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COLLEGE OF ENGINEERING

AUTOMATED DEFECT DETECTION TOOL FOR SEWER PIPELINES

BY

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ABSTRACT

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Title: Automated Defect Detection Tool for Sewer Pipelines

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In sewer networks, the economic effects and costs that result from a pipeline break are rising sharply. In Qatar, majority of the sewer network pipelines were installed in the last 20 years and are currently in poor condition and constantly deteriorating. As a result, there is huge demand for inspection and rehabilitation of sewer pipelines. In addition to being inaccurate, current Practices of sewer pipelines inspection are time consuming and may not keep up with the deterioration rate of the pipelines. Consequently, this research aims to develop an automated tool to detect different defects such as cracks, deformation, settled deposits and joint displacement in sewer pipelines. The automated approach is dependent upon using image-processing techniques and several mathematical formulas to analyze output data from CCTV camera photos. Given that one inspection session can result in hundreds of CCTV Camera footage, introducing an automated tool would help yield faster results. Additionally, given the subjective nature of most defects, it will result in more systematic results since the current method rely heavily on the operator's experience. The automated tool was able to successfully detect cracks, displaced joints, ovality and settled deposits in pipelines using CCTV Camera inspection output footage. Using two different data sets, the constructed Matlab code could successfully differentiate between cracks and displaced joints with an overall crack detection success rate of 84% and an overall displaced joint detection rate of 94%. The code was also able to efficiently detect settled deposits in the pipelines with a detection rate of 90%. In addition, the automated ovality detection resulted in 100% compatibility with the manual circularity detection.

Keywords: Sewer Pipelines, Defect Detection, non-destructive evaluation, CCTV inspection, image processing, sewer inspection

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CHAPTER 1: INTRODUCTION

1.1 Sewer Networks

Sewer pipeline networks play a role of high importance as an underground infrastructure. This especially applies to populated and congested urban areas due to their role in the public health, safety and environmental aspects, not to mention the economic benefit it can provide. Like most of the utility networks, wastewater is collected through a network of underground infrastructure. The underground infrastructure consists of a network of pipes that transports the water from one point to another by gravity flow. Normally, sewer networks can operate for a prolonged period before any issues can be noticed or reported, which will lead to sudden failures in the network. Road collapse, water bleeding through pavement layers or surface disruption can be signs of serious defects in a pipe. This can be the result of either poor pipe design/installation or poor supports/soil conditions (Khan, Zayed, & Moselhi, 2009). This caused many authorities to ignore the network, mostly since it is invisible and doesn't affect the public's perception. This could lead to negligence in the inspection, maintenance and rehabilitation of the network.

Authorities around the world constantly face challenges when it comes to sewer pipeline networks and its rehabilitation management. Many cities around the United States are frequently faced with the difficult task of maintaining the sewer system, and whether to replace or rehabilitate the deteriorated parts (Koo & Ariaratnam, 2006). According to the United States Environmental Protection Agency, the average age of the sewer systems is more than 50 years old, given that the majority of the sewer network infrastructure was constructed after the Second World War The American Society of Civil Engineers (ASCE) reported that overall, sewer networks in the US are failing ("2013 Report Card", 2013).

The United States (U.S.) Environmental Protection Agency (EPA) reported back in 2007 that the frequency of water main breaks is increasing tremendously, to reach 240,000 breaks per year.

In the Midwest area, large utility beaks are reported to have increased from 250 to 2200 breaks per year in the period from 1988 to 2007. According to the United States Geological Survey, defects and breaks in the water distribution networks around the U.S. costs the country $2.6 billion yearly (U.S. Environmental Protection Agency, 2007). Example of how a defect or break in water networks can cause serious cost impact can be found In Pittsburgh, Pennsylvania, where a defect in a water main caused a 7.6m hole in the road. The city's authorities were forced to close the street where the defect happened. After inspection, authorities discovered that a break in a 20cm pipe caused the sewer pipe to completely collapse. The defect in the pipe was not detected fast enough, which led to the excess water seepage that caused the enormous underground hole that eventually caused the collapse in the road (Post-Gazette, 2009).

1.2 Sewer Network in Qatar

Given that the infrastructure in the State of Qatar is still developing, the sewer network in the country is still under heavy expansion works. Overall, the current sewer network per the Public Works Authority's (Ashghal) inventory consists of more than 2,000 km of pipelines. The pipeline ages span from the 1980s with only 8% of the current sewer network constructed in that era. The intensity of the sewer network expansions has been rising in the recent years with the booming construction and development of the country with nearly half of the current sewer network assets constructed in the last 10 years. The distribution of the sewer network by age is shown in Figure 1. The network composes of pipes with different materials; mainly ductile iron pipes, UPVC and Concrete pipes.

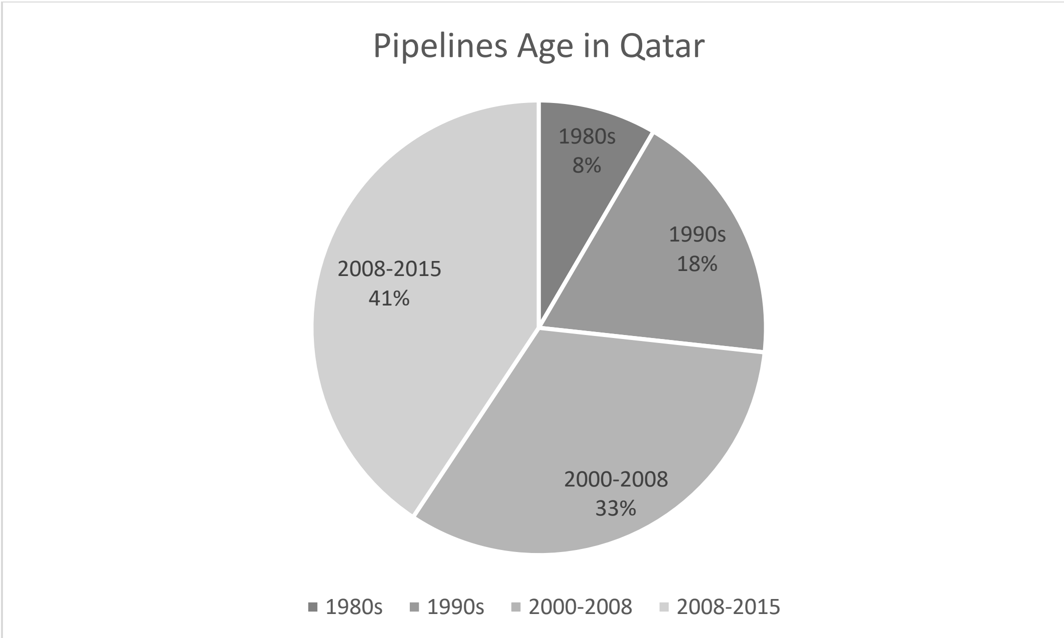

Figure 1, Qatar Sewer Network Pipelines Classified by Age (PWA)

However, the sewer network's presence is limited for only certain areas and a high percentage of the current network is running with over-capacity operations and needs additional assets to carry the current country loads. Thus, several nation-wide projects were introduced by the Public Work Authority (Ashghal). One of those projects is the Inner Doha Re-Sewerage Implementation Strategy (IDRIS) as shown in Figure 2. This project is a landmark program being implemented by Ashghal with the objective of upgrading and expanding the sewerage infrastructure in the Doha South area and to accommodate the projected population growth by an additional one million people. The main drivers for the program are the hydraulic overloading of the existing sewerage network which often results in flooding of the streets as well as the over-capacity operation of the key existing assets. The extensive on-going and planned development within the catchment area is expected to worsen the current situation. The program also aims in generation of treated sewage effluent for irrigation purposes. Other similar large-scale projects include the refurbishment and upgrading of sewer networks in areas such as Meseimer, Doha West, Ain Khaled and Alrayyan in addition to the introduction of new network schemes in areas like Al-Khor southern and northern regions (PWA, n.d.).

Figure 2, IDRIS Project Scheme

With the introduction of all the new sewer network schemes, it becomes a bigger challenge to efficiently manage the assets. In the Operations & Maintenance department in the Public Work Authority (Ashghal), CCTV cameras are being used to inspect the existing sewer network pipelines as shown in Figure 3. It provides essential information that play a big role in the determination of the most suitable rehabilitation techniques and replacement decision and solution. The Operation & Maintenance department has a contract with a private contractor to carry out CCTV camera inspections for a certain period. This contractor has crews that perform CCTV inspections in support of operational activities. The Operation & Maintenance department has a team of experts that analyze and make decisions based on the outcome of the contractor's work to decide on the rehabilitation and replacement program. The inspections and assessments are performed by trained personal that use a defect coding system related to the severity of the pipeline condition to document and categorize each pipeline's condition.

Figure 3, Sewer Pipeline CCTV Inspection

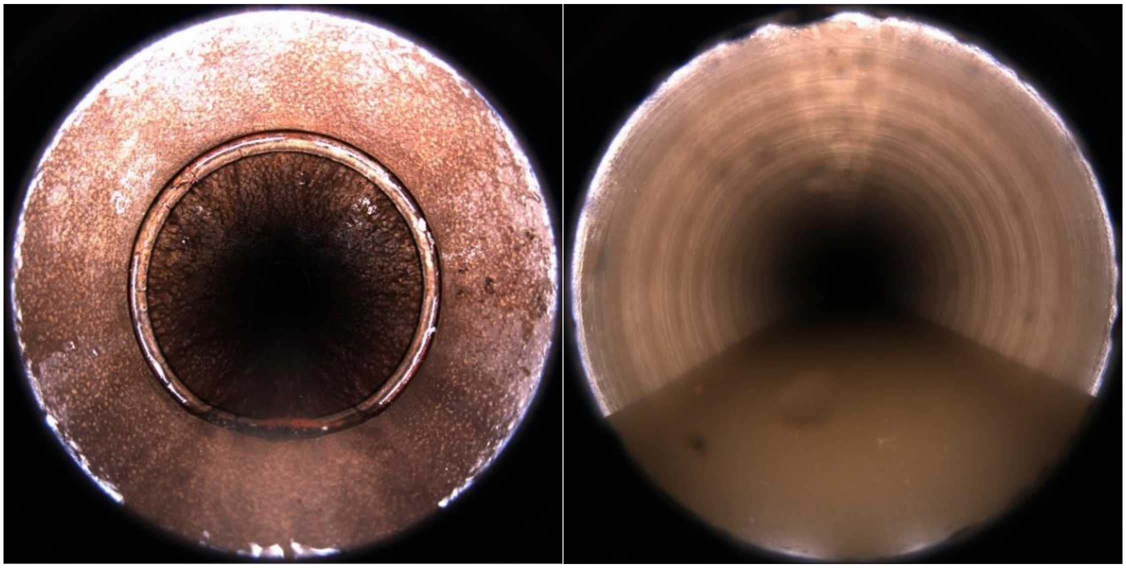

Figure 4, Sample of CCTV Camera Footage

1.3 Research Aim

In sewer networks, the economic effects and costs that result from a pipeline break are rising sharply. In Qatar, majority of the sewer network pipelines were installed in the last 20 years and are currently in poor condition and constantly deteriorating. In addition to being inaccurate, current practices of sewer pipelines inspection are time consumers and may not keep up with the deterioration rate of the pipelines. Consequently, this research aims to develop an automated tool to detect different defects such as cracks, deformation, settled deposits and joint displacement in sewer pipelines. The automated approach is dependent upon using image-processing techniques and several mathematical formulas to analyze output data from CCTV camera photos. Given that one inspection session can result in hundreds of CCTV Camera footage, introducing an automated tool would help yield faster results. Additionally, given the subjective nature of most defects, it will result in more systematic results since the current method rely heavily on the operator's experience. Even with the presence of systematic guidelines and coding systems, it is not unusual for a defect to be categorized incorrectly or even overlooked.

1.4 Research Methodology

Based on the research aim, an extensive methodology was set to be executed during the lifetime of the project as shown in Figure 5. A literature review was done to explore different inspection techniques as well as different image processing techniques for the detection of different types of cracks.

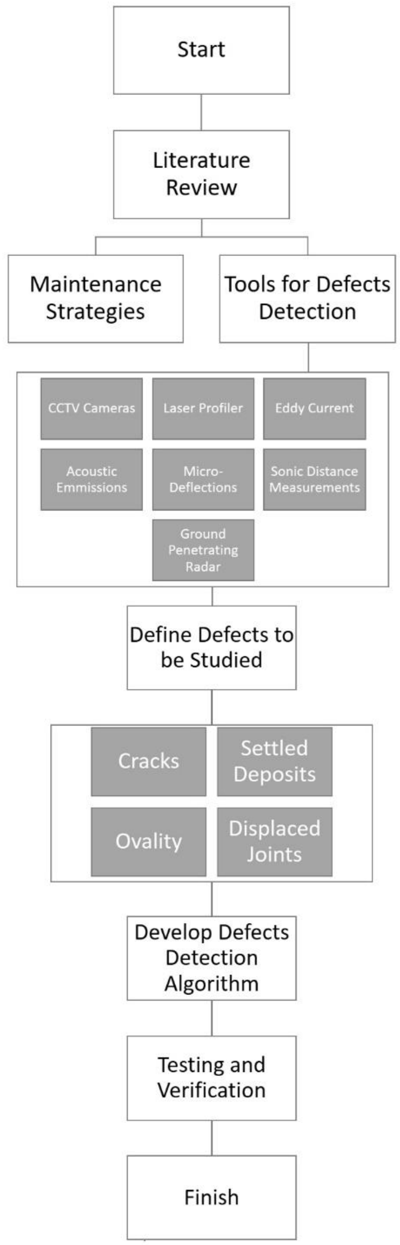

Figure 5, Research Methodology Flowchart

1.5 Thesis Organization

The research is divided into Six Chapters, discussing the following:

1. Chapter One introduces the topic, gives an introduction on sewer networks and its importance and discussed the sewer networks in Qatar and the current practices in the country.
2. Chapter Two provides an extensive literature review on the topic of asset management and the inspection techniques for sewer networks. The chapter summarizes the different methods used for the sewer pipelines inspections such as CCTV camera and Laser Profiler. In addition, the current practices in sewer pipeline condition assessment are explored including image processing techniques for defects detection.
3. Chapter Three discusses the data collection process and identifies the cracks that will be considered in the research. Each crack is defined for further analysis in the following chapter.
4. Chapter Four discusses the development of the automated tool for image processing. A Matlab code is developed and explained in the chapter for each defect type.
5. Chapter Five testes the developed automated tool to detect the different types of defects. Visual inspection is used for results verification and determination of the accuracy of the automated tool.
6. Chapter Six concludes the research by providing a summary of the results. Some recommendation and future research area related to this work are also provided in this chapter.

CHAPTER 2: LITERATURE REVIEW

The objective of this chapter is to explain explore sewer network asset management and maintenance strategies approaches used around the world. Moreover, the chapter studies several sewer pipelines inspection techniques, mainly the CCTV Camera inspection, and discusses their prose and cones. Finally, the chapter examines the previous research work in the field of sewer pipeline condition assessment and the use of image-processing tools to inspect and asses the condition of sewer pipelines. Several researches in this field are studied and the objective, results and limitations of each work is discussed.

2.1 Asset management

According to ISO 55000, the international standard covering management of physical assets, Asset Management (AM) is defined as the “Coordinated activity of an organization to realize value from assets". In turn, any item or entity that is of value to an organization is considered an asset. This concept form an important aspect for most organizations even though it is a very general definition than a physical asset. The process of asset management involves various aspects such as cost balancing, risk assessment and different kinds of analysis to achieve the organizational objectives.

The ability of asset management to provide an organization with tools to examine assets, assets performance and compare between different asset systems are few of its merits. Not to mention its ability to provide analytical approaches that aids in managing assets during the life cycle of a project (BS ISO 55000, 2014).

For sewer networks, asset management is basically managing the assets and the infrastructure with the goal of minimizing the cost of owning, operating and rehabilitating the network while maintaining the intended level of service to the public. It can be applied anywhere to improve the performance of the network financially and operationally. Even though many organizations and authorities use sophisticated systems and great human resources to build asset management plans, it can be achieved by a simpler collection system and the existing human resources to start an inventory of the existing assets. The asset management plan can then be expanded with continuous improvement planning to achieve wider coverage of the network as the work progresses in other aspects. This plan can be developed to prolong the age of infrastructure through a cost-effective basis by making executive decisions to meet better environmental targets and achieve financial goals. Most of the sewer networks investment in Qatar have been directed to the expansion of the network to meet the population growth demand. However, the operations and maintenance of the sewer networks are only recently grabbing the attention of authorities, as the maintenance budget was mostly allocated for emergencies and rehabilitation of failed assets. In the meantime, sewers network elements that have not yet experienced failures are aging and problems will appear sooner or later if no proactive measures are taken.

2.2 Maintenance Strategies

The main goal and outcome of an asset management program is developing an appropriate maintenance strategy plan. Maintenance strategies are usually categorized according to the availability of assets and the costs. As shown in Table 1, maintenance strategy can be classified based on the presence of a condition assessment or the ranking of the importance of this asset. This can only be achieved depending on the available data of the assets conditions.

Table 1, Classification of Maintenance Strategies

Condition		Importance: Not Considered	Importance: Considered
Condition	Considered	**Condition Based Approach** • Occasional inspection works • Maintenance is performed when Required	**Maximal Maintenance Strategy** • Assets routine inspection • Assets condition assessment • Prioritizing of maintenance and rehabilitation works
Condition	Not Considered	**Corrective Approach** • No inspection or any maintenance work until a break is reported	**Time-Based Maintenance** • Fixed time interval for inspection and maintenance
		Not Considered	Considered
		Importance	

The simplest maintenance strategy as per the above classification is the Corrective approach. This has been the carried-out strategy in many parts of the developing world due to its simplicity and its cost with relation to other methods. The assets in this strategy would operate until it fails, with no preventive measures undertaken what so ever. Only after failure a decision of repairing or replacing the asset is taken. Even though this strategy may appear less-costly when considering direct costs, preventive actions proved more economical when considering the long-term effects on the overall network of assets.

Subsequently, preventive maintenance plans are more desirable as so to prevent damages to assets and thus reducing the overall costs. Time-based maintenance strategy is the simplest way to perform preventive maintenance. Inspection sessions are scheduled over a pre-determined schedule to oversee the condition of the assets. The inspection schedule is usually the result of past experience with this particular asset. The schedule, however, can change over time if the inspection results reveal extreme issues or alternatively, no issues at all.

One of the main concerns that follows the inspection works is determining the condition of the assets. The current condition of an asset needs to be described by certain ratings, which is the essence of the condition-based assessment methods. For this to be achieved, the proper tools for defect-detection needs to be carried out.

2.3 Current Maintenance Strategies Approaches

Throughout the world, authorities have adapted various forms of maintenance strategies for sewer pipeline networks. The common idea is to develop a plan that aids the decision makers in making choosing the appropriate approaches as well as allowing for prioritization of maintenance and rehabilitation of the network assets. This involves (Kulandaival, 2004):

- Performing routine inspections of the sewer network pipelines and infrastructure
- Undertaking pipe condition assessment based on standard rating protocols and systems
- Developing models that help in systematically prioritizing and planning assets inspection

The first part of the typical sewer management plan is performing routine inspections of the sewer network pipelines and infrastructure. As agencies realized the importance of forming an inventory of their assets, new techniques were developed for the inspection of the underground infrastructure. In the 1960s, Closed-Circuit Television (CCTV) camera was first used to inspect sewer pipelines. Other technologies followed such as ultrasonic and laser profiling (Wirahadikusumah et al, 2001). Yet, CCTV camera inspection remains to this day the most commonly used technique around the world. Section 2.4 explores few techniques that are used for sewer pipelines inspection.

The second part of the typical sewer management plan is the assessment of pipe condition based on a systematic and standard rating protocols and systems. The used protocols are typically a combination of weighted factors used to rate the level of severity of each defect that appear on a pipeline. The outcome at the end is a condition rating for each pipeline. One of the first sewer condition assessment protocols to be developed was in London by the Water Research Center (WRc) in 1978. Many protocols followed since, such as the Pipeline assessment and certification program manual by NASSCO in the United States and the North American Association of Pipeline Inspectors (NAAPI) in Canada (Thornhill et al 2005).

The third and last part of the typical sewer management plan is the development of prediction models. Prediction model development can help in systematically prioritizing and planning assets inspection. Many tools have been introduced previously to assist decision makers for better decisions with regards the utilities inspection and condition assessment. However, most of the current decision tools are in the form of general guidelines and considerations where certain indicators observed in a pipeline are interpreted as asset condition state (Kleiner, 2001).

2.4 Tools for Inspection and Defects Detection

In many parts of the world, inspection of sewer network pipelines was generally neglected until a failure is reported. This was mainly due to their low visibility. This only led to costlier measures and rehabilitation decisions. The absence of appropriate information with regards to the condition of the network and the previous maintenance records is a major challenge when selecting the appropriate rehabilitation technology. To assess a pipeline condition, physical inspection is usually used. Physical inspection may involve the entry of a maintenance crew worker into a pipeline that is currently not in service. This technique is, however, very hazardous and requires proper safety precautions to be followed. Thus, alternative approaches are more recommended.

Typically, two approaches can be followed when it comes to sewer network failures: Proactive and Reactive. The proactive approach’s goal is to prevent a failure from occurring by assessing the condition of the pipeline. The reactive approach's goal is to detect an existing failure while minimizing its economic impact by minimizing the reaction time. Authorities around the world are leaning towards the proactive approaches due to the economic impact that is associated with the reactive approaches and the accompanying rehabilitation techniques.

Generally, sewer pipelines inspection techniques can be classified into three categories:

- Inner-surface Inspection
- Pipeline Structure Inspection
- Bedding Material Inspection

This categorization is shown in Figure 6. The first category consists of techniques that can inspect and detect defects and breaks in a pipeline. The most widely used technique in this group is the CCTV Camera inspection. The second group consists of techniques that can determine the overall strength of a pipeline rather than specific defects. The third and last group consists of one technique that is able to detect any issues with the pipeline bedding material (Makar, 1999).

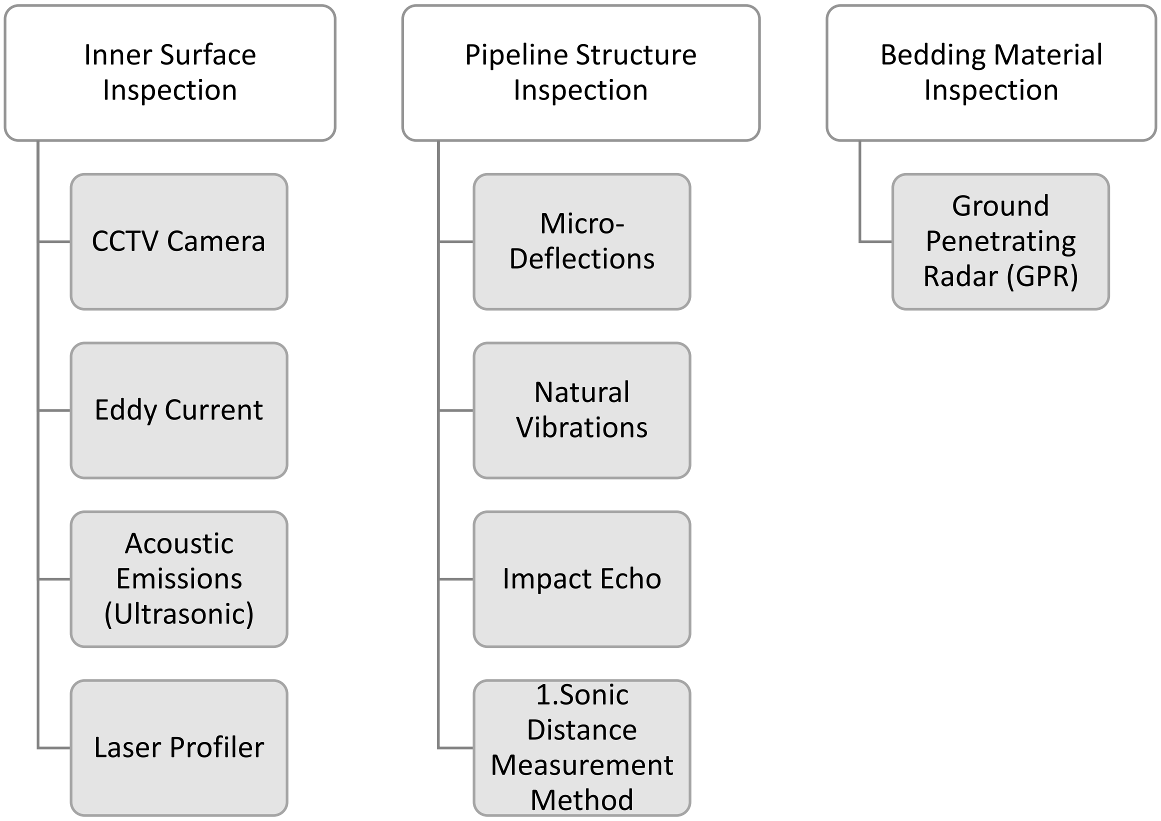

Figure 6, Inspection Techniques for Sewer Pipelines

Among the inner-surface inspection category, the selection of an appropriate inspection method is heavily dependent on the pipeline material and size. Some inspection techniques are preferable when it comes to metal pipelines, such as Eddy Current technique. Other techniques are more suitable to concrete pipelines, such as Acoustic Emissions and CCTV Camera inspection (Trenchless Technology Networks, 2002). These inspection tools are explored in the following sections.

2.4.1 Closed-Circuit Television (CCTV)

Closed Circuit Television (CCTV) is a widely-used technique for sewer inspection. It is mainly utilized to record videos or photos of the underground pipeline network. This inspection technique is an economical and more appropriate replacement to the traditional and dangerous technique of human-being's inspection of a pipeline, especially if a pipeline is too small or dangerous for human entry. Over time, the inspection process evolved from having a CCTV camera being pulled between two manholes to mounting the camera on top of a crawler or a float. Operators were able to control the movement of the robot, as well as that of the camera, from far distances. With this technique, operators can control the movement of a small vehicle that is equipped with the CCTV camera. The camera is usually a pan-tilt-zoom camera (PTZ) so that the operator can control the camera as well to obtain footage from far distances in case of a blockage that denies full access and movement of the vehicle. The camera continuously records videos and footage of the condition of the inner surface of the pipeline above the flow-line. Commonly, after the footage and videos are acquired, experts use them to base their interpretation and conclusion of the pipeline's condition. CCTV can be used to identify the following types of defects:

- Different types of Cracks
- Fractures and deformation
- Settled Deposits
- Pipeline Ovality
- Collapses in the pipeline
- Displaced joints
- Polished aggregates or surface abrasion
- Penetration of tree routs

The most commonly used manual process is the condition-based assessment. Each pipeline is assessed and rated based on the frequency of defects occurrences in addition to the severity of each defect. Based on this rating, the operator assigns each pipeline a score, usually on a scale from 1 to 5 (Sarshar, Halfawy & Hengmeechai, 2009).

However, many researchers pointed out several limitations of this method. Tuccillo et al. (2010) mentioned that CCTV can only provide information above the flow-line. More importantly, it does not quantify the detected defects such as deformation, settled deposits and surface damage. Therefore, the researcher concluded that CCTV inspection is used only as an evidence to locate defects. Its inability to exactly quantify certain defects results in subjective conclusions which led to the use of other techniques to lessen some of the CCTV limitations.

Mainly, CCTV camera inspection is carried out to do the internal inspections of the pipeline. Since an operator's decision and judgment is involved, the degree of reliability of the information or conclusions obtained using CCTV camera inspection is highly reliant upon the skills and knowledge of this inspector in addition to the reliability of the CCTV camera footage. The field technician is expected to identify defects be able to classify the defect degree of deterioration and the overall pipe condition subjectively. However, due to the human nature, the operator's judgement causes uncertainty in the results. This is not the only reason of uncertainty in the CCTV Camera footage inspection, as the quality and reliability of the CCTV footage play a major role. For instance, there is a considerable possibility that serious cracks can be hidden beneath settled deposits or any residual water accumulation. Such defects will not be identified while other lesser defects can be classified as damages in the pipe. Not to mention the time restrains that accompanies such inspection processes. The time required to inspect a pipeline is difficult to be estimated since it depends on the nature and the frequency of the defects present in a pipeline (Wirahadikusumah et al, 1998). This led many researchers to seek solutions to enhance the outcome of the defect detection systems. Su, Yang, Wu & Lin (2011) were able to effectively segment the morphologies of sewer pipe defects based on edge detection (MSED) using CCTV camera footage.

2.4.2 Laser Profiler

Laser Scan can accurately determine the profile of interior side of pipe through the length. This method could also help in finding the corrosion loss and amount of leftovers along with pipe side deflections. The theory behind laser survey is reviewed by Vickridge and Leontidis (1997) and Hodgkinson (2000). This technology consists of a continuous laser beam that is deployed on the pipe's interior wall. This laser beam highlights and profiles the pipe's wall at any point of the length only above the waterline. However, and since there is possibility of laser diffraction in water, this technique is only used during the low-flow times like night or in dewatered pipes. There is no report of any underwater laser scanning in research (Liu et al., 2012). Figure 7 shows the results of a laser profiler inspection.

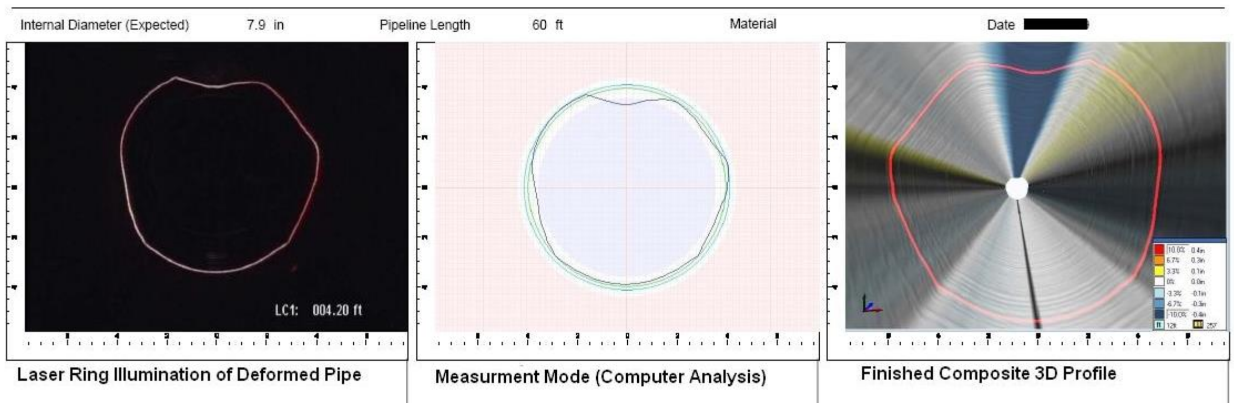

Figure 7, Laser Profiler Inspection of a Pipeline (Maverick Inspection, n.d.)

Laser scan basically comprise a spinning apparatus which control the laser beam. There is no need of illumination and the survey could be done through complete darkness. The resolution of the images is affected by carrier's velocity, speed of spinning, sampling rate, roughness and color of the pipe wall. Separate images could be compiled together with pattern and marks on the surface through special software. By the aid of 3D laser scanning, it is possible to provide a 3D representation of the pipeline's interior wall in addition to the 2D images of the pipe's cross-section at any location (Liu & Kleiner, 2013).

2.4.3 Eddy Current

Eddy Current method for pipeline inspection uses an alternating current magnetic coil to introduce a magnetic field that is time-dependent. An electric current is generated in the pipeline material – assuming the material is conducting – due to the magnetic field. This will cause impedance of the magnetic coil due to the magnetic fields that are around the pipeline material, which opposes the Eddy Current magnetic field. Different information about the pipeline can be obtained by measuring this impedance, such as pipeline thickness and pipeline discontinuities.

However, this method is only applicable for pipelines with conductive materials. If used for concrete pipeline, information about the reinforcement bars can be obtained (Trenchless Technology Network, 2002).

One of the drawbacks of Eddy Current is the limitation when it comes to thickness of the pipeline. This is directly related to the depth of current penetration. To overcome this problem and allow a wall thickness inspection, Schmidt, Atherton & Sullivan (1989) proposed the Remote Field Eddy Current (RFEC), which introduced a second magnetic field penetrates the wall thickness. A commercial Remote-Field Eddy Current based Hydroscope technology was later produced by PICA (n.d.) comprising of transmitting and processing electronics. This technology collects data such as corrosion pits sizes and the wall loss with a high level of accuracy, as tested and verified by Makar & Chagnon (1999).

2.4.4 Acoustic Emissions

Acoustic Emissions technique is defined as “the release of transient elastic waves produced by a rapid redistribution of stress in a material” (Shull, 2002). After the waves are released, a specific sensor will detect the waves that is a resultant from a variation inside the pipe’s material. This method can’t detect any defect, only a defect that is changing with time. An example of this can be the propagation of a crack in a pipeline or issues with reinforcement in a reinforced concrete pipeline (Shull, 2002).

A linear array of sensors was proposed by Shehadeh, Steel and Reuben (2006) to estimate the source location of acoustic emissions in steel pipes. Different techniques were proposed to detect the simulated source on section of a pipeline. However, this approach didn’t prove to be suitable for real field application. A new methodology was then introduced by Ozevin & Harding (2012) for localization of leaks in pressurized pipeline networks. The approach, as demonstrated on a laboratory scale model, was to use cross-correlation functions to determine arrival time differences.

After the introduction of the geometric connectivity, the leak waves path can be identified since it propagates to reach the acoustic emissions sensors. Using an array of sensors helped in effectively identifying the leak location in a three-dimensional space (Ozevin & Harding, 2012).

Currently, the available systems collect signals following an acoustic event. After analysis and comparison with the previously obtained acoustic data, the event type is determined. This can be inaccurate since the method can only detect propagating defects and completely ignores defects that happened but stopped propagating (Al-Wardany, 2008).

2.4.5 Micro-Deflections

Measuring a pipeline's material micro-deflections is one of the ways to examine and inspect the pipeline's structure. A micro-deflection in a pipeline surface can be achieved through applying pressure on the inner surface of the pipeline to cause slight deformation. The intention is to measure the variation in the position of a point against the change in the applied pressure. Even though it can be used for concrete pipelines to measure its strength, this technique was developed specifically to inspect brick sewer pipelines. Unlike most other inspection methods, this method indicates the overall condition and strength of the pipeline rather than detecting defects and breaks (Makar, 1999).

2.4.6 Sonic Distance Measurement Method

The Sonic distance measurement method is a non-destructive technique that transmits sound waves and measures the travel time from the device to the target. The change in the velocity of the wave is interpreted as change in the medium density (i.e. air or water). This application can be used for sewer pipelines condition assessment (Wirahadikusumah et al, 1998). The most critical limitation of this technology is its inability to operate in multiple media. It can either be functional in air or in water, but not both. This leads to partial detection of the pipeline, either above or below the flow line (Vickridge & Leontidis, 1997).

2.4.7 Ground Penetrating Radar

As a technology that uses remote-sensing diagnostics, Ground Penetrating Radar (GPR) is mainly used for pipe bedding material inspection. It includes transmission of electromagnetic waves from the ground surface into the pipe direction. Changes in the material properties and densities are represented as reflected waves as received back by the GPR's antenna. Different information can be obtained about the examined area, such as the type of materials present beneath the ground, different materials layer thicknesses and densities in addition to the structural condition. In addition of the output results not yielding the condition of the pipeline, the output data are difficult to interpret which requires a trained personal to carry-out the inspection works (Wirahadikusumah et al, 1998).

2.5 Sewer Pipeline Condition Assessment

Many researches previously conducted several approaches to encounter the disadvantages of the different inspection tools for sewer pipelines. For CCTV Camera inspection processes, researchers previously aimed to overcome the disadvantages of this long process by introducing automated tools to reduce processing time of the footage. Other inspection techniques such as laser scanning, acoustic emissions and eddy currents a wide research area. However, those technologies were not able to replace the CCTV camera inspection technique that remains to be the most commonly used around the globe mainly due to its easiness and practicality. Thus, several automated approaches for CCTV camera inspection were proposed in previous research.

Random Forests analysis approach was used for faults automatic detection in wastewater pipelines in the United Kingdom. The aim was to classify the CCTV inspection footage into two categories, faulty and non-faulty. This method can lead to the reduction of the amount of data to be processed down from hours of footage to just a selection of the faulty footage (Myrans, Kapelan & Everson, 2016). Even with the high efficiency detection rate, the tool needs further processing from experienced engineer or operator for complete fault detection and categorization.

Classification of defects in pipelines was tested by proposing a neuro-fuzzy classifier that combines both, fuzzy-Logic testing with Artificial Neural Networks (ANN). Applying the fuzzy-logic model on flush-clean CCTV footage of pipelines helped in identifying key characteristics that resembles a defect, which are the intensity of the light, texture, size, shape and organization. Following the fuzzy process, ANN process is performed to classify the defect. This approach could classify defects by extracting features from CCTV footage, with a 90% accuracy (Sinha & Fieguth, 2006). However, this tool was developed to only detect cracks and holes in the pipeline. In addition, the approach was tested on footage of clean and flushed pipelines rather on real CCTV inspection footage. Thus, the accuracy and real world application of this tool is not tested.

Another image-based model was developed to assess defects in wastewater pipelines. The model was successful in predicting and categorizing the level of severity of cracks with a 90% accuracy (Khalifa, Elsayed & Sayed, 2013). However, the model only focus was detecting cracks and was performed on images with cracks in them. Model performance is not known for random images with different sorts of defects.

Another automated defect detection tool was developed to detect pipeline's inner surface defects using CCTV camera image processing. This novel approach integrates a laser profiler with the CCTV camera and uses intensity information for defects recognition in addition to the development of the defect detection method. The final product of the analysis is an image of the pipeline wall that is easier to be processed by operators (Safizadeh & Azizzadeh, 2012). Even though this process results in a pipeline wall profile that reduces the defect detection time by the operator, it does not automatically detect any defects and the expertise and judgement of the operator or the engineer is still required.

CHAPTER 3: METHODOLOGY

This chapter is focusing on the methodology that is being carried out to inspect sewer pipelines using CCTV cameras. The collected data for the automated tool testing is explored and the different types of defects to be studied are identified.

3.1 Inspection procedures

The procedures documented in this section are what is being carried out by the Public Work Authority (Ashghal) Operation & Maintenance department with regards to sewer inspections, as explained in section 1.2. An appointed contractor performs the following procedures to acquire the desired CCTV Camera footage.

The first step is to ensure that the sewer pipelines to be inspected are clean. Prior to the process of CCTV inspection, water is introduced into the upstream chamber or manhole. The downstream manhole is observed for this water stream. This step will help identifying any locations with pipeline sagging/belly. A belly or a sag is a segment of a pipeline that is lower than the rest of the pipeline and thus, causes water and dirt accumulation as shown in Figure 8. To ensure visibility, one step that might not be always applicable in Qatar is to ensure that all fog is removed from the pipeline.

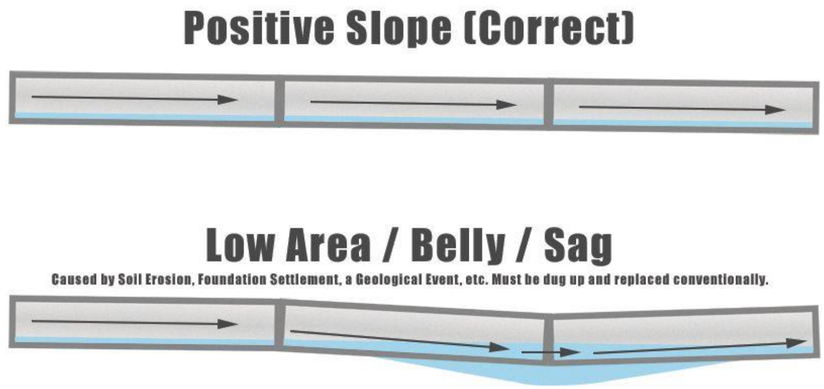

Figure 8, Belly or Sag in a sewer pipeline (Wilson, 2016)

Once all of the above steps were performed, the inspection process can be undertaken. The inspection is preferably done for each pipeline separately (section between two manholes). In case of the presence of any obstacles that prevents the CCTV Camera vehicles from accessing any pipeline segment, the contractor may redirect it to inspect adjacent pipelines that require inspection in one set-up if possible. However, the contractor must insure that the CCTV Camera footage of each pipeline segment are distinguishable by resetting the footage counter.

As explained in section 1.2, after the CCTV Camera footages are acquired, a team of trained personnel examine the footage, observe and record the defects present in each CCTV footage and finally use a defect coding system to describe the severity of the pipeline condition to document and categorize each pipeline's condition. Given that one inspection session can result in hundreds of CCTV Camera footage, this process proved inefficient and needs some automation to yield faster results. Additionally, given the subjective nature of most defects, introducing an automated process would result in more systematic results since the current method rely heavily on the operator's experience. Even with the presence of systematic guidelines and coding systems, it is not unusual for a defect to be categorized incorrectly or even overlooked.

3.2 Data Collection

CCTV Camera inspection footage were requested from the Public Work Authority (Ashghal) Operation and Maintenance department to develop the image processing tools. PWA generously provided inspection footage of more than 2 km sewer pipelines. These images included two different sets of pipelines, old and new. Figure 10 shows examples of the new pipelines while Figure 12 shows examples of the older pipelines. The two sets of CCTV camera footage are acquired from Alwaab Area and New Salata Area as shown in Figure 9 and Figure 11, respectively. After further visual analysis were done, a sample of images were chosen that included the defects to be studied; cracks, settled deposits, ovality and displaced joints. Those images were essential in developing the automated tool as well as verifying the results.

Figure 9, Sample 1 Footage Area

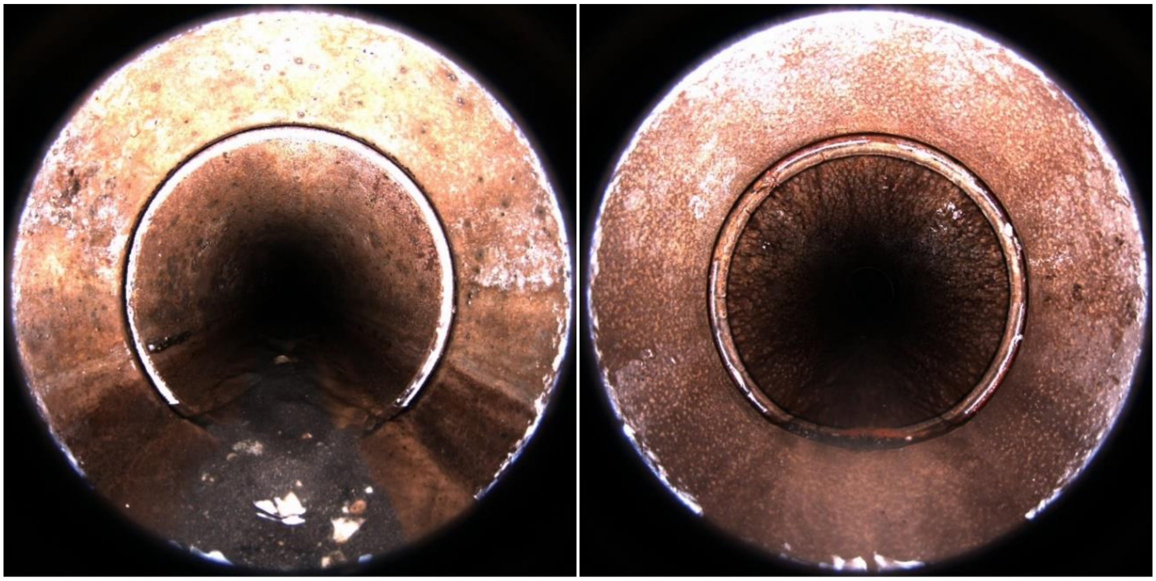

Figure 10, Sample of First Data Set CCTV Images

Figure 11, Sample 2 Footage Area

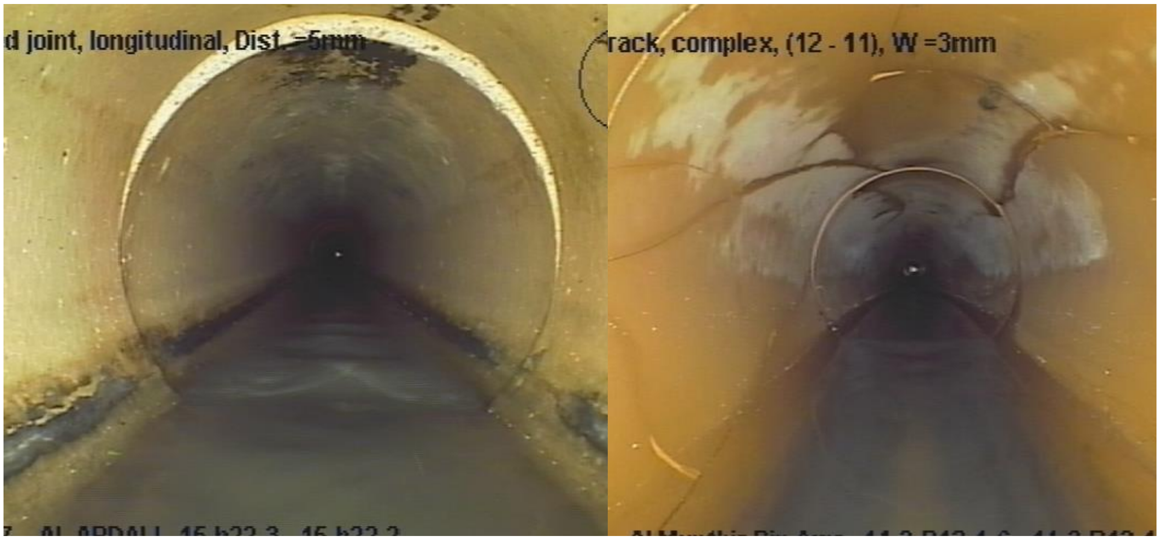

Figure 12, Sample of Second Data Set CCTV Images

3.3 Types of Defects

To properly create an automation tool to detect defects in a pipeline, the defects need to be properly identified. The defects considered in this research are cracks, settled deposits, Ovality and displaced joints as the defects that most affects a pipeline performance and can be detected by CCTV Camera inspection. The defect definitions are in line with NASSCO's sewer pipeline inspection and condition assessment standards (NASSCO, 2001).

3.3.1 Cracks

Cracks, which are breaks in the pipeline’s material, are one of the most common forms of defects that can occur in a pipeline. Figure 13 shows a crack in footage obtained from a CCTV Camera inspection. Cracks in a sewer pipeline can be the result of various causes, including lack of or improper soil support, improper installation techniques as well as aging of the pipe causing pipe deterioration. In addition to its effects to the pipe structure, cracks can allow the infiltration of ground water into the sewer network or ground water contamination due to sewer leakage.

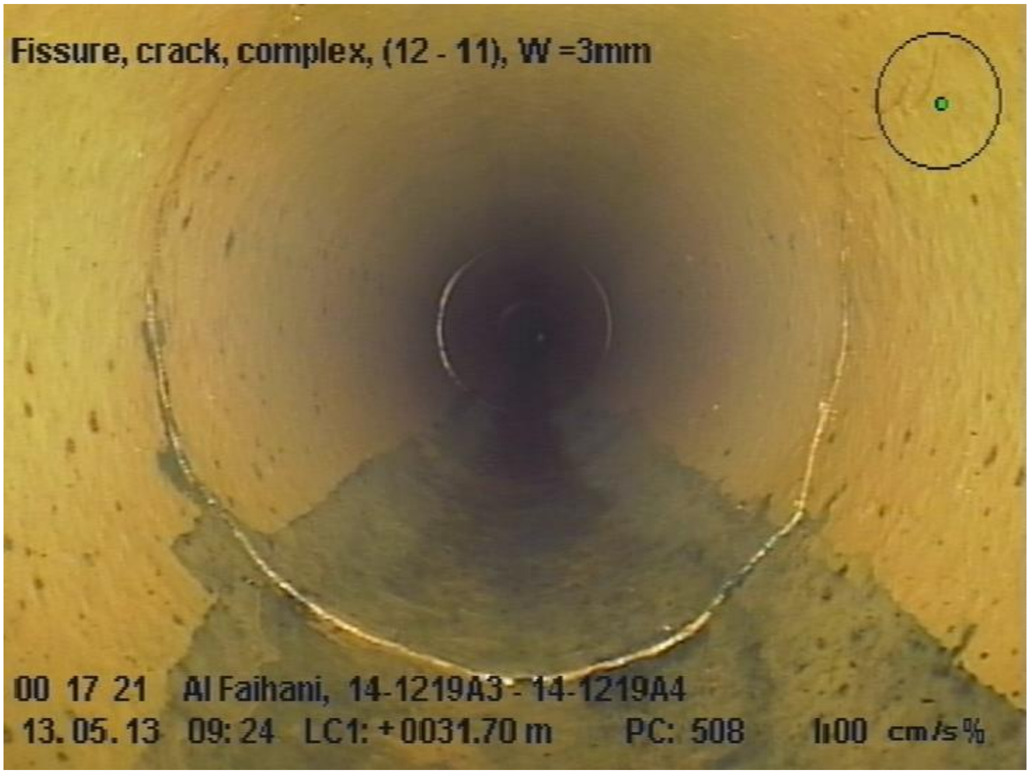

Figure 13, Example of a crack from a CCTV Camera Footage

Cracks can appear on a pipeline with different shapes, as shown in Figure 8. Type A represents a longitudinal crack while Type B represents a vertical crack. A crack that is composed of different vertical and longitudinal crack is considered a complex crack.

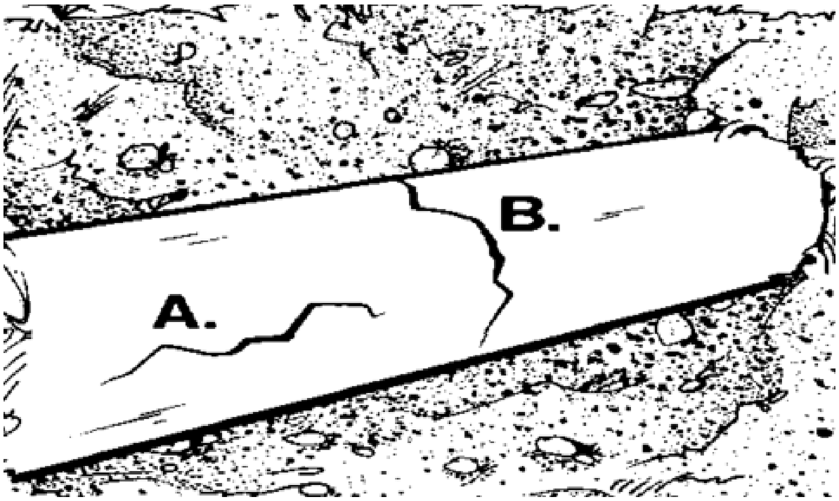

Figure 14, Crack Types in Sewer Pipelines (Trupply, n.d.)

3.3.2 Settled Deposits

Accumulation of deposits in sewer pipelines was overlooked by operators as it may not appear as an apparent risk. However, settled deposits can severely affect the operational performance of the sewer network (Mattsson et al. 2014). Deposits can settle in a sewer pipeline if there are structural defects or obstructions in the pipe, such as displaced joints or sags. Figure 15 shows settled deposits in a footage obtained from CCTV Camera. Settled deposits can cause obstruction of the flow due to some items being flushed down the drains or due to improper pipeline slope. If the slope is insufficient, the flow will not move fast enough causing solids to build up in the pipe. If settled deposits are severe enough in a pipe, it can build up over time and eventually cause complete pipe blockage.

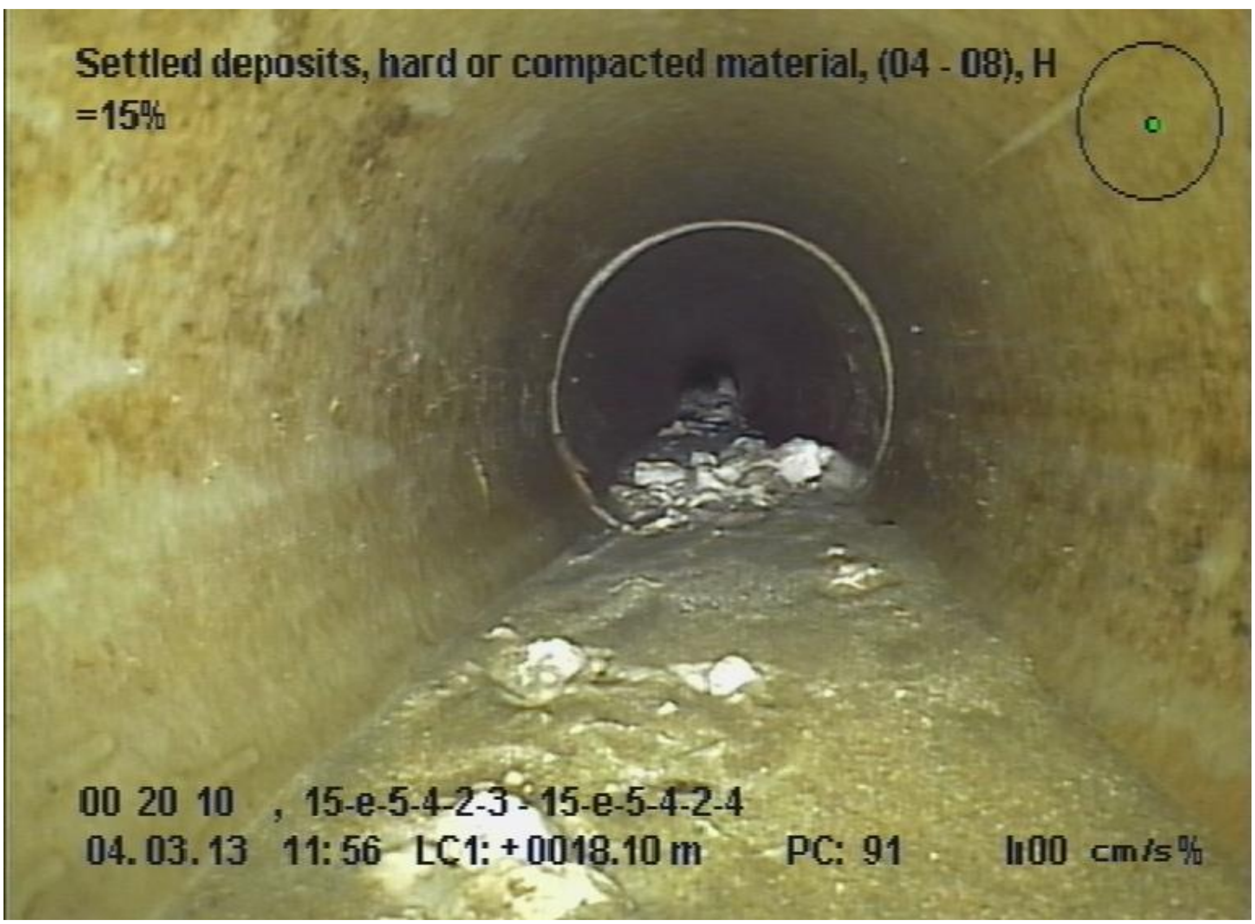

Figure 15, Example of settled deposits from a CCTV Camera Footage

3.3.3 Ovality

Ovality or non-circularity is a reference to the deviation of a pipeline's cross-section from perfect circularity, as shown in Figure 16, Ovality of a Pipeline. Ovality of a pipeline can be an indication of a bigger structural issue, such as high load on the pipe or not enough wall thickness. Other factors can also cause this type of deformation in a pipeline, such as improper installation of pipelines. That deformation or presence of ovality in a pipeline can significantly decrease its life expectancy and reduces its overall performance (Rinker Materials, 2009). Minor ovality in a pipeline is often difficult for operator to observe in normal CCTV inspection processes. Automating the inspection process can help in better detection of this defect, given that the algorithm can easily detect the change in a pipe's cross-section.

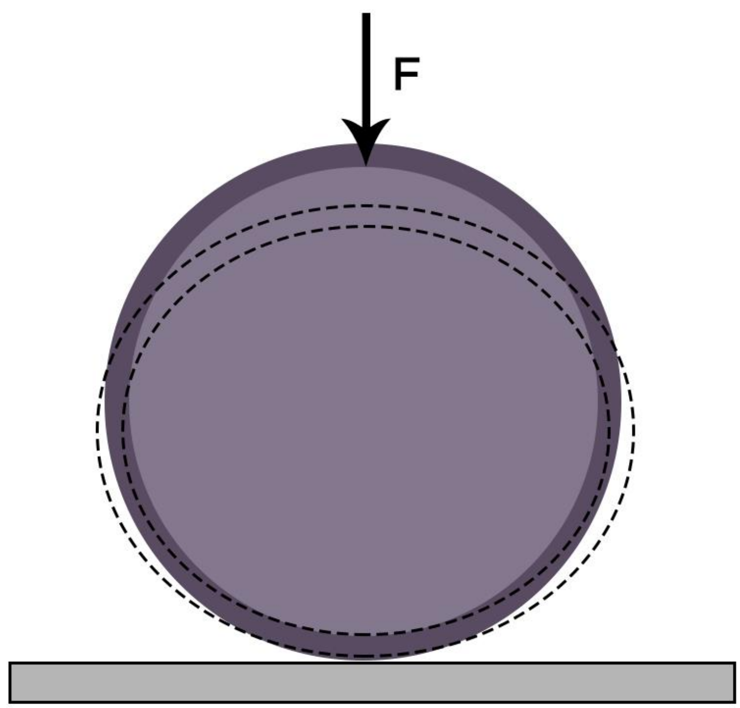

Figure 16, Ovality of a Pipeline

To quantify the ovality of a pipeline, a roundness factor is used. It is a dimensionless factor that is used to identify the circularity of an object. It is a function of the area and the perimeter of this object. This factor was used to measure the circularity of a medical tablet (Law & Deasy, 1998). The factor was also used in human pathology, as researchers uses the factor to determine the circularity of the nuclear factor in detecting prostate cancer (Montironi, et al., 2005). The roundness factor is used in this application to measure the deformation of the pipeline using the following equation.

$$Roundness\ factor = \frac{4\pi \times Area}{Perimeter^2}$$

3.3.4 Displaced Joints

Sewer pipelines are typically constructed from multiple segments that are connected at pipeline joints. Figure 17 shows an example of a displaced joint obtained from CCTV Camera footage. A displaced joint occurs when the pipes don’t fit perfectly and one of the pipes is offsetted from the other. Displaced joints can eventually cause a debris build-up on the joint area, which can cause blockage. Additionally, if the joint is displaced more than the pipe thickness, the soil surrounding the pipeline could be exposed, leading to soil being washed into the pipeline which causes voids around the pipes. This may eventually lead to collapse of the pipelines as the voids turn into sink holes. Joints are not typically watertight, which means there is a risk of ground water contamination or ground water infiltration into the sewer network, which is typically not accounted for in the network design process.

Figure 17, Example of a displaced joint from a CCTV Camera Footage

CHAPTER 4: ANALYSIS

In the past years, the introduction of automated tools for sewer network pipeline defects detection has been a topic for intense study. This research area was limited by image processing, Image recognition and analysis techniques in addition the limitation of the acquired data. Matlab software was used in this research to construct a detection code for each studied defect. This section explains each detection code for the four types of defects. An important step that was overlooked in previous research is identifying a region of interest for each defect, as researchers focused more intensely on classifying the types of various defects. In this research, and to help detect the defects more efficiently, some regions of interests were introduced to the automated tool. With the introduction of this step, the error that may result from the automated tool is greatly minimized.

4.1 Cracks

The method proposed in this paper uses a morphological segmentation. This method has been carried out previously for Robust segmentation of vessels from retinal angiography (Zana & Klein, 1997). Morphological image processing is particularly good at extracting image features with known shapes. Morphology provides an effective solution for detecting quasi-linear shapes -such as cracks- in an image. The process of detecting the cracks in a pipeline using a CCTV Camera footage is summarized in the following diagram.

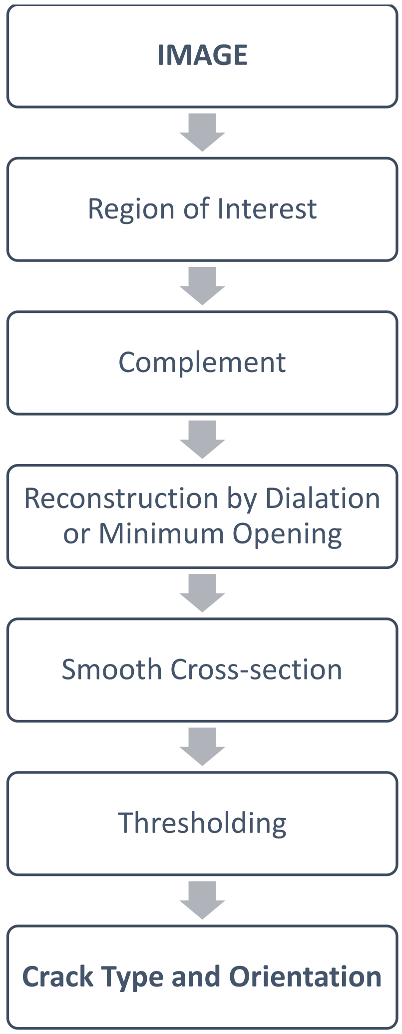

Figure 18, Crack Detection Flow Diagram

4.1.1 Region of Interest

The first step is to extract the region of interest where the cracks may be found. The crack detection analysis is only undertaken in region of interest (RoI). The RoI is defined and generated in a trapezoidal shape as shown in Figure 19.

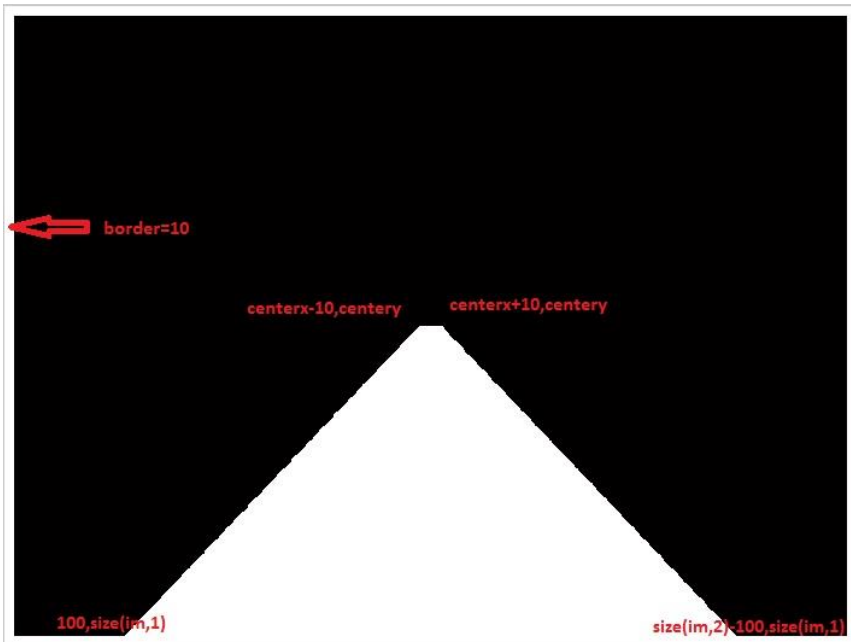

Figure 19, Region of Interest for Crack Detection

The image is then complemented, where bright areas become darker and alternatively, dark areas become brighter.

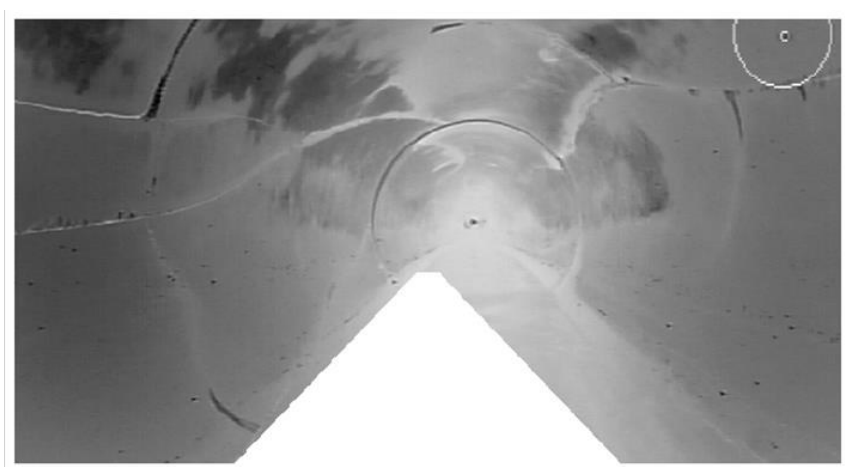

Figure 20, Complemented Image

4.1.2 Reconstruction by dilation

Consider an image containing many bright linear shapes (the cracks) as well as flat homogeneous areas such as the background. After complementation of the image, a linear shape is defined as a bright part of an image with a minimum length L and a maximum width W (where usually W<L). The aim of the initial processing is to preserve image structures which satisfy the criteria of being at least L pixels long, and no more than W pixels wide. Morphological opening with a structuring element of a given shape preserves image structures that may contain the structuring element and removes those that cannot. Thus, opening the image with a linear structuring element, B, of length L and width 1 preserves linear shapes when the structuring element and the shape are approximately parallel. If many such structuring elements are used, with different angular rotations, then all linear shapes with length greater than or equal to L should be preserved by at least one rotation. Noise and other non-cracks structures that cannot contain the structuring element at any rotation will not be preserved by such an operation. Thus, a cleaner version of the image can be obtained by taking the supremum of the image openings with linear structuring elements with many different rotations. Figure 21 shows the image after construction by dilation (Image ic). Note that bright spots have been removed.

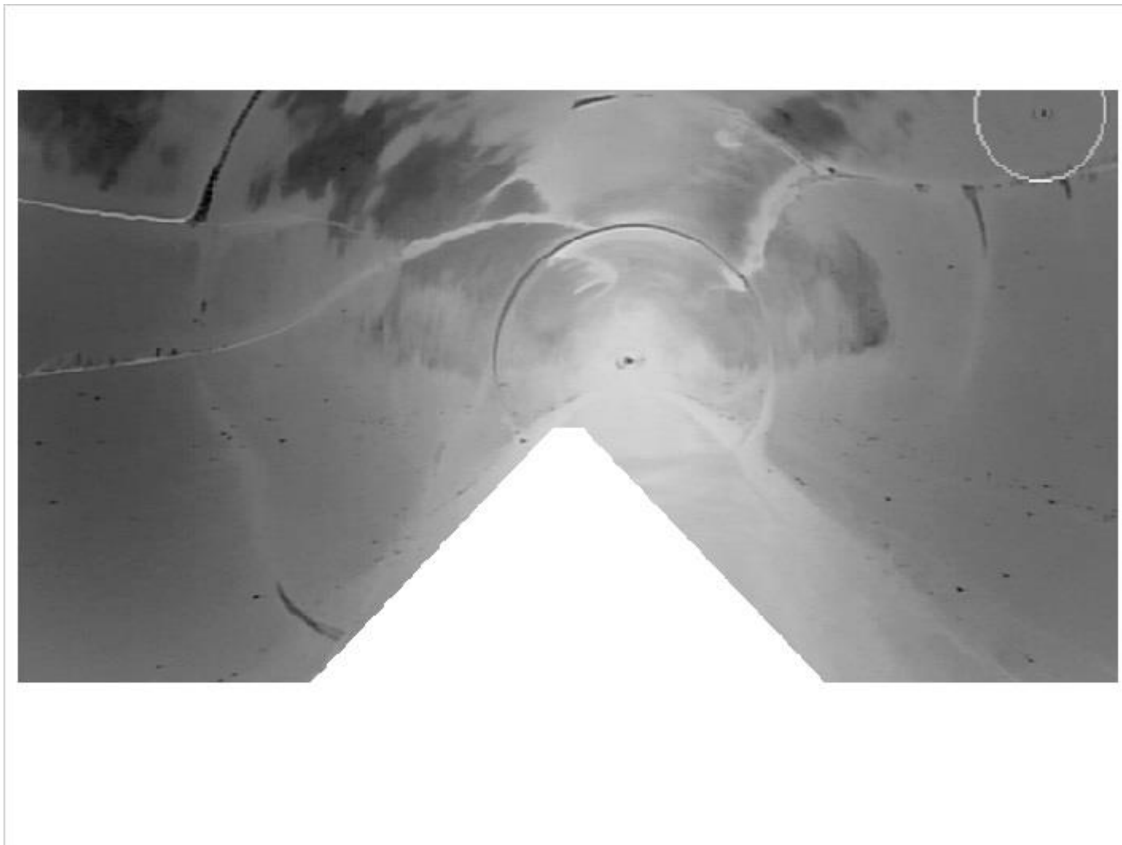

Figure 21, Image after construction by Dilation (Image ic)

4.1.3 Minimum Opening

Removing the linear shapes from an image corresponds to replacing them by their local background. Thus, for a linear shape of width less than L there is at least one direction in which opening with a linear structuring element B of length L2 will remove the shape. Thus, the local background image can be obtained by taking the minimum of openings with a linear structuring element B of length L taken in many directions. The outcome of this step can be expressed as the background image (Image io), as shown in Figure 22.

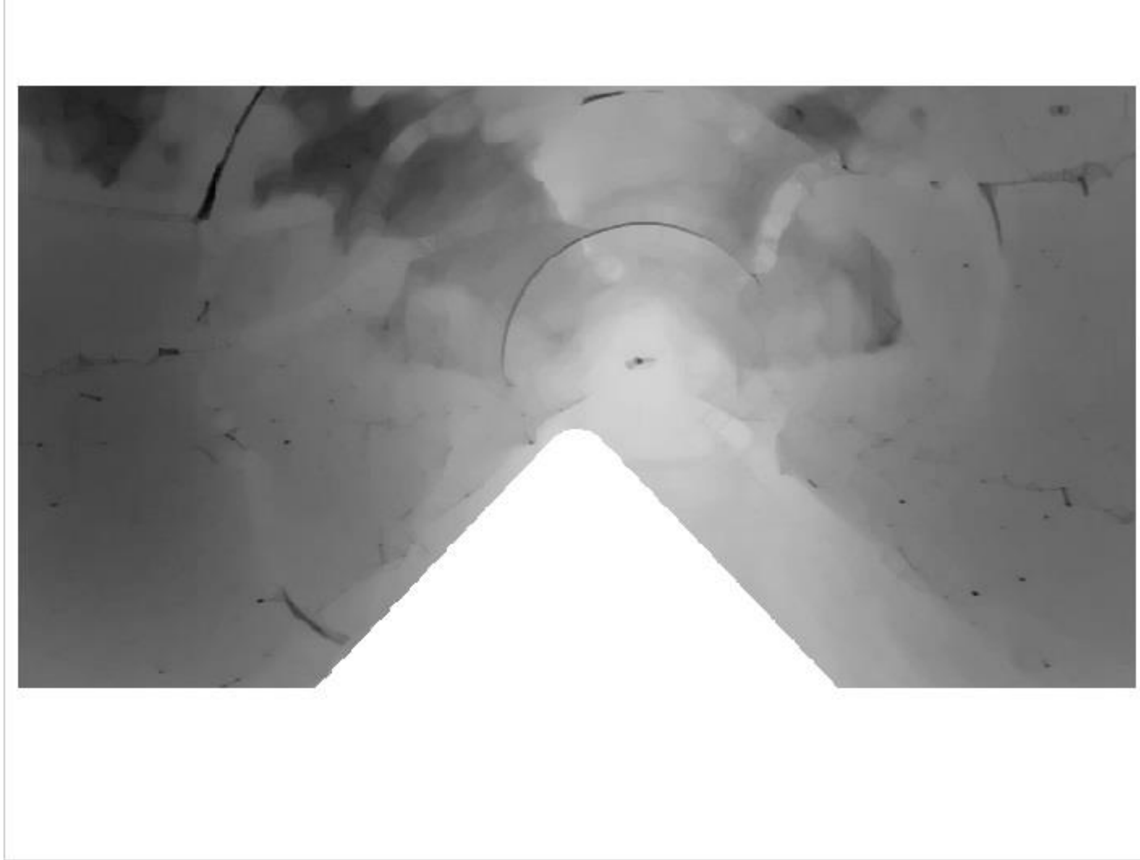

Figure 22, Image after Minimum Opening

The process so far yielded two images, one is constructed by dilation (ic) and the other shows the minimum openings (io). The image ic shows both linear shaped as well as homogeneous surfaces while the image io shows only homogeneous surfaces. Those two images can be subtracted from each other to yield only the linear shapes, as shown in Figure 23.

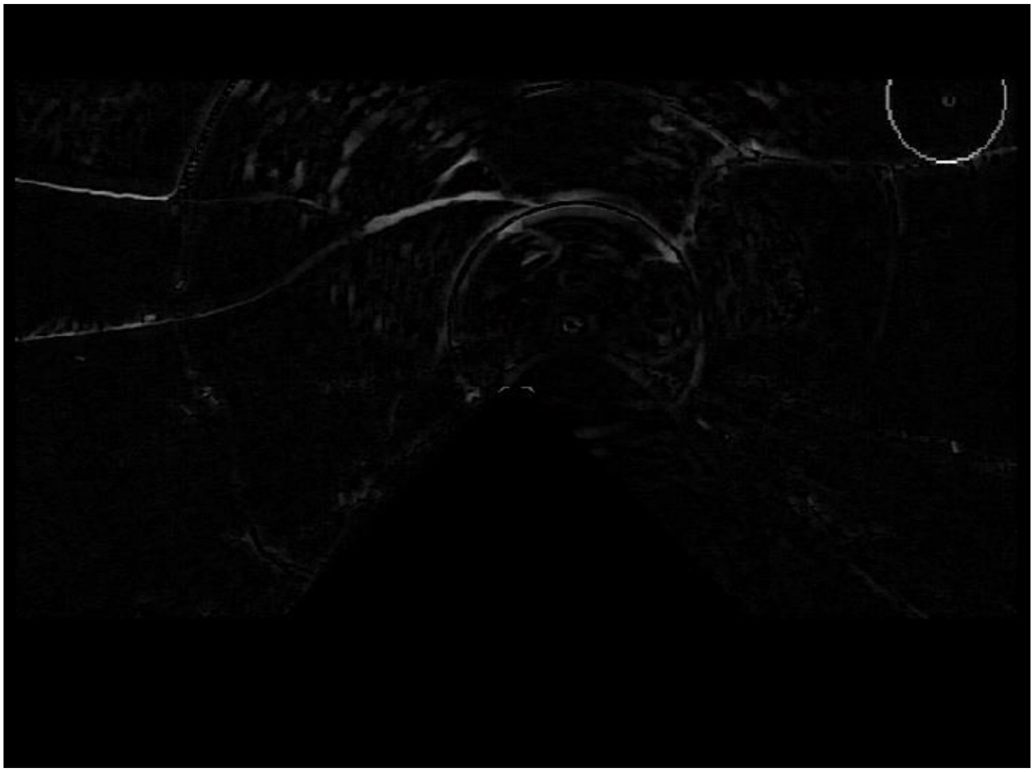

Figure 23, Image with Linear Shapes Only

4.1.4 Smooth Cross-section

The aim of this stem is to brighten the cracks and darken any other objects. Taking the negative of the second derivative in the cross-sectional direction at a point in a crack will yield a positive value inside the crack and a negative value just outside. Cracks should be brightened by this operation, while other structures with zero or positive second derivatives in their cross-sectional direction will be darkened. The bright non-crack parts tend to be non-linear (not made up of line-segments) and can thus be removed by another reconstruction by dilation process. The result of this operation is as shown in Figure 24, where cracks appear brighter and other non-cracks are darkened.

Figure 24, Image after Smoothing

4.1.5 Thresholding

The final step is to produce the binary output mask of the cracks. This can be achieved by thresholding the image. Two greyscale limits (Upper and lower limits) are set in order to come up with an acceptable outcome. Any pixel with greyscale value above the upper limit is set to 1. In addition, pixels that have a greyscale value above the lower limit and are connected to pixels with greyscale values above upper limit are also set to 1. This will ensure that cracks are connected and appear fully in the image. All pixels below the lower limit are set to 0 in addition to isolated pixels above the lower limit. The outcome of this step is shown in Figure 25 after removal of objects.

Figure 25, Image After Thresholding

4.1.6 Crack Type and Orientation

For each object, and in order to check if the crack is complex, the vector v1 and v2 are extracted, as shown in Figure 26. v1 is the vector from the first pixel to the central pixel, and v2 is the vector from the central pixel to the last pixel. If the cos(a) < 0.95 then the crack is complex, where a is the angle between the 2 vectors.

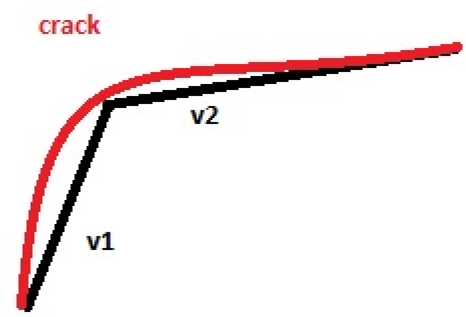

Figure 26, Vectors for Crack Type Detection

In order to find the orientation of the crack, an angle a is calculated as shown in Figure 27. If the angle between the crack center and the center of the image (a) is greater than 35 degree, the crack is considered vertical. Otherwise, the crack is longitudinal.

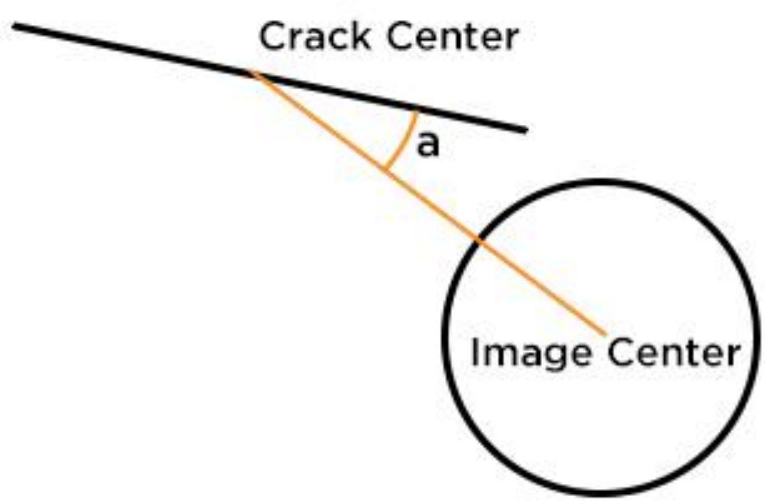

Figure 27, Crack Orientation Detection

4.2 Settled Deposits

The proposed method to detect the settled deposits is fundamentally based on the Gabor Filter. Gabor Filter was used to detect defects in texture surfaces (Hu, 2015). The process of detecting the cracks in a pipeline using a CCTV Camera footage is summarized in the following diagram.

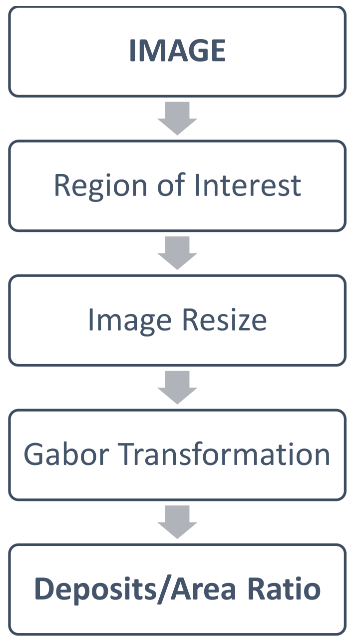

Figure 28, Settled Deposits Flow Diagram

4.2.1 Region of Interest

The first step is to extract the region of interest where the settled deposits may be found. The settled deposits detection analysis is only undertaken in this region of interest (RoI). The RoI is defined and generated as a trapezoidal shape as shown in Figure 29.

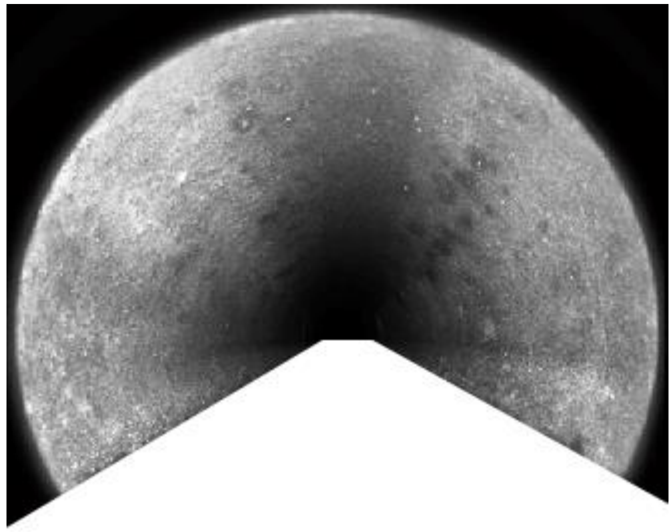

Figure 29, Region of Interest for Settled Deposits Detection

4.2.2 Image Resize

The image is then resized. This step is performed to decrease the processing time, since the Gabor Transform will take longer time with larger images. The image is resized to half the size of the original image size. Bicubic interpolation is used to perform this step, which results in an output pixel value in the nearest 4X4 neighborhood.

4.2.3 Gabor Transform

Gabor filter is mainly used for edge detection in an image. The process of a Gabor filter transformation can be compared to that of the human eye, as it detects and discriminates texture representation. It basically gives the highest response at edges and at points where texture changes, which is applicable to settled deposits. In this application, multiple Gabor transforms are performed with varying parameters to detect the settled deposits in the CCTV Camera footage.

The Gabor filter Matlab code is obtained from Haghighat (2016). Figure 30 shows a CCTV Camera footage while being tested using Gabor Filter with varying parameters.

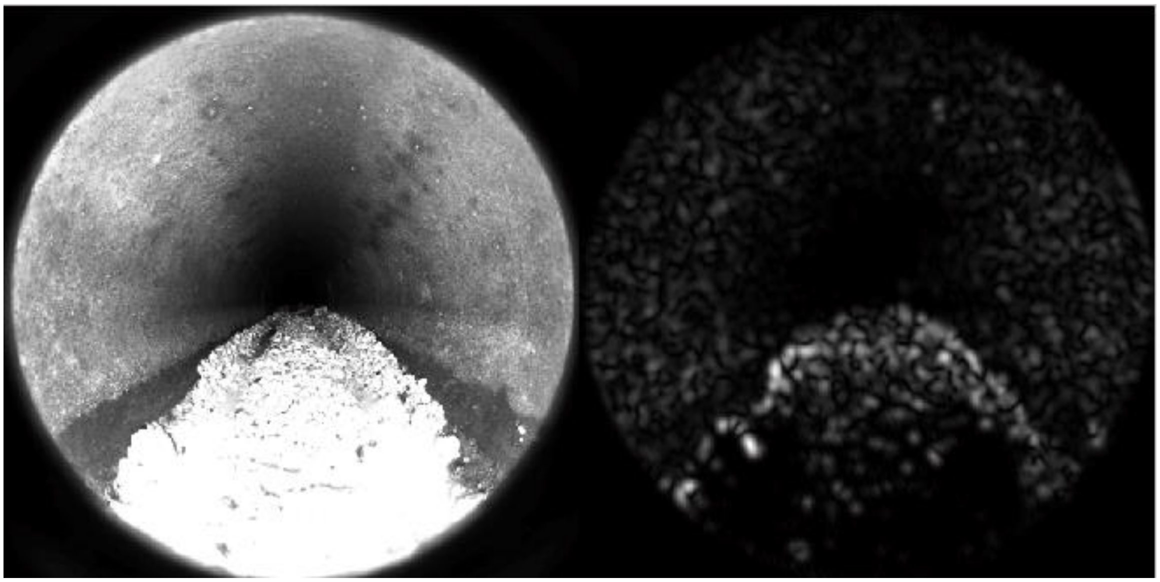

Figure 30, CCTV Camera Footage while Testing Using Gabor Filter

4.2.4 Deposits/Area Ratio

For each image, the settled deposits area, if any, is detected from the pipeline's section using the previous processes. The settled deposit area can then be found. A ratio between the settled deposits area in relation to the region of interest total area is then calculated using the following equation:

$$Settled\ Deposits\ Ratio = \frac{area_{deposit}}{area_{roi} - area_{deposit}}$$

4.3 Ovality

The process of detecting the ovality of a pipeline using a CCTV Camera footage is summarized in the following diagram.

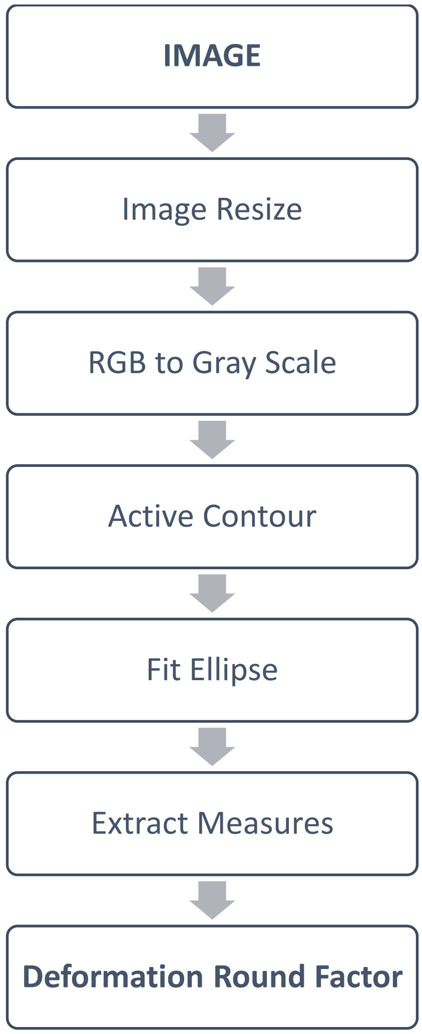

Figure 31, Ovality Detection Flow Diagram

4.3.1 Image Resize

The first step is to resize the image. This step is performed to decrease the processing time. The image is resized to half the size of the original image size. Bicubic interpolation is used to perform this step, which results in an output pixel value in the nearest 4X4 neighborhood.

4.3.2 RGB to gray scale conversion

This step is necessary as it converts the true-color image (RGB) to a grayscale by forming a weighted sum of the Red (R), Green (G) and Blue (B) components as follows:

$$0.2989\,R + 0.5870\,G + 0.1140\,B$$

4.3.3 Active Contour

For creating an active contour, the Active Contour Segmentation code is used (Lankton, 2016). The active contour model's aim is to detect an object in an image by developing a curve that is subject to certain constrains in this image. The algorithm is iterative as it starts from an initialization of a mask and continues until the maximum number of iterations (Chan & Vese, 1999). In Figure 32, the initialization mask is just the image border.

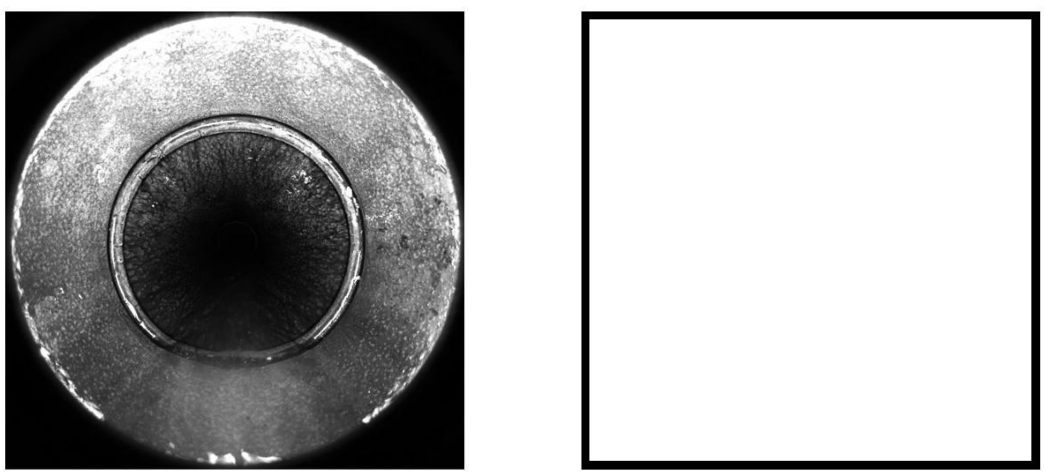

Figure 32, Grayscale image I and initialization mask m

In each iteration, the algorithm minimizes an energy function. It starts with a curve, or in this case a border that encloses the intended object. This border iteratively converges and eventually stops on the boundary of the object (Chan & Vese, 1999). This step is performed as shown in Figure 33.

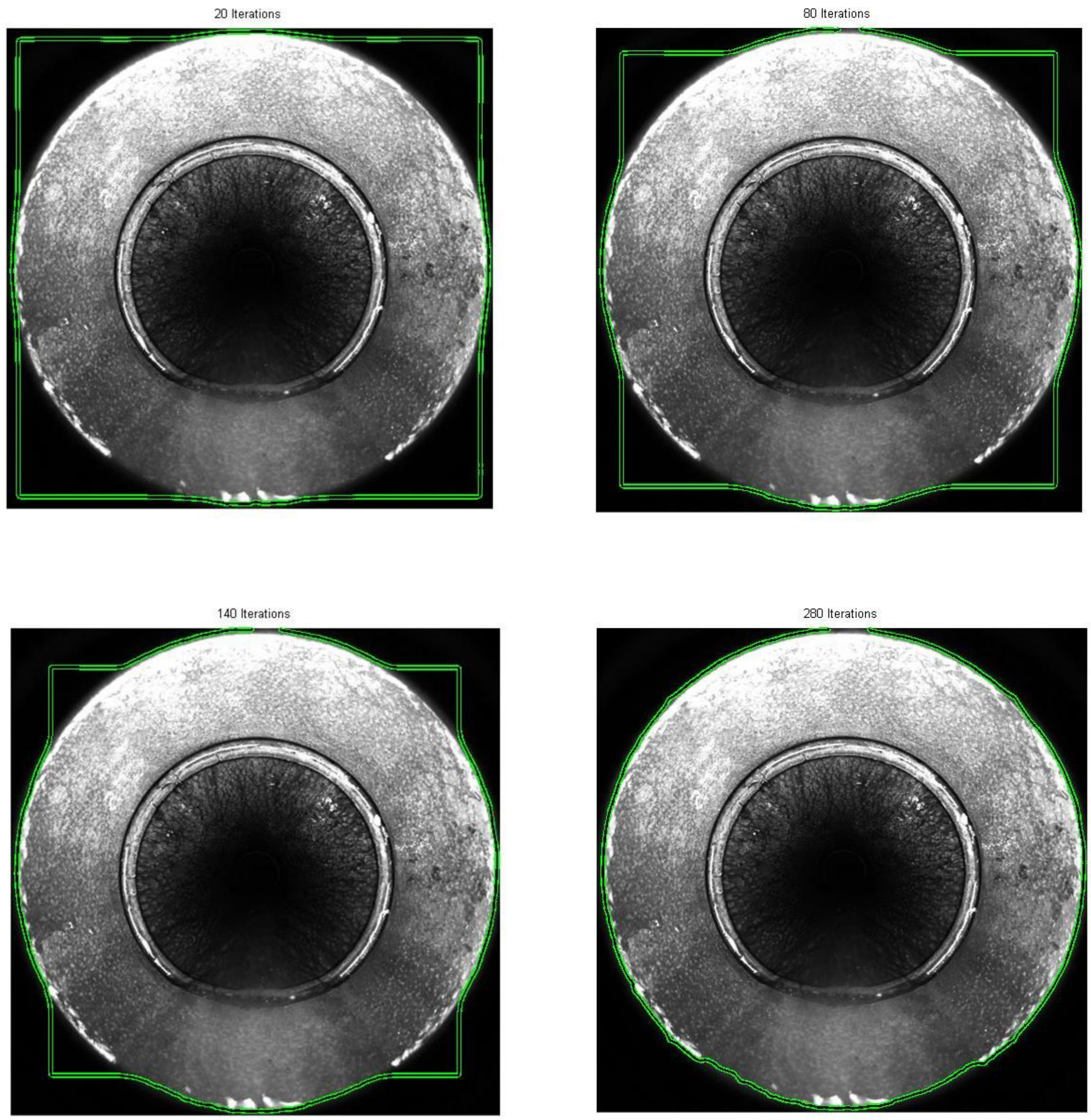

Figure 33, Active Contour Convergence around the Object

The final output of the active contour process is the segmentation mask, where the foreground (i.e. the pipe cross-section) is set to white color and the background is set to black color as shown in Figure 34.

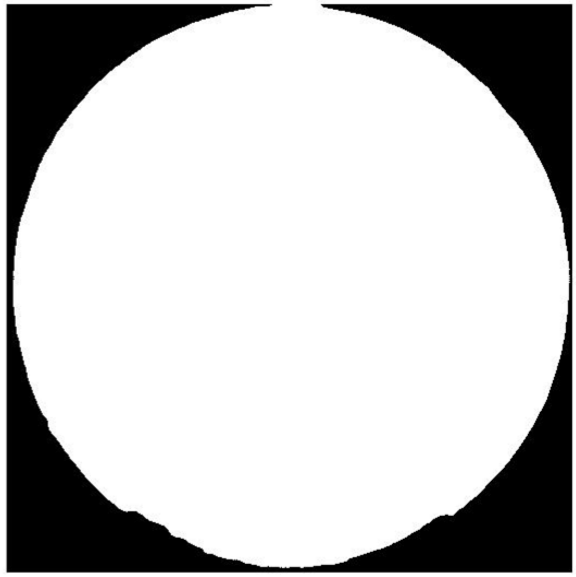

Figure 34, Segmentation Mask

The segmentation mask is cleaned to maintain only the biggest connected component. The perimeter is then extracted as shown in Figure 35.

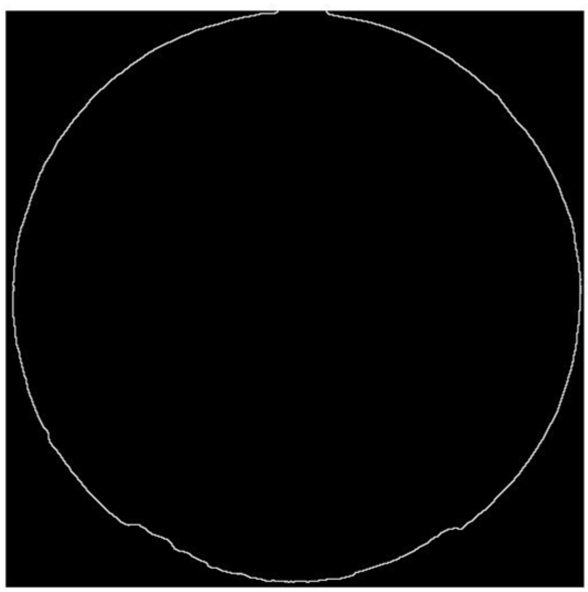

Figure 35, Perimeter Mask

4.3.4 Fit ellipse

To perform the ellipse fit step, the Ellipse Fit code (Taubin Method) is used (Chernov, 2009).

This code has been implemented previously for the estimation of planar curves, surfaces and nonplanar space curves defined by implicit equations (Taubin, 1999). With this algorithm, the best fitting ellipse around the perimeter mask is obtained. The fitted ellipse is shown in red in Figure 36.

The output of this process is obtained as follows:

$$A = [a\ b\ c\ d\ e\ f]'$$

This output represents the algebraic parameters of the fitted ellipse equation, in the form of a vector. The ellipse equation is as follows:

$$ax^2 + bxy + cy^2 + dx + ey + f = 0$$

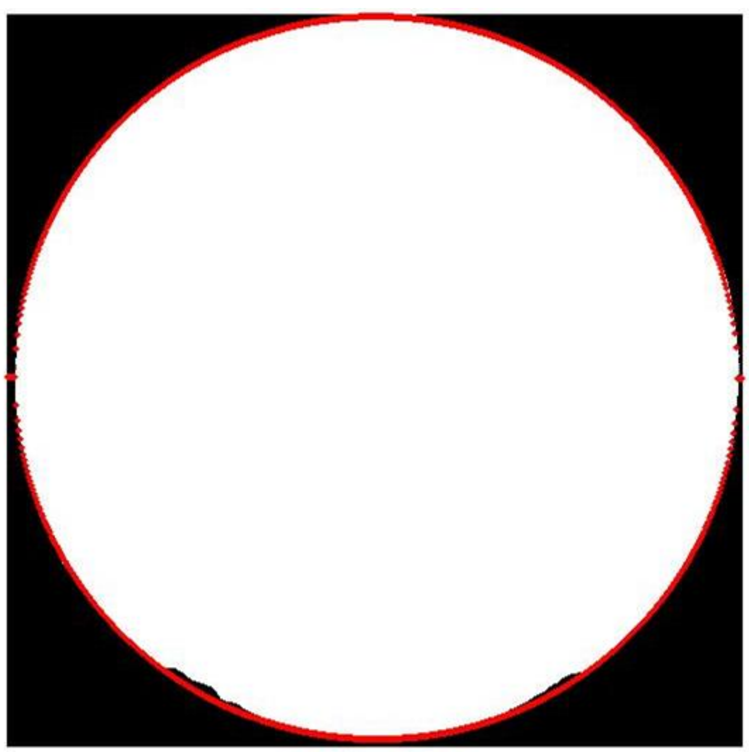

Figure 36, Fitted Ellipse

4.3.5 Extract measures

The ellipse parameter vector, obtained in section 4.3.4, is in the form of $A = [a\ b\ c\ d\ e\ f]$.

To convert this vector A to the geometric parameters (semi-axes, center, etc.), Standard formulas are used to calculate the two axis (dmax and dmin) in addition to the area and the perimeter of the ellipse (Wolfram Mathworld, n.d.). The final outcomes are the deformation and roundness factors.

$$Deformation = \frac{dmax - dmin}{dmax + dmin}$$

$$Roundness\ Factor = \frac{4\pi \times Area}{Perimeter^2}$$

4.4 Displaced Joints

The process of detecting cracks in a pipeline CCTV Camera footage is summarized in the following diagram.

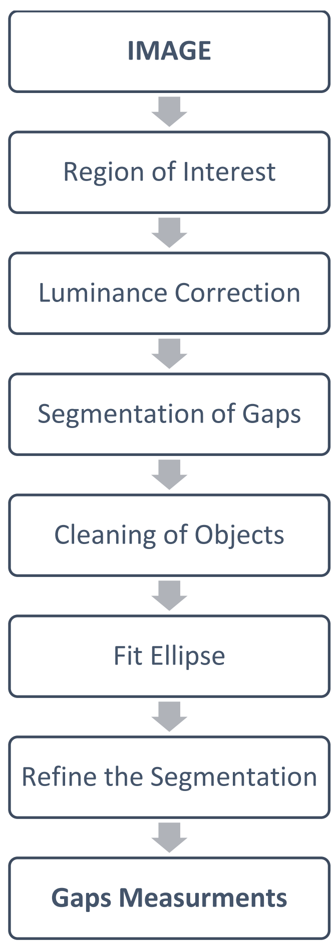

Figure 37, Displaced Joint Detection Flow Diagram

4.4.1 Region of Interest

The Region of Interest (RoI) is a trapezoidal area where cracks could exist in this footage. It is basically the pipeline inner wall that is visible in this footage, which is defined as in the crack detection module from which a ring is extracted as shown in

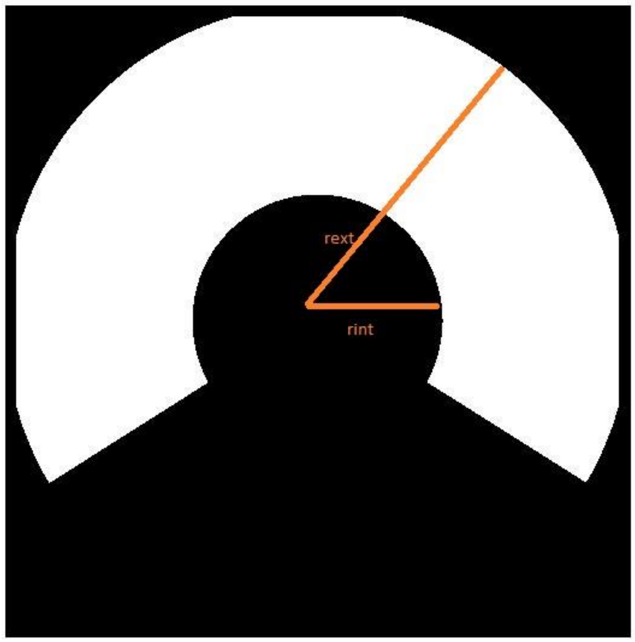

Figure 38, Region of Interest

4.4.2 Luminance correction

Figure 39, Image before correction

The aim of this step is to correct the luminosity of the image that is darker in the center and radially brighter towards the edges. First, the image is transformed from Cartesian to Polar coordinates, as shown in Figure 40.

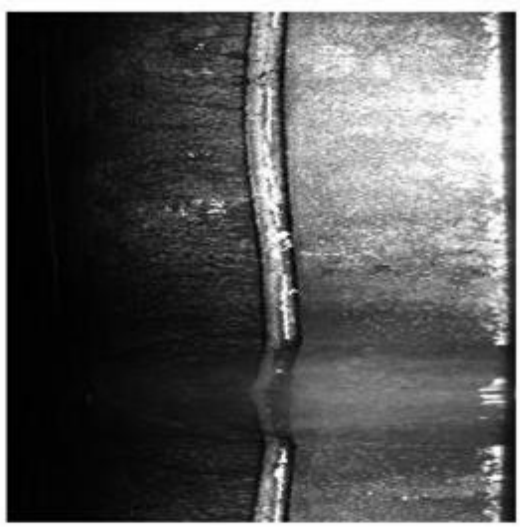

Figure 40, Image Transformed to Polar Coordinates

Following the coordinates system transformation, a polynomial of degree 1 along the radius direction is set to estimate the luminance in the polar coordinates. This luminance is then transformed back to the Cartesian coordinates as shown in Figure 41.

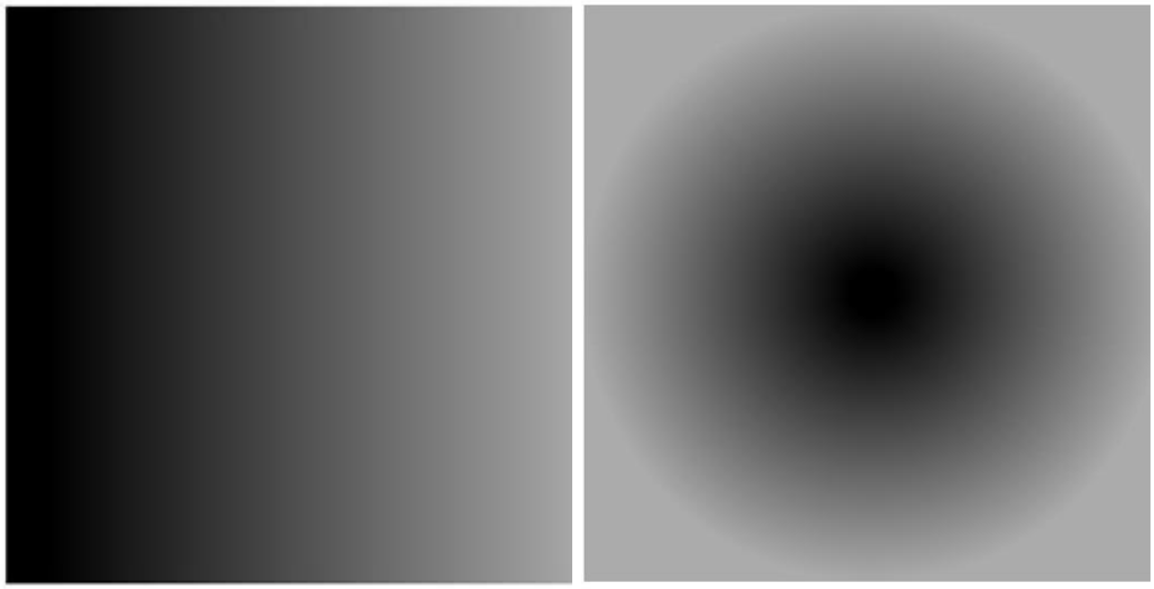

Figure 41, Estimated Luminance in Polar and Cartesian Coordinates

Finally, the estimated luminance is subtracted from the original image, yielding what is shown in Figure 42.

Figure 42, Image After Luminance Correction

4.4.3 Segmentation

Following the luminance correction, two different thresholds are created based on the standard deviation and the mean inside the RoI (±1.3*Standard Deviation). This yields two image, one with segmentation of the darker pixels of the original image, and the other with the brighter pixels. Figure 43 shows the image segmentation of the darker pixels while Figure 44 shows the image segmentation of the brighter pixels.


Figure 43, Image Segmentation of Darker Pixels


Figure 44, Image Segmentation of Brighter Pixels

4.4.4 Cleaning

The following step is cleaning the two images and selecting the areas with the highest concentration of pixels. Isolated objects with area < 50 pixels are removed.

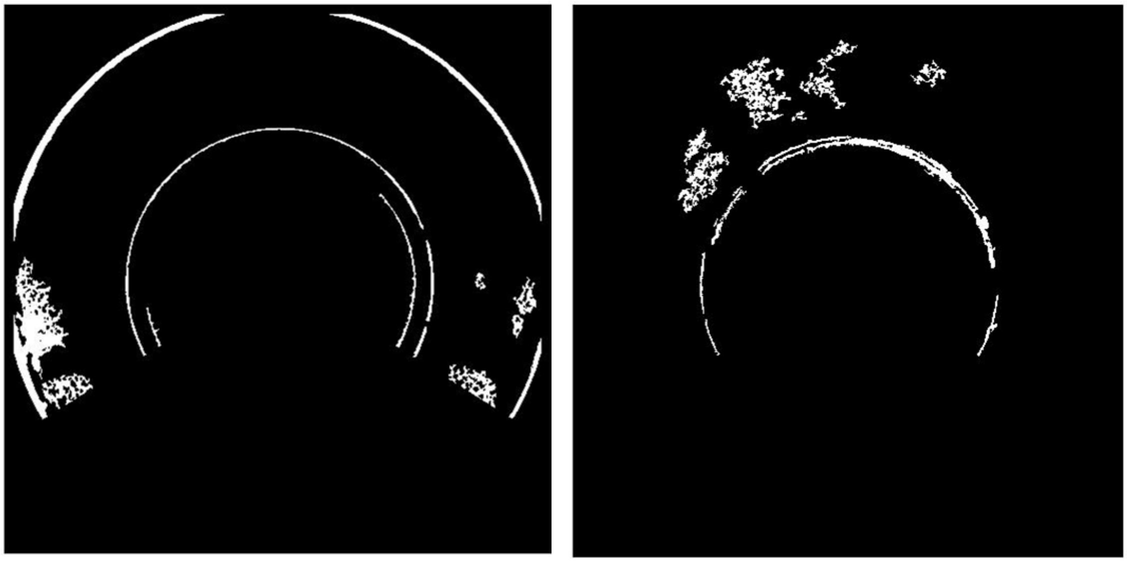

Figure 45, The two Segmented Images After Cleaning

4.4.5 Ellipse Fit

After the images are cleaned, it is ready for processing and gap detection. Each connected component in the image is tested as a potential gap. Figure 46 shows a sample connected component resembling a gap.

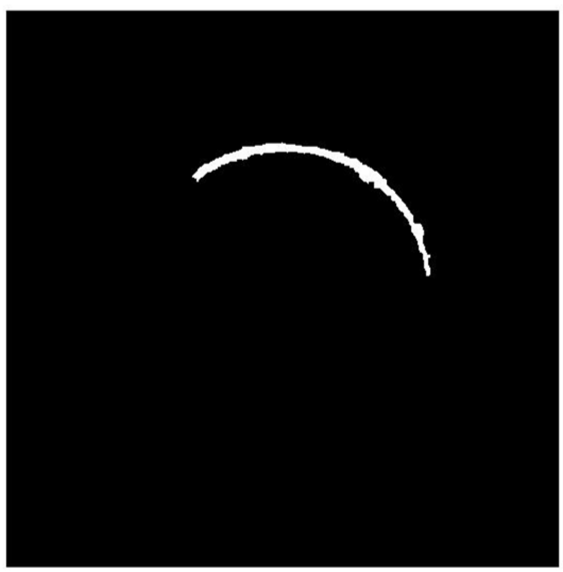

Figure 46, Connected Component

The first step is to confirm that this connected component is a good candidate to being a gap.

A shape feature is extracted from this component's distance transform; which is an operator that is typically applied to binary images as in this application. This transform results in a new image that displays the intensity of the pixels next to it rather than just its own gray-scale color. This can be explained as a pixel's color is relative to its distance from the nearest boundary, as shown in Figure 47 (Frisken, Perry, Rockwood, & Jones, 2000).

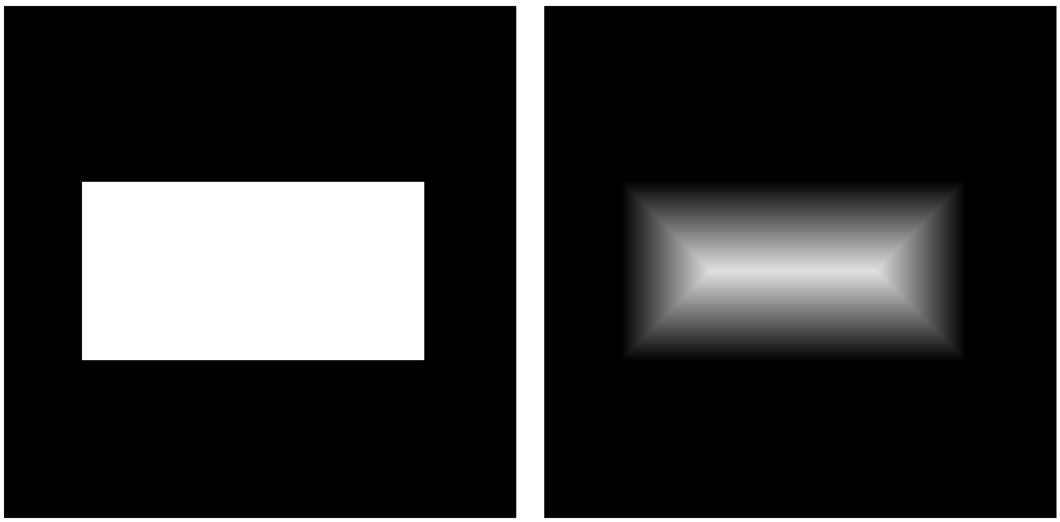

Figure 47, Distance Transform of a Rectangle

The 90 percentile and median are extracted from the histogram of the distance transform values as shown in Figure 48.

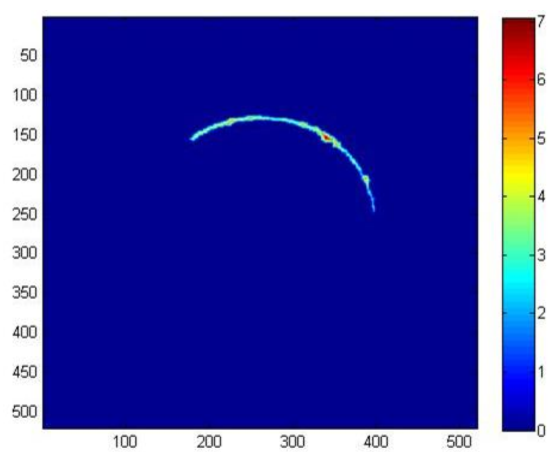

Figure 48, Distance Transform Graph

The intention here is to only keep an object as gap candidate only if it has a regular thin shape.

So only if the object has a ratio of $\frac{90th\ percentile}{median} < 2.5$, the object is maintained as a candidate and the parts with irregular shapes are removed from the object.

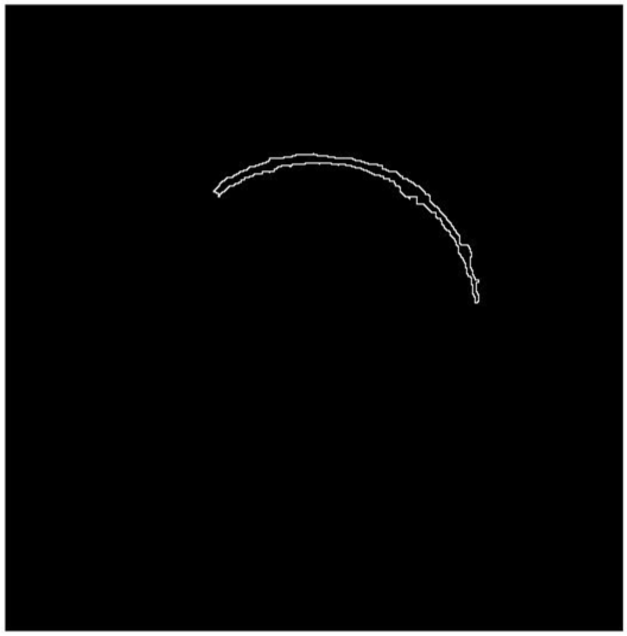

Figure 49, Object Perimeter

The final step is to fit an ellipse on the perimeter of the object. The best fit parameters are found using the optimizer function fmincon, as shown in Figure 50.

Figure 50, Fitted Ellipse

In order to check weather this process was a success and the candidate fallows an elliptical shape, some values are obtained. Those parameters are length, ratio between width of the gap and length, circularity (ratio of min and max axis), and then the fit error. If all those values are below certain parameters, then this shape is chosen as a gap in this footage.

4.4.6 Refinement of Gap Segmentation

The previously obtained ellipse is used to enhance the segmentation of the detected gap. The segmentation gap before refinement is shown in Figure 51 (in white), along with the fitted ellipse (in red).

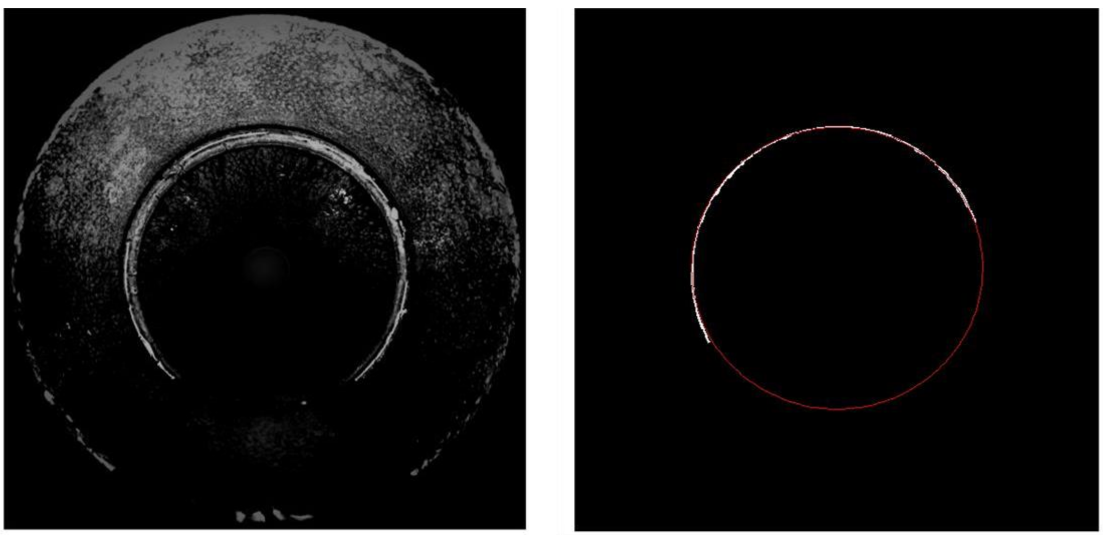

Figure 51, Segmentation Gap Before Refinement

New values of standard deviation of pixels around the ellipse are calculated and a new segmentation is performed to obtain the final gap shown in Figure 52. Finally, the length and width of the gap is obtained.

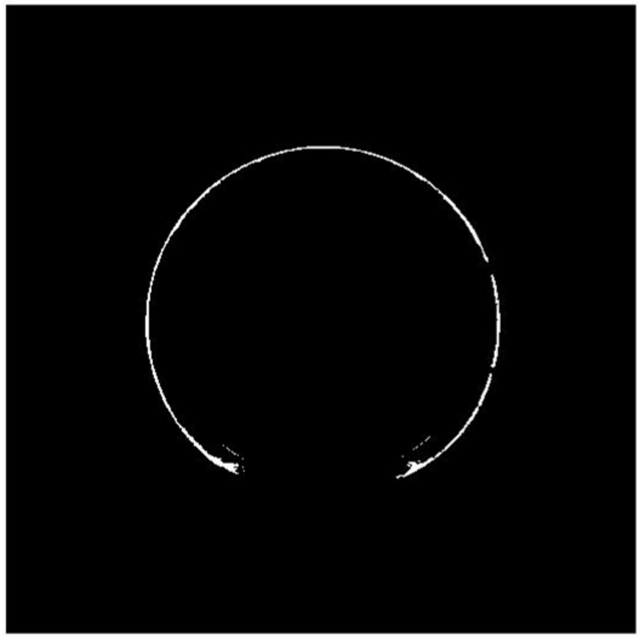
Figure 52, Final Segmented Gap After Refinement

CHAPTER 5: RESULTS AND DISCUSSION

The analysis of the automated tool was performed on two samples. The first sample was selected footage out of CCTV camera footage raw data as acquired from the Public Works Authority's (Ashghal) inspection works on recent pipelines in Qatar. Since those pipelines are relatively new, not many defects were present on those pipelines and footage with defects were selected as a test sample. Another sample was selected out of a different set of CCTV inspection footage as acquired from the Public Works Authority. This second set were inspection works for relatively older pipelines. Thus, it is an advantage that the tool was tested on a sample of old and new pipelines in Qatar. Given that the two data sets were acquired by different CCTV cameras with different sizes and different viewing angles, the code was slightly modified for each data set to account for the minor differences.

In addition to the data being examined and analyzed by the codes described in CHAPTER 4:, the CCTV Camera Footage were visually inspected to verify the results and to test the accuracy and reliability of these tools. The following sections discusses the obtained results from the automated tool and compares it to those from the visual inspection.

5.1 Cracks Detection

5.1.1 Sample 1

The sample features images with displaced joint that can be mistaken for cracks. The code during the development stages considered the displaced joints as cracks. To overcome this issue, the code was then updated to overlook the previously detected displaced joints and only detect the real cracks in the pipelines. The code was able to overlook displaced joint in 14 out of 16 pictures with a success rate of 88%.

However, the main goal here is to verify the crack detection algorithm. This sample included only very minor cracks and no cracks were undetected. Thus, it is difficult to verify the efficiency of the code via testing on this sample. Those minor cracks, nonetheless, were detected by the code and were verified by visual inspection as shown in Figure 53.

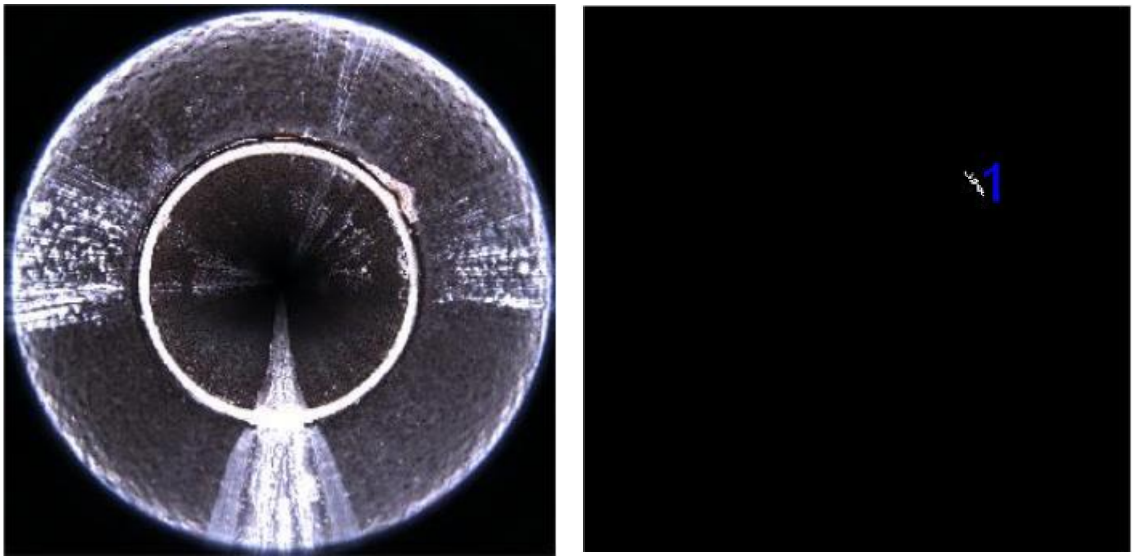

Figure 53, Minor Crack Detection

5.1.2 Sample 2

Given that the second sample are of older pipelines, the sample included a more crack-intense images in comparison with the first sample. Table 2 shows the crack detection results in comparison to the visual inspection. The accuracy in this case was 84%.

Table 2, Cracks Detection (Sample 2)

IMAGE	CRACK #	LENGTH (Pixels)	WIDHTH (Pixels)	Visual Inspection
1	1	172.15	19.55	Crack
2	1	151.57	20.38	Crack
	2	64.28	7.81	Crack
	3	106.84	18.69	Crack
3	0	0.00	0.00	No Crack
4	0	0.00	0.00	No Crack
5	1	130.78	32.98	Crack
	2	211.25	33.08	Crack
	3	23.37	3.16	No Crack
	4	68.87	11.22	Crack

IMAGE	CRACK #	LENGTH (Pixels)	WIDHTH (Pixels)	Visual Inspection
6	1	123.32	29.32	Crack
	2	66.42	18.09	Crack
7	0	0.00	0.00	No Crack
8	0	0.00	0.00	No Crack
9	0	0.00	0.00	No Crack
10	1	74.11	17.94	Crack
	2	81.77	12.80	Crack
	3	101.01	15.85	No Crack
	4	177.68	30.71	No Crack

Figure 54, CCTV Image with Cracks and Displaced Joint

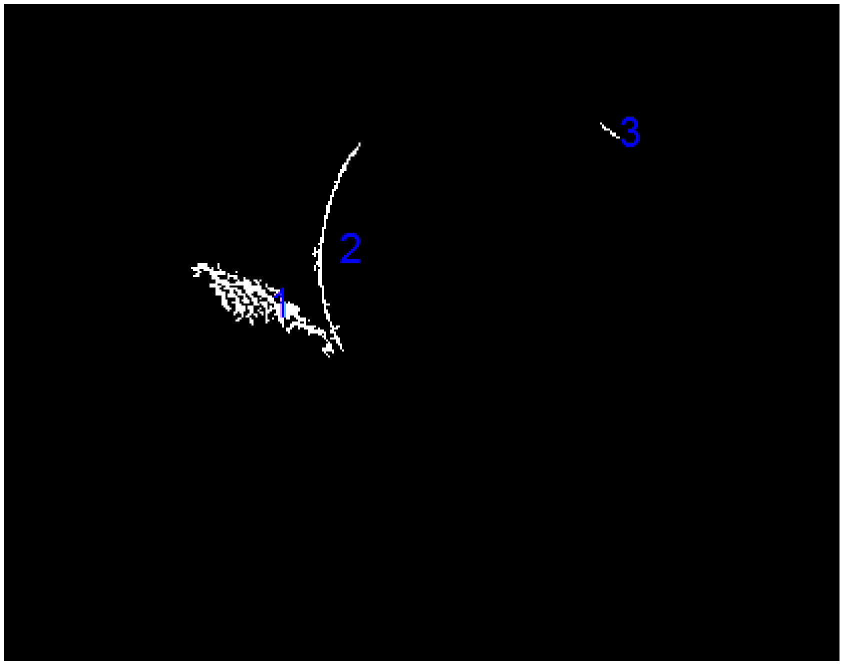

Figure 55, Detection of Cracks and Displaced Joint

5.2 Settled Deposits

5.2.1 Sample 1

As the code calculates the ratio of deposits in the region of interest, a percentage threshold was set to 0.02 (i.e. images with ratio more than 0.02 is considered detected with settled deposits). The comparison between the code and the visual inspection is shown in Table 3. The code was successful in identifying settled deposits with an accuracy of 86% in the first sample. A sample of the detected settled deposits is shown in Figure 56 and Figure 57. However, the error percentage is misleading as the automated tool in some instances detected discoloring in the region of interest and classified it as settled deposits. This lead to a higher percentage of error. However, there were no instances of settled deposits that were overlooked by the Matlab code and thus, it is safe to say that the tool has a higher accuracy than what is calculated against the visual inspection.

Table 3, Settled Deposits Detection Results (Sample 1)

IMAGE	SETTLED DEPOSITS RATIO	VISUAL INSPECTION
1	0.0013	NOT PRESENT
2	0.0325	PRESENT
3	0.0079	NOT PRESENT
4	0.0053	NOT PRESENT
5	0.0062	NOT PRESENT
6	0.0040	NOT PRESENT
7	0.0027	NOT PRESENT
8	0.0037	NOT PRESENT
9	0.0027	NOT PRESENT
10	0.0287	NOT PRESENT
11	0.0087	NOT PRESENT
12	0.0308	PRESENT
13	0.1672	PRESENT
14	0.1477	PRESENT
15	0.1219	NOT PRESENT
16	0.0636	NOT PRESENT
17	0.0289	PRESENT
18	0.0466	PRESENT
19	0.2977	PRESENT
20	0.0012	NOT PRESENT
21	0.0019	NOT PRESENT
22	0.0053	NOT PRESENT

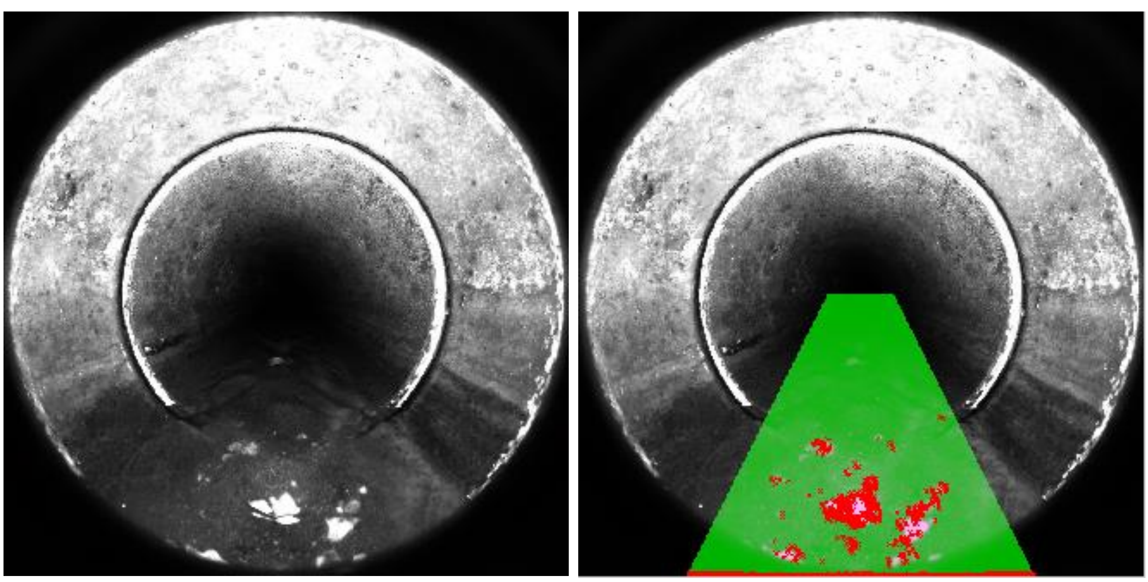

Figure 56, Settled Deposits Detection 1

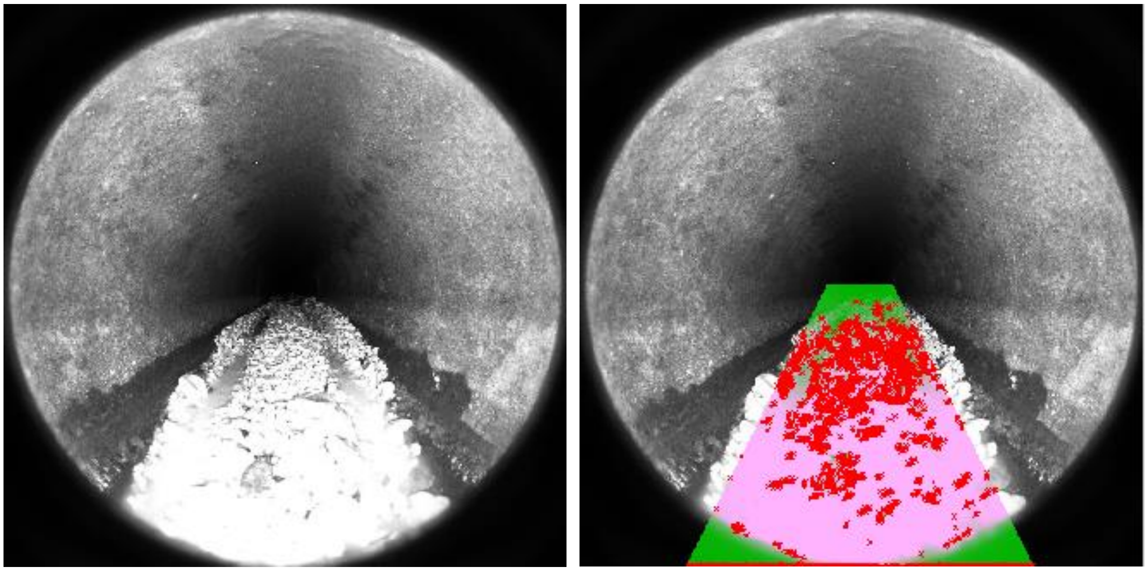

Figure 57, Settled Deposits Detection 2

5.2.2 Sample 2

For the second sample, a threshold was set to 0.2 (i.e. images with ratio more than 0.2 is considered detected with settled deposits). Table 4 shows the results of settled deposits detection from the 2nd sample. The success rate for the settled deposits detection in this case is 100%.

Table 4, Settled Deposits Detection Results (Sample 2)

IMAGE	RATIO	VISUAL INSPECTION
1	0.023	NOT PRESENT
2	0	NOT PRESENT
3	0.288	PRESENT
4	0.325	PRESENT
5	0.002	NOT PRESENT
6	0	NOT PRESENT
7	0	NOT PRESENT
8	0.004	NOT PRESENT
9	0.001	NOT PRESENT
10	0.100	NOT PRESENT

5.3 Ovality

A code for detection of ovality in the pipe was only constructed for the 1st sample. Due to the lack of images with deformed or non-circular pipelines, it was difficult to test the accuracy of the tool when it comes to ovality. Given that it is difficult to detect minor ovality of a pipeline with the human eye, other tools were used to manually assess the circularity of a pipeline. AutoCad software was used to fit an ellipse around the pipe's circumference and around the joints to verify that it is perfectly circular as shown in Figure 59. A roundness threshold of 0.95 was set to consider a pipe perfectly circular. The automated tool achieved a 100% accuracy for ovality detection with the existing footage. Table 5 shows the comparison between the detection tool and the manual ovality inspection. Figure 58 shows the detection of the pipeline circularity using the Matlab code while Figure 59 shows the manual detection of the pipeline's circularity.

Table 5, Ovality Detection Results

IMAGE	DETECTED ROUNDNESS	VISUAL INSPECTION
1	0.99999	Round
2	0.999982	Round
3	0.99996	Round
4	0.999999	Round
5	0.999992	Round
6	0.999999	Round
7	0.999968	Round
8	0.999991	Round
9	0.999988	Round
10	1	Round
11	0.999994	Round
12	0.999981	Round
13	0.999992	Round
14	0.999985	Round
15	1	Round
16	0.999999	Round
17	0.999997	Round
18	1	Round
19	0.999921	Round
20	0.999947	Round

IMAGE	DETECTED ROUNDNESS	VISUAL INSPECTION
21	0.999973	Round
22	0.999997	Round

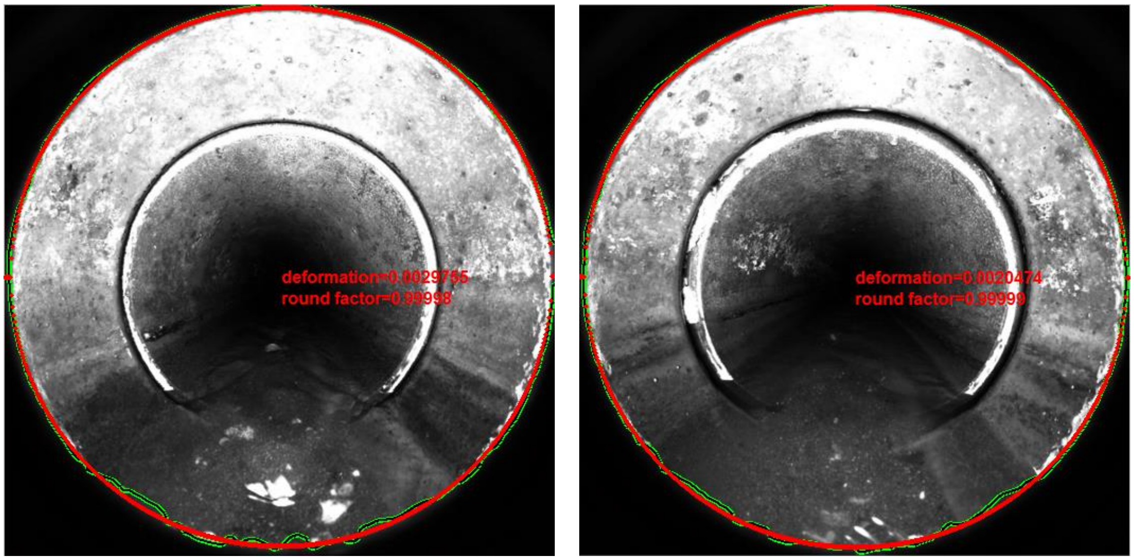

Figure 58, Ovality Detection

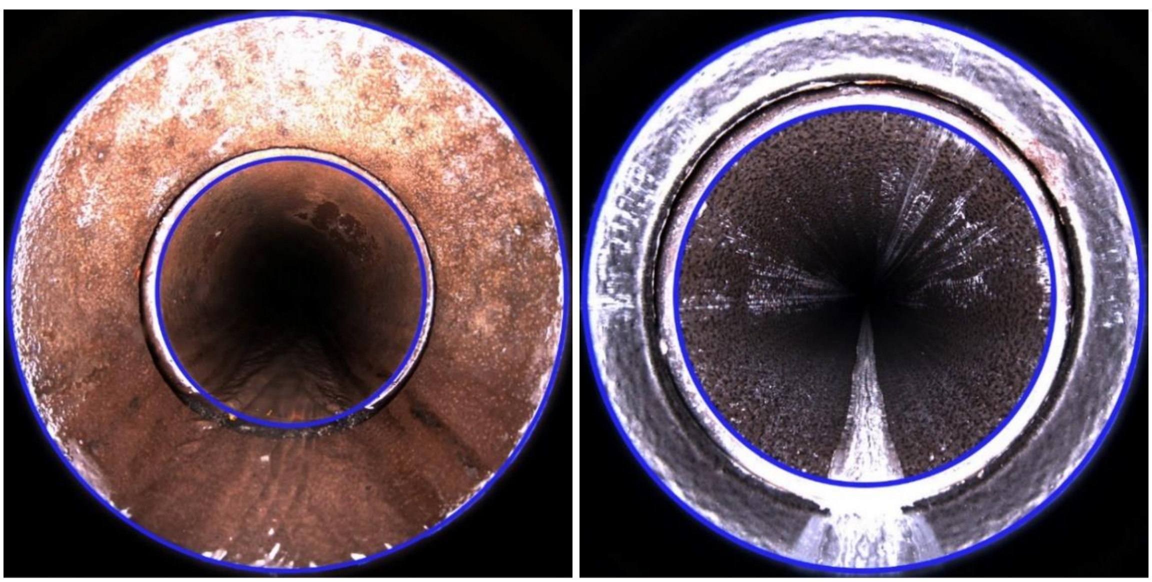

Figure 59, Manual Ovality Detection

5.4 Displaced Joint

5.4.1 Sample 1

In comparison with the visual inspection, the code was able to detect all the displaced joints in the CCTV camera footage (100% success rate) for the first sample. Table 6 shows the displaced joints detection results in comparison with the visual inspection while Figure 60, Displaced Joint Detection shows a sample of the detected joints.

Table 6, Displaced Joint Detection Results (Sample 1)

IMAGE	DISPLACED JOINT LENGTH	DISPLACED JOINT WIDTH	VISUAL INSPECTION
1	461.0	8.3	GAP
2	648.5	16.0	GAP
3	1246.0	11.3	GAP
4	973.5	14.6	GAP
5	573.5	15.0	GAP
6	1057.0	12.4	GAP
7	849.0	20.5	GAP
8	370.5	8.3	GAP
9	965.0	7.3	GAP
10	849.0	9.1	GAP
11	313.5	8.1	GAP
12	645.0	22.0	GAP
13	0	0	NO GAP
14	0	0	NO GAP
15	620.0	9.0	GAP
16	780.5	16.1	GAP
17	375.0	5.0	GAP
18	1085.0	11.3	GAP
19	0	0	NO GAP
20	0	0	NO GAP
21	0	0	NO GAP
22	0	0	NO GAP

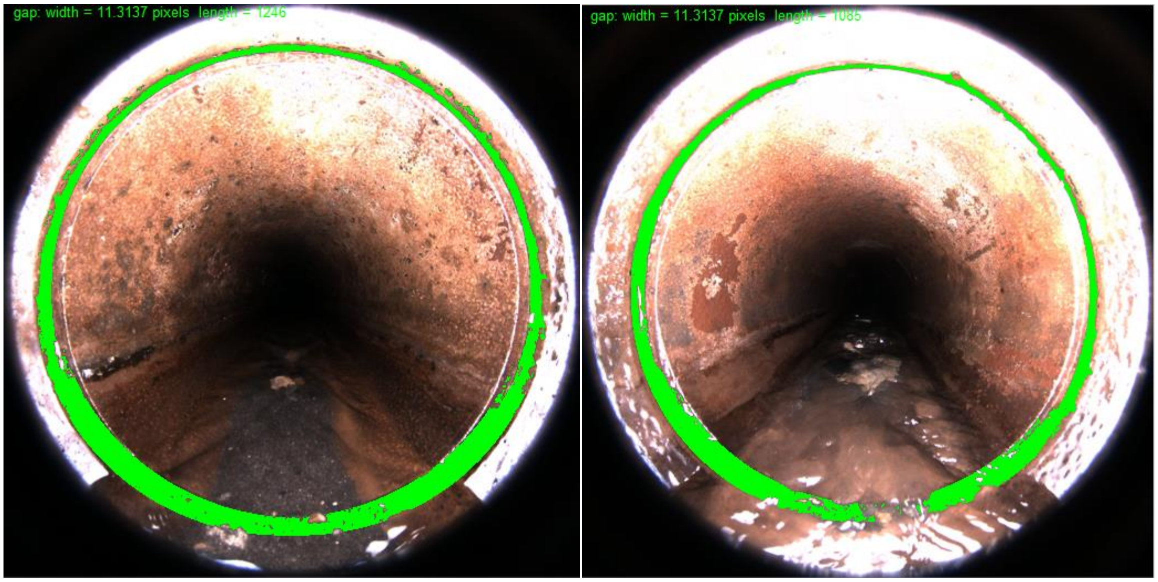

Figure 60, Displaced Joint Detection

5.4.2 Sample 2

The accuracy of displaced joints detection for the second sample was 80%. The results are tabulated in Table 7, Displaced Joints Detection Results (Sample 2) Figure 61 shows an example of a detected displaced joint.

Table 7, Displaced Joints Detection Results (Sample 2)

IMAGE	DISPLACED JOINT LENGTH	DISPLACED JOINT WIDTH	VISUAL INSPECTION
1	0	0	NO GAP
2	0	0	NO GAP
3	0	0	GAP
4	0	0	NO GAP
5	325	5	GAP
6	287	7.21	GAP
7	413	10	GAP
8	0	0	NO GAP
9	0	0	NO GAP
10	0	0	GAP

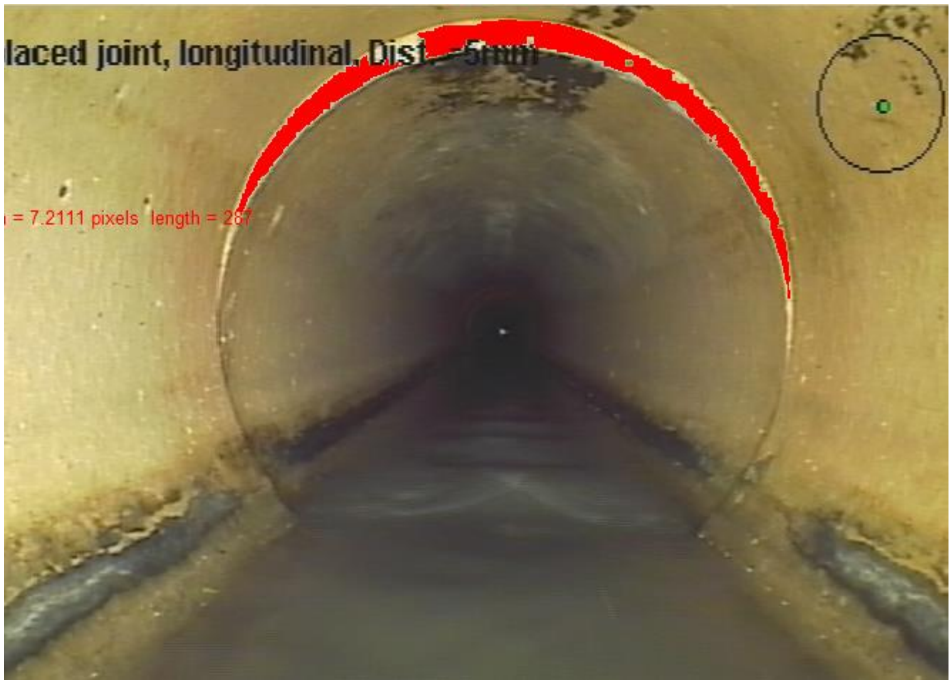

Figure 61, Example of Detection of Displaced Joint

5.5 Results Summary

Figure 62 summarizes the accuracy levels of the automated tool in detecting the four types of defects. The accuracy level is measured via visual inspection verification.

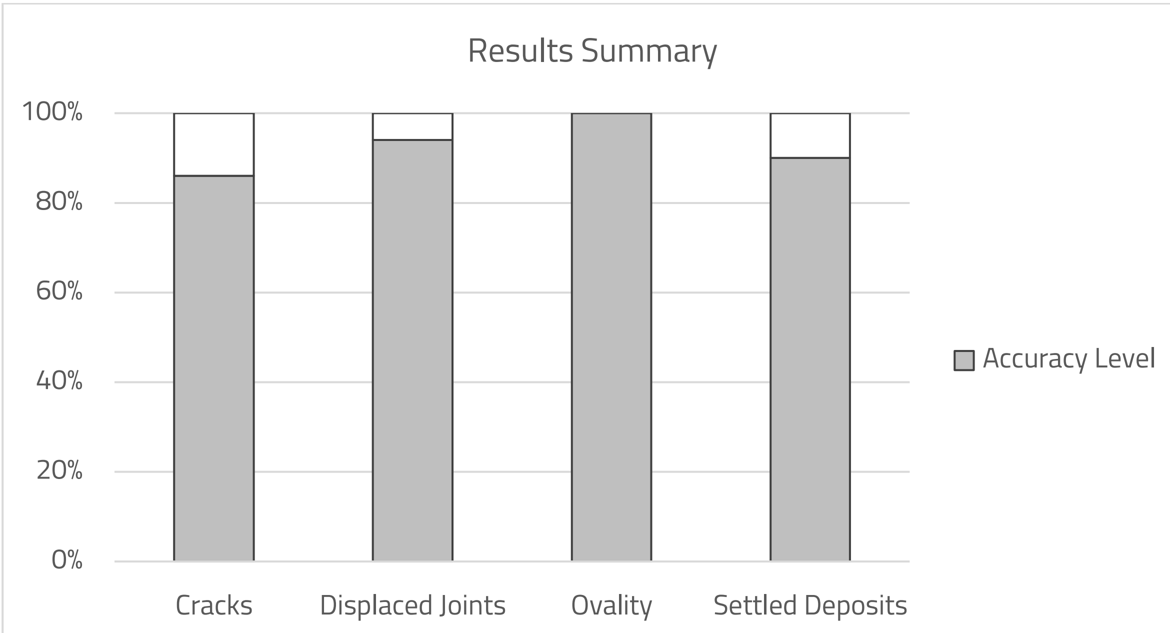

Figure 62, Summary of the Automated Tool's Results

CHAPTER 6: CONCLUSION

The costs that accompany sewer pipelines defects and breaks are rising sharply in modern sewer networks. In Qatar, many pipelines were installed in the last 20 years and are currently in poor condition and constantly deteriorating. The breaks result in costs related to the inspection and repair of the assets, water loss costs and damaged properties and infrastructures (Misiunas, 2005). The current practices for sewer pipelines inspections utilizes the use of CCTV camera, which is time-consuming, as one CCTV camera inspection session can result in several hours of intensive visual inspection and condition assessment by a trained operator. In addition, this conventional assessment method can lead to subjective results as it highly depends on the operator or engineer's experience and judgement. Consequently, this research aims to develop an automated tool to detect different defects such as cracks, deformation, settled deposits and joint displacement in sewer pipelines. The automated approach is dependent upon using image-processing techniques and several mathematical formulas to analyze output data from CCTV camera photos. It simply yields faster results in a more systematic approach than the conventional method.

Several image processing and segmentation techniques were used to develop the automated tools to detect the different types of defects. The automated tool was able to successfully detect cracks, displaced joints, ovality and settled deposits in pipelines using CCTV Camera inspection output footage. Using two CCTV Camera footage samples for old and new pipelines, the Matlab code could successfully differentiate between cracks and displaced joints with an overall crack detection success rate of 84% in the two samples and an overall displaced joint detection rate of 94%. The code was also able to efficiently detect settled deposits in the two samples with a detection rate varying between 86% for the first sample and perfect accuracy of 100% for the second sample. The automated ovality detection resulted in 100% compatibility with the manual circularity detection.

6.1 Recommendations and Future Extension Areas

To have an incorporated all-in-one automated tool, the Matlab code can be upgraded to consider other types of defects; such as pipeline collapses, penetration of tree roots and inner pipeline surface abrasion. Even though some of those defects might not be very common in Qatar, a maximal system is required to have a complete picture of the network and its defects.

Additionally, other inspection techniques can be incorporated with the CCTV camera inspection to cover a wider range of defects. For example, ground penetrating radar can be considered as well to inspect and detect any structural problem with the pipe bedding material which have costly implications if not inspected and maintained.

The issue that is clearly crucial for the practicality of this tool is its integration with the authorities' bigger systems. It is known that the Public Work Authorities (Ashghal) use a Graphical Information System (GIS) to keep an inventory of all their assets. The recommended integration of this tool with the GIS system can be on a detailed level; CCTV images can be captured and automatically referred to a certain location in the pipeline to allow for the defect detection by the automated tool to have a bigger picture on where defects are located and find locations with high concentration of defects. This will aid in better asset management and justified rehabilitation and maintenance prioritizing decisions on a project level and network level.

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