AI-facilitated Coating Corrosion Assessment System for Productivity Enhancement

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***Abstract*—Application of protective coatings is the primary method used to protect marine and offshore structures from coating breakdown and corrosion (CBC). Assessment of CBC is the major aspect in coating failure management. Subjective assessment methods cause unnecessary maintenance cost and higher risk of failure.To improve efficiency and productivity, an integrated coating breakdown and corrosion (CBC) assessment system is developed. This AI-facilitated CBC inspection system implements a deep transfer learning technique to automate CBC assessment, it includes a faster region-base convolutional neural network (faster R-CNN) architecture and a vgg19 model for deep transfer learning, an instance-aware semantic segmentation method is developed for CBC measurement and grading. This method provides efficient inspection techniques for marine and offshore industries.**

***Index Terms*—coating breakdown and corrosion (CBC) inspection, deep transfer learning, instance-aware semantic segmentation, AI-facilitated CBC assessment system (A-CAS)**

I. Introduction

For many years, coating inspection has been plagued by many problems, such as inefficiency, safety and reliability. When ballast tanks are surveyed, adequate air ventilation and air quality tests are required before the surveyor can enter. The key problem is that surveyors have to rely on their experience in order to estimate the amount of coating breakdown and corrosion (CBC). Not only does the challenging environment make the coating failure inspection process inefficient, results are subjective [1, 2]. According to the International Maritime Organization, regular inspection and repair is an important part of global fleet maintenance. The large surface area of ballast tanks is subject to harsh conditions such as seawater, high temperatures and algae and bacterial accumulation. As a result, they must be inspected for damage once every five years. It has been estimated that the total cost of marine corrosion worldwide is among $50-80 billion per year [3]. Additional costs are incurred by the shipping industry during dry-dock for coating inspection work to be carried out and completed.

Application of protective coatings is the primary method used to protect marine and offshore structures from corrosion. As coating breakdown will quickly lead to corrosion, detection of areas with coating breakdown even before the metal has started to corrode is critical for corrosion management.

To enhance the coating inspection efficiency and reliability, to reduce the inspection related cost and time and to decrease the dependence on the expertise and experience of coating surveyors, an AI-facilitated coating corrosion assessment system (A-CAS) is proposed as shown in Fig. 1. In the project, an anti-collision micro-aerial vehicle aided by the latest technological innovations is developed to facilitate data collection for places which are not easily accessible. In this paper, only data analysis (steps 5 and 6) is focused for providing an objective coating assessment report through the development of an advanced coating inspection algorithm, which is combined with an inspection application, providing a more efficient, convenient and user-friendly inspection solution for the industry.

This paper is organized as follows. Section II lists relate works for CBC assessment. Section III introduces the image-based coating corrosion assessment method. Section IV explains the experimental result. Finally, conclusions are drawn in Section V.

II. Related work

Referring to automated vision-based coating corrosion detection, to the best of the authors' knowledge, In [4], Jahanshahi and Masri utilize color wavelet-based texture analysis for corrosion detection. Ji et al. [5] apply watershed transform over the gradient of gray images. Siegel et al. [6] choose wavelets for characterizing and detecting corrosion texture in airplanes, Zaidan et al. [7] focus on corrosion texture using standard deviation and entropy as discriminating features. Last but not the least, Ortiz et al. [8] present a solution for coating corrosion detection, the solution adopts a semi-autonomous micro air vehicle (MAV), and an artificial neural network (ANN) which discriminates between pixels suspected/not suspected corresponding to coating corrosion areas through sufficient color and texture descriptors.

III. Algorithm Development

Algorithm development is categorized into five different stages. They are: region of interest (ROI) proposals, feature extraction, feature learning, classification & prediction, feature detection and CBC measurement.

A. Feature Extraction

Nineteen layer deep learning network Vgg19 is used for feature extraction. The three categories of coatng corrosion and breakdown are surface-based CBC, edge-based CBC and

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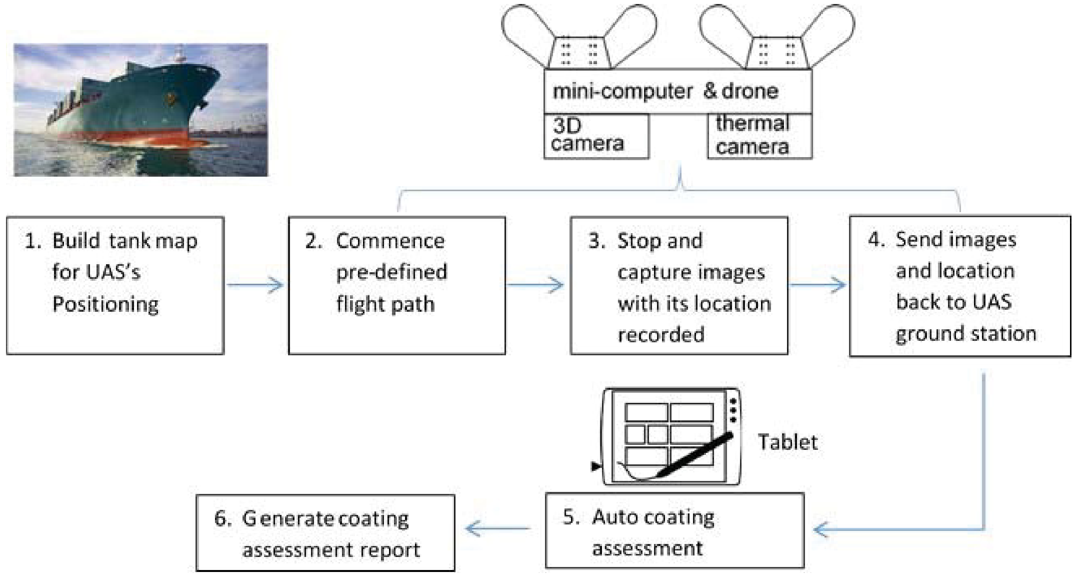

Fig. 1: AI-faciliated drone inspection system for coating failure

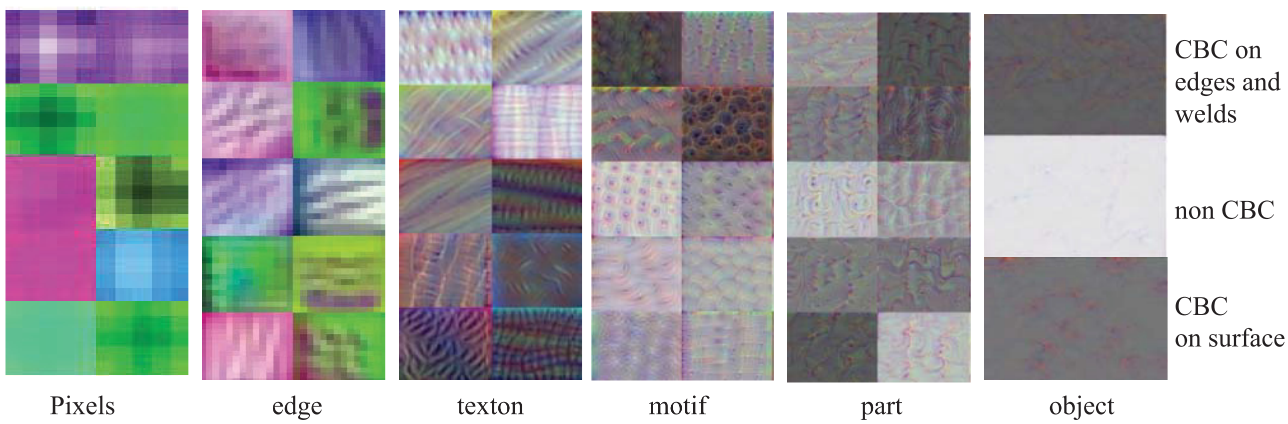

Fig. 2: visualized feature map

non-coating-failure. Supervised learning is chosen for feature learning and prediction. Due to limited dataset, TLCAF deep transfer learning network [9] is referred for feature learning and prediction. We generate a model for coating failure prediction, segmentation, coating corrosion condition quantitative measurement and grading. Auto-learned feature map in different levels are visualized by Deep Dream Generator[10]. Deep transfer learning's hierarchical composition are visualised in Fig. 2 , from first layer pixel feature, second layer edge feature, to deeper layers' texton, motif and part features, till the last fully connected layer's visualized object features. The three types of CBC can be distinguished and in the last fully connected layer for feature prediction.

B. Feature Learning and Prediction

Deep transfer learning on convolutional activation feature (TLCAF) network [6] is referred for feature extraction and learning. Fig.3 visualizes the labelled features through t-distributed stochastic neighbor embedding (t-SNE)[11]. High-dimension CNN features of the three types of CBC including surface-based CBC (yellow), edge-based CBC (green) and non-coating-failure (deep sky blue) can be easily distinguished in hyper-plane for feature prediction. Followed by the R-CNN features, softmax [12] is applied for multi-class feature classification and prediction.

Random selected 2000 CBC image features are choose for t-SNE high-dimension feature visualization experiment. Fig.3 represents the distribution of three types of CBC features. It clearly indicates that the high-dimension R-CNN features are linearly separated.

In the experiment, vgg19 is chosen for network training, stochastic gradient descent with momentum is used for loss function optimization, the learning rate is set to 1e-6, the

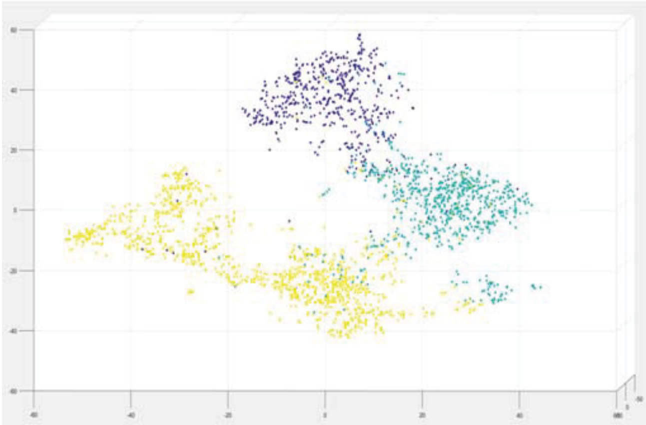

Fig. 3: Feature visualization

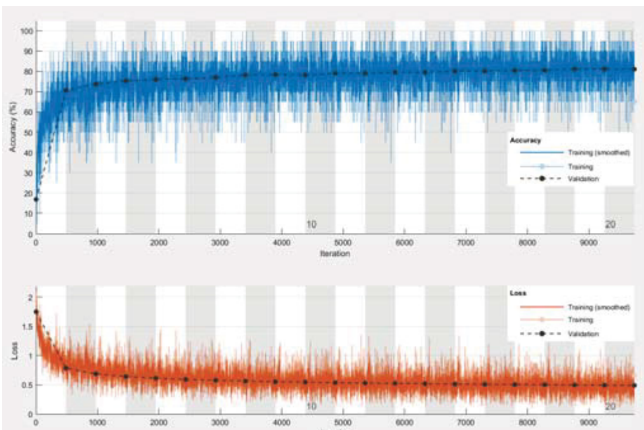

Fig. 4: Training and validation

maximum number of epochs for training is 20, and a mini-batch with 487 observations is used at each iteration. The max iteration is 9740. Fig.4 plots the training and validation process. Validation frequency is set to 487 iterations duration. Validation patience is set to 5, the validation patience value is the number of times that the loss on validation set can be larger than or equal to the previously smallest loss before network training stops. During the experiment, the training process stops at when it reaches final iteration.

C. Feature Detection

Randomly generated bounding boxes are used to propose region-of-interest (ROI) for different categories of CBC prediction. The predicted CBC regions of interest are reconstructed with background removal. Instance-aware segmentation is developed for CBC instances' background removal.

The predicted CBC region of interests are reconstructed with background removal. Then, the reconstructed image is sent to the next step for active segmentation [13] and CBC measurement. Fig. 5 show edges detection and active segmentation effect, where the background has been masked by active

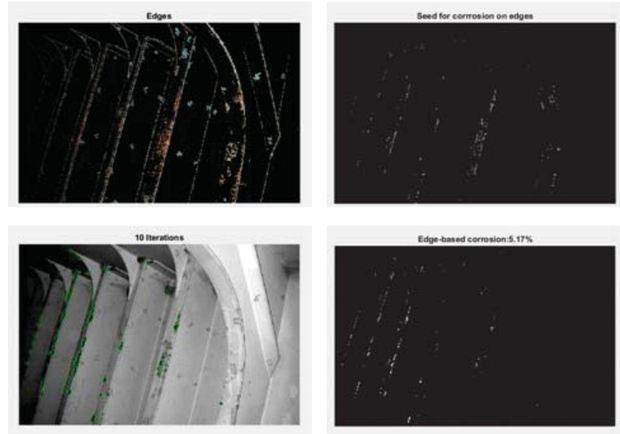

Fig. 5: Active instance-aware semantic propagation

Fig. 6: Activations

segmentation. The CBC measurement result is more accurate and constant compared with the ground truth images which are indicated in [14].

Activations are the output of a channel in the convolutional layers. Fig. 6 (right) demonstrates a typical strong activation of the CBC feature of Fig. 6 (left). In activations, white pixels represent strong positive activations and black pixels represent strong negative activations. A channel that is mostly gray does not activate as strongly on the input image. The position of a pixel in the activation of a channel corresponds to the same position in the original image. A white pixel at some location in a channel indicates that the channel is strongly activated at that position.

D. CBC Measurement

Instance segmentation is challenging because it requires the correct detection of all objects in an image while also precisely segmenting each instance. In this study, object detection and segmentation are combined together for object instance segmentation.

For CBC measurement, the extracted Hue, Saturation and Value (HSV) data is used to identify the possible pixels values for coating failure detection. The pre-extracted HSV dataset contains all the necessary information needed for pixel-level CBC detection.

The work flow description is listed in Table I. Fig.7 shows the result of preliminary studies done on CBC prediction and

TABLE I: CBC assessment algorithm

input: raw images
output: coating failure assessment result

1. input image and go through different layer convolutional networks
2. propose objects and relative region of interestes (ROI)
3. ROI pooling
4. fully connected layer ans softmax for classification and prediction
5. get processed_image by using morphology method for edge and corrosion texture analysis
6. if edges are detected
   - edge-based CBC ROIs reconstruction
   - hough transform to find lines
   - active selection for progagation
   - edge-based CBC measurement

   endif
7. if CBC on surface is detected
   - surface-based CBC ROIs reconstruction
   - active instance semantic segmentation
   - surface-based CBC measurement
8. adjust weights for CBC on welds and/or surface CBC on hard rust if there is.
9. grade for overall condition

end

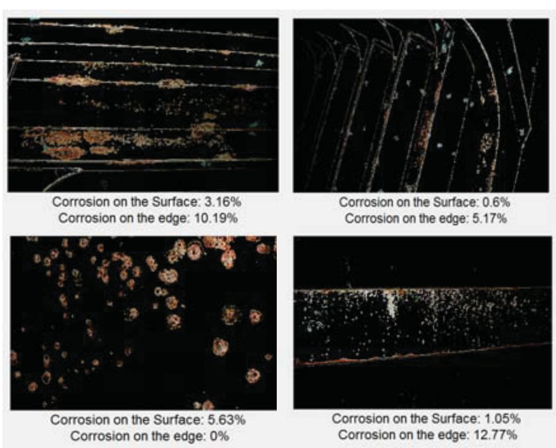

Fig. 7: CBC assessment report

detection.

Document Object Model (DOM)-Object based word report is developed for report generation. The assessment report of coating condition is automatically generated according to International Association of Classification Societies (IACS) standard and International Maritime Organization (IMO) recommendation.

Fig. 8: Classification and prediction result

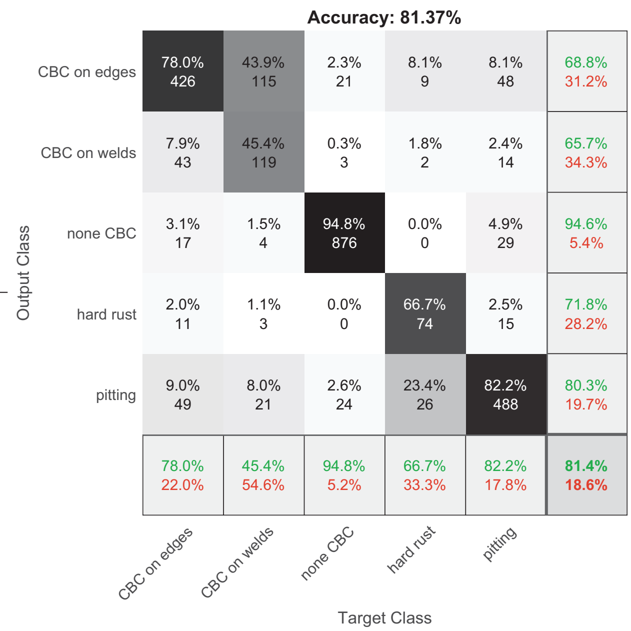

Fig. 9: Confusion matrix

IV. Experiment Results

In the preliminary study, 1900 images with CBC were labelled for feature learning; 12,184 features were extracted and classified into five groups which are CBC on edges, CBC on welding joins, non-coating-failure, surface-based CBC including hard rust and pitting. Randomly selected 2437 features (20% of the total 12,184 features) are used for validation. Figure 8 lists some typical samples of CBC classification and prediction result. Confusion matrix in Figure 9 shows the validation accuracy rates. The observed total recognition rate is 81.4%. We will continuously clean and augment the data and fine-tuning the model to improve generalization and maintain accuracy rate.

According to International Maritime Organization (IMO) [15] and International Association of Classification Societies

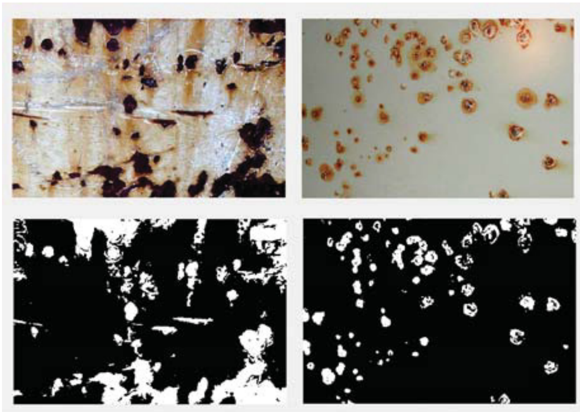

Fig. 10: CBC assessment. (**Top**) original images; (**Bottom**) processed CBC assessment.

(IACS) Recommendation standards, the A-CAS system's result matches with that of subjective measurements from the surveyor. Fig. 10 shows typical examples of active segmentation method for coating failure assessment. Fig. 7 includes several CBC measurement results which match with the ground truth. The system will continue to collect on-site data for optimization of the algorithms and correlate the results to that obtained by the conventional method.

V. Summary

The system [16] accurately recognizes major types of coating failure features including CBC on surface and CBC on edges and welds. This study provides a comprehensive automated coating failure assessment system for marine and offshore industry. To the best of the authors' knowledge, no such automated coating condition assessment systems are currently available. This method can be used as a scanning tool to help surveyors to identify and classify coating failures. Gone are the days whereby coating inspection is a tedious and inefficient process. The A-CAS system developed will make maritime coating inspection faster, more efficient and reliable.

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