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Research Article

Restoring and Enhancing Degraded Underwater Images for Identifying and Detecting Corrosion

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Abstract

The visibility of scene was compensated by the object-camera distance to recover the colors of the background and objects. Subsequently, by analyzing the physical property of the point spread function, we developed a simple but efficient low-pass filter to debut degraded underwater images. A wide variety of underwater images with different scenarios were used for the experiments. A new method for subsea pipeline corrosion estimation by using color information of corroded pipe. As precursor steps, an image restoration and enhancement algorithm are developed for degraded underwater images. The developed algorithm minimizes blurring effects and enhances color and contrast of the images. The enhanced colors in the imaging data help in corrosion estimation process. The image restoration and enhancement algorithm are tested on both experimentally collected as well as publicly available hazy underwater images. A reasonable accuracy is achieved in corrosion estimation that helped to distinguish between corroded and non-corroded surface areas of corroded pipes. The qualitative and quantitative analyses show promising results that encourage to integrate the proposed method into a robotic system that can be used for realtime underwater pipeline corrosion inspection activity. Underwater image degradation, surveys the state-of-the-art intelligence algorithms like deep learning methods in underwater image harm and restoration, demonstrates the performance of underwater image harm and color restoration with different methods, introduces an underwater image color evaluation metric, and provides an overview of the major underwater image applications

Keyword: *Corrosion detection, Image process, Deep Learning, DCNN*

1. Introduction

Therefore, we need detection and testing techniques based on deep learning methods that alert us to the first access to water in surface images and insulation. Deep learning to prepare rust estimates and develop perspectives. Create different corrosion picture parameters of the pipeline under different tests and estimates which utility doesn't count. Execution of trains as well as testing with different fold assumptions. Exterior sunshine is caused by internal pipeline oxidation, resulting in general corrosion Due to thin internal walls (homogeneous rust), pitting (local rust), and fracture rust and microbiological rust. The most common problem is insulation repair (ICC). In the oil and gas industry. In the proposed research work, using deep learning algorithm, design and implement a system for detecting and predicting corrosion on the data set of the underwater pipeline image. The system uses different deep learning algorithms to classify algorithms as well as to predict the possibility of detecting corrosion.

2 Literature Survey

There are several methods used today to test the CUI. Not a single method is used by itself. Many methods complement each other for the best results. The most common and straightforward One way to check for corrosion under insulation is to break the plug in the insulation Must be removed to allow ultrasonic testing. Other commonly used methods are radiography, and complete separation. More advanced methods include Pulse Eddy Current. Here are some of the most common methods of examining CUIs.

Existing Methodologies

Red-dark channels were previously defined and removed for background light and estimation the outbreak of this disease. Visualization compensation for object-camera distance retrieval Background and color of objects by analyzing the physical properties of We developed a simple but efficient low-pass filter to debug the point spread function, Debiler Underwater imagery. Different types of water surface images were used under different conditions For experiments. The experimental results indicate that the proposed

algorithm effectively Underwater images were recovered while absorbing and dispersing effects. [1]
The reason for damaging the surface image of the water is to survey sophisticated intelligence algorithms. As a sophisticated method of deicing and refining underwater images, Underwater image decorating performance and color restoration in various ways, The underwater image identifies color evaluation metrics and provides an overview of the key Underwater image applications. Underwater environment, which contains numerous organisms Resources and energy are the main factors needed to sustain sustainability Human development. People often use videos or images to get valuable information when studying the underwater environment. Underwater imagery is the enhancement of contrast widely used techniques for color correction. Contrast is an enhancement of contrast has attracted a lot of attention in recent years. [2]

Deals for using Side Scan Sonar (SSS) for underwater testing Objects (cables and pipelines). It is suggested to use an autonomous body of water Purpose. The problem is in processing acoustic images to find communication lines fixed c-bottom and underwater robot control function. The actual cable search results and Pipeline tracking modeling experiments are discussed. A mind or tethered device The case is limited due to their radius of work area and the need for supporting characters (it grows) Cost of inspection work). Effect of processing actual SSS-images (meanwhile obtained via AUV) Cable detection) and pipeline-tracking modeling experiments allow us to conclude that this Methods can be used in acoustic vision movement control systems of underwater robots for investigation Underwater communication [3]

Events in visual and hydro acoustic tracking are discussed, such as theoretical and Practical Concerns This review also describes the methods and tools for finding communication At the end of the Kinoff, it is necessary to create a simple reliable system Subia cables must be in place to estimate the position of the subta transmission line and the depth of burial Regular maintenance and movement are monitored, regardless of their location and burial room. This task is difficult due to the dynamic environment on the ocean floor, which can be caused Access to position, depth, visibility and utilities. With technological advancement, The task of visual inspection can now be performed by operator-controlled ROV Before processing the surface they give instructions on processing the image The cable must have localization and direction [4].

Introduced two vision-based erosion detection algorithms developed in MINOAS European Project Reference. Both are based on the idea of combining algorithms Weak classifier to achieve good global performance. After evaluating their performance, the Obtaining a percentage of the wrong category is not zero for both algorithms. These results Misclassification can be explained by analyzing what kind and area they look. On the one hand, the FN percentage is not zero as detectors mark the rust the center of the unsafe area; the boundaries are usually not completely labeled. On the other hand, the FP percentage is not even zero due to the presence of different compositions Images are categorized according to faults [5].

Describes the process of automated analysis of the inside surface of a pipeline by Digital Image Processing (DIP). The entire platform includes inspection mobile robots there is a linelaser and CCTV camera to detect defects in the internal pipeline structure it is not readily available to human observers. A simple algorithm is enabled Detecting cracks in the inner surface of pipes with approximately 80 percent accuracy the end result shows the main purpose of the vision system and the use of the DIP technique. Pipe Investigation is not a new topic in the field of education, industry. There are many different methods the proposed but remote environment for direct human observation is still one to investigate Favorite topic [6].

A novel systematic approach to enhance underwater imagery by damaging algorithms Consequences of attention, inconsistency, and transmission the possible presence of an artificial light source in consideration. Once a room map that is Distance between objects and camera, foreground and background is approximate a scene is divided. The light intensity of the foreground and background are compared to determine whether an artificial light source is working during the image capture process. Later Side effects of artificial light, opacity and brightness the camera needs to focus on the underwater transmission path. Next, the water the depth of appearance in the image is determined by the residual energy ratio of the different colors existing channel in background light. Based on the relative capacity scale for each light wavelength, color change compensation is taken to restore the color balance. Performance of the proposed algorithm for wavelength compensation and image debasing (WCID) is objectively and subjectively evaluated using geo-truth color patches and the video was downloaded from the YouTube website [7].

In the criterion, the corrosion rate can be calculated using any industrially accepted internal corrosion prediction model (ICPM), such as the Norsok model [8]. However, the results of the respective ICPMs may deviate from the realistic corrosion rates when the internal environmental parameters of the inspection segments are not within the scope of the prediction model. Then, the selected excavation points based on the ICPM's results may not provide an effective means for identifying areas that are "above average" in terms of weight loss.

The internal corrosion rate of wet gas gathering pipelines is influenced by the fluid composition, temperature, pressure, flow velocity and many other factors [9]. It is difficult to develop a theoretical model that is capable of describing the relationship between all of these factors and the associated corrosion rates. However, a variety of methods can be used to predict future data based on the historical data of the system; these methods include the statistical prediction method, artificial neural networks (ANNs) and fuzzy logic methods [10].

3 proposed system details

3.1 problem statement

In the proposed research work, using deep learning algorithm, design and implement a system for detecting and predicting corrosion on the data set of the underwater pipeline image. The system uses different deep learning algorithms to classify algorithms as well as to predict the possibility of detecting corrosion.

3.2 Objective

- Creating and developing approaches for corrosion prediction models for oil and gas pipelines using underwater imagery and deep learning approaches.
- Design and build rust detection systems using water-influencing pipeline images.
- Developing an algorithm to detect harmful patches from input images using the DCN N algorithm deep learning foundation.
- Defining the image restoration technique using the CNN approach.
- Exploring and validating the proposed efficacy of the program with certain existing sy stems.

3.3 System Architecture

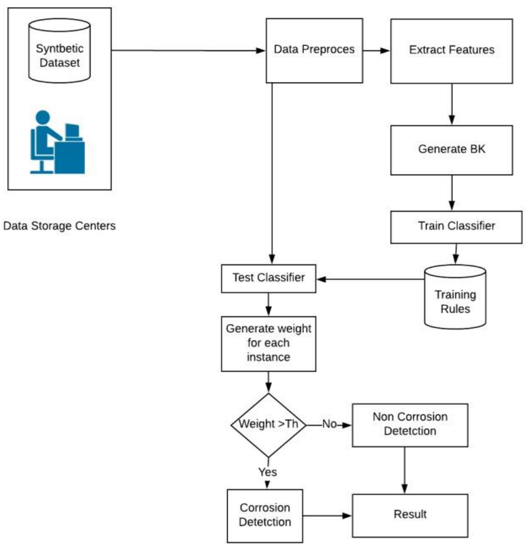

Figure 1: Proposed system architecture

The BK is nothing but a background knowledge that is generated based on extracted values from sensing systems. According to the proposed algorithm, each event gives reward or penalty respectively, based on that each event changes weight state, and based on that system generates BK rules during the execution.

3.4 Algorithm Design

Input: Test Dataset which contains various test instances Test_DBLits [], Train dataset which is built by training phase
Train_DBLits[] , Threshold Th.

Step 1: For each read each test instances using below equation TestFeature (m) **Step 2**: Extract each feature as a hot vector or input neuron from test-Feature(m) using below equation.

Extracted_Feature [t……..n]
Extracted-Feature-Set x[t] contains the feature vector of respective domain
Step3: For each read each train instances using below equation
Train_Feature (m)
Step 4: Extract each feature as a hot vector or input neuron from test-Feature(m) using below equation.
Extracted_Feature [t……..n]
Extracted-Feature-Set x[t] contains the feature vector of respective domain.
Step 5: Now map each test feature set to all respective training feature set
Weight
Step 6: return instance [label [weight]

Output: HashMap <class label, Similarity_Weight> all instances which weight violates the threshold score.

3.5 Mathematical Model

Let, S be a system that creates rust in the pipeline underwater image data-set collection, Such that,
S = {S1, S2, S3} Where,
S1 represents data set generates.
S2 represents corrosion detection.
S3 counter measures.
The result with corrosion detection.
Define pattern form incoming data
Let S1 be an array list having pipeline underwater image data-set details
S1= {Packet 1, Packet 2…Packet-n} Where,
Choose the packet subset
R= {Rule1, Rule2, Rule3... Rule-n}
R=is the set of rules which is store in database for check the distance Threshold=0.5;
So, (Train-DB [Test-Db [Packet (i) Accuracy]])

Coloration as well dependent set in system
(Packet (i) Test-Db class)
NP Analysis Problem

For the proposed system, we define p as x time for execution of proposed system with all operations.
The system has executed under the x time, that why the proposed system is NP Complete system.

Results and Discussions

For experiment analysis of proposed system evaluate entire execution in two different open source platforms. First system create network simulator environment to generate sensor nodes, the entire simulation log has used as IoT communication log which is generated by various analogue sensors. The techniques basically define in base approach which is carried out to calculate the various parameter between two sensors called trustor and trustee weight. For each transaction system automatically calculate some values which is denoted in matrix X. K-means clustering unsupervised learning approach has used to generate the data labels and DCNN has used as a supervised learning algorithm.

Table 1 : Performance evaluation with DCNN and SVM

	SVM	**DCNN**
Accuracy	0.9892	0.9925
Precision	0.9867	0.9897
Recall	0.9933	0.9963
F-Score	0.9899	0.9929

Conclusions

The main purpose was to use underwater image processing techniques For the pipeline network, the same error was found in each file. This paper is presented. The internal as well as external damage by corrosion in gas pipeline is a complex phenomenon, and the integrity of the structure is critical aspect considering the natural gas transport and the corrosion actions factors. Steel damage that occurs on this pipeline system can be identified by careful examination of the corrosion deposits found during pipeline excavation. The mechanism of corrosion is based on the formation of a galvanic couple between microbiologically produced iron sulfides and the steel surface. Using this research we can easily predict the corrosion using Machine learning algorithms. A new image-based method for sub-pipeline corrosion estimation.

Image A self-collected inspection of restoration and enhancement was also carried out in a pre-emptive estimation According to the publicly available underwater image dataset, the two have shown promising results. Since the corrosion rate is based on the color information of the carotid shaft, The experiment color was taken in conjunction with the evaluation of the color variation of the traditional image Metrics. The research will provide data for risk assessment models used for maintenance repair And functions of the pipeline system. The bald question asks the rest of the question Some possible perspectives on the safe life of the tube can be applied or developed Studying rust-related cracking and pitting events.

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