operator to virtually pan, tilt and zoom in the image time series means that they can code individual defects in accordance with the conventional coding systems used in many countries. Digital scanning requires the use of a crawler so this inspection method is used in pipes in the diameter range between 150 mm to 1500mm (Feeney et al., 2009). The capability to scan laterals is limited due to hardware size restrictions. Digital scanning can be used with any pipe material. This method of sewer inspection has been continually developed with more capable cameras, improved wheel encoders for relative location and diffuse illumination and end user software. This method is offered as a standard inspection service by several commercial organisations (Feeney et al. 2009, Envirosight, 2017).

Using a laser profiler as an addition to a CCTV survey was proposed by Thomson et al. (2010) to assess pipe cross-sectional shape and wall loss. Duran et al. (2003) stated that the difficulty in obtaining such laser based measurements was the alignment and orientation of any laser profiling system as even small misalignments can result in significant measurement error in the internal geometry of a pipe, so making estimates of pipe shape and wall loss (which requires repeated measurement) are subject to error. More recent work has further developed laser scanning approaches and delivered commercially available systems. These followed two approaches: the first was a rotating laser displacement sensor, for example in the Rauschusa Mobile PRO system with pipe scanning capabilities and the second are based on the projection of a laser line onto the internal pipe wall, for example the Maverick laser profiling system. However, for either system to provide accurate repeatable measurements, their exact position and angular alignment to the pipe axis is still required, this limited their use for accurate repeatable measurement of internal pipe wall condition.

Stanic et al. (2016) used a laser projection and camera-based system and integrated it with a laser-based alignment system in which the laser line projection and image plane relative to the pipe alignment could be more accurately placed. They developed a static calibration system that was fixed in an adjacent manhole and used a laser light to link with the more conventional laser scanning system based on a moving platform that contained the laser profiler and camera similar to the earlier commercial systems within the pipe. The new system was subject to a comprehensive series of laboratory tests in which moist and fat covered walls and pipe defects were simulated to resemble field conditions and then its measurement capabilities was quantified (Lepot et al., 2017). The various sewer defects simulated were: fractures, deposits, roots, lateral pipe connections, discrete objects (blockages), and infiltration points. The measured linear accuracy was always better than 7mm, and the imaged based measurements were insensitive to different materials. Most defects could therefore be characterised (deposit depth, intrusive connections) and to more limited extent change in wall position and fractures. A later study reported on more complex testing using new and used concrete pipes revealed measurement accuracy is mainly determined by the accuracy in the positioning of the laser sheet and camera (Clemens et al., 2015). It was postulated that the best accuracy such systems could achieve would be of the order of +/- 4 mm (95% confidence level).

4.2. Non-visual Inspection Techniques

Electroscanning is a technology that is used to identify leaks in non-ferrous pipes (e.g. vitrified clay, concrete, brick and plastic). It is carried out by generating an electrical voltage between an electrode (sonde) in the pipe and an electrode in the soil adjacent to the pipe. This external electrode is moved along the pipe direction during testing (Tuccillo et al., 2011). The high electrical resistance of non-ferrous pipe walls inhibits the electrical current from flowing between the two electrodes unless there is a defect in the pipe such as defective joint, crack of non-water tight lateral connection through which water can pass. Pipes have to be fully filled with water, as electroscanning can only identify defects that create a water leak, so for typical combined sewers these need to be surcharged before an inspection can begin – this can be accomplished by surcharging the whole pipe length or pulling the sonde behind a moveable plug that surcharges a section of the pipe being inspected. If a pipe is only partially filled during testing only defects below the water line can be identified. The need to surcharge the pipe, means that use in combined/gravity sewers is focussed on smaller diameter pipes. As the ground electrode is moved along the pipe direction, changes in electrical current reflect local defects, the shape and size of the current spikes are used to identify the location of potential defects that have caused exfiltration into the soil (e.g. cracks, displaced joints and leaking lateral connections).

Field testing in small diameter vitrified clay pipes (diameter range 200-250mm) reported by Tuccillo et al. (2011) and undertaken as part of the USEPA’s Aging Infrastructure Program indicated that electroscanning inspection identified a larger number of leakage-related pipe defects than a contemporaneous CCTV survey, but many were considered small and so of little practical consequence. Around 40% of the defects were interpreted as faulty pipe joints, over 90% of lateral connections were indicated to be not water tight. There was good reproducibility between repeated scans of the same pipe. The cost estimate in 2011 was around €10/m. Electroscanning has been able to explicitly identify leaking defects both within a sewer segment/length and at the connections with intervening manholes. Stegeman et al. (2022) reported that using the electroscanning approach where an operator interpreted the measured current between an internal and external electrode had a number of factors that influenced any inference of the characteristics of a defect. It was shown that defect location was a robust measurement, however the quantification of leakage could be subject to a number of systematic uncertainties especially the physical position of the internal electrode with regard to the leak, and the spatial pattern of the resistivity of surrounding soil, therefore the estimates of leakage rate may have considerable uncertainty.

Horoshenkov et al. (2013) describes the principles of an acoustic method designed for sewer pipe defect location and identification. This method is based on the principle of sound reflectometry and relies on the analysis of reflected sound intensity to locate and identify in-pipe defects. Acoustic surveys can be carried out by a single operator from either the upstream or downstream manhole of a pipe. The equipment is small so that the operator does not need to enter the sewer and all the activity can be carried out from ground level. The acoustic equipment is inserted into a manhole for a short period of time, of the order of one minute and a multi-frequency sound wave is emitted. The reflected sound is then recorded in a digital form and analysed. This analysis is able to provide information on defects and so the internal condition of the pipe (Bin Ali, 2010). Measurement times are short and analysis is carried out immediately after the measurement and is rapid and provides a near real time indication of defect type and location. The main practical advantages of this method over traditional inspection methods, such as CCTV, are the speed of measurement and analysis and the removal of the need for man entry. The acoustic technology was designed to identify a number of common in-sewer defects: junctions, obstacles, joints, cracks and connections. Cross-correlation analysis of the multi-frequency reflections was used to identify these defects. Romanova et al. (2013) reported on a series of field tests in which a direct comparison could be made between defect identified by conventional CCTV and acoustic reflectometry. The acoustic method was able to successfully locate and identify around 80% of the defects identified with CCTV with a variance in defect location between the two methods of 0.33m on average. This is a similar level of uncertainty associated with the manual analysis of CCTV. Acoustic based methods may not eliminate the use of CCTV based surveys but may offer a more rapid survey technique for sewer networks that has a similar level of uncertainty when locating and identifying certain types of defects to conventional CCTV surveys.

A range of advecting sensor platforms for use in pressurized sewers have been developed, for example SmartBall technology (Smartball, 2021) makes use of a passive sensor that travels with water flow and detects the presence, location and size of leaks. The SmartBall is deployed in a pressurized pipe and is carried by the flow and captured at a downstream location. It is a watertight ball that contains an acoustic sensor, accelerometer, magnetometer, ultrasonic transmitter and a temperature sensor. It acquires high quality acoustic data that is used to identify the leak site, the on-board 3D accelerometers are used to provide accurate position data after recovery. The ultrasonic transmitter is used to allow operatives to track its progress and arrange for its downstream capture. As there is no noise associated with the SmartBall, it can identify small leaks down to 0.4 litres/minute (Thomson et al., 2010). The Sahara inspection (Sahar, 2021) utilises a hydrophone to locate leaks. This tethered platform, has a single hydrophone, a tether that transmits data in real time and a drogue that drags the platform through the pressurized sewer. It has been shown that it is capable of identifying leaks as small as 1 litre/minute (Thomson et al, 2010).

Sensors based on fibre-optic cable technology have started to be applied in sewer-based inspection. Optical fibres have been extensively used for communications and remote or distributed sensing since the 1970s, when losses in them were reduced to 20 dB/km. There are several relevant advantages for sewer-based sensors using optical fibre technology. Fibre-optic sensors do not require electrical power and combined with low optical transmission losses and little signal deterioration any signal can be transmitted over long distances (>1km). Fibre-optic sensors, if well designed can withstand harsh environments. They are also highly sensitive to physical disturbances such as strain, temperature and pressure. The same fibre can be used for sensing and transmitting information. This is especially beneficial when using attempting to accomplish distributed sensing throughout a network as one fibre can act as multiple sensors and a data acquisition system. Prisutova et al. (2021) outlines the several measurement principles that can be used by fibre-optic based measurement systems in pipes. In sewer systems there has been a focus on distributed temperature sensing (DTS) rather than strain sensing based systems. DTS has been used in several studies to locate illicit stormwater/foul connections by analysing spatial/temporal patterns of wastewater temperature. The capability of this technology is now well understood (Nienhuis et al. 2013). Several commercial operators now offer DTS via the temporary installation of a protected fibre-optic in a sewer. Distributed strain sensing is less common, though systems are starting to appear that are able to measure pipe joint movement and hydraulic parameters via permanently installed FO-based sensing systems (Aigner et al. 2021).

As well as non-contact inspection techniques there are a small number of contact-based inspection techniques. IKT, a German based institute has developed the MAC system, the system comprises a powerful hydraulic actuator that applies a controlled force via two bearing plates onto the opposite walls of large man-entry sewers. The local displacements are measured and earlier FEM analysis has produced relationships that can be used to estimate the stiffness of the pipe wall and surrounding soil. Moving the inspection equipment along a pipe allows for the identification of zones in which either the pipe wall stiffness is insufficient, due to corrosion, or cracking or if the surrounding soil support is limited (Thums, 2017).

4.3. Hybrid Approaches

In recent years new inspection systems have emerged that integrate multiple technologies on a single inspection platform in order to obtain more comprehensive and accurate data on pipe defects.

Kirkham et al. (2000) reported on the development and testing of the PIRAT system which was developed to automatically provide quantitative assessment of a wide range of in-pipe defects. The platform contained a number of sensing systems integrated with bespoke software. The system aimed to image and measure the internal geometry of sewers and then analyse these data to identify, classify and rate the severity of defects automatically using AI based approaches. Kirkham et al. (2000) reported that they believed that the automated assessment of CCTV images was not likely to be successful and that any effective inspection system would need to collect more quantitative data. PIRAT was equipped therefore with a laser scanning and sonar scanning system as well as a forward-looking CCTV capability. The laser scanner combined with the CCTV camera to provide “lightline” type images that were subsequently analysed to obtain the geometry of the pipe. This information was combined with the platform odometry system to produce a single log of the pipe geometry. For flooded sewers it was intended that the scanning sonar system would be used. The interpretation of radial laser scanning measurements was accomplished using AI based techniques that were trained using "surrogate" defect data generated using mathematical means and data obtained from "manufactured" defects in a laboratory pipe. During laboratory testing it became apparent that missing scan radii were an issue, as these were often associated with the edges of artefacts such as cracks and joints. The system was tested in a small number of vitrified clay and concrete sewer sections. PIRAT defect data was compared with defect data obtained from manual analysis of CCTV images. Depending on the pipe segment there was agreement on between 50-80% of the defects. Sections with more complete radial scan data provided better results. Unfortunately, organisational changes in the water utility funding PIRAT's development resulted in the development program being halted.

In Germany, in the late 90's, a number of R&D projects (e.g. LAOKOON, MAKRO) aimed to develop a multi-sensor autonomous robotic platform. Kirchner et al. (1997) reported on the development of KURT an autonomous robotic platform equipped with ultrasonic sensors and inclinometers. KURT was based on a small rigid chassis platform. It was equipped with two levels of control, the first to react to unforeseen events and the second to navigate using a prior map. KURT demonstrated that it was able to navigate through a simple, above ground laboratory pipe network. In a follow-on study Rome et al. (1999) report on the development of an articulated sewer robot equipped with multiple IR, ultrasonic and stereo cameras for navigation and defect classification and measurement. However, no assessment of this system was reported.

Hunter et al (2010) reported on the use of a tethered remotely operated vehicle (ROV) multi-sensor platform to inspect a large wastewater interceptor. This ROV was equipped with CCTV, laser scanning and sonar scanning. The study recovered information on wall corrosion, rebar damage, ovality, and joint damage, however build up on the wall, especially close to the water line affected the laser scanning measurements and meant that accurate wall position data was not possible. The sonar scanning system was able to define the volume of deposited sediment. Overall, the use of combined sensing systems provided a range of information on the interceptor condition, needed to assess rehabilitation needs that would not be available using more traditional inspection approaches.

A study by Plihal et al., (2016) reports on the use of a combined optical and acoustic inspection system to improve the efficiency and accuracy of locating and identify defects. The system integrated a manhole zoom camera and an acoustic reflectometry device. The results indicated that the visual and acoustic methods had different performances for different defects. For example, the manhole zoom camera was very successful in identifying displace joints, unlike the acoustic method and similarly the manhole zoom camera struggled to accurately locate defects unlike the acoustic reflectometry. This study clearly indicated the potential for improved inspection performance by combining technologies.

5. Development of Inspection Technologies

In the 1980’s, there were a number of UK research projects that focussed on developing the structured classification of in-pipe defects, the system that emerged, defined defect types and their coding that are still in use today. The classification system developed was expanded at it was adopted by water utilities and industry and standards bodies in Europe, the US and Australia. The originators of this standard assumed that the only source of defect data was from internal images of pipes obtained from CCTV systems that had travelled through a pipe. There was an appreciation that imaged based condition classification was inefficient and contained inherent uncertainties and this was reflected in the asset management frameworks set up to make decisions on sewer rehabilitation in which defect data was aggregated into simple condition classes and the concept of “critical” pipes was adopted to justify the practical resource limitations for pipe inspections in large sewer networks.

In the 1990’s, there were research programs in Australia and Germany to attempt to develop multi-sensor platforms and inspection systems that had a limited level of autonomy so as to address the data uncertainty and cost challenges, however both these programs were halted before practical outputs could be achieved. In the 2000’s, the USEPA and WERF both initiated programs to assess the cost and effectiveness of various commercially available pipe inspection technologies, several of which had originated in the other industrial sectors, such as the oil/gas sector. This led to the availability of inspection technologies to water utilities especially in North America (USA/Canada) that had not been used before in the water sector.

In the last decade, as attempts have been made to implement pipe deterioration models to predict the failure of assets to deliver acceptable performance, there has been more interest in measuring parameters that impact on actual system performance such hydraulic capacity and structural strength (likelihood of collapse). It has been realised that CCTV derived data does not provide such information. It is also clear that there are a group of deterioration processes that act predominantly outside the pipe, for example corrosion due to aggressive groundwater and soil voids leading to reduced structural stability. CCTV derived data will not help to identify such deterioration process therefore there has been renewed interest in developing inspection technologies with enhanced capabilities. Makara et al. (2021) attempted to systematically identify the parameters needed for physically based pipe deterioration models and Noshahn et al. (2021) also examined what inspection methods would be needed to provide the data needed for robust condition assessment. Both studies used systematic analysis of “domains” to identify missing pipe data needs. Noshahn et al. (2021) tabulated promising inspection technologies to address these gaps, they noted that studies on visual based technologies were abundant, but identified that inspection technologies to assess the structural and environmental “domains” that impact on buried pipes were lacking. The Dutch government funded the TISCA program (Joint Program Technology Innovation for Sewer Condition Assessment), see NWO (2015), this supported a number of projects that looked at the potential of different inspection technologies especially those capable of use in multi-sensor platforms, techniques for data fusion and methods to measure the structural condition/deterioration of sewer pipes. In the UK government funding was made available for novel senor development, the development of autonomous inspection systems and ML approaches to CCTV image. As well as government funding a number of commercial organisations are continuing to develop inspection technologies and analysis techniques for water utilities that have originated from other industrial sectors.

5.1. Emerging Inspection Technologies

It is clear that CCTV image collection will still be the most popular inspection technique for many years to come. However, there is strong evidence that the poor performance of human-based defect identification persists and even with improved training and quality assurance procedures predictive performance is not likely to improve significantly. It is also not possible to obtain measurements of key parameters from CCTV images, for example residual structural strength. However, even with these constraints CCTV derived data will continue to be widely collected and used. Automated image analysis approaches using ML and DL approaches (require less human intervention) to identify defects are now continuing to be developed. Currently, these have similar levels of performance to manual identification, but their development is at an early stage and current results show that they are dependent on the size and quality of training data sets. ML/DL image analysis approaches are also improving in terms of their precision, accuracy and computational effort so it is likely that the effectiveness of these approaches will improve. To compare ML and DL approaches, it is usually stated that since ML requires manual feature extraction, it is more suitable for situations where the features are well known. In contrast, DL is suitable for when the knowledge on the features is poorer as it extracts the inherent features of the object automatically. This implies that DL usually needs more data for training. However, it should be noted that the optimal size of training data sets, efficiency, accuracy and suitability of the models always depend on the complexity of the problem and quality of the data being analysed and this area needs to be further explored in the context of sewer inspection.

The platforms used to collect in-sewer images is also changing. In man entry sewers drone and buoyant advecting platforms are now being used to collect image data of the position and condition of internal sewer walls (e.g. Subterra, Obermayer et al., 2022, Tan et al. 2018). Whilst these techniques have the advantage of not requiring man entry, the detail of the images and the analysis algorithms is sufficient to obtain the internal geometry, identify certain defects such as root intrusion and deposits but not of sufficient resolution to accurately characterise defects such as cracks.

Image analysis techniques are advancing building on computational approaches used to support computer vision control and mapping (Aitken et al., 2021), this will continue but whether these techniques can provide the resolution needed to identify individual defects in such a feature-less environment found within sewer pipes is uncertain. Commercial organisation, drawing on capabilities from other industrial sectors will be likely to offer more cloud based data-driven analysis of collected (mainly image-based) inspection data, e.g. VAPAR 2021, and eventually deeper analysis of the location and severity of defects using ML-based predictive approaches (Kazemi et al., 2022). These efforts will increase the efficiency of sewer inspection by more objective prioritisation, but these new approaches are rarely reported in the open literature and it will be difficult for water utilities to objectively test any new data-based algorithms.

Under the TISCA program in the Netherlands (NWO, 2015), two out of the six funded projects are focussed on understanding the parameters that control the structural robustness of degraded sewers. Testing on recovered degraded sewer pipe lengths reported by Luimes et al., (2022) and on new pipes by Scheperboer et al., (2021) indicated that when a pipe fails there are typically four distinct failure cracks, two on the internal wall and two only visible on the external surface of the pipe. These observations provided a better understanding of the typical structural failure mode of a sewer pipe, subject to ground loading and highlighted that for a robust inspection approach then information on the condition of the external and internal wall of the pipe may be required, or at least a reliable relationship to link the structural failure mechanisms at these four distinct crack locations. Such information is currently not available using CCTV based approaches.

In terms of sensor development, new sensing technologies have been tested such as IR cameras (Lepot et al, 2017) to identify leaks. Makris et al. (2022) reported on a technology that potentially allows for quantifying material properties of PVC pipes in-situ, this technology is in its infancy but shows promise. The use of acoustic and ultrasonic technologies to better identify and characterise defects is also being investigated based on enhanced understating of vibration sensing and the propagation of ultrasonic waves (Yu et al., 2021). There are also developments in FO based distributed sensing technologies, for structural assessment with more permanent installations now a practical possibility within the sewer environment (nuron, 2022). Given the intensity of research and development activities, the available operational sensing approaches for both pressurised and unpressurised sewer pipes is likely to broaden in the coming years. Many of these approaches have been specifically developed for the in-sewer environment and they aim to provide new types of quantitative data on pipe defects that is currently not available.

In Europe there are a small number of projects attempting to develop autonomous multi-sensor robotic inspection platforms, for example the ASIR project in Denmark (ASIR, 2018), Equanostic's platform for inspection pressurized pipes and the "pipebots" research program in the UK (Shepherd et al. 2022). All these programs are working to develop robotic platforms that can operate in sewer pipes, with varying levels of autonomy and all use multi-sensor approaches to identify and quantify the severity of in-pipe defects. The technology readiness level of these project is around 6-7, with prototype systems being or are close to being demonstrated in a relevant/operational environment. The use of multi-sensor autonomous inspection platforms is likely to lead to a significant improvement in inspection capabilities for water utilities. However cost and reliability challenges needs to be addressed and the conservative nature of the water sector overcome to persuade water utilities to utilise inspection data that has not been derived from conventional CCTV surveys.

6. Conclusions

CCTV (visual) based technologies have and still dominate the inspection of sewer and drainage pipes. This dominance has developed as many of the existing national and water utility pipe condition coding schemes used to inform sewer rehabilitation decisions are structured around defects that are easy to identify visually. Operational procedures within water utilities are structured to purchase and use CCTV data for asset inspection. For utilities cost is a major factor and as the service market is composed of many small/medium sized companies with limited capital and R&D budgets there is limited desire by all actors to accept the business risk inherent in innovation. These historical factors have caused significant inertia in water utilities developing and adopting alternative technologies that may be better at identifying and characterising specific types of defects that may for example be the cause of significant system performance failures such as defects causing infiltration/exfilltration. There is now an appreciation that image-based inspection, with human interpretation of images has significant drawbacks in terms of data uncertainty and cost.

Given the dominance of CCTV inspection, new AI based methods are being developed and tested to examine whether these can displace the current practice of human based analysis of CCTV images. Currently these approaches have similar levels of performance to human based approaches, but there is evidence that AI based approaches may improve if more training data and different ML approaches could be employed. There are emerging image based technologies that can recreate 3D surfaces but the computational resources required would be high and their practicality would need to be assessed for the in-sewer environment. However, even with improved automated defect identification the inherent disadvantages of image-based inspection remains that only the internal wall of the pipe is visible and several physical parameters such as pipe structural strength cannot be obtained from images.

There is strong evidence of improved defect identification and characterisation if more than one sensor technology is used. Some attempts have been made to adopt a multi-sensor approach for sewer inspection and then combine data to gain a better understanding of pipe condition however commercial inspection systems still tend to be focussed on use of a single sensing technology.

Sensing technologies are being adapted for application in sewer inspection applications for example use of infra-red sensors to identify infiltration/exfiltration, permanently installed distributed fibre-optic systems to assess damage and ultrasonic based sensors to more reliably and accurately measure defects in and behind pipe walls.

There have been attempts to develop multi-sensor, autonomous inspection systems suitable for deployment in sewer networks. Early attempts were halted due to funding issues, currently there is a renewed focus on developing such a technology for deployment in sewer networks. These efforts are still at relatively low TRL levels so the practical deployment of robust autonomous sensing in sewer is still several years away however they offer the promise of being able to deploy the most appropriate type of sensor to accurately characterise particular defect types. Accurate location of inspection platforms offers the opportunity to fuse defect data from different sources (inspection/environment data) to provide a richer assessment of the structural and operational condition of a buried sewer pipe.

However, these future technological developments are hindered by the reluctance of water utilities to move from CCTV based inspection technologies, even though their inherent limitations are now well evidenced.

7. References

AFNOR (2011) NF EN13508-2+A1. Investigation et évaluation des réseaux d'évacuation et d'assainissement à l'extérieur des bâtiments – Partie 2: Système de codage de l'inspection visuelle, www.afnor.org, accessed 20/02/2019.

Aigner M., Kingsley S., Horoshenkov K., Tait S., (2021) Fibre optic pressure sensing apparatus employing longitudinal diaphragm, Patent No.GB2567610.

Aitken J.M, Evans M., Worley R., Edwards S., Zhang R., Dodd T., Mihaylova L., Anderson S. (2021) Simultaneous location and mapping for robots in water and sewer pipe networks: a review IEEE Access, 9, 140173-140198, doi: 10.1109/ACCESS.2021.3115981

ASIR (2018) Autonomous Sewer Inspection Robot, collaborative project funded by Innovation Fund Denmark. https://inlocrobotics.com/en/engineering/autonomous-robots/, accessed 19/09/22.

Binali M.T. (2010) Development of Acoustic Sensor and Signal Processing Technique, PhD thesis, University of Bradford, UK.

Baur R., Herz R. (2002) Selective inspection planning with aging forecast for sewer types. Water Science and Technology 46(6-7) 389-396, doi: doi.org/10.2166/wst.2002.0704

BS EN 13508-2:2003 Condition of Drain and Sewer Systems outside buildings. Visual inspection coding systems. British Standards Institue, www.bsi-global.com, updated 2007, and 2011.

Cheng J.C.P., Wang M. (2019) Automated detection of sewer pipe defects in closed-circuit television images using deep learning techniques. Automation in Construction 95, 155-171, doi: 10.1016/j.autcon,201808.006

Clemens F., Stanic N., Van der Schoot W., Langeveld J., Lepot M. (2015) Uncertainties associated with laser profiling of concrete sewer pipes for the quantification of the interior geomery. Structure and Infrastructure Engineering, 11, 9 1218-1239, doi:10.1080/15732479.2014.945466

Dirksen J., Clemens F.H.L.R, Korving H., Cherqui F., Le Gauffe P., Ertl T., Muller K., Snaterse T.M. (2013) The consistency of visual sewer inspection data. Structure and Infrastructure Engineering 9(3), 214-228, doi: 10.1080/15732479.2010.541265

Duran O., Althoefer K., Serieviratne L.D. (2003) Pipe inspection using a laser-based transducer and automated analysis techniques. IEEE/ASME Transactions on Mechatronics, 3, 401-409. doi: 10.1109/TMECH.2003.816809

Envirosight (2017) Side-scan sewer inspection comes of age: a guide to understanding and evaluating side-scan technology.

https://blog.envirosight.com/side-scan-sewer-inspection-an-introduction, accessed 13/08/22.

Equanostic (2022) Pipe scanner demonstration at World Water Congress, accessed 30/09/22. https://www.equanostic.com/thinking/pipe-scanner-demonstration-at-world-water-congress/

Feeney C.S, Thayer S, Bonomo M., Martel K., (2009) Condition Assessment of Wastewater Collection Systems, US Environment Protection Agency Report EPA/600/R-09/049 nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P1003ZQY.TXT, accessed 03/09/22.

Horoshenkov K.V., Tait S.J., Binali M.T. and Long R. (2014) Patent EP2326933: Improvements in and relating to apparatus for the airborne acoustic inspection of pipes. April 2014

Hunter W.K., Hines W.B, Corbin D., Martinez W. (2010) Application of robotics in diagnostic analysis of large diameter pipelines. Proc. NASTT No-dig North American Society of Trenchless Technologies, Liverpool, New York, Paper A-2-04. https://nastt.org/resources/bookstore/ accessed 18/09/2022.

Iseley T. Ratliff A. (2002) Digital imaging for characterizing pipe defects, Proc. NASTT No-dig North American Society of Trenchless Technologies, Liverpool, New York, Paper 42, https://nastt.org/resources/bookstore/ accessed 3/09/2022.

Joseph S., Di Tullio W. (2002) Diagnosis of a wastewater collection system using zoom camera and software. Proc NASTT No-dig Montreal, Canada, North American Society for trenchless technology, Liverpool, New York, Paper 43. https://member.nastt.org/products/product/2002-43.pdf, accessed 07/09/22.

INNOKANIS (2011) Innovative inspection methods for optimisation of selective sewer operation strategies, Research project based at Institute of Sanitary Engineering and Water Pollution Control, University of Natural Resources and Life Sciences, Vienna, Austria. http://efern.boku.ac.at/fis/suchen.projekt_uebersicht?sprache_in=en&ansicht_in=&menue_id_in=300&id_in=8763

Kazemi E., Shepherd W., Tait S., Machine learning to improve understanding of sewer pipe failures, Proc. 10th Int. Conf. on Sewer Processes and Networks, Graz, Austria.

Kirkham R., Kearney P., Rogers K., Mashford J. (2000) PIRAT: A system for quantitative sewer pipe assessment, Int. Jour. Robot Res. 19(11), 1033-1053.

Kirchner F. Hertzberg J. (1997) A prototype study of an autonomous robot platform for sewerage system maintenance, Autonomous Robots 4, 319-331, doi: 10.1023/A:1008896121662

Knight M., Younis R., Darrall B., Russin M., Manners C. (2009) Advances in pipeline asset management using digital side scanning evaluation technology. Proc NASTT No-dig, North American Society for Trenchless Technology, Liverpool, New York, Paper 56.

https://nastt.org/resources/bookstore/ accessed 3/09/2022.

Kumar S.S., Abraham M.R., Jahanshahi M.R., Iseley T., Starr J. (2018) Automated defect classification in sewer detection in sewer closed circuit television inspections using deep convolution neural networks, Automation in Construction, 91, 273-283. doi: 10.1016/jautcon.2018.08.005

Lepot M., Stanic N., Clemens F.H.L.R (2017) A technology for sewer pipe inspection (Part 2): Experimental assessment of a new laser profiler for sewer defect detection and quantification. Automation in construction, 73, 1-11. doi: 10.1016/j.autcon.2016.10.010

Lepot M., Makris K., Clemens F.H.L.R (2017) Detection and quantification of lateral, illicit connections and infiltration in sewers with infra-red camera: conclusions after a wide experimental plan. Water Research 122, 678-691, doi: 10.1016/j.watres.2017.06.030

Lester J., Farrar D.M., Gale J. (1978) Classification of defects in sewerage systems observed in close circuit television surveys., Ministry of Transport and Department of Environment Report (SR)377 Transport and Road Research Laboratory, available from the UK National Archives.

Luimes R.A., Scheperboer I.C., Suiker A.S.J., Bosco E. Clemens F.H.L.R. (2022) Effect of biochemical attack on the mechanical performance of used concrete sewer pipes, Construction and Building Materials, 346, 128390, doi: 10.1016/j.conbuildmat.2022.128390

Makana L.O., Shepherd W., Tait S., Rogers C.D.F., Metje N., Boxall J.B., Schellart A.N.A. (2022) Future Inspection and Deterioration Prediction Capabilities for Buried Distributed Water Infrastructure". ASCE Journal of Pipeline Systems - Engineering and Practice. doi:10.1061/(ASCE)PS.1949-1204.0000656

Makar J.M. (1999) Diagnostic techniques for sewer systems, Journal of Infrastructure Systems, 5(2), 69-78, doi: 10.1061/(ASCE)1076-0342

Makris K., Langveld J.G., Clemens-Meyer F., Watts J., Begum H. Horoshenkov K. (2022) Sonic assessment of physical aging of plastic pipes. Accepted for publication in Journal of Sound and Vibration.

Martel, K., Tuccillo M.E., Feeney C. (2011) Field Demonstration of Condition Assessment Technologies for Wastewater Collection Systems. U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-11/078.
https://nepis.epa.gov/Exe/ZyPDF.cgi/P100C8E0.PDF?Dockey=P100C8E0.PDF,accessed 20/09/22.

Maverick Inspection Ltd. (2022) Laser inspection systems.
www.maverickinspection.com/services/laser-pipe-profiling/laser-pipe-rofiling-intro, accessed 16/08/22.

Meijer D., Scholten L., Clemens F., Knobbe A. (2019) A defect classification methodology for sewer image sets with convolutional neural networks, Automation in Construction 104, 281-298, doi: 10.1016/j/autcon.2019.04.013

Moradi S., Zayed T., Golkhoo F. (2019) Review on computer-aided sewer pipeline defect detection and condition assessment, Infrastructures, 4(10), doi: 10.3390/infrstructures4010010

Myrans J., Everson R., Kapelan Z. (2019) Automated detection of fault types in CCTV sewer surveys, Journal of Hydrinformatics, 21(1)153-163, doi: 10.2166/hydro.2018.073

Nederlands Normalisatie-Instituut (2011) NEN-EN 13508-2:2003+A1:2011 Onderzoek en beoordeling van de buitenriolering - Deel 2: Coderingssysteem voor visuele inspectie [Examination and assessment of the outdoor sewerage system - Part 2: Coding system for visual inspection]. www.nen.nl/nen-en-13508-2-2003-a1-2011-nl-167789, accessed 20/03/2020

Nienhuis J., de Hann C., Langveld J., Klootwijk M., Clemens F. (2013) Assessment of detection limits of fibre optic sensing for detection of illicit connections. Water, Science and Technology, 67, 12, doi: 10.2166/wst2013.176

Noshahri H., olde Scholtenhuis L.L., Doree A.G., Dertien E. (2021) Linking sewer condition assessment methods to asset managers' data-neeeds. Automation in Construction 131, 103878, doi: 19.1016/j.autcon.2021.103878

nuron (2022) https://www.nuron.tech/, accessed 20/09/22.

NWO (2015) TISCA – Joint program innovation for sewer condition assessment, www.nwo.nl/en/researchprogrammes/joint-programme-technology-innovation-sewer-condition-assessment-tisca, accessed 20/10/22.

Obermayer A., Jilg K., Tong S. (2022) Application of sewer drone inspection of large sewers and special structures. Proc. 10th Int. Conference on Sewer, Processes and Networks, Graz, Austria.

Panguluri S., Skipper G., Donovan S. (92014) Demonstration of Innovative Sewer System Technology SewerBatt, USEPA Technology Evaluation Program Report EPA/600/R-14/081.

https://nepis.epa.gov/Exe/ZyPDF.cgi/P100KSTW.PDF?Dockey=P100KSTW.PDF, accessed 04/06/22.

Plihal F., Kretschmer F., Bin Ali M.T., See C.H., Romanova A., Horoshenkov K.V, Ertl T. (2016) A novel method for rapid inspection of sewer networks: combining acoustic and optical means. Urban Water Journal, 13:1 3-14, doi: 10.1080/1573062X.2015.1076857

Plihal H., Kretschmer D., Schwarz D., Ertl T. (2014) Innovative sewer inspection as a basis for optimised condition-based maintenance strategy. Water Practice and Technology, 9(1), doi: 10,2166/wpt.2014.01

Pristutova J., Krynkin A., Tait S., Horoshenkov K. (2022) Use of fibre-optic sensors for pipe condition and hydraulics measurements: a review. Civil Engineering, 3, 85-113 doi: 10/3390/civileng3010006

Rauschua (2022) Mobile PRO system https://rauschusa.com/products/cctv-inspection/portable-units/mobile-pro/, accessed 16/08/22.

Romanova A., Horoshenkov K., Tait S.J., Ertl T. (2013) Sewer inspection and comparison of acoustic and CCTV methods. Proc. of the Inst. of Civil Engrs, WM2, 70-80, doi: 10.1680/wama.11.00039

Rome E., Hertzberg J., Kirchner F., Licht U., Christaller T. (1999) Towards autonomous sewer reports: the MAKRO project, Urban Water 1 57-70, doi:10.1016/S1462-0758(99)00012-6

Sahara—Leak and Gas Pocket Detection—Pure Technologies. 2021. Available online: https://puretechltd.com/technology/sahara-leak-gas-pocket-detection, accessed on 21 September 2021.

Scheperboer I.C., Luimes R.A., Suiker A.S.J., Bosco E., Clemens F.H.L.R (2021) Experimental-numerical study on the structural failure of concrete sewer pipes, Tunnelling and Underground Space Technology, 116, 104075, Tunnelling and Underground Space Technology, doi: 10.1016/j.tust.2021.104075

Shepherd W. Schellart A., Boxall J., Evans M.H., Yu Y. Tait S. (2022) Passive sensing for buried wastewater collection and drainage networks, Proc 10th Int Conference on Sewer Processes and Networks, Graz, Austria.

SmartBall—Leak and Gas Pocket Detection—Pure Technologies. 2021. Available online: https://puretechltd.com/ technology/smartball-leak-detection, accessed on 21 September 2021.

Selvakumar A., Tuccillo M.E., Martel K.D., Mathews J.C., Feeney C. (2014) Demonstration and Evaluation of State-of the Art Wastewater Collection Systems Condition Assessment Technologies, Journal of Pipeline Systems and Practice 5(2) doi: 10.1061/(ASCE)PS.1949-1204.0000161

Stanic N., Lepot M., Catieau M., Langeveld J., Clemens F.H.L.R (2017) A technology for sewer pipe inspection (Part 1) Design, calibration corrections and potential applications of a laser profiler. Automation in Construction 75, p91-107, doi: 10.1016/j.autcon.2016.12.005

Stegeman B., Hoffmann R., Hopman V., Langeveld J., Clemens-Meyer F. (2022) The assessment of a mobile geo-electrical measurement system: a study on the validity and contributing factors to quantify leakage in sewer systems. Urban Water Journal 19(4) 374-387, doi: 10.1080/1573062X.2021.2020298

Tan C.H., Ng M., Shaiful D.S.B., Win S.K.H. Ang W.J., Yeung S.K. Lim H.B., Do M.N. Foong S. (2018) A smart unmanned aerial vehicle (UAV) based imaging system for inspection of deep hazardous tunnels, Water Practice and Technology 13(4), doi: 10.2166/wpt.2018.105

Thums F. (2017) MAC: Innovative sewer assessment. Trenchless International, Fall 2017, 34-37.

Thomson J., Morrison R.S., Sangster T. (2010) Inspection guidelines for wastewater forced mains. Report 04-CTS-6URa, Water Environment Research Foundation, available from IWA Publishing, ISBN 978-1-8439-286-6.

Tuccillo M., Wilmut C., Feeney C., Martel K. Selvakumar A. (2011) Field demonstration of the electroscan defect location technique for condition assessment of wastewater collection systems, Proc. Collection Systems, Water Environment Research Foundation, Alexandra Virginia. http://www.electroscan.com/wp-content/uploads/2012/01/2011-06-12-WEF-Collection-Systems-Whitepaper-on-EPA-Field-Trial.pdf, accessed 14/09/22.

Van der Steen A.J., Dirksen J., Clemens F.H.L.R (2014) Visual sewer inspection: detail of coding system versus data quality? Structures and Infrastructure Engineering, 10 (11), 1385-1393, doi: 10.1080/15732479.2013.816974

VAPAR (2021) Vapar pipe defect guide – a data driven guide to defects in sewer and stormwater pipes, v1.1, https://www.vapar.co/vapar-pipe-defect-guide, accessed 21/09/22.

Wirahadikusumah R., Abraham D., Iseley T. (2001) Challenging issues in modelling deterioration of combined sewers. Journal of Infrastructure Systems, 7(2) 77-84, doi: 10.1061/(ASCE)1076-0342(2001)7:2(77)

Yu Y., Safari A., Niu X., Drinkwater B., Horoshenkov K. (2021) Acoustic and ultrasonic techniques for defect detection and condition monitoring in water and sewerage pipes: a review, Applied Acoustics, 183, 108282, doi: 10.1016/j.apacoust.2021.108282