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Pipe corrosion recognition through image processing using fault detector robot

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Abstract: In industrial literature, damages that occurred due to various reasons on the material are called corrosion. Corrosion cause fatigue and failure of systems and other risks such as financial losses for replacing the system, leakage and pollution of contacted products. In accessible surfaces corrosion detection is done easily, but in cases such as tanks, pipes and particularly long tubes, there is no access to the inside of the pipes so more complex systems are needed. In this research, a new approach is proposed to detect corrosions in industrial pipes. The proposed method is based on image processing algorithms hence it is a kind of non-destructive inspection method. The proposed method offers a new innovative processing algorithm to identify corrosion and also provides a proper lighting method. For this purpose, first the correct lighting system is performed , then obtained images from inspection would be preprocessed for detection phase. Preprocessing step includes color format changing, denoising and smoothing operations. Then corrosions are identified by edge detection algorithms and amount of it, is estimated by morphological operations.

Key words: Corresion, Robotics, Detector, Pipelines.

Introduction

Pipeline performance monitoring, particularly focused on minimizing leakage, has been crucial since the pipeline's inception, especially when its primary function was to transport water. During the early days, monitoring was conducted visually from the pipeline's exterior since the pipes were not buried. Any leakage was easily discernible with the naked eye. As such, there was no need for specialized equipment to peer inside the pipes. This method of observation can be considered the genesis of visual pipe inspection, as referenced by Black (1992). Given the results and limitations of this basic approach, there was a clear need to transition to more precise monitoring techniques, paving the way for internal pipeline inspections. This progression led to the introduction of camera systems that could be inserted inside the pipes, giving engineers a direct view of the interior conditions.

In the nascent stages of these systems, primitive methods were adopted, such as utilizing ropes to guide cameras within the pipelines. These cameras could capture and store images, recording their entire journey. Alternatively, images could be transmitted in real time to a central location through a communication cable. While the direct transmission method had advantages like real-time observation, it also faced challenges. The weight and volume of the connecting cables, the limitations in recording length, and issues like cable breakage, reduced image quality, and energy-intensive operations were common drawbacks, as highlighted by Mashford, Rahilly et al. (2010). One upside was that defects could be spotted instantly, facilitating quicker decision-making. In scenarios where images were stored, engineers would assess the footage after each segment, with these segments determined by factors such as storage capacity, cable length, and, occasionally, the camera's energy consumption. It is worth noting that the images captured in these early systems lacked high resolution. Moreover, the staggered filming process, coupled with the need to frequently recharge cameras, replace film, and conduct manual reviews, resulted in considerable time, energy, and cost inefficiencies. Filming complications and human errors further compromised accuracy. These challenges ultimately compelled researchers to explore automated systems and data analysis for pipeline inspections.

As the use of extensive pipelines—spanning hundreds of kilometers—became more prevalent, and with these pipelines being buried underground for protection, the challenges of inspecting them for blockages, damages, corrosion, and leaks intensified. The buried nature of these pipes rendered visual inspection of potential soil material changes and water infiltration around them nearly impossible. Consequently, visual inspection, which was the primary and most trusted method of the time, shifted its focus to enhanced imaging and thorough

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analysis of captured images (Mashford, Rahilly et al. 2010). This spurred a demand for systems that could position cameras within these pipelines to yield better imaging results.

From the inception of pipeline systems, internal navigation served several purposes. For instance, identifying and rectifying blockages was a primary concern for engineers. Their goal was to address defects using tools that eliminated the need to excavate and reopen the pipeline, ensuring that blockages—whether due to prolonged use or the accumulation of salts and suspended particles—were efficiently cleared. To tackle such issues, it was paramount to accurately determine the location, nature, and root cause of the defect. By doing so, engineers could prevent recurring problems, address issues cost-effectively and efficiently, and select the right tools that would not harm the pipeline. To this end, engineers from the earliest days devised and trialed various equipment, including balls, wheeled miniature robots, and devices tailored for specific conditions.

When considering task automation, robots are often the first systems that come to mind. They have carved a significant niche for themselves across industries, including the pipeline sector. From the outset, a multitude of mechanisms were conceptualized to navigate diverse pipes, varying in size, design, and purpose. Over time, these ideas expanded and branched into various specialized solutions.

Take, for instance, wheeled miniature robots designed for pipelines; they have become prominent in the realm of non-destructive testing. Their ability to safely and efficiently access areas where manual inspection is either unfeasible or not cost-effective has solidified their importance (Dobie, Summan et al. 2013). Figure 1-1 showcases some of these robotic marvels.

Figure 1-1 simple miniature robots

For straightforward pipelines, basic robotic designs suffice. However, navigating pipelines with bends, elbows, or those oriented vertically demands robots equipped with specialized mechanisms. When dealing with pipes filled with fluids that are either hazardous or expensive to drain, robots capable of seamlessly navigating through these materials are essential. Consider inter-city gas or oil pipelines: they house explosive fluids, cannot be easily drained, rank high in leak incidents, and carry hefty maintenance expenses. The metallic composition of such pipelines makes them prone to severe corrosion, adding to operational costs. On the other hand, necessitating uniquely designed robots that can maintain optimal positioning while navigating. Encountering obstructions within these pipelines poses additional navigation challenges for robots. However, the pressing demand for robotic solutions in this area has spurred extensive research, leading to the creation of efficient mechanisms. Monitoring gas &oil pipelines, given the nature of the contained fluid, yields invaluable insights, making visual inspection in these contexts one of the most effective non-destructive evaluation methods.

Pipeline navigation systems must be chosen by weighing the pros and cons of each system against the specific working conditions of a given project. While the choice of the robot depends on the unique conditions of the task, different lighting techniques and processing algorithms can be employed to glean corrosion insights from the acquired data. In this section, we provide a cursory overview of the methods introduced to date. Chapter 5 will delve into a visual examination of these methods for a more detailed comparison and evaluation.

Introduced in the past decade, the DiRAT system (Kirkham, Kearney et al. 2000) is a notable pipeline inspection system. It is predicated on limited imaging (Mashford 1995) and is most effective when the resulting images display a significant disparity in pixel surface values. Otherwise, the system tends to grapple with data replete with complications and substantial errors. DiRAT amalgamates neural network algorithms with more traditional techniques. Such neural network algorithms have been widely applied to pipe inspections

ISSN NO: 2770-4491
Date of Publication:21-10-2023

(Moselhi and Shehab-Eldeen 2000; Sinha and Karray 2002) and have gained increased traction recently. Noteworthy contributions in this arena include works by Choi and Kim (2005), Mashford, Rahilly et al. (2010), Safizadeh and Azizzadeh (2012), and Dobie, Summan et al. (2013).

Safizadeh and Azizzadeh (2012) utilized a unique lighting approach in their research. They employed a centralized, circular lighting technique within the pipe, processing solely the reflections emanating from the pipe's surface. This approach effectively delineates cavities, but it lacks clear indicators for corrosion and its extent. Furthermore, the lighting used is imprecise, leading to noticeable disparities in light intensity across various parts of the image. Achieving uniform lighting within the pipe seems to be a recurring challenge for many systems. In Safizadeh and Azizzadeh's method, corrosion zones are demarcated by intense light reflections. To put it another way, the image's pixel brightness intensity serves as the tell-tale sign of corrosion. The underlying rationale for this technique is the pronounced reflection of light from cavities. It is important to highlight that in this approach, corrosion is solely identified by cavity presence, with no regard for sediment, deformations, or superficial corrosion.

The method outlined in (Dobie, Summan et al. 2013) utilizes cameras oriented perpendicular to the inspected surface, emphasizing vertical imaging. However, this technique is less effective for internal pipe inspections due to the subsequent increase in camera count, complexities in lighting, the substantial growth in data volume, and the prolonged analysis time.

In the study by (Mashford, Rahilly et al. 2010), the authors discuss image analysis employing morphological algorithms, SVM, and features drawn from both RGB and HSB color spaces. Here, images are sectioned into various regions, with a primary emphasis on segmenting the pipe and its junctures.

Choi and Kim's work (2005) delves into analyzing different corrosion forms by scrutinizing images of vertical surfaces. Their analytical approach centers around color, texture, and edge characteristics. Of the methods described in their paper, the HIS method stands out. While their findings prove highly effective for open surfaces, applying this imaging technique within pipes presents challenges

Corrosion manifests in several ways, and its classification can vary based on criteria. The methodology adopted in this research hinges on the physical appearance and structure of the corroded metal. Through mere observation, the corrosion type can often be discerned. While a cursory look typically suffices to categorize the corrosion, magnification tools, like magnifying glasses or low-power microscopes, can occasionally be invaluable. Often, the key to resolving corrosion issues lies in meticulously examining corroded samples or parts that have succumbed to corrosion. It is crucial to study these samples, ideally before cleaning, to gather insightful data.

Distinctly, eight corrosion types can be identified. While they share some common traits, each possesses unique characteristics. They include:

1. Uniform Attack
2. Galvanic or two metal corrosion,
3. Crevice corrosion,
4. Pitting
5. Intergranular corrosion,
6. Selective leaching,
7. Erosion corrosion
8. Stress corrosion

It is worth noting that while this classification is comprehensive, it may not be exhaustive. Nonetheless, it provides a solid foundation that encapsulates the majority of corrosion-related concerns and damages. The sequence listed above does not imply any hierarchy in terms of significance.

Corrosion not only results in material loss but also incurs the costs linked to its production. This underscores the significance of material protection and its optimal utilization. Thus, it becomes imperative to ascertain the reasons behind metal deterioration and to establish conditions that prevent such degradation.

Modern industrialists, including those in the oil and gas pipeline sectors, have come to recognize the financial merits of preventive actions. Early detection of flaws in pipelines, combined with proactive interventions, can yield substantial economic benefits. The ideal maintenance and repair system would entirely eliminate unplanned halts due to unforeseen malfunctions. The key to this lies in leveraging cutting-edge, non-destructive testing and evaluation technologies. Among these, imaging systems stand out as exemplary non-

ISSN NO: 2770-4491
Date of Publication:21-10-2023

destructive inspection tools. They do not necessitate the introduction of any substances into the system, present no environmental hazards, and are largely automated. However, they also permit human intervention for final analysis and validation. With their outputs being lucid and illustrative, their user-friendliness is apparent, explaining their rising popularity in recent times.

Materials And Methods

Proposed Algorithms and Systems for Pipeline Fault Detection

From the existing literature, it is evident that closed-circuit cameras are predominantly employed for both operator-driven and automated optical control systems. These imaging and data analysis techniques face several challenges, with optimal image capture and appropriate lighting at the forefront. In this section, we introduce a proposed system that aims to improve image accuracy, quality, and lighting within the pipeline.

Pipeline Simulator System

For this design, drawing parallels with the approach in (Safizadeh and Azizzadeh 2012), a six-inch metal pipe with a 6-millimeter wall thickness, a standard in many industries, was utilized. This pipe was drilled to mimic pipeline leaks. By creating holes of varying diameters, the system's precision and detection capabilities are put to the test. Tools and bits with diameters spanning 2, 3, 4, and 5 millimeters were employed for the drilling. Besides inspecting leaks through the automated visual monitoring system, this research introduces a fresh dimension in visual monitoring: the examination of pipe sediments. To simulate these sediments, soil was introduced within the pipe. While this scenario has been explored manually (via human operators) in the past, it has not been addressed within automated systems. The subsequent figures offer diverse perspectives of the test pipe, the simulated leak holes, and the sediments:

Figure 1-2. Vertical view of the test pipe.

Figure 1-3. Close-up vertical perspective showcasing the pipe and its perforations.

ISSN NO: 2770-4491
Date of Publication:21-10-2023

Figure 1-4. Cross-sectional depiction of the pipe, highlighting the internal sediments.

For data processing, the system employs a standard-grade computer, underscoring that there is no need for high-end processors or extensive memory; even a rudimentary system suffices. MATLAB software has been designated for handling data processing tasks.

Experiments were conducted under conditions simulating an underground environment in absolute darkness. This ensures that results align more closely with real-world scenarios and remain unaffected by external light sources.

To facilitate the camera's internal navigation within the pipe, a specialized tall stand was employed. This not only enabled easy camera maneuvering but also ensured its stability and central alignment, emulating robot-assisted navigation. The camera consistently moved at a set speed within the pipe, capturing data at a filming rate of 20 frames per second. Additionally, the snapshot speed was set at 1/500 seconds (duration required for one complete capture), guaranteeing that the camera's transit speed remained inconsequential to the final output.

 ISSN NO: 2770-4491
Date of Publication:21-10-2023

Figure 1-5. Hardware of the Proposed System

To simulate the natural conditions of a longer pipeline using our test pipe of limited length, we tackled internal reflections by placing a reflective wooden board 2 meters from the pipe's end. This board was angled at 60 degrees relative to the pipe's cross-sectional line, ensuring that reflections would not interfere with the primary experiment.

Historically, analog systems dominated the realm of internal pipeline filming. These systems boasted advantages like soft imagery and adaptability to varied lighting conditions. However, as data was transmitted—whether through wired or wireless means—particularly over extended distances, a discernible drop in image quality was observed. Furthermore, any subsequent image processing required the data to be digitized, necessitating analog-to-digital converters, which further compromised the image quality. Given the strides made in digital camera technology and its capability to process light while maintaining image integrity, our attention naturally gravitated toward these cameras. In our modernized system, digital data ensures zero image degradation during transmission, be it wired or wireless. The ease of transfer, storage, and elimination of the need for analog-to-digital converters adds to its appeal.

For the imaging component, we opted for a camera akin to those referenced in earlier studies—a fixed lens with an all-encompassing focus. Emphasis was placed solely on the camera's imaging and lighting capabilities. Given its alignment parallel to the pipe's axis, it was crucial for the camera lens to have a wide field of view, capturing images over an extensive-angle. To this end, we recommend a 2.8-millimeter lens equipped with a 1/3-inch light sensor, boasting a broad view of approximately 105 degrees—a considerable improvement over analog counterparts. A 3-megapixel camera (resolution of 2048*1536 pixels at 50Hz), possessing a light sensitivity spectrum from zero to 0.07 lux in infrared mode and fortified by both 3D and 2D digital noise reduction systems, emerges as the optimal choice for contemporary digital cameras tailored for pipeline settings. Contemporary setups facilitate image compression via the H.264 format, transferring imagery through networked systems using either Category 6 cabling or wireless network data transmission technologies. These setups also champion power delivery via the same interface cable, harnessing the POE (power over Ethernet) standard. This standard accounts for cable length, optimizing energy use, and subsequently minimizing power expenditure. Being innately digital, this data can be seamlessly integrated into digital systems and computers, as it is compatible with most digital system ports. Given these stipulated attributes for our envisioned system, the DS-2CD2432F-I camera model by HIKVISION, manufactured in China, emerges as a prime candidate. Detailed technical specifications can be found in Appendix 1, with a visual representation of the camera presented in figure 1-6.

Figure 1-6. The First Proposed Camera with Point-Source Lighting

As illustrated in the above image, this camera benefits from a focused infrared light source. Such a lighting method has been identified in previous studies as the primary approach. What distinguishes this camera is its incorporation of a cutting-edge technology termed uniform infrared lighting—a patented innovation by the camera's manufacturer. This system deploys a specialized lens to distribute infrared throughout the environment, ensuring consistent lighting. The decision to opt for this specific manufacturer's camera was primarily driven by this groundbreaking technology. Past research indicated that inconsistent lighting posed significant challenges in image acquisition and subsequent data analysis.

A novel lighting solution for closed-circuit systems is introduced. Contrary to the previous design that harnessed a single focused light source complemented by a lens, this new approach integrates multiple focused light sources positioned around the camera. The motivation behind our second proposition is to scrutinize the effects of expansive lighting on the internal pipe environment and contrast it against focused lighting—a facet not delved into in prior research.

For our second imaging proposition, we have incorporated features from the initial proposal but added a lens with adaptable zoom and focus capabilities. This ensures optimal focus on the pipe's inner surface, resulting in sharper imagery. In line with these specifications, the DS-2CD2632F-I camera model by Hikvision, originating from China, is recommended. Its visual representation presented in figure 1-7.

Figure 1-7. The Second Proposed System with Broad Lighting

Proposed Image Processing Method

In this segment, we delineate our proposed image processing algorithm. This method operates autonomously, eliminating the need for human supervision or interference. While users can access the captured images, there is no mandate for manual parameter tweaks or human intervention in the corrosion detection process. The computations are executed using MATLAB software, leveraging functions primarily from the robust Image Processing Toolbox. For clarity, specific codes relevant to each segment are cited. However, to ensure the narrative flows seamlessly, we have refrained from delving into the detailed code functions.

Images captured by infrared cameras inherently have a grayscale appearance. However, due to design considerations by manufacturers, they often save these images in RGB format. The initial step in our preprocessing algorithm involves converting the image type from RGB to grayscale. This conversion does not modify the image's visual properties; it merely trims down computational demands and data storage requirements. As an example, the left portion of Figure 1-8 displays an RGB image represented by a data size of $m \times n \times 3$. In this representation, m and n designate the number of rows and columns in the image, respectively. The third dimension in the RGB image accounts for the red, green, and blue color intensities, which together determine the hue of each pixel. The right-hand side of Figure 1-8 showcases the grayscale counterpart of the left image. Noticeably, the image details remain intact; only the data volume has been downsized to a $m \times n$ matrix. In this grayscale rendition, each pixel's value ranges between 0 (black) and 255 (white), hence the term "grayscale" image.

ISSN NO: 2770-4491
Date of Publication:21-10-2023

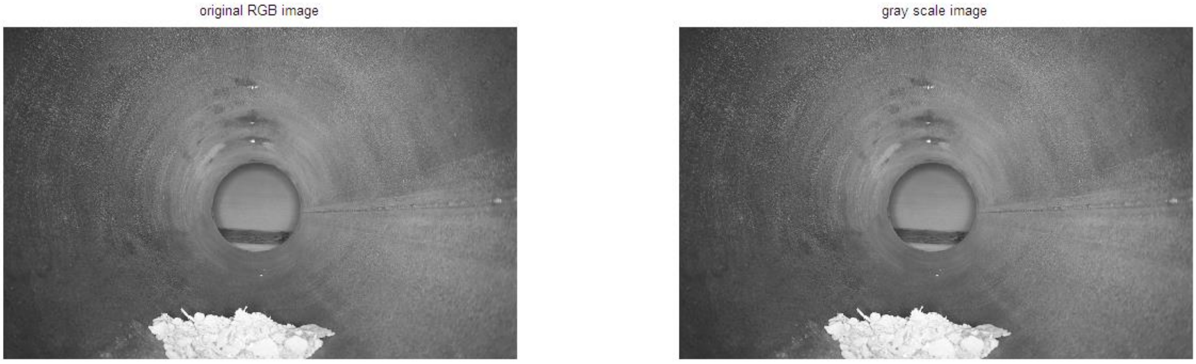

Figure 1-8. Left: Initial RGB image; Right: Equivalent grayscale image.

Post the grayscale conversion, established image processing algorithms are harnessed to eradicate noise and refine the image. The rationale for this enhancement step stems from the inherent imperfect and uneven surfaces of many pipes. During detailed inspections, a pipe's coarse texture could be erroneously flagged as corrosion. Image refinement effectively circumvents this. Additionally, any incidental noise—like that arising from camera vibrations during its movement within the pipe—is also nullified. A plethora of algorithms cater to image refinement, encompassing mean filters of varied kernels, median filters, and Gaussian filters. In this research, we have deployed a mean filter equipped with a circular kernel. Despite its straightforwardness and computational efficiency, this filter yields commendable outcomes, precluding the inadvertent extraction of extraneous boundaries in subsequent algorithm stages.

Figure 1-9 presents a side-by-side comparison of a non-smoothed image and its consequent edge extraction. Notably, without image refinement, the pipe's innate lines and textures are also perceived as edges, blurring the line between them and true corrosion-induced boundaries. Conversely, Figure 1-10 illustrates the edge extraction from a refined image. Here, only the boundaries corresponding to actual corrosion are discernible, clearly emphasizing the efficacy of the smoothing process.

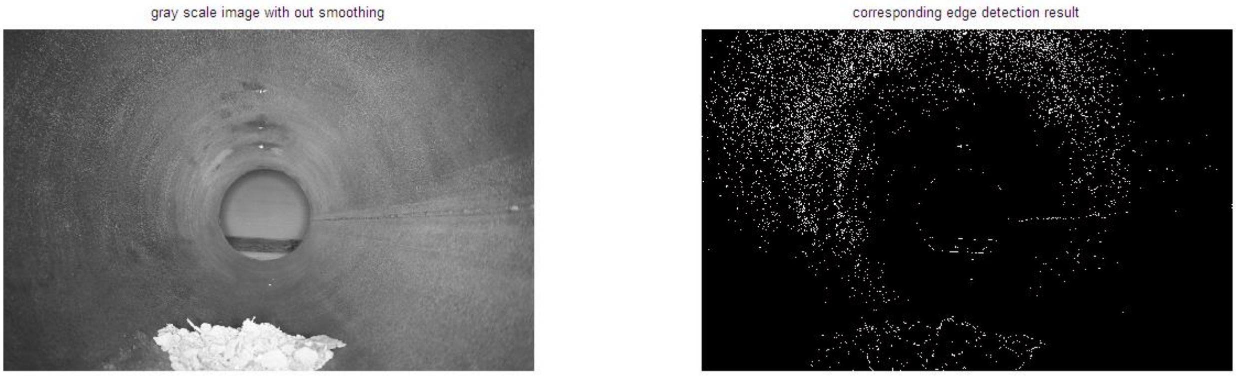

Figure 1-9. Non-smoothed image juxtaposed with its resultant edge extraction.

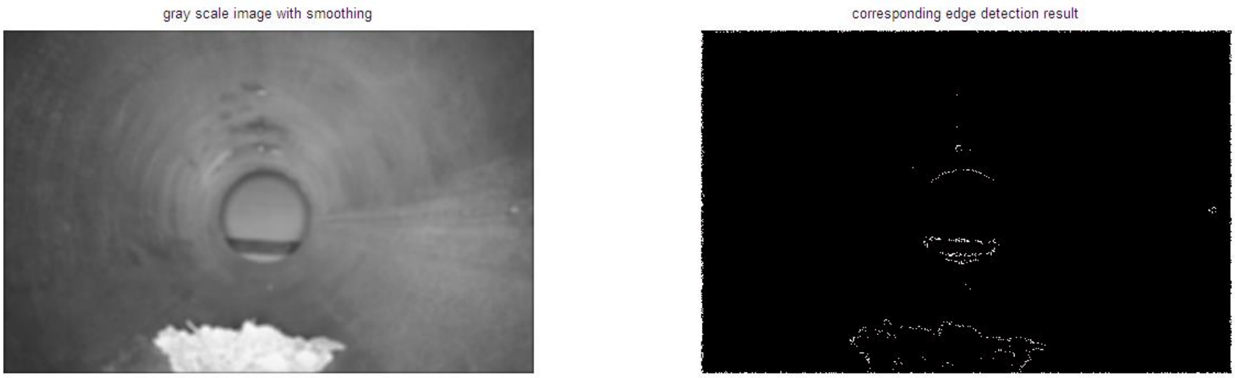

Figure 1-10. The refined image paired with its resultant edge extraction.

After the image has been smoothed, the next step involves the identification of the edges present in the image. Edges typically denote shifts in light intensity across various sections. Leveraging the principle that foreign

ISSN NO: 2770-4491
Date of Publication:21-10-2023

objects or cavities within the pipe often lead to the introduction of novel edges in the image, we can pinpoint areas affected by corrosion. Multiple widely used edge detection algorithms, such as Sobel, Prewitt, Roberts, and Canny, were assessed for their effectiveness in this context. The outcomes of these edge detection algorithms can be observed in Figure 1-11. While the differences between these algorithms might seem minimal at first glance, the Prewitt algorithm was selected based on its superior capacity for detail recognition during image analysis.

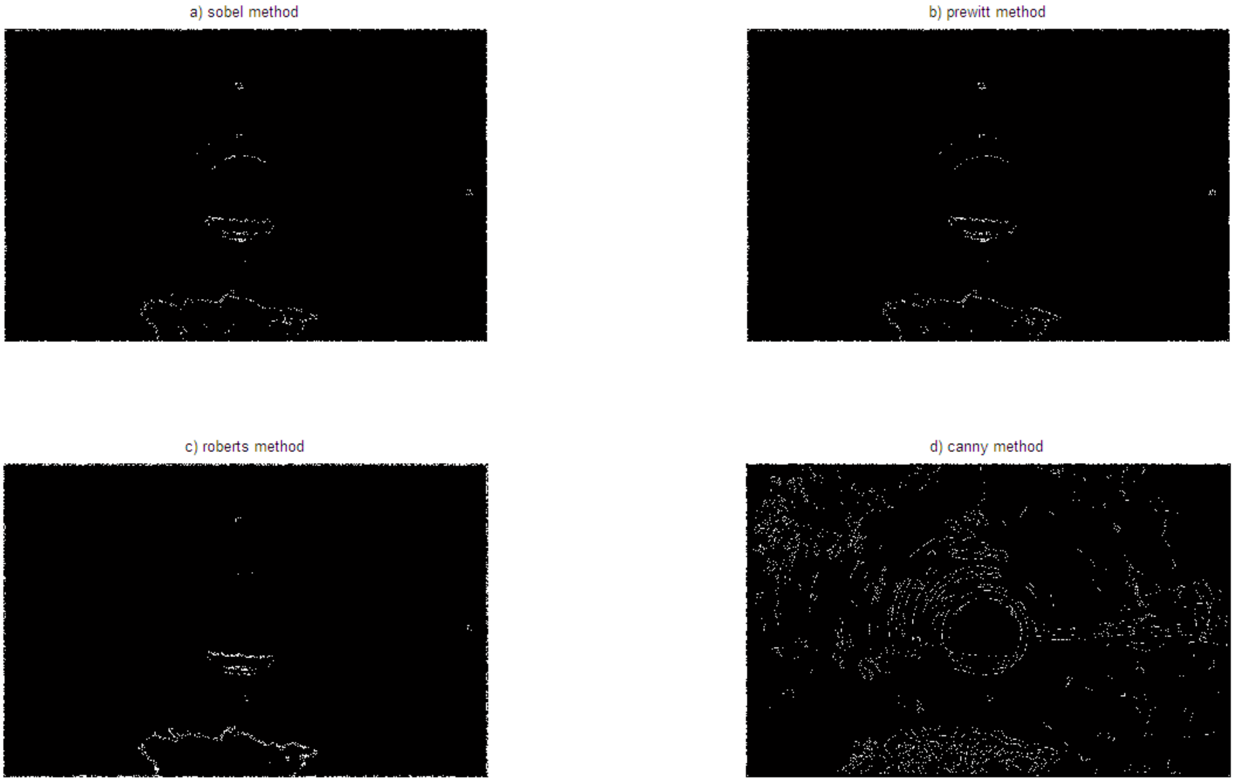

Figure 1-11. Results from Four Distinct Edge-Detection Algorithms.

It is noteworthy that the images under discussion provide a comprehensive view of the pipe's cross-sectional surface. Given varying distances from the camera and light source, these images exhibit disparities in light intensity and viewing angles. Evaluating these areas uniformly would not yield accurate results. Thus, specific annular zones closer to the camera are demarcated, and only the edges present within these zones are scrutinized.

A pertinent question arises: Why weren't these areas delineated from the onset? The rationale is straightforward. If the non-relevant zones were excluded at the algorithm's outset, the resulting image would display an unnatural boundary stemming from the exclusion process. Consequently, even in corrosion-free areas, pronounced edges resulting from this exclusion would be erroneously identified. To avoid such complications, the proposed algorithm first identifies all the edges, and subsequently, the irrelevant edges are disregarded. Figure 1-12 illustrates this valid region on the original image. As evident, the loop closest to the camera exhibits uniform radiant light. The green circle demarcates the inner boundary, while the blue circle highlights the outer boundary of this region.

ISSN NO: 2770-4491
Date of Publication:21-10-2023

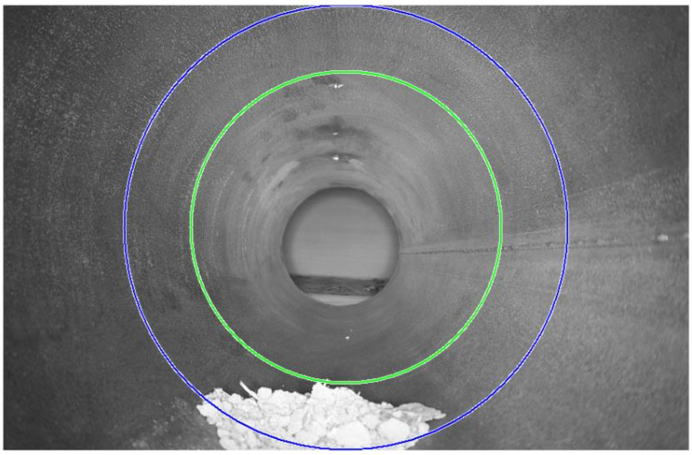

Figure 1-12. The delineated valid zone targeted for corrosion detection.

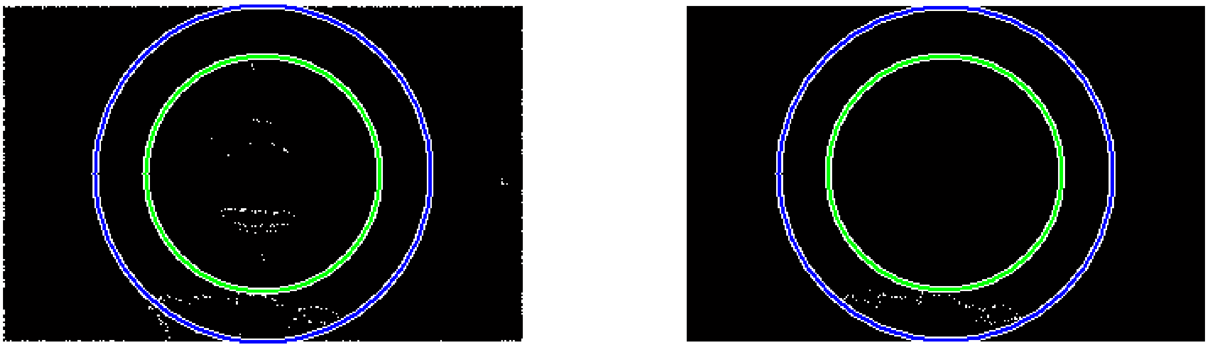

Figure 1-13. Process of Edge Extraction and Exclusion of Edges Pertaining to Invalid Zones.

While edge extraction might be sufficient to identify the presence of corrosion in the evaluated image, for a more comprehensive understanding of the severity or spread of the corrosion, the incorporation of morphological filters is advised. Initially, edges proximate to one another, which correspond to a corrosion site, are linked through a thickening operation. Subsequently, the interiors of regions encased by these closed boundaries are populated.

Figure 1-14. Left: Extracted Edges from the Valid Region. Right: The Process of Thickening and Filling.

To gauge the magnitude of corrosion across different images, we introduce a metric termed the 'corrosion observation ratio.' This ratio represents the proportion of the identified corrosion area to the entire valid region under assessment, given by:

$$corrosion.visiblity = \frac{corrosion.area}{total.valid.search.area} = \frac{S_{corrosion}}{S_{search.area}} \qquad \text{Equation (1-1)}$$

This parameter's value spans between zero and one. A value approaching zero indicates minimal observable corrosion. It is crucial to understand that this metric solely offers a rough estimate of the perceivable corrosion and does not directly reflect the severity of the corrosion. For instance, cavities induced by corrosion are typically quite severe, and the damages stemming from these cavities can be substantial. Nevertheless, if the cavity's size is minimal, its visibility in the image might be limited. Nonetheless, any non-zero value for this metric signifies the presence of corrosion in the evaluated area.

Results

In alignment with the protocols, the 2432 camera was employed for the initial testing phase, producing results exemplified in figure 1-15.

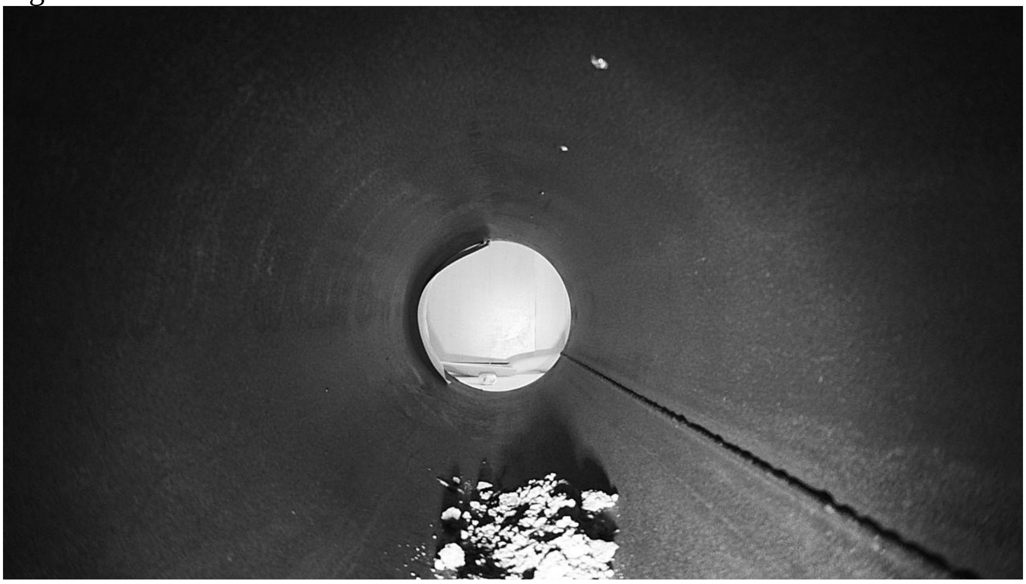

Figure 1-15. Sample Snapshot from the 2432 Camera.

As discernible in the image above, with this mode of imaging, leakages are starkly evident, and holes are pinpointed with precision. Analyzing such data becomes relatively straightforward. However, for irregular scenarios, such as sediment accumulations, distortions in the pipe's structure, or indentations, shadows become prominent in the image. This outcome is inherently associated with this form of point-source illumination, as it invariably casts well-defined shadow outlines. In this snapshot, shadows created by the sediments and the welding on the pipe are conspicuous, thereby tainting the data. Such issues can inadvertently induce inaccuracies, both in automated analyses and human interpretations. If leakage occurs within a sediment's shadow or an alteration in the pipe's structure (regions typically susceptible to corrosion or leakages), it evades detection, both by automated systems and human inspectors.

Within this test phase, users could effortlessly pinpoint defective sites, be they leakages, corrosion, alterations in the pipe's structure, or sedimentary deposits. Additionally, any curvatures or bends become distinguishable due to the noticeable variations in reflected light intensities, which provide cues about the type, condition, and extent of defects.

From the amassed data, it is evident that the proposed camera type excels in aspects like image quality, sensitivity to light, and viewing angle breadth. However, it does confront challenges under specific circumstances, which are elaborated upon in the subsequent sections.

1. Lighting Issue:

The point lighting, considering the pipe's small diameter combined with the minor height difference between the center of the lighting and the sediment, results in a prolonged shadow. Owing to the inherent characteristics of a point light, this shadow is all-encompassing, consequently obstructing a segment of the pipe's view from our observation.

Solution: To counteract this, we advocate for the incorporation of broad-spectrum lighting in these systems for the first time, as it manifests a shadow that's notably shorter and more luminous. This modification has been integrated into our second proposal.

2. Camera Focal Length Concern:

ISSN NO: 2770-4491
Date of Publication:21-10-2023

As depicted in the figure, owing to the camera's proximity to the pipe, the image edges are not crisp, leading to a pronounced blurriness. Although this effect attenuates at greater distances from the camera, closer shots are undeniably superior for extracting finer details. Moreover, shadows also reduce in size at closer proximities.
Solution: To overcome this, in our second proposal, we have chosen to employ vector imaging lenses with adjustable focal points to attain heightened clarity over a broader targeting range.
3. Off-center Light Source Dilemma:
Given the necessity for the camera to remain centralized within the pipe for an automated detection system, positioning the light source at the pipe's center was not feasible. This positioning discrepancy induced a variance in light intensity across the pipe's two sides. This anomaly was evident across all prior studies yet remained unaddressed.
Solution: To rectify this, in tandem with our primary solution, where we identified broad-spectrum light as the solution, our strategy is to situate the camera at the light source's epicenter, thereby ensuring consistent illumination throughout the pipe. Nevertheless, to obviate the possibility of direct light reflections impinging on the camera lens, the broad-spectrum light source should be strategically positioned slightly rearward of the camera.
With the aforementioned suggestions geared towards rectifying the imaging challenges, our subsequent steps will focus on detailing and implementing our refined second proposal.

1-2. Results of the Second Proposed System

Upon analyzing the attributes of the second camera, the second proposal clearly emerged as a superior solution for attaining optimal image quality. The images produced by this camera provide compelling evidence of its efficacy.

Figure 1-16 showcases a snapshot taken by the second camera.

The improvements in this new image are undeniable. The absence of shadows, coupled with the uniform lighting throughout the pipe, signifies a marked enhancement in imaging capability. The heightened clarity, such that even the subtle texture of the pipe is evident, solidifies the imaging prowess of this design. The camera's capacity to identify nuances as minute as 0.1 millimeters establishes it as a paragon in the realm of intrapipeline imaging. This precision aids users in flawlessly pinpointing any aberrations, a level of detail that even manual inspections often miss.

1-3. Comparison and Conclusion Between the Two Proposed Data Collection Systems

Figure 1-16 offers a comparative visualization, juxtaposing images from both the first and second proposed systems against their processed outcomes. This segment emphasizes discerning the comparative advantages and challenges of each system based on the visual results.

From the visual comparison, it becomes evident that point lighting accentuates inherent edges while simultaneously introducing unwanted shadows, primarily due to the weld line of the pipe. The heightened prominence of innate edges, though enhancing the image's detail in some scenarios, also introduces visual noise. This type of lighting might excel in environments where pipes exhibit a smooth facade. However, given the weld line on the pipe used for this research, its applicability proved less than ideal.
Conversely, the second proposed system, with its broad lighting, emerged as a more effective and holistic solution. It was aptly equipped to navigate the challenges posed by the pipe's structure and yielded superior imaging results, thereby making it the chosen system for subsequent applications.

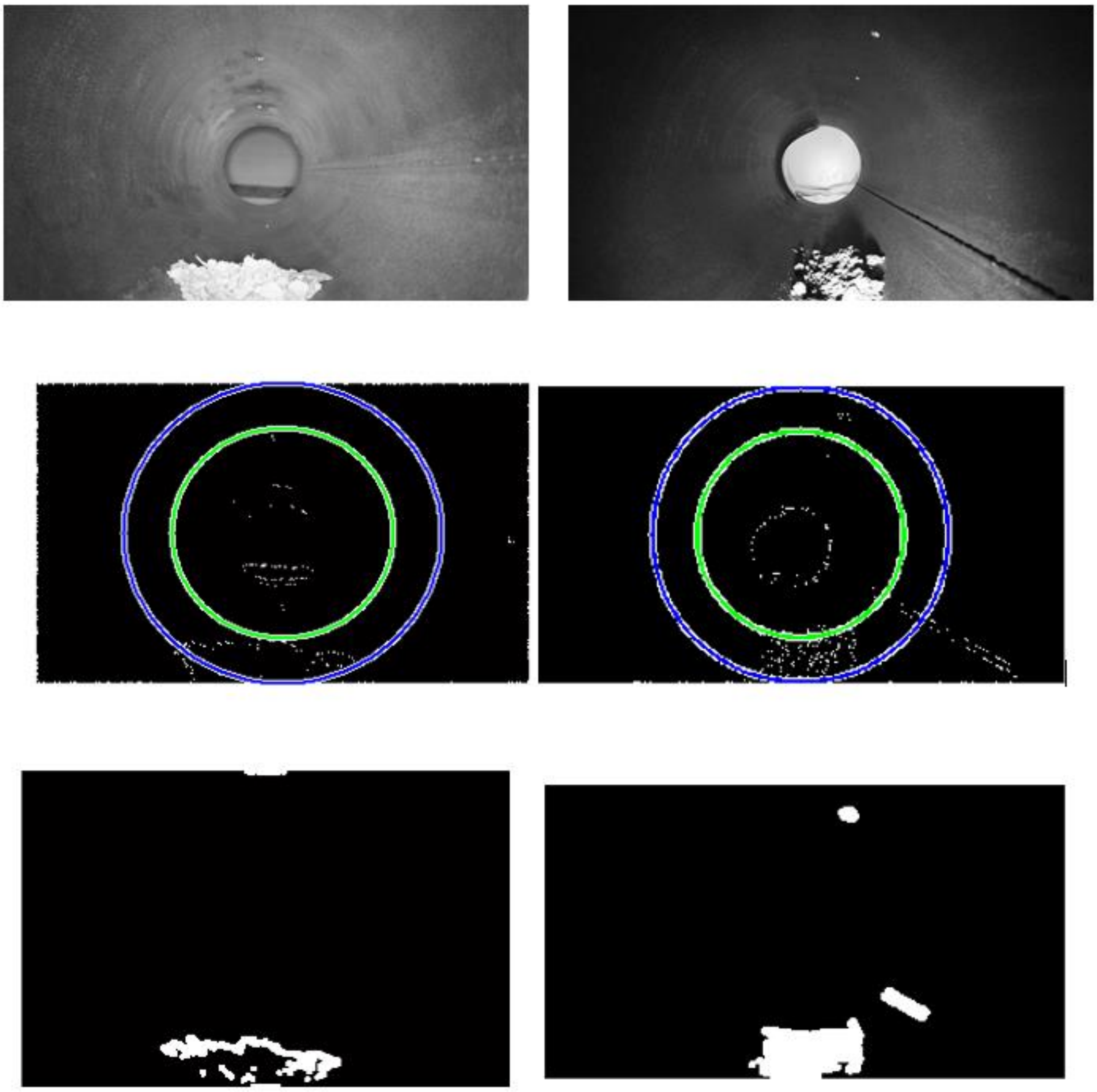

Figure 1-17. Right column: Point-lighting and its processing result; Left column: Broad-lighting and its processing result.

Conclusion
The use of image processing for corrosion detection offers several advantages. Firstly, image processing can detect minor corrosions that may not be easily visible to the human eye. Early detection can save industries millions of dollars by preventing catastrophic failures, extending the life of equipment, and reducing maintenance costs. Moreover, the proposed algorithm's ability to provide accurate and quantifiable data on the extent and location of corrosion is invaluable for decision-making processes regarding repair or replacement strategies.
The lighting method introduced in this paper sets it apart from previous research in this domain. Proper lighting ensures high-quality images, which are pivotal for accurate corrosion detection. Shadows and uneven light

ISSN NO: 2770-4491
Date of Publication:21-10-2023

distribution, prevalent in conventional methods, often hinder accurate analysis. By addressing these challenges, the proposed method guarantees images that are well-suited for processing and analysis.

Furthermore, by employing non-destructive testing methods, this research ensures that the integrity and function of the pipes remain uncompromised during inspections. This aspect is of paramount importance, especially in critical sectors such as oil and gas, where any breach could lead to significant economic and environmental implications.

However, while the proposed method promises superior results, it is not devoid of limitations. The proposed lighting system, although more efficient than traditional methods, might not be universally applicable to all types of pipes. In environments where pipes have an inherent texture or weld lines, the algorithm might produce false positives. Thus, further refinement and tailoring based on specific industrial applications could enhance its efficiency and accuracy.

In conclusion, as industries worldwide grapple with the challenges of corrosion, research such as this, which leverages advancements in image processing and lighting technology, can be a beacon of hope. By ensuring timely and accurate corrosion detection, industries can adopt proactive maintenance strategies, thus safeguarding their assets and guaranteeing the safety and efficiency of their operations. The future beckons for further research in this area, fine-tuning the algorithms and possibly integrating artificial intelligence and machine learning techniques for even more accurate and timely corrosion detection.

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