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Robotic Digital X-Ray Scanning System for Deep Water Flexible Riser Inspection

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Abstract. Flexible subsea risers are highly complex structures with multiple layers and varying material types. They are being used worldwide for oil and gas extraction in deep water. The complexity of these flexible risers and the hostile conditions in a deep-water environment present major challenges for non-intrusive, in-service inspection. This paper presents a novel automated radiography inspection system to detect defects from X-ray images of such flexible risers. The concept of a robotic digital X-ray scanning system which addresses the needs and challenges of deep-water flexible riser inspections has been studied. The proposed radiography inspection system is an ideal solution for flexible risers as it penetrates through all the layers in the riser structure, providing detailed information on any damage to the various layers. The system integrates the advanced technologies of image processing, machine learning, and robot crawlers to automatically detect abnormal textures such as erosion, corrosion and strand damage, foreign objects and other critical features from flexible risers. The performance of feature extraction, feature normalization, image processing, and machine learning for the purpose of defect detection have been tested and analysed. With smart integration and enhancement of different techniques, the limitations of each algorithms have been mitigated while the overall performance has been improved significantly. The detailed stages of the implementation are also discussed. The key features of the subsea riser inspection system are: (i) Real-time radiographic inspection result, (ii) Robotic system adaptable to various pipe types and sizes, (iii) High accuracy and reliability.

Keywords. Flexible riser, X-ray, image processing, machine learning, non-destructive testing, automated defect recognition.

1. Introduction

RobotX(Robotic digital X-ray scanning system for deep water flexible riser inspection), a project funded by Innovate UK, investigated the concept of a robotic digital X-ray scanning system to solve the needs and challenges of deep-water flexible risers' inspections. The project successfully demonstrated a powerful see-through scan system as it crawls and processes the data using innovative image processing and machine learning technologies to defect and classify the defects. The RobotX system is designed to withstand harsh deep-water environmental conditions to allow safer inspection.

The inspection of flexible risers is difficult due to the complexity of riser structure, and hostile environments in deep water. The conventional direct monitoring methods (e.g. visual inspection) cannot inspect all layers. Current non-destructive testing (NDT) techniques, such as ultrasound or eddy current, cannot reliably assess their condition

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unless a significant failure has occurred. They often require removal of the flexible protective coating and cannot penetrate all the layers of the pipe. The CT methods can see through each layer however it's not practical for inspection of flexible riser under deep sea environment.

Our research work investigated the X-ray Digital Radiography technique and developed a significantly enhanced non-destructive examination (NDE) capability for in-service inspection of flexible risers. The process is non-intrusive and do not require shutdown. It penetrates coatings to detect and monitor flaws and anomalies of sophisticated multi-layers. The project achievements and developed technologies will also be applicable to other applications like the inspection of wind or aircraft turbine blades.

2. Sample Images

2.1. The structure of flexible risers

Flexible subsea risers are mainly designed to transfer fluid material, typically oil or natural gas, from the sea-bed wells or sources to the floating production facilities. Their structure is highly complex **(Figure 1)** to provide the adequate flexibility whilst withstanding the required pressure conditions and the harsh subsea environment [1][2].

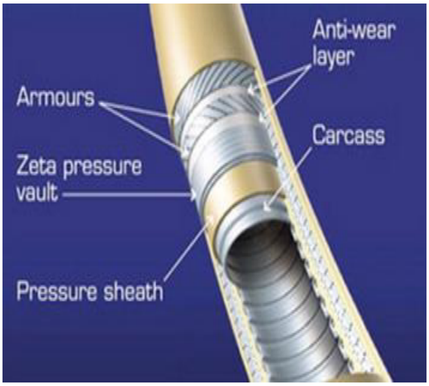

Figure 1. General structure of a flexible subsea riser pipe [2]

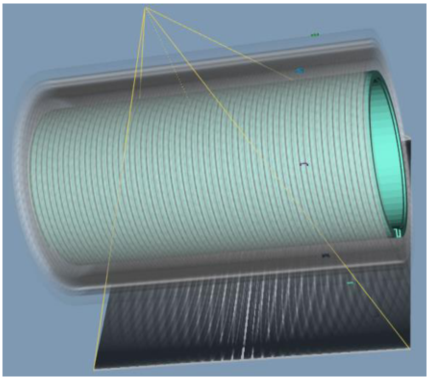

Figure 2. An example of the model setup in the simulation

2.2. Simulation of X-ray images of flexible riser

Due to the limited number of sample parts that we were able to access, some of the images were generated through simulation software using Moderato [3] and aRTist [4]. These simulated images are based on three dimensional solid models of real pipe sections, where the most common defect features were also represented. The quality and the features of simulated X-ray images were very close to those real ones that were made with an X-ray scanner. Figure 2 shows an example of the model set up in the Artist simulation. It is worth noting that during actual deployment the X-ray images for training need to be captured on-site to improve the system accuracy.

3. The system implementation

3.1. System overview

The system consists of:

1) A robot crawler moving along the subsea riser, revolve about the axis, and generate a series of continuous X-ray images.
2) The image processing and machine learning system (Figure 3) to detect and identify defects from each X-ray image, and give a report of defect list.

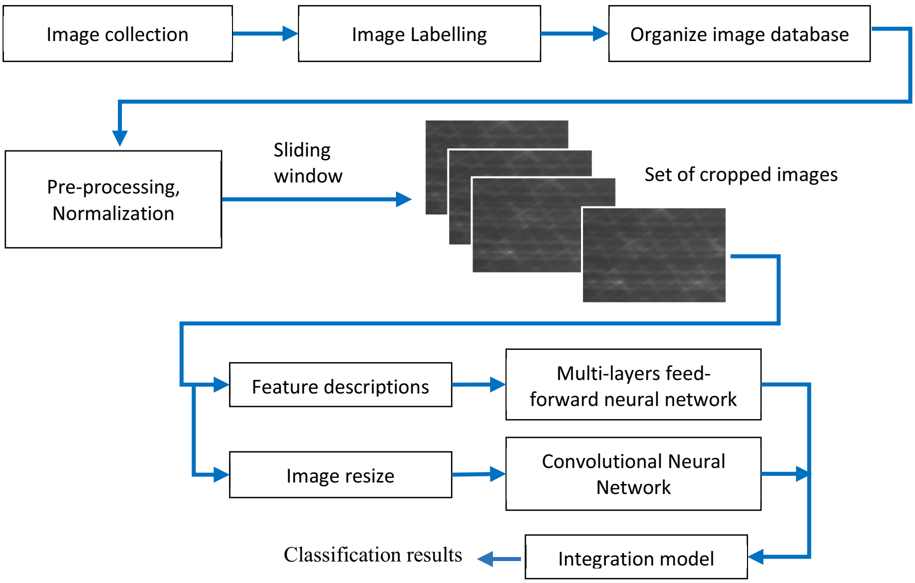

Figure 3. Algorithm flowchart

The complexity of detecting defects in a multilayered composite riser requires intricate processing steps. The purpose of pre-processing and normalization is to convert the image format if necessary, remove noise, normalize image brightness and contrast, crop images, and remove unusable areas (i.e. areas which are too dark or too shiny). A Median Filter is used to remove sparkle noise and preserve the edge information.

To detect, locate, and classify defects, the algorithm applies a sliding window over the image. At each position, the algorithm analyses the image block cropped by the sliding window. Two different models to classify the cropped images were developed:

- Training and recognizing the cropped image directly by CNN (Convolutional Neural Network) using transfer learning.
- Extract specific features from the cropped image, and classify the feature descriptors using a multi-layers back-propagation neural network.

The size of the sliding window and step of sliding depends on the complexity of text feature, and the average size of a defect.

3.2. Feature descriptors

Feature descriptors are widely used in Object Detection, Image Classification and Image Understanding, and Non-Destructive Testing [5][6][7][8]. The purpose of Feature Descriptors is to highlight the difference between healthy images and defected images. Based on the text style of material and type of defects, we find the following feature descriptors are suitable to highlight defect areas:

- Line Projections at the directions: horizontal, vertical, and diagonals. It highlights the feature of missing tensile armour strand.
- Normalized central moments (up to 4^{th} order), which reflect the texture features of probability distribution. It is represented by the specified integer power of the deviation of the random variable from the mean.
- Main inertial axis (eigenvalues of inertial tensor), an important feature of rich texture, which reflect the complexity of texture along each direction.
- Hu Moments (a series of moments that are invariant to scale, position, and size of object) [9][10][11].

3.3. Normalization of feature descriptors

All the feature descriptors must be normalized in order to make them irrelevant to the changing of image brightness and contrast. This is implemented by weighting the value of each coefficient using an appropriate power of image intensity, depending on how the coefficients were calculated. Experiments show that the normalization significantly improved the robustness and tolerance of the system. The accuracy was not influenced by the fluctuation of performance of the X-ray machine when the image brightness and contrast were adjusted manually.

3.4. Classifying Feature Descriptors using back-propagation neural network

The normalized feature descriptors are classified by a three layer neural network. More hidden layers will result in overfitting, a common complication when training data is insufficient comparing to complexity of features. The neural network is trained by the back-propagation algorithm. Due to the perspective effect of X-ray scanning, the texture appearance is changing along both horizontal and vertical directions. The change along the vertical direction is more prominent. Therefore, different neural network models are required at different locations along the vertical direction.

3.5. Classifying cropped images using a CNN (Convolutional Neural Network)

We use a deep CNN (Convolutional Neural Network) [12] to train and classify image blocks cropped by the sliding windows. The training method is called Transfer Learning (Fine-Tuning a pre-trained CNN). Fine-tuning begins with copying (transferring) the weights from a pre-trained network to the network we wish to train. The exception is the last fully connected layer whose number of nodes depends on the number of classes in the dataset. We replaced the last 3 fully connected layers of the pre-trained CNN with a new fully connected layer that has as many neurons as the number of classes in the new target application. In general, the early layers of a CNN learn low level image features, which are applicable to most vision tasks, but the late layers learn high-level features, which are specific to the application at hand. Therefore, fine-tuning the last few layers is usually sufficient for transfer learning. We tested GoogleNet and AlexNet, and we find that AlexNet gives the better accuracy and is more suitable for flexible riser X-ray image classification. The AlexNet contained 8 layers. The first 5 layers are convolutional layers, some of them followed by max-pooling layers. The last 3 layers are fully connected layers. The type of activation function is a non-saturating ReLU, which shows improved training performance over tanh and sigmoid.

3.6. Integration of recognition results

After each sub image is recognized, the results need to be integrated into the result of the whole image. The results of feature recognition and image recognition are integrated according to the confidence score of the specific defect detected.

4. Test results and conclusion

Figure 4 is an example of sample with defect "Holes in the anti-wear tape separating the tensile armor layers". It’s almost impossible to find this type of defect by human eyes from such complicated texture in an X-ray image of multi-layers materials. **Figure 5** shows the classification result. The system successfully detects and localizes the defects (marked in red). The overall accuracy of defect detection is above 90% which demonstrate the applicability of the proposed system.

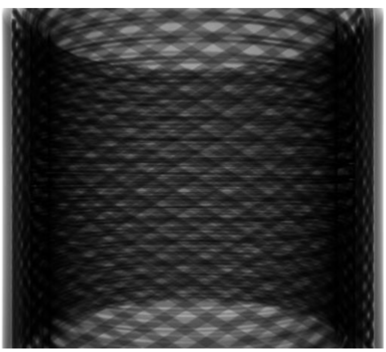

Figure 4. Riser 1 with defect type 4 "Holes in the anti-wear tape separating the tensile armour layers"

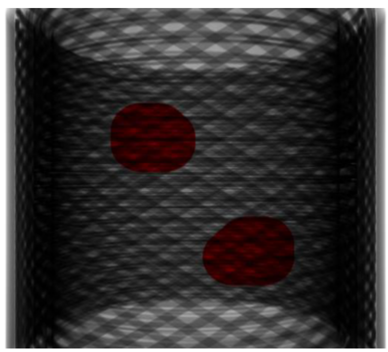

Figure 5. The system successfully detected the defects and marked the approximate position of defects as red colour.

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