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A Novel Image-Based Framework for Process Monitoring and Fault Diagnosis of Mooring Lines

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Abstract: Mooring lines play a vital role in offshore marine operations by limiting marine vessels' free movement on the water. Problems in mooring lines must therefore be detected and solved beforehand to guarantee successful and loss-free offshore operations. Sudden and undetected failure of mooring lines has caused significant disruptions of operations. Many studies focus on mooring lines failure and give ts comprehensive description. Available solutions to detect faults in mooring lines comprise the conventional line tension measurements. Circle-based GPS approaches are less accurate, unreliable, expensive, difficult to install, and maintain. They usually have a limited lifetime or the most recent Deep Learning-based techniques, which are computationally costly, data-hungry, and inefficient to localize thin mooring lines from images. In this research study, we present MoorFDM: Mooring Fault Diagnosis and Monitoring- a novel image-based framework for process monitoring and fault diagnosis of thin mooring lines. MoorFDM monitors and detects faults well in the thin mooring lines from images using our novel line pooling algorithm. Our proposed framework is validated using web-based light mooring line images and images from an oil and gas company with accurate results.

Keywords: mooring lines, process monitoring, and fault diagnosis (PFD), thin objects detection, computer vision, deep learning.

一种基于图像的新型系泊线过程监控和故障诊断框架

摘要：繫泊纜通過限制海上船隻在水上的自由移動，在海上海上作業中發揮著至關重要的作用。因此，必須事先發現並解決繫泊纜中的問題，以確保成功且無損失的海上作業。繫泊索突然而未發現的故障已導致嚴重的操作中斷，並且有據可查。用於檢測繫泊纜線故障的可用解決方案包括常規的纜線張力測量和基於監視圈的 GPS 方法，這些方法精度較低，不可靠，價格昂貴，難以安裝和維護，並且使用壽命通常有限或基於最新的深度學習這些技術在計算上昂貴，數據匱乏且無法從圖像中定位細繫泊纜線。在這項研究中，我們介紹了 MoorFDM：繫泊故障診斷和監視-一種基於圖像的新穎框架，用於細繫泊纜的過程監視和故障診斷。使用我們新穎的線池算法，顯示 MoorFDM 可以很好地監視和檢測圖像中的細繫泊纜中的故障。我們提出的框架已使用基於網絡的細繫泊纜圖像以及來自石油和天然氣公司的圖像進行了驗證，從而獲得了準確的結果。

关键词：繫泊纜，過程監控和故障診斷（PFD），薄物體檢測，計算機視覺，深度學習。

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1. Introduction

Offshore marine operations such as hydrocarbon product drilling and offloading employ mooring systems to restrict the vessel motion and heading variation for the mobile floating marine structures [1]. Someone can carry maritime operations efficiently. Thus, mooring systems are temporary or permanent structures that obviate the free movement of the hydrocarbon production FPSOs [2], [3], [4], mobile offshore drilling units MODUs [5],[6] and shuttle tankers on the water during their relevant offshore operations. In the case of MODUs, mooring systems accompany a dynamically positioned system that aims to maintain the marine vessel's position automatically (either a fixed position or a pre-defined track) using exclusive thruster systems [7]. Mooring systems are, therefore, vital for the successful offloading and drilling of hydrocarbon products in the offshore oil and gas industry. These systems typically comprise mooring lines, anchors, and connectors. Environmental conditions such as winds, waves, and currents [8]influence the mooring lines' constituent materials. Mooring systems most widely used for FPSOs are the Turret mooring [9, 10] and Spread mooring systems [11]; MODUs are also commonly equipped with Spread mooring systems while the shuttle storage tankers usually employ Single Point Mooring (SPM) Systems [12-14].

1.1. Rationale: The Issue of High-Cost and Inefficient Process Monitoring and Fault Diagnosis of Mooring Systems

There are various risks associated with the mooring systems, mainly when they operate under severe environmental conditions. According to statistics, 80% of the risk of offloading operations for these mooring systems concern safety and efficiency [15]. The high impact consequences of mooring arrangement failures include vessel drifting, riser rupture, production shutdown for FPSOs, major hydrocarbon release to the environment, and a considerable repair cost for the damaged lines [16]. As per viable literature, the price of a single mooring line failure is approximately £2M for 50,000 BPD (barrels/day) and £10.5M for 250,000 BPD for FPSOs in the North Sea and West Africa, respectively [17].

These costs are still nothing compared to those resulting from catastrophic failures such as the Gryphon FPSO mooring failure in Scotland with a loss exceeding approximately $1 billion [18]. Thus, it is evident that the potential cost of not detecting such failures is far greater than the cost of implementing a real-time mooring monitoring solution. Despite the highly sought-after advantages of mooring monitoring solutions, the petroleum companies limit their deployment due to the high operational and maintenance costs associated with these solutions. A mooring monitoring solution is estimated to be around USD 1 million to 2 million per moored unit, which is very expensive. Monitoring of mooring lines and the mooring hawser generally detects the mooring systems' faults. But unfortunately, the available approaches for the fault detection of mooring lines are expensive to install and maintain, unreliable, inaccurate, and come with a brief lifetime. Hence, the hour's need is an effective and low-cost solution for the timely process monitoring and fault diagnosis of the mooring lines. Since each mooring line has its characteristics, dimensions, and mooring configuration, therefore, the fault detection system must be generic and extendable to other mooring lines and compositions.

This research work presents MoorFDM – a novel image-based framework to address the mentioned issue of high-cost and inefficient process monitoring and fault diagnosis of mooring lines. MoorFDM efficiently monitors and detects faults in the mooring operation via departure angle monitoring of the mooring lines and is expected to reduce the cost of mooring monitoring and fault detection by 70-80% compared to the existing approaches.

2. Methods/ Materials

In this research work, we propose to monitor and diagnose faults in the mooring operation via the departure angle monitoring of the mooring lines as a shift in the moored line's angle is an indication of subsequent marine vessel drift. One calculates the departure angles of the mooring lines after detecting them. We propose to see mooring lines from images via a two-step process that is:

1. Mooring region identification via an SVM and sliding window object detector
2. Localization of the mooring lines in the detected mooring region via probabilistic Hough transforms followed by line refinement via our novel line pooling algorithm.

The proposed line pooling algorithm reduces the naively detected lines by probabilistic Hough transform to meaningful mooring lines. We calculate the departure angles for the detected mooring lines using geometric line measures. We do not utilize deep learning object detectors to detect and localize mooring lines from images because they appear as thin objects. The coarse bounding box-based deep learning detectors do not localize delicate items accurately.

2.1. Contributions and Expected Impact

The contributions of our research work are three-fold, namely:

- A novel image-based framework (MoorFDM) for low-cost and efficient process monitoring and fault diagnosis of mooring lines via departure angle monitoring.
- A novel line pooling algorithm for the refinement

and redundancy suppression of the lines detected via probabilistic Hough transform.

- Validation of the proposed approaches with accurate results.

MoorFDM has a significant impact on the oil and gas industry by reducing the cost of mooring monitoring and fault diagnosis by 70-80% compared to the existing mooring monitoring solutions. MoorFDM, being an end-to-end computerized solution, is also expected to reduce the fatality accidents and hazards associated with the installation and maintenance of traditional mooring monitoring approaches as elaborated in [19]. Moreover, the shortcomings identified in this work regarding the inappropriateness of the deep learning detectors proposed by us and our novel line pooling algorithm for redundancy suppression can further pave the way towards designing generic deep learning architectures for thin object detection and localization. In turn, it could prove to be useful in a variety of research areas such as wire detection for uncrewed aerial vehicles, road-lane line detection, plant stem detection in biological studies, and so on.

As to the rest of the paper, Section 1 discusses the available mooring monitoring approaches in detail and their corresponding disadvantages. Section 2 provides insight into the workings of our proposed framework MoorFDM and our novel line pooling algorithm. Section 3 sheds light on the validation of our proposed approaches, followed by results discussion in Section 4 and the conclusion.

2.2. Available Mooring Monitoring Approaches and Their Disadvantages

The available methods to detect failures in the mooring lines are either based on mooring line tension measurements and watch circle approaches with GPS based integrity assessments or the most recent deep learning-based techniques.

2.2.1. Line Tension Measurement Methods

The movement of the moored marine vessel, due to reasons such as environmental factors, causes

Fig. 1 Mooring line tension measurement devices

tension in the mooring lines. Hence, mooring line tension measurements are often employed to detect the vessel drift. Devices that aid in the mooring line tension measurements are described below and depicted in Fig. 1.

1. Inclinometers (Mooring Line Inclination)
2. Topside Tension or Instrumented Chain Stopper
3. (Load Cell)
4. Incline Tension (inter-M Pulse), Strain gauge on Chain Link
5. Sonar; Acoustically linked sensor and receiver

The disadvantage of using the line tension measurement devices for the fault detection and monitoring of mooring lines is that they are challenging to maintain and have a lifetime of merely a few years. Moreover, several severe injuries and fatal accidents occurred in the past during the maintenance and installation of these devices [19].

2.2.2. Watch Circle and GPS based Approaches

The watch circle approaches use GPS-based readings to determine the vessel's risers' optimal position within a ring or a circle. The risers connect the floaters on the surface to the oil-producing wellheads at the sea bed [20]. The vessel operates accurately with all the mooring lines intact within the rin,g which forms the vessel's excursion limits [21]. A vessel stray outside the ring's excursion limits indicates a problem in the mooring lines and a need to suspend oil flow from some or all the wellheads [22].

The watch circle approaches are problematic for effective fault detection in mooring lines because they rely on environmental data to decide the risers' optimal position. Such data may not be available readily. Moreover, these approaches provide the operator with limited information and excessive delay. There is already a severe problem with the mooring arrangement when the vessel drifts out of the watch circle.

2.2.3. Deep Learning-based Approaches

Deep learning (DL) has incredible potential to process, comprehend, and extract useful information from vast amounts of data [23]. The latest work for predicting mooring lines failure in a turret moored FPSO employs a deep learning convolutional neural network (CNN) based on secondary data obtained from numerical simulations about the vessel's position and motion [24]. CNN trains with the image data about the ship's situation and activity labeled in a way as to associate the images with the mooring system conditions generated via simulations. The CNN identifies the horizontal position features and associates them with mooring system conditions. While the system claims to reduce the cost of mooring monitoring by half as compared to the current approaches [21], it is still inappropriate for efficient mooring line monitoring due to the reasons listed as follows:

The system's trustworthiness and reliability are questionable as it has been developed and tested with

secondary data generated via numerical simulations.

1 It relies on excessive data about the vessel's position and motion, which might not be readily available for a real case scenario.

2 The applicability and feasibility of the system for real-time data are not known yet.

3 It requires a clear understanding and in-depth study of the relationship between the vessel's position and motion and the associated mooring system condition.

4 They were developed and tested for secondary data of one kind of mooring structures (turret mooring) only.

An alternative approach to the one mentioned above can be using primary image data for CNN training with visible mooring lines captured under diverse conditions (varying viewpoints, illumination, and so on.) instead of secondary image data about the position and motion of the marine vessel. The process monitoring and fault detection pipeline would then comprise of:

1 Mooring lines object detection via CNN from the images captured at regular time intervals.

2 Angle calculation of the detected mooring line objects where the angle would help determine the mooring line drift, if any.

3 Mooring lines fault determination via monitoring the calculated angles over regular intervals.

However, the feasibility of the pipeline, as mentioned above, is limited by the inability of the deep learning CNNs to accurately detect and localize thin image objects due to the following reasons:

- Use of coarse region-based object proposals and bounding boxes to detect and localize thin and compact image objects which only occupy a minimal portion of the whole bounding box, making other pixels meaningless and irrelevant.
- Due to excessive downsampling in CNNs, insufficient spatial information accurately and precisely localizes the thin image objects due to the inherent convolution operations.
- The large scale dataset to train and test the deep CNNs is unavailable.
- Reliance on local object shape makes a thin image object resemble other ordinary items in the image.

Since the mooring lines under discussion appear as thin objects in the captured images, they would not be detected and localized appropriately via Deep CNNs. The notes section of Table 1 gives a detailed explanation of the inappropriateness of various generic and application-specific deep CNN object detectors for seeing and localizing thin image objects. Table 1 reviews the mooring line image objects that look like thin lines in the images; hence, application-specific deep CNNs for line detection. Table 2 represents a comparative analysis of the available mooring monitoring approaches from various aspects. The table reveals that all the solutions available for fault detection and monitoring of mooring lines have limitations, are expensive, and demand excessive time and installation and maintenance efforts.

3. Results and Discussion

3.1. MoorFDM: A Novel Framework for Process Monitoring and Fault Diagnosis of Mooring Lines

Computer vision approaches including but not limited to content-based image retrieval [25], image classification [26],[27], object detection, learning, scene reconstruction, event detection, video tracking, and so on [28] have penetrated almost every field of work in the current era. They are widely used in the oil and gas industry and various applications such as oil exploration, drilling, reservoir engineering and so on. Keeping up with the trend, we present MoorFDM: a low-cost and efficient image-based optimized framework for the process monitoring and fault diagnosis of mooring lines in this research work.

Table 1 Inaccurate deep learning detection for thin image objects

S.#	Approach	Domain	Category	Dataset	Comments	Ref.
1	You Only Look Once (YOLO)	Deep learning (One-stage)	Generic	PASCAL VOC 2012	Rely more on speed rather than **accuracy** of detections. Box ground data and output **bounding box-based detections** aren't suitable for detecting thin and slender objects. Moreover, these approaches rely on pre-defined anchor boxes to generate object proposals that introduce bias in the detection process.	[29]
2	YOLO v2	Deep learning (One-stage)	Generic	COCO		[30]
3	Single-Shot-Detector (SSD)	Deep learning (One-stage)	Generic	COCO		[31]
4	Deeply Supervised Object Detector (DSOD)	Deep learning (One-stage)	Generic	COCO		[32]
5	Region-CNN (RCNN)	Deep learning (Two-stage)	Generic	PASCAL VOC 2012	**Region-based proposals and bounding box detections** are not suitable for detecting thin objects because the delicate items consume only a **small proportion of pixels** in the **course bounding box**. Hence, the course bounding box contains most redundant pixels not corresponding to the actual thin object.	[33]
6	Fast-RCNN	Deep learning (Two-stage)	Generic	PASCAL VOC 2012 COCO		[34]
7	Faster-RCNN	Deep learning (Two-stage)	Generic	PASCAL VOC 2012 COCO		[35]
8	Region-Fully Convolutional Network (R-FCN)	Deep learning (Two-stage)	Generic	PASCAL VOC 2012 COCO		[36]
9	Mask-RCNN	Deep learning (Two-stage)	Generic	COCO	Detection of thin objects may not directly be a **pixel-classification** task. Hence, **complex computations** associated with the pixel-level annotation, classification, and additional post-processing tasks may be unnecessary for detecting and localizing thin objects.	[37]
10	Image UNet	Deep Learning	Generic line detection Application-specific: Road lane-line detection	Synthetic dataset of 512x512 binary images containing lines and circles	It relies on simple **synthetic binary images** for line detection only and will struggle with complex natural ideas. Moreover, it wouldn't **generalize** well for thin object detection and localization in diverse, realistic photos.	[38]
11	Line CNN	Deep Learning	Application-specific: Road lane-line detection	MIKKI TuSimple	Detects road lane lines by inspecting the left, right, and lower image boundaries only; hence, it will fail to detect sequences present in other portions of the image. Might struggle with the issue of **generalizing** to thin objects detection and localization.	[39]
12	Mask-RCNN Line Detection	Deep Learning	Application-specific: Road lane-line detection	TSD-MAX Road Dataset	It does not contain **enough spatial information** for accurate **boundary generation**. Thus, it cannot precisely detect thin objects requiring definite boundaries for precise localization.	[40]
13	EL-GAN	Deep Learning GANs	Application-specific: Road lane-line detection	TuSimple Road Dataset	Fails to capture the **lines' uniqueness due to the use of the single-class technique and require** a time-consuming training process. Moreover, application-specific hence wouldn't **generalize well** for thin objects from diverse natural images.	[41]

Table 2 Comparative Analysis of Mooring Monitoring Approaches [42]

Aspect	**Load cell**	**Inclinometer**	**GPS**	**Deep CNN**
Maturity	Number of applications	Limited applications	Number of applications	Limited applications
Intent	Monitor mooring line load for the detection of line failure, overloading, or fatigue assessment	To measure mooring lines angles for the line failure detection	To monitor and measure FPSO locations and hence to derive the mooring line load	Monitor and detect mooring line overloading, failure, and provide operation advisory
Applicability	All mooring types except submerged turret mooring system	All mooring types but most suitable for a catenary system for derived line tension	All mooring types	All mooring types
Deployment	New and existing systems. For inline load cell; retrofit is relatively difficult	New and existing systems	New and existing systems	New and existing systems
Advantages	•Relatively simple •Low-cost installation	•Direct measurement of line angle and not affected by other parameters •Relatively simple system with low cost.	•Easy installation at a low cost •Equipment on board the vessel and easy to maintain	•Accurate •Reliable •Inexpensive installation and maintenance •A comprehensive system for real-time monitoring •Provides advisory for mooring operations
Advantages	•Unreliable and less accurate measurement in case of low mooring line load, friction, temperature, signal drafting, recalibration, the durability of transmission cables •A temporary lifetime with complicated and expensive maintenance •Doesn't provide mooring operation analytics and advisory	•Unreliable and less accurate •Can only derive quasi-static mooring line tension without accounting for dynamic and nonlinear effects. •Needs careful calibration for the model of mooring line angles and mooring line load. •Temporary lifetime with complicated and expensive maintenance •Doesn't provide mooring operation analytics and advisory	•Less accurate • It requires a clear understanding and in-depth study of the relationship between the vessel's position and mooring line load •It involves information about environment measurement (wind, wave, and current). •Doesn't provide mooring operation analytics and advisory	•Requires a lot of data •Struggles with detecting and localizing thin image objects •Relatively new with the unverified effectiveness of the advisory system

We propose to detect thin mooring line image objects using a computationally inexpensive SVM classifier. The proposed detection method also engages the Probabilistic Hough transform. It also includes a novel line pooling technique intended for suppressing redundantly detected thin mooring line objects. Moreover, we propose to detect faults in mooring lines via the departure angle monitoring of the detected thin mooring lines. The departure angle aids in the fault detection process by indicating potential drifts in the detected mooring lines and subsequently in the moored marine vessel. Lastly, MoorFDM would reduce the overall costs (CapEx and OpEx) of the mooring monitoring by 70-80% for a moored unit than the existing solutions that would further be reduced during the scaling up operation extend the framework to other moored companies. The subsequent sections stipulate the details of MoorFDM for mooring lines process monitoring and fault detection via monitoring of mooring departure angle. Figure 2 illustrates the complete framework.

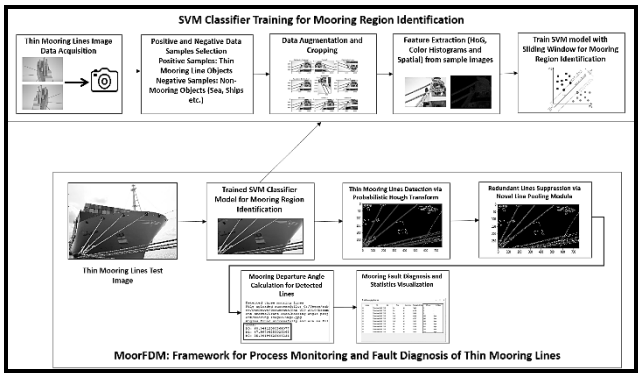


Fig.2 MoorFDM: A novel image-based framework for process monitoring and fault diagnosis of thin mooring lines

The bottom part of Figure 2. depicts the core framework activities while the top part depicts the sub-activities from one of the core activities, namely: the mooring region identification. Figure 2 shows an RGB channel test image fed into the framework pipeline consists of thin mooring line objects. We consider the core modules of the framework further on.

3.2 Mooring Region Identification

Since the thin mooring line image objects are only present within a small portion of the complete image data, the mooring region identification module identifies and detects the image region, which has a high probability of containing the thin mooring lines. The detection of the specified mooring region of interest is done by a linear support vector machine (SVM) with a sliding window search object detector. Experimental Setup ik4e sub-section of Section 3 describes the details of the SVM detector training.

3.3. Mooring Lines Detection

Mooring line image objects appear as thin straight lines in the images and can therefore be detected via the application of a probabilistic Hough transform [43], which represents lines mathematically using the line equation as:

$$r = x \cdot \cos\theta + y \cdot \sin\theta \qquad (1)$$

Probabilistic Hough Transform in the mooring region identified by the SVM detector aims at detecting thin mooring line image objects.

3.4 Novel Line Pooling Algorithm for Redundancy Suppression

Probabilistic Hough transforms although detects thin mooring line objects in the SVM detected mooring region, but these mooring line detections are redundant per each mooring line object instance. Thus, the Hough transform detects more than one line for each thin mooring line object. To represent each mooring line object with exactly one output line, we propose a novel line pooling algorithm for suppressing redundant lines per mooring line object and pooling them to create one representative line output. The pseudocode in Algorithm 1 describes our Novel Line Pooling algorithm, which takes a line set *LS* comprising of redundant line detections and outputs the unique line set *US*. Since mooring lines usually appear at certain angles in the images and cannot be horizontal or vertical lines, we state that each detected line *L* belongs to a mooring object *M* if it is neither vertical nor horizontal. The Formula below expresses the mooring line condition:

$$L \in M \; iff \; (\Phi \notin [90 \pm v] \; or \; \Phi \notin [0 \pm v]) \mid v=5 \qquad (2)$$

V is chosen as a constant after careful inspection of the mooring images to discard the lines like horizontal or vertical lines and hence, cannot be potential mooring lines. Let's represent each mooring line L that satisfies the criteria in (2) by two representative points (x_1,y_1) and (x_2,y_2). Formula (3) calculates the center point C(x,y) of each line:

$$C(x,y)=((x_1+x_2)/2,(y_1+y_2)/2) \qquad (3)$$

All such L detected lines constitute the line-set LS. Two or more lines in the set LS are considered redundant per mooring object line M if and only if these lines lie spatially close to each other that is the distance *Dt* between these L lines lies within the range of [0,10] units, and they share similar inclination angles Φ such that the Difference *Df* (must be a whole number W) between the inclination angles of these lines lies within a range of [0,1]°. All the other lines in LS which do not satisfy these redundancy conditions

are considered unique *UL* and added to the unique line-set US. Formula (4) describes these conditions:

$$L \text{ is redundant } iff: \\ Dt \in [0,10] \text{ and } (Df \in [0,1]° \mid Df \in W) \quad (4)$$

Every line L from LS is compared against the US's lines using the redundancy conditions stated in (4). If a match is detected, our line pooling algorithm pools the redundant *UL* lines (the line originally stored in *US*). It also pools L with a single representative line L' with end-points ((x_1',y_1'), (x_2',y_2')) and angle Φ' which are obtained by averaging the representative end-points ((x_1,y_1), (x_2,y_2)) and angles of the redundant lines respectively. Finally, *UL* is redundant with L from LS replaced by the pooled version L' in the US's unique set. The distance *Dt*, angle difference Df and the pooling calculations between each line L from the set LS and each UL from the set US are complete. If all the lines in LS and US have been used, the calculations are complete. If only one of the conditions from (4) occurs, the lines are unique for different mooring objects and added to the *US* set. The inclination angles ($\Phi_{s=}$ $\Phi_{1,}$ $\Phi_{2.....}$ $\Phi_{n)}$ of all the lines are calculated via the slope *m* derived from the slope-intercept form of the line represented mathematically as:

$$\Phi = tan^{-1}(m) \mid m=(y_2-y_1/x_2-x_1) \quad (5)$$

If we assume the redundant lines to be parallel, then according to Euclidean geometry, the distance Dt between them is calculated by computing the perpendicular distance from any point on one line to the other line as shown in (6). We take the center point calculated from (3)).

$$Dt = |Ax_1 + By_1 + C| / \sqrt{(A^2 + B^2)} \quad (6)$$

3.4.1 Algorithm

Input: LS **Output:** US
$count \leftarrow 1$
while line L in LS do
  $found \leftarrow False$
  if count is 1 **then**
    move first line L to US for initialization
  else
    while line UL in US **do**
      Calculate inclination angles Φ_{UL} and Φ_L using (5)
      Df= abs(Φ_{UL}-Φ_L)
      Dt= $|Ax_1 + By_1 + C|/\sqrt{(A^2 + B^2)}$ where A,B and C are coefficient of line L represented by line equation Ax+By+C=0 and (x_1,y_1) is the center point C_{UL} of line UL calculated from (3).
      if Df<1 and Dt<10 **then**
        $found \leftarrow True$ (redundancy detected)
        L' ((x_1',y_1'), (x_2',y_2'))= $((x_{1ul}+x_{1l})/2,(y_{1ul}+y_{1l})/2)$, $((x_{2ul}+x_{2l})/2,(y_{2ul}+y_{2l})/2)$
        L' (Φ')= (Φ_{UL}+Φ_L)/2
        Replace UL with L' in US
        break
      end if
    end while
    if found is False **then**
      move line L to US
    end if
  end if
end while

Lastly, all the lines in the final set US, which are unique per each mooring line object M are localized by plotting them on the image.

3.5 Mooring Departure Angle Calculation for Detected Mooring Lines

So far, we have detected the mooring lines and localization using the Hough transform with our novel line pooling method from the SVM detected mooring window region in the image. The corresponding angles of the detected mooring lines are calculated using (5) stored in the storage for determination of the angle shift ahead. The mooring lines detection and the corresponding angle calculation are done in intervals to ensure consistent monitoring. The time interval for the line detection and angle calculation is adjusted to meet the requirements.

3.6 Mooring Fault Diagnosis and Statistics Visualization

We established the mooring line faults are via the shift calculation of the detected mooring departure angles. We calculate the angle shift for a mooring line as the difference between the last calculated mooring line angle and the initially computed angle. The difference is then compared with a threshold value to decide the shift category. Suppose the difference is greater than a specified threshold value. In that case, the shift is **significant** and **minor**. The shift category decides the severity of the moored vessel's drift, and accordingly, mitigation strategies are added. The complete statistics of the mooring line angles are finally displayed. Other relevant information such as the camera for image taking, the date, and angle shift, if any, show the shift category.

4. Validation of Proposed Framework

4.1 Experimental Setup

We implement MoorFDM using Python with OpenCV and Sci-kit Image libraries. As specified in

section III, a linear SVM classifier with sliding windows search is used as an object detector to identify the mooring region of interest containing the thin mooring line objects from the input images. The top of Figure 5 shows the SVM object detection pipeline. The RGB image data containing minor mooring line objects (positive samples are the mooring line regions) and some non-mooring items train the detector. The latter comprise negative examples likely to occur with mooring objects in the image data such as the ship, sea, deck, etc. We obtain the data via web scraping and Malaysian oil and gas company indicators during their daytime offshore activities. The web-based images were obtained from the search engines using the keywords "mooring lines," "mooring," and "mooring hawser." Duplications, if any, are removed from the acquired data. Data augmentations are performed on the positive and negative sample subsets to account for the scarcity of data in training the detector. Figure 3 provides the data augmentations employed for training. All the samples are cropped and resized to a patch size of 120x120. We extracted Histogram of Gradients (HoG), color histograms, and spatial features for all the image samples. The resulting feature maps are scaled, shuffled, and then split into training, cross-validation, and test sets for training the linear SVM classifier. One makes hard harmful mining to retrain the classifier on the augmented dataset containing false-positives from the cross-validation set before evaluating the test set. A variable-sized sliding window search is conducted on the bottom part of the image only to reduce computations. There should be no mooring region above the horizon or in the upper part of the picture. Features are computed for all the windows during the window search and provided to the trained SVM classifier to identify mooring objects of interest. The windows which contain the object features are classified as positive while the others are negative. Redundant windows per item are suppressed using a non-maximal suppression technique, and a final output

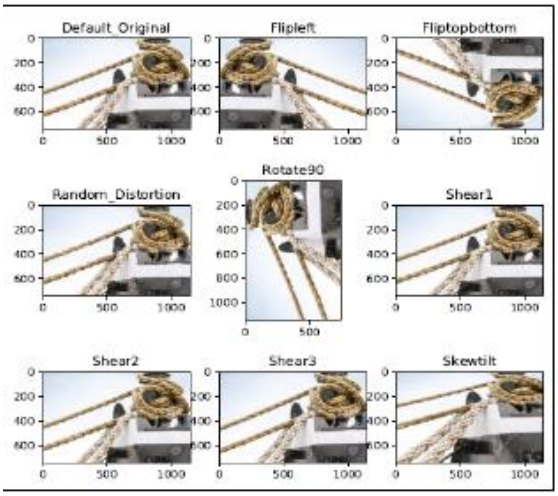


Fig.3 Data augmentations for training data

bounding box outlines the detected mooring region of interest. We train the linear SVM classifier with squared hinge loss, L2 penalty, and C regularization [44]. It achieves a test-set accuracy of 80% with 75%/20%/5% split for the train/cross-validation/test datasets. Table 3 provides the parameters employed for the experimental setup and identified via tweaking, trial, and error.

Table 3 Optimal parameter values for MoorFDM training and testing

Type	Parameter	Value
Feature Descriptor	Color space	YUV
	HOG features	True
	Color histogram features	True
	Spatial binning features	True
	HOG library Channels	3
	Patch size	(120,120)
	Cell size	(8,8)
	Block size	(2,2)
	HOG bins (orientations)	20
	Signed gradients	False
	Color histogram bins	16
	Spatial bin size	(20,20)
SVM	Loss	Squared Hinge
	Penalty	L2
	C (Regularization Parameter)	1000
Sliding Window Detector	Sliding window initial size	(90, 90)
	Sliding window x overlap	0.7
	Sliding window y step	0.01
	Sliding window x range	(0.02, 0.98)
	Sliding window y range	(0.55, 0.89)
	Sliding window scale-up	1.3
Probabilistic Hough Transform	r	1
	θ	π/180
	Voting threshold	100
	Min line length	100-250
	Max line gap	15
Line Pooling	Distance Dt threshold	[0,10] units
	Angle difference Df threshold	[0,1]°
Departure Shift	Angle Threshold	10°

4.2 Performance Evaluation

4.2.1 Line Pooling Algorithm Results for Redundancy Suppression

We report the results of our novel line pooling algorithm that detects redundant lines from the probabilistic Hough transform according to the redundancy criteria in (4). We also use a single pooled line output, which is the average of the redundant lines, on full-sized images instead of cropped mooring regions detected by the SVM object detector for better error analysis. Figure 4 presents the results.

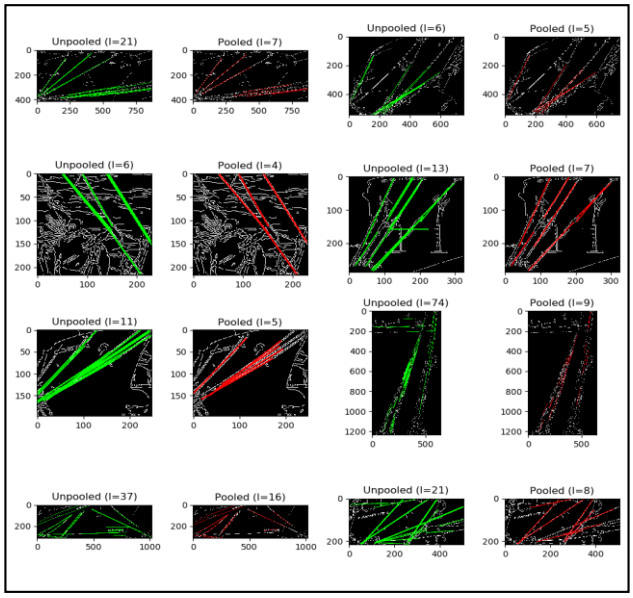


Fig.4 Redundant Lines (in green) from Hough Transform *vs.* Refined Lines (in red) from Proposed Line Pooling Algorithm

The images with green lines represent the unpooled lines from the probabilistic Hough transform. In contrast, the images with red lines represent the unique mooring lines identified and refined by our novel line pooling algorithm. Our line pooling algorithm effectively reduces the redundant lines and the lines that do not correspond to mooring objects that are the horizontal and vertical lines. A total line count of the sequences detected by the probabilistic Hough transforms in images from Fig. 4. We summarized those left after identifying a mooring object and refinement by our line pooling algorithm in Figure 5. It is evident from the results depicted in Figs. 4-5 that our novel line pooling algorithm significantly reduces the non-motoring and redundant line detections while preserving only the meaningful ones for the full-sized images. Hence, we can achieve a further improvement in the results if detection and pooling are performed only within a specified area of interest (the region containing mooring lines only) specified in the products depicted in Figs. 6-9.

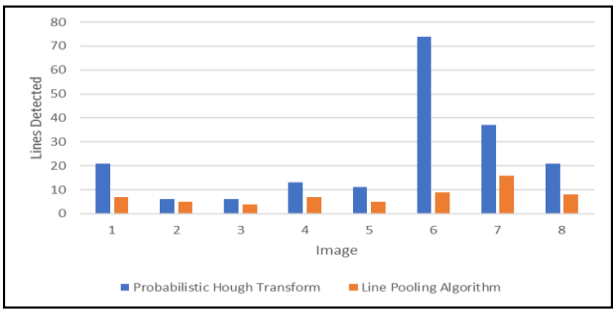


Fig.5 Line detection count results from Hough Transform (in blue) vs. from Proposed Line Pooling Algorithm (orange).

4.2.2 Thin Mooring Lines Detection and Fault Diagnosis Results for Web-based Images

Figures 8-9 illustrate the results of the proposed framework MoorFDM on the web-based images containing visible sets of mooring lines from different perspectives. We can see from Figs. 8-9, the MoorFDM successfully detects the mooring lines (RHS of the image) using the probabilistic Hough transform algorithm along with our novel line pooling algorithm in a specific area of interest (lower part of the ship in the picture) only. This particular area of interest contains the mooring lines detected by our SVM and sliding window detector. The mooring line object detection is followed by angle calculation in degrees (LHS of the image) for each detected line. The identified mooring lines are assigned labels (M0, M1, and M2) according to their spatial positions, where M0 is the mooring line with the smallest x2 coordinate and likewise so on.

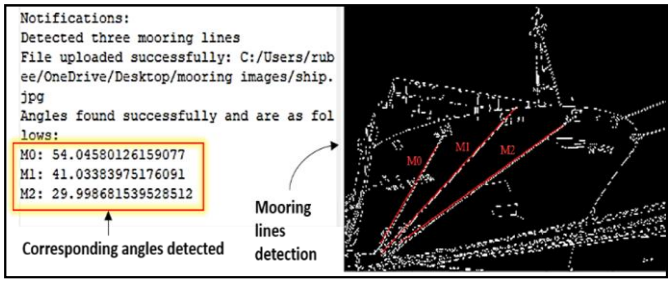


Fig.6 Right: mooring lines and left: corresponding angles detection in degrees by MoorFDM result 1

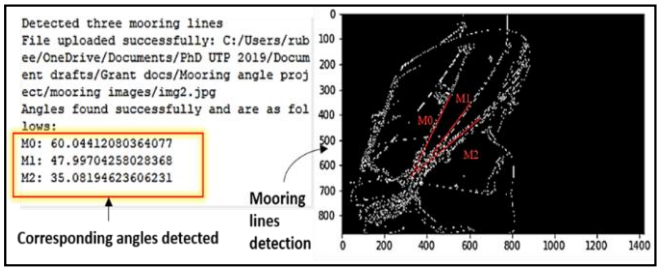


Fig.7 Right: mooring lines and left: corresponding angles detection in degrees by MoorFDM result 2

4.2.3 Thin Mooring Lines Detection and Fault Diagnosis Results for Mooring Images from Oil and Gas Organization

Figure 8 the validation result of the proposed framework MoorFDM on images obtained from a Malaysian oil and gas company during their offshore operations. The photos contain partially submerged mooring lines and were taken in bright daylight by the marine vessel crew members, as shown in Fig. 8. The result of mooring lines and corresponding angle detection in Fig. 9 reveals that the proposed method works sufficiently well for real-time sea images despite the visible sea clutter depicted in them (Figs. 8-9).

Fig.8 Right: Mooring lines image from offshore operations

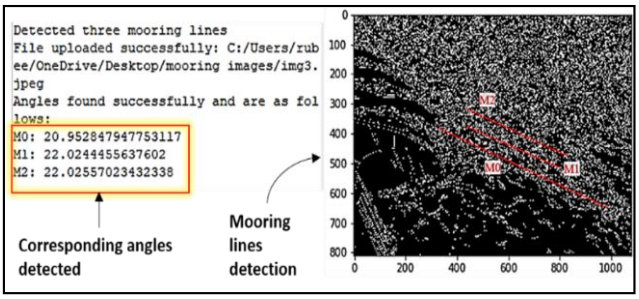
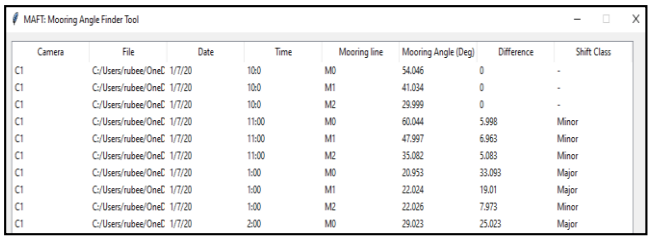


Fig.9 Right: Mooring lines and left: corresponding angles detection in degrees by the proposed method for image data from an oil and gas company



MAFT: Mooring Angle Finder Tool

Camera	File	Date	Time	Mooring line	Mooring Angle (Deg)	Difference	Shift Class
C1	C:/Users/rubee/OneD	1/7/20	10:0	M0	54.046	0	-
C1	C:/Users/rubee/OneD	1/7/20	10:0	M1	41.034	0	-
C1	C:/Users/rubee/OneD	1/7/20	10:0	M2	29.999	0	-
C1	C:/Users/rubee/OneD	1/7/20	11:00	M0	60.044	5.998	Minor
C1	C:/Users/rubee/OneD	1/7/20	11:00	M1	47.997	6.963	Minor
C1	C:/Users/rubee/OneD	1/7/20	11:00	M2	35.082	5.083	Minor
C1	C:/Users/rubee/OneD	1/7/20	1:00	M0	20.953	33.093	Major
C1	C:/Users/rubee/OneD	1/7/20	1:00	M1	22.024	19.01	Major
C1	C:/Users/rubee/OneD	1/7/20	1:00	M2	22.026	7.973	Minor
C1	C:/Users/rubee/OneD	1/7/20	2:00	M0	29.023	25.023	Major

Fig.10 Summary of the detected mooring line angles and their corresponding shift class

4.3 Statistics and Summary Visualization

After the mooring line detections and their corresponding angles, the proposed method generates a complete summary of all the mooring line angles detected for all image inputs along with their shift classes/categories. Fig. 10 illustrates the result with the full summary details.

In Fig 10, the first four columns viz the **Camera, File, Date and Time** describe the information regarding the image input such as the camera which captured the image containing the mooring lines, the image file saved to the storage the image date and time. The **Mooring line** and **Mooring Angle** columns describe the mooring lines detected from the captured inputs and their corresponding angles in degrees, respectively. Finally, the **difference** and the **Shift Class** columns help in the identification of the mooring lines fault. The difference is calculated by subtracting the mooring lines' current angles from the first angles and then compared with a threshold value, which helps identify the shift class. A threshold value of **10 degrees** is assumed for the intended angle shift monitoring but can be adjusted as per the requirements accordingly. Then, we select mitigation strategies based on the shift class.

4.4 Discussion

4.4.1 Cost Reduction Analysis

We implement the proposed MoorFDM framework smoothly using low-cost devices such as a Raspberry PI Processor, I/O devices, storage devices, and few cameras for primary data acquisition. The total cost of our proposed MoorFDM framework per moored unit would therefore be considerably less than a full-fledged mooring monitoring solution. Table 4 provides a comparative analysis of the total estimated cost for a full-fledged mooring monitoring solution and the proposed MoorFDM for a single moored unit.

Table 4 Cost reduction analysis of MoorFDM with existing mooring monitoring solutions

Mooring Monitoring	**CapEx**	**OpEx**	**Total Estimated Cost (USD in Million)**
Existing Mooring Monitoring Solutions	Sensors		1.02-2.04
MoorFDM	Cameras Raspberry PI	Maintenance and Repair	
	I/O and Storage Devices		0.047

4.4.2 Comparative Analysis with Existing Systems

Table 5 presents a comparative analysis of the MoorFDM framework for detecting and localizing thin mooring line objects.

It comprises the SVM mooring region detector, Hough transforms, and our novel deep CNNs object detectors.

Table 6 provides the comparison of MoorFDM for mooring fault diagnosis and monitoring with other available approaches. The information in Table 5 demonstrates the effectiveness of the proposed method against the deep CNNs for thin image object detections and localizations due to the use of:

- accurate boundaries for line localizations instead of coarse bounding boxes
- mooring region detection via an SVM sliding window object detector, which only requires a minimal amount of data.

Lastly, Table 6 validates the efficacy of MoorFDM

for the mooring fault diagnosis and monitoring process compared to other available solutions. We compared the simplicity, accuracy, reliability, inexpensiveness of the proposed method for various mooring configurations.

This research demonstrates that our proposed MoorFDM framework is implemented via SVM sliding window detector and probabilistic Hough transform, and a novel line pooling algorithm. However, it works effectively for thin mooring lines detection and subsequent monitoring and fault diagnosis but is only applicable to image input comprising visible mooring lines. Moreover, parameter tuning and optimization for SVM sliding window object detector for mooring region identification and probabilistic Hough transform for mooring lines object detection and localization are achieved via hand-crafted tweaking, trial, and error instead of a fixed rule. Hence, these selected parameters might not work optimally for some class of input images, which is a separate research topic on its own. The SVM sliding window object detector is extremely slow as it performs feature calculation and classification at each location of the sliding window search space. Lastly, MoorFDM uses a static threshold value to decide the shift class/category for the detected mooring lines' angles, likely replaced with an intelligent shift prediction mechanism.

Table 5. Comparative analysis of MoorFDM with Deep CNNs for thin image object detections and localizations

Approach	**Principle**	**Image Feature Extraction Mechanism**	**Detection Speed**	**Localization Mechanism**	**Dataset**	**Mechanism**
Deep CNNs	Line detection through bounding box-based region proposals and classifications.	Automatic	Fast (automatic feature extraction)	Coarse bounding boxes	Huge and extensive	Complex
MoorFDM	Line detection through probabilistic Hough transforms in a specified region of interest and redundancy suppression via line pooling algorithm.	Hand-crafted via tweaking, trial, and error	Slow (uses sliding window)	Actual lines	Minimal	Simple

Table 6 Comparative Analysis of MoorFDM with Available Mooring Monitoring Approaches

Approach	**Simple**	**Low-Cost**	**Accurate**	**Reliable**	**Timely**	**Advisory**	**Generalization**
Line Tension Measurements	✓	×	×	×	✓	×	×
Watch Circle	✓	✓	×	×	×	×	✓
Deep CNNs	×	×	✓	✓	✓	✓	
MoorFDM	✓	✓	✓	✓	✓	✓	✓

5. Conclusion

Mooring operation fault diagnosis and monitoring is a critical and expensive task in the oil and gas industry. An image-based optimized framework MoorFDM is proposed in this research to effectively monitor and diagnose the faults in the mooring operation of marine vessels via object detection and departure angle monitoring of thin mooring lines from images. MoorFDM reports positive results on web-based nautical photos and marine pictures of offshore mooring operations obtained from an oil and gas company. We reduce the cost of mooring monitoring and fault diagnosis by 70-80% compared to the existing solutions that are expensive, inaccurate, and less reliable. Moreover, the proposed research also presents a viable alternative to the inefficient deep CNNs.

Currently, MoorFDM relies on hand-crafted features for thin mooring lines detection and localization and subsequent departure angle monitoring. Employing deep learning mechanisms as a part of future research work improve the procedure. Lastly, we can use photogrammetry to display the final statistics in a realistic graphical view of mooring operations.

References

[1] BROOK A. The design of catenary mooring systems for offshore vessels. In: DYKE P., MOSCARDINI AO, ROBSON EH (eds.) *Offshore and coastal modeling*. New York: Springer-Verlag, 1985, pp. 303-322.

[2] BABICZ J. *Wartsila encyclopedia of ship technology*. Gdańsk: Baobab Naval Consultancy, 2008.

[3] CHAN, J. (2018, Jan 29). *Floating Production Storage and Offloading – FPSO*. Available: https://www.investopedia.com/terms/f/fpso-floating-production-storage-and-offloading.asp

[4]*What is an FPSO?* (2020, Jan 29). Available: https://www.bluewater.com/fleet-operations/what-is-an-fpso/

[5]*Mobile Offshore Drilling Unit (MODUs)*. Wärtsilä Encyclopedia of Marine Technology (14-06-2020). Available: https://www.wartsila.com/encyclopedia/term/mobile-offshore-drilling-unit-(modus)

[6] SUN Y. Mobile offshore drilling unit," ed: Google Patents, 2014.

[7] GIDDINGS I. C. IMO Guidelines for vessels with dynamic positioning systems. In: *Proceedings of the*

Dynamic Positioning Conference, Houston, October 15-16, 2013. Houston: MTS DP, pp. 15-16.
[8] *How do Mooring Systems Work?* RigZone. (Jun 14, 2020). Available: https://www.rigzone.com/training/insight.asp?insight_id=358&c_id=#:~:text=A%20mooring%20line%20connects%20an,Units%20and%20Floating%20Production%20Systems.&text=The%20mooring%20line%20can%20be,a%20combination%20of%20the%20three.
[9] *How Do FPSOs Work?* RigZone (Jan 29, 2020). Available: https://www.rigzone.com/training/insight.asp?insight_id=299&c_id=
[10] *Mooring Systems* (Jan 18, 2019). Available: http://abc-moorings.weebly.com/mooring-systems.html
[11] *Spread Mooring systems* (Mar 23, 2018). Available: https://www.bluewater.com/products-technology/mooring-systems/turret-mooring-systems/
[12] BAI Y. Risk Assessment applied to offshore structures. In: BAI Yong and WEI-LIANG, Jin Marine structural design. 2nd ed., Banbuey: Butterworth-Heinemann Elsevier, 2016, pp. 529-554,. doi: 10.1016/B978-008043921-1/50030-7
[13] JIA Xiaoxu, SUN Ningtao, DIAO Zhidong, CUI Jianwei. Single point mooring system device - Google Patents, 1973. Available: https://patents.google.com/patent/CN102963501A/en
[14] *Choosing Between SPM CALM and CBM Mooring*. Available: https://epcmholdings.com/spm-vs-cbm/
[15] DAUGHDRILL W. H. and CLARK T. OTC 14000 -A. Considerations in reducing risks in FPSO and shuttle vessel lightering operations. In: *Proceedings of Offshore Technology Conference, May 6-9, 2002, Houston, Texas, USA*. Red Hook, New York: Curran Associates, Inc., 2002: 95-101
[16]MA K.-t., SHU H., SMEDLEY P., L'HOSTIs D., and DUGGAL A. OTC-24025-MS- A historical review on integrity issues of permanent mooring systems. In: *Proceedings of Offshore Technology Conference, May 5-8, 2003, Houston, Texas, USA*. Red Hook, New York: Curran Associates, Inc., 2003: 223-229.
[17] LUGSDIN A. Real-time monitoring of FPSO mooring lines, risers. *Sea Technology*, 2012, 53(7): 21-24.
[18] *Gryphon FPSO dislodged by storms*. Offshore. (Mar 19, 2011,). Available: https://www.offshore-mag.com/production/article/16777360/gryphon-fpso-dislodged-by-storms
[19] *Fatality results from failure of ship's mooring fittings and supporting structure*. IMCA. (Feb 06, 2003). Available: https://www.imca-int.com/alert/190/fatality-results-from-failure-of-ships-mooring-fittings-and-supporting-structure
[20] BAI Yong. and BAI Qiang (eds.) *Subsea pipelines and risers*. Beijing: Elsevier Science, 2005.
[21] *Machine learning can make mooring safer and more cost effective*. (Feb 06, 2003) Available: https://www.dnvgl.com/oilgas/perspectives/machine-learning-can-make-mooring-safer-and-more-cost-effective.html
[22] FURLOW W. Monitoring, maintenance of mooring systems help to extend design life of production facilities. *Oil and Gas Facilities*, 2015, 4(04): 020-025. doi: 10.2118/0815-0020-OGF
[23] LECUN Y., BENGIO Y., and HINTON G. Deep learning. *Nature*, 2015, 521: 436-444.
[24] JAISWAL V. and RUSKIN A. Mooring line failure detection using machine learning. In: *Proceedings of Offshore Technology Conference, May 6-9, 2019, Houston, Texas, USA*. Red Hook, New York: Curran Associates, Inc., 2019: 124-132. doi: 10.4043/29511-MS
[25] HUSSAIN S., HASHMANI M., MOINUDDIN M., YOSHIDA M., and KANJO H. Image retrieval based on color and texture feature using artificial neural network. In: *Proceedings of 2nd International Multi-Topic Conference* (IMTIC 2012) *Jashmoro, Pakistan, March 28-30, 2012*. Chennai: Springer Nature: 2012: 501-511:.
[26] ALHUSSAIN H. and BUDIMAN A. A Fully adaptive image classification approach for industrial revolution 4.0. In: *Proceedings of the 3rd International Conference of Reliable Information and Communication Technology (IRICT 2018) Kuala Lumpur, Malaysia, July 23–24, 2018*. Chennai: Springer 2018, 843:311.
[27]JAMEEL S. M., HASHMANI M. A., ALHUSSAIN H., REHMAN M., and BUDIMAN A. An optimized deep convolutional neural network architecture for concept drifted image classification. *Proceedings of SAI Intelligent Systems Conference, London, September 5-6, 2019*. London: SAI, 2019: 932-942.
[28]MORRIS T. *Computer vision and image processing*. London: Palgrave Macmillan, 2004.
[29]REDMON J., DIVVALA S., GIRSHICK R., and FARHADI A. You only look once: Unified, real-time object detection. In: *Proceedings of the 2016 IEEE conference on computer vision and pattern recognition, Las Vegas, June 27-30, 2016*. Piscataway, New Jersey: IEEE, 2016: 779-788.
[30]REDMON J. and FARHADI A. YOLO9000: better, faster, stronger. In: *Proceedings of the 2017 IEEE conference on computer vision and pattern recognition, Honolulu, July 21-26, 2017*. Piscataway, New Jersey: IEEE, 2017: 7263-7271.
[31]LIU W., ANGUELOV D., ERHAN D., SCZEGEDY C., REED S. SSD: Single shot multibox detector. In: *Proceedings of the European conference on computer vision, Amsterdam, October 11-14, 2016*. Amsterdam: Springer, 2016: 21-37.
[32]FU C.-Y., LIU W., RANGA A., TYAGI A., and BERG A. C. DSSD: Deconvolutional single shot detector, *arXiv preprint arXiv:1701.06659*, 2017.
[33]GIRSHICK R., DONAHUE J., DARRELL T., and MALIK J. Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proceedings of the 14th IEEE conference on computer vision and pattern recognition, Columbus, USA, June 23-28, 2014*. Piscataway, New Jersey: IEEE, 2014:580-587.
[34]GIRSHICK R. Fast R-CNN. *Proceedings of the IEEE international conference on computer vision, Santiago, December 11-18, 2015*. Los Alamitos, California: IEEE, 2015:1440-1448.
[35]REN S., HE K., GIRSHICK R., and SUN J. Faster r-cnn: Towards real-time object detection with region proposal networks. In: JORDAN M., LECUNN Y., SOLLA S. (eds.) *Advances in neural information processing systems*, Cambridge, MA: MIT, 2015:91-99.
[36]DAI J., LI Y., HE K., and SUN J. R-FCN: Object detection via region-based fully convolutional networks. In: Advances in Neural Information Processing Systems *29: Annual Conference on Neural Information Processing Systems* 2016, *Barcelona, December 5-10, 2016*. Cambridge,

MA: MIT, 2016:379-387.
[37]HE K., GKIOXARI G., DOLLÁR P., and GIRSHICK R. Mask R-CNN. In: *Proceedings of the 2017 IEEE conference on computer vision and pattern recognition, Honolulu, July 21-26, 2017*. Piscataway, New Jersey: IEEE, 2017: 2961-2969.
[38]HUSSAIN MAS (Sept 21, 2018). *Line Detection using Convolutional Neural Networks*. Available: https://github.com/muneebaadil/line-detection-using-cnns/blob/master/docs/report.pdf
[39]LI X., LI J., HU X., and YANG J. Line-CNN: End-to-End Traffic line detection with line proposal unit. *IEEE Transactions on Intelligent Transportation Systems*, 21(1),2019:248-256.
[40]LIU B., LIU H., and YUAN J. Lane Line Detection based on Mask R-CNN. In: *3rd International Conference on Mechatronics Engineering and Information Technology (ICMEIT 2019), Dalian, March 29-30, 2019*. Beijing: Atlantis Press.
[41]GHAFOORIAN M., NUGTEREN C., BAKA N., BOOIJ O., and HOFMANN M. EL-GAN: embedding loss driven generative adversarial networks for lane detection. In: *Proceedings of the European Conference on Computer Vision (ECCV), Munich, September 8-14, 2018*. Berlin: Springer Science+Business Media, 2018: 234-243.
[42]WANG S.and LU P. On the monitoring of mooring system performance. In: *Proceedings of the 21st SNAME Offshore Symposium, Houston, USA, Feb 16, 2016*. Houston: SNAME Texas Section, 2016:345-351.
[43]KIRYATI N., ELDAR Y., and. BRUCKSTEIN A. M. A probabilistic Hough transform. *Pattern Recognition*, 24(4), 1991: 303-316.
[44]ROSASCO L., VITO E. D., CAPONNETTO A., PIANA M., and VERRI A. J. N. C. Are loss functions all the same? *Neural Computation*, 16(5), 2004:1063-1076.

参考文:

[1] BROOK A. 布魯克 A.近海船的懸鏈繫泊系統的設計。於：DYKE P.，MOSCARDINI A.O.，ROBSON E.H. （合編）海上和沿海建模。紐約：施普林格出版社，1985 年，第 303-322 頁。
[2] BABICZ J. Wartsila 船舶技術百科全書。格但斯克：猴麵包樹海軍顧問公司，2008 年。
[3] CHAN J.（2018 年 1 月 29 日）。浮動生產存儲和卸載 – FPSO。可用：https://www.investopedia.com/terms/f/fpso-floating-production-storage-and-offloading.asp
[4] 什麼是 FPSO？（2020 年 1 月 29 日）。可用：https://www.bluewater.com/fleet-operations/what-is-an-fpso/
[5] 移動式海上鑽井平台（MODU）。瓦錫蘭海洋技術百科全書（14-06-2020）.. 可用：https://www.wartsila.com/encyclopedia/term/mobile-offshore-drilling-unit-(modus）
[6] SUN Y. 移動式海上鑽井裝置，” 編輯：Google Patents，2014。
[7]招標書 I. C. IMO 具有動態定位系統的船舶準則，” “動態定位會議論文集”，2013 年 10 月，第 15-16 頁。
[8]繫泊系統如何工作？ RigZone。（2020 年 6 月 14 日）。可用：https://www.rigzone.com/training/insight.asp?insight_id=358&c_id=#:~:text=A%20mooring%20line%20connects%20an,Units%20and%20Floating%20Production%20Systems.&text= ％20 繫泊％20line％20 可以％20be，％20combination％20of％20the％20three。
[9] FPSO 如何工作？ RigZone（2020 年 1 月 29 日）。可用：https：//www.rigzone.com/training/insight.asp？insight_id = 299＆c_id =
[10] 繫泊系統（2019 年 1 月 18 日）。可用：http：//abc-moorings.weebly.com/mooring-systems.html
[11] 繫泊系統（2018 年 3 月 23 日）。可用：https://www.bluewater.com/products-technology/mooring-systems/turret-mooring-systems/
[12] BAI Y.。風險評估適用於海上結構。在：白勇和魏良，金海洋結構設計。 Banbuey 第 2 版：巴特沃思·海涅曼·愛思唯爾，2016 年，第 529-554 頁。 doi：10.1016 / B978-008043921-1 / 50030-7
[13] J IA ξ AO 卹, sunning 套, DI A oz Hi 動, Cu IJ Ian 為 ..-Google Patents，1973。可訪問：https：//patents.google.com/patent/CN102963501A/en
[14] 在 SPM CALM 和 CBM 繫泊之間選擇。可用：https：//epcmholdings.com/spm-vs-cbm/
[15] DAUGHDRILL W. H.和 CLARK T. OTC 14000 -A。減少 FPSO 和穿梭船打火機操作風險的考慮。在：《離岸技術會議論文集》，2002 年 5 月 6 日至 9 日，美國德克薩斯州休斯頓。紐約紅鉤：Curran Associates，Inc.，2002：95-101
[16] MA K.-t.，SHU H.，SMEDLEY P.，L'HOSTIs D.和 DUGGAL A. OTC-24025-MS-關於永久性繫泊系統完整性問題的歷史回顧。在：《離岸技術會議論文集》，2003 年 5 月 5 日至 8 日，美國德克薩斯州休斯頓。紐約 Red Hook：Curran Associates，Inc.，2003：223-229。
[17] LUGSDIN A. FPSO 繫泊纜，立管的實時監控。海洋技術，2012，53（7）：21-24。
[18] 獅 ry FPSO 被暴風雨沖走。離岸（2011 年 3 月 19 日）。可用：https://www.offshore-mag.com/production/article/16777360/gryphon-fpso-dislodged-by-storms
[19] 死亡是由於船舶的繫泊設備和支撐結構故障所致。IMCA。（2003 年 2 月 6 日）。可用：https://www.imca-int.com/alert/190/fatality-results-from-failure-of-ships-mooring-fittings-and-supporting-structure
[20] 白勇。和白強（ed。）海底管道和立管。北京：愛思唯爾科學，2005。
[21] 機器學習可以使繫泊更安全且更具成本效益。（2003 年 2 月 6 日）可用：https://www.dnvgl.com/oilgas/perspectives/machine-learning-can-make-mooring-safer-and-more-cost-effective.html
[22] FURLOW W.繫泊系統的監視，維護有助於延長生產設施的設計壽命。油氣設施，2015，4（04）：020-025。 doi：10.2118 / 0815-0020-OGF
[23] LECUN Y.，BENGIO Y.和 HINTON G.深度學習。自然，2015，521：436-444。
[24] JAISWAL V.和 RUSKIN A.使用機器學習檢測繫泊纜故障。於：《海洋技術會議論文集》，2019 年 5 月 6 日至 9 日，美國德克薩斯州休斯頓。紐約紅鉤：Curran Associates，Inc.，2019：124-132。 doi：10.4043 / 29511-

MS
[25] HUSSAIN S.，HASHMANI M.，MOINUDDIN M.，YOSHIDA M.和 KANJO H.使用人工神經網絡基於顏色和紋理特徵進行圖像檢索。於：2012 年 3 月 28-30 日，第二屆國際多主題會議論文集（IMTIC 2012），巴基斯坦 Jashmoro。金奈：Springer 性質：2012：501-511 ：。
[26] ALHUSSAIN H.和 BUDIMANA。工業革命 4.0 的完全自適應圖像分類方法。在：2018 年 7 月 23 日至 24 日，第三屆可靠信息與通信技術國際會議論文集（IRICT 2018），馬來西亞吉隆坡。金奈：施普林格 2018，843：311。
[27] JAMEEL S. M.，HASHMANI M. A.，ALHUSSAIN H.，REHMAN M.和 BUDIMANA。一種用於概念漂移圖像分類的優化的深度卷積神經網絡體系結構。 SAI 智能係統會議的會議記錄，倫敦，2019 年 9 月 5 日至 6 日。倫敦：SAI，2019 年：932-942。
[28] MORRIS T.計算機視覺和圖像處理。倫敦：帕格雷夫·麥克米倫（Palgrave Macmillan），2004 年。
[29] REDMON J.，DIVVALA S.，GIRSHICK R.和 FARHADIA。您只需查看一次：統一的實時對象檢測。於：2016 年 IEEE 計算機視覺和模式識別會議論文集，拉斯維加斯，2016 年 6 月 27 日至 30 日。新澤西州皮斯卡塔維：IEEE，2016 年：779-788。
[30] REDMON J.和 FARHADI A. YOLO9000：更好，更快，更強大。於：2017 年 IEEE 計算機視覺與模式識別會議論文集，檀香山，2017 年 7 月 21 日至 26 日。新澤西州皮斯卡塔維：IEEE，2017 年：7263-7271。
[31] LIU W.，ANGUELOV D.，ERHAN D.，SCZEGEDY C.，REED S. SSD：單發多盒探測器。在：歐洲計算機視覺會議論文集，阿姆斯特丹，2016 年 10 月 11 日至 14 日。阿姆斯特丹：施普林格，2016 年：21-37。
[32] FU C.-Y.，LIU W.，RANGA A.，TYAGI A.和 BERG A.C. DSSD：反捲積單發檢測器，arXiv 預印本 arXiv：1701.06659，2017 年。
[33] GIRSHICK R.，DONAHUE J.，DARRELL T.和 MALIK J.豐富的特徵層次結構，用於精確的對象檢測和語義分割，“在第 14 屆 IEEE 計算機視覺和模式識別會議上，美國哥倫布，6 月 2014 年 23 月 28 日。新澤西州皮斯卡塔維：IEEE，2014 年：580-587。
[34] GIRSHICK R.快速 R-CNN。 IEEE 關於計算機視覺的國際會議論文集，聖地亞哥，2015 年 12 月 11 日至 18 日。加利福尼亞州洛斯阿拉米托斯市：IEEE，2015 年：1440-1448 。
[35] REN S.，HE K.，GIRSHICK R.和 SUN J. Faster r-cnn：通過區域提議網絡實現實時目標檢測。在：JORDAN M.，LECUNN Y.，SOLLA S.（編輯）神經信息處理系統的進展中，馬薩諸塞州劍橋：麻省理工學院，2015：91-99。
[36] DAI J.，LI Y.，HE K.和 SUN J. R-FCN：通過基於區域的全卷積網絡進行對象檢測。在：神經信息處理系統的進展 29：2016 年神經信息處理系統年會上，2016 年 12 月 5 日至 10 日，巴塞羅那。馬薩諸塞州劍橋：麻省理工學院，2016：379-387。
[37] HE K.，GKIOXARI G.，DOLLÁRP.和 GIRSHICK R. Mask R-CNN。於：2017 年 IEEE 計算機視覺與模式識別會議論文集，檀香山，2017 年 7 月 21 日至 26 日。新澤西州皮斯卡塔維：IEEE，2017 年：2961-2969。
[38] HUSSAIN M.A.S. （2018 年 9 月 21 日）。使用卷積神經網絡的線檢測。可用：https://github.com/muneebaadil/line-detection-using-cnns/blob/master/docs/report.pdf
[39] LI X.，LI J.，HU X.和 YANG J. Line-CNN：採用線路提議單元的端到端交通線路檢測。 IEEE Transactions on Intelligent Transportation Systems，21（1），2019：248-256（英文）。
[40] LIU B.，LIU H.和 YUAN J.基於模板 R-CNN 的車道線檢測。於：第三屆機電工程與信息技術國際會議（ICMEIT 2019），2019 年 3 月 29 日至 30 日，大連。北京：亞特蘭蒂斯出版社。
[41] GHAFOORIAN M.，NUGTEREN C.，BAKA N.，BOOIJ O.和 HOFMANN M. EL-GAN：嵌入損失驅動的生成對抗網絡以進行車道檢測。在：歐洲計算機視覺會議（ECCV）會議錄，2018 年 9 月 8 日至 14 日。柏林：施普林格科學+商業媒體，2018 年：234-243 頁。
[42] WANG S. and LU P.關於繫泊系統性能的監測。於：2016 年 2 月 16 日在美國休斯敦舉行的第 21 屆 SNAME 離岸研討會論文集。休斯頓：SNAME 德州分會，2016：345-351。
[43] KIRYATI N.，ELDAR Y.和。 BRUCKSTEIN A. M.概率霍夫變換。模式識別，24（4），1991：303-316。
[44] ROSASCO L.，VITO E. D.，CAPONNETTO A.，PIANA M.和 VERRI A. J. N. C.損失函數都一樣嗎？神經計算，16（5），2004：1063-1076。