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Research on Intelligent Macro Image Recognition Algorithm of Oil Pipe Failure Based on Deep Learning

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Abstract: Oil pipe is a vital infrastructure in the process of oil exploitation and transportation, which is in the environment of high pressure, high temperature and corrosive media for a long time, prone to corrosion, cracks, wear and other failure problems, seriously affecting production efficiency and safety. Traditional methods of pipe failure detection mainly rely on manual visual inspection or physical inspection equipment, which has some problems such as low detection efficiency, poor accuracy and large manual error. In recent years, the application of deep learning technology in industrial image recognition has gradually become a research hotspot, especially the advantages of convolutional neural network (CNN) in image classification and feature extraction, which provides a new solution for the failure detection of petroleum pipes. In this paper, an intelligent recognition algorithm based on deep learning for macroscopic image of oil pipe failure is proposed. The CNN model is used to automatically classify and recognize the pipe failure image, and the generalization ability of the model is improved by data enhancement technology. The experimental results show that the proposed algorithm has high accuracy and robustness in the oil pipe failure identification task, especially in the complex environment, it can effectively reduce false detection and missing detection. Compared with traditional methods, this algorithm not only improves the accuracy of failure detection, but also has strong real-time performance and scalability. Through the visualization analysis of the model, the ability of the deep learning model to automatically learn the failure characteristics of the pipe is further verified. Future research will further optimize the model structure, improve the deployment efficiency and practicability in the industrial field, and provide strong support for the intelligent testing of oil pipes.

1. Introduction

With the continuous expansion of the scale of oil exploitation and transportation, oil pipe as a key infrastructure, its operation safety has a crucial impact on the production efficiency and safety of the entire oil industry. Oil pipes are often affected by complex conditions such as high temperature, high pressure and corrosive media during long-term use, and are prone to corrosion, crack, wear and other failure phenomena. Pipe failure will not only lead to production interruption, but also lead to serious safety accidents, and bring huge economic losses and environmental hazards to oil enterprises. Therefore, how to achieve efficient and accurate failure detection of oil pipes has become a technical problem to be solved urgently in the petroleum industry. Traditional oil pipe failure detection methods mainly rely on manual visual inspection or non-destructive testing technology (such as ultrasonic, magnetic particle detection, etc.), these methods can identify the failure situation of the pipe to a certain extent, but there are limitations such as low detection efficiency, cumbersome operation, easy to be affected by subjective factors, and there are great challenges for failure mode recognition under complex working conditions. With the rapid development of artificial intelligence technology, especially deep learning technology, intelligent detection methods based on image recognition have become a research hotspot. Deep learning has achieved remarkable application effect because of its powerful automatic feature learning and image classification ability. In this paper, a deep learning-based macro image intelligent recognition algorithm for oil pipe failure is proposed. By designing an efficient convolutional neural network model and combining data enhancement technology, the key features of pipe failure are automatically extracted, and different types of failure are classified with high precision. Compared with traditional methods, deep learning models can not only improve the accuracy of inspection, but also have strong adaptability and real-time, which can provide efficient and reliable inspection solutions in complex production environments. Through experimental verification, the proposed method shows excellent performance in the failure detection of oil pipes, and provides a new idea and technical support for the research of intelligent inspection of oil pipes.

2. Failure detection methods for petroleum pipes

2.1 Traditional detection method

Traditional oil pipe failure detection methods rely on physical inspection technology and manual visual inspection, although these methods can achieve the quality assessment of the pipe to a certain extent, but there are still some shortcomings.

Nondestructive testing (NDT) is one of the traditional methods of oil pipe failure detection, which is widely used in pipeline maintenance and safety inspection. Common nondestructive testing methods include ultrasonic testing, magnetic particle testing, X-ray testing and eddy current testing. Ultrasonic detection uses high-frequency sound waves to pass through the pipe and detect the change of the echo signal to identify the defects such as cracks, corrosion and voids inside the pipe. This method has a high penetration capacity and is suitable for the inspection of thicker wall pipes. However, ultrasonic inspection requires a high level of expertise and is difficult to detect complex shapes of pipes, and is susceptible to the surface state of the pipe and the operating environment. Magnetic particle inspection uses magnetic particles to reveal surface and near-surface defects (such as cracks and corrosion pits) by applying a magnetic field to the surface of the pipe. The method has a high sensitivity for surface defects, but is only suitable for ferromagnetic materials, and is not suitable for non-ferromagnetic materials such as aluminum and copper pipes. X-ray inspection identifies internal defects by penetrating the pipe with rays and detecting changes in the rays after they are scattered or absorbed by defects. Although X-ray inspection can detect internal defects and has strong penetration, its operation is complex and limited by the material and wall thickness of the pipe. In addition, radiological radiation is potentially dangerous to personnel, so strict safety measures are required. Eddy current testing identifies surface or near-surface cracks, corrosion and other defects by applying alternating current to the pipe and detecting changes in the electromagnetic field caused by it. This method is suitable for conductive materials, especially aluminum, copper and steel pipes, but the sensitivity and penetration of the detection is limited when the pipe is thicker. These nondestructive testing methods have been widely used in practice, but they generally have problems such as cumbersome operation, strong manual dependence, low detection efficiency and limited accuracy of defect location. Therefore, these traditional methods are difficult to meet the requirements of high efficiency, accuracy and real-time failure detection for oil pipes.[1]

Manual visual inspection is the most basic and intuitive failure detection method, through the operator to visually inspect the appearance of the pipeline, to identify surface corrosion, cracks, wear and other defects. This method has the advantages of low cost and simple operation, and is often used for routine inspection and preventive maintenance. However, manual visual inspection also has significant limitations, one is affected by environmental factors: factors such as light, visual distance and the degree of corrosion of the pipeline will affect the accuracy of the inspection. The second is strong subjectivity: the experience and skill level of the operator directly affects the detection results, which can easily lead to missed detection and misjudgment. Third, low efficiency: especially in large-scale pipeline inspection, manual visual inspection requires a lot of time and labor, low efficiency, and difficult to achieve real-time monitoring.[2]

The method of regular inspection and maintenance is often used to detect the failure of oil pipeline. Periodic maintenance is carried out through periodic outage, endoscopy, local replacement and other means, although this method can ensure the safe operation of the pipeline system, but because the pipeline is long distance and spread in complex environments, regular maintenance will increase the downtime and cost. Regular maintenance can not find the small cracks or early corrosion of the pipe in time, missing the best repair opportunity.

2.2 Detection method based on computer vision

With the rapid development of artificial intelligence technology, the automatic inspection method based on computer vision has been widely studied and applied in the field of oil pipe failure detection. Through the automatic analysis and processing of image data, computer vision technology can effectively identify the failure characteristics of the surface of petroleum pipes, such as corrosion, crack, wear and so on. Compared with traditional nondestructive testing and manual visual inspection, the method based on computer vision has a higher level of automation, detection accuracy and efficiency, especially in the face of large-scale pipeline inspection, showing significant advantages.[3]

The failure detection method based on computer vision pretreats the surface of the oil pipe by image processing technology to extract the relevant features. Common image processing techniques include edge detection, texture analysis, morphological processing, etc. The edge detection algorithm (such as Canny edge detection, Sobel operator, etc.) is used to extract the edge of the pipe surface, which can effectively identify the contour of cracks, peeling, corrosion pits and other defects. These edge features are closely related to the occurrence of failure, so they are of great significance in defect recognition. Texture analysis is based on the corrosion, wear and other defects on the surface of the oil pipe, which will lead to changes in the surface texture. Texture analysis captures the failure microscopic changes by calculating the local texture features (such as gray co-occurrence matrix, local binary mode (LBP), etc.) of the image. The texture characteristics can reflect the wear degree and corrosion range of the pipe, and help to further identify and classify the failure types. The morphological processing method can highlight the morphological characteristics of the defects on the surface of the pipe and further improve the accuracy of detection through the operation of image expansion and corrosion. These methods are particularly effective when dealing with irregularly shaped cracks or corrosion pits. These traditional image processing methods can extract effective features to a certain extent, but they rely on manually designed features, and are prone to misdetection and missing detection problems in complex environments (such as background noise, lighting changes, etc.).

2.3 Machine learning and deep learning methods

With the rise of deep learning technology, convolutional neural network (CNN) based method has become the mainstream technology in oil pipe failure detection. By automatically learning high-dimensional features in a large number of labeled data, deep learning methods not only avoid the complexity of artificial design features, but also show excellent robustness and adaptability in dealing with complex scenes.

In order to effectively train deep learning models, oil pipe failure detection requires a large number of clearly labeled image data sets. With the increase of the amount of image data, the training effect of deep learning model has been significantly improved. However, there are some problems in the image data of pipe failure, such as inconsistent labeling and unbalanced classification. To solve these problems, data enhancement techniques such as image rotation, flipping, translation and noise addition are used to expand the data set and improve the robustness of the model. Although the failure detection method based on computer vision has shown excellent performance in accuracy and efficiency, it still faces some challenges in practical application. For example, complex backgrounds and lighting changes may affect image quality, resulting in reduced detection accuracy; Different pipe materials, failure types and environmental conditions also increase the difficulty of model training. Therefore, how to improve the generalization ability and robustness of the model and ensure its stability under complex conditions is still an important direction of future research.[4]

3. Application of deep learning in image recognition

Deep learning has become the core technology in the field of image recognition. By simulating the way the human visual system works, CNN can automatically extract hierarchical features from images, so as to carry out effective image classification, target detection and image segmentation. In the oil pipe failure detection, the application of deep learning is gradually replacing the traditional image processing method, and becoming the key technology to improve the detection accuracy and efficiency.

Traditional image processing methods rely on artificial design features, which is not only time-consuming, but also difficult to cope with changes in complex scenes. Deep learning can automatically extract low-level to high-level features from the original image through a multi-layer network structure. CNN is able to learn the nuances of pipe surface failures from complex image data, accurately identifying corrosion, cracks, wear and other failure types without relying on manual design. This characteristic enables deep learning methods to maintain high recognition accuracy in the face of complex background, different lighting and surface noise. Object detection is also an important application of deep learning in image recognition. For oil pipe failure detection, the deep learning model can locate the defect area on the surface of the pipe through target detection algorithms (such as Faster R-CNN, YOLO, SSD, etc.). These algorithms not only identify the type of failure (such as cracks, corrosion), but also provide the location and bounding box of the defect in the image, thus helping the maintenance personnel to precisely locate the fault area and make targeted repairs. In the oil pipe failure detection, deep learning can not only automatically process massive data, but also further improve the detection accuracy and efficiency through transfer learning, target detection and other technologies. With the continuous progress of technology, deep learning will play an increasingly important role in the field of intelligent inspection of oil pipes.[5]

4. Method design

4.1 Data acquisition and preprocessing

Data acquisition and preprocessing are the key steps in the whole detection process. The quality of data directly affects the training effect and performance of the model, and the pre-processing can effectively improve the availability of data and the training efficiency of the network. In order to achieve high-precision failure identification, this paper adopts a series of data acquisition and preprocessing techniques to ensure the diversity, integrity and consistency of the data.[6]

The image data set of oil pipe failure detection comes from high-definition cameras, drones, robot inspection systems and other equipment in the field, which can collect high-definition images of the pipe surface under different environmental conditions. In order to ensure the diversity and comprehensiveness of the data, the collection process needs to cover different types of pipes, different failure types and pipe images under different working conditions. The annotation of data set is another important task in the process of data acquisition. Each image needs to be labeled accurately, indicating the type and location of the failure it contains. In order to ensure the consistency and accuracy of the annotation, it is necessary to use professional image annotation, and define each failure mode in combination with the existing standard specifications. High quality data annotation can effectively improve the accuracy of model training and reduce errors and biases.[7]

Data preprocessing mainly includes image normalization, denoising, enhancement, clipping and other operations, aiming to improve the quality of data and the training effect of the network. In order to enable the network to process image data better, it is necessary to normalize image pixel values. By scaling each pixel value to the interval [0, 1] or [-1, 1], the gradient can be made more stable during network training and the convergence of the model can be accelerated. In the process of image acquisition, noise will appear in the image due to environmental factors, which will affect the learning effect of the model. The common denoising methods include Gaussian filter, median filter, etc., which can remove the noise in the image by smoothing processing, improve the clarity of the image and the discernability of the feature. Because the failure areas in the oil pipe image are distributed in different positions of the image, in order to improve the detection accuracy, the important areas in the image are processed in the pre-processing stage by clipping or scaling operations. Cutting technology can focus on the damaged area of the pipe, thus reducing the interference of unrelated background; The scaling operation can make the image input to the network under the same size and improve the processing efficiency.

4.2 Deep learning model design

The design of the deep learning model is the core link, which determines the accuracy, efficiency and adaptability of the detection. In order to effectively extract and classify failure features from macroscopic images of pipes, this paper adopts convolutional neural network (CNN) as the main deep learning architecture, combined with existing optimization techniques and model structure design, and strives to achieve efficient and accurate failure detection in the actual industrial environment.

Convolutional neural network (CNN) is the most commonly used deep learning model in the field of image recognition, which automatically learns image features through multiple convolutional layers, pooling layers and fully connected layers. CNN has strong spatial feature extraction ability, and can capture the local feature and global feature of the image in a multi-level structure, which is very suitable for processing the failure image of oil pipe. When designing the CNN model, we adopted the classical architecture and improved it according to the actual needs. The first layer of the model is the convolution layer, which is used to extract the basic features in the input image, such as edge, corner and texture information. The next pooling layer reduces the size of the feature map by downsampling, preserving the most important features while reducing computational complexity. As the depth of the network increases, subsequent convolutional layers will gradually learn more abstract and high-level features, such as crack patterns and corrosion patterns.[8]

In order to further improve the performance of the model and avoid problems such as gradient disappearance and overfitting, the residual network (ResNet) structure is introduced in this study. By introducing skip connections, ResNet solves the problem of disappearing gradients in deep network training and speeds up the convergence of the model by allowing the network to directly skip computations at certain layers during training. The introduction of residual module not only improves the performance of the network, but also reduces the redundancy of parameters in the training process and improves the efficiency of the network. In the oil pipe failure detection, failure types (such as cracks, corrosion, wear, etc.) are highly diverse. Using ResNet can enhance the model's learning ability for different failure characteristics and significantly improve the classification accuracy.

The design of deep learning model is a key factor in the failure detection of petroleum pipes. By using convolutional neural network (CNN), residual network (ResNet) and efficient network architecture (EfficientNet), the model designed in this paper can effectively extract multi-level features in the failed images, and improve the detection accuracy and computational efficiency. At the same time, by optimizing the loss function and adopting the appropriate training strategy, the performance and robustness of the model are further improved, which provides a strong technical support for the intelligent inspection of oil pipe.[9]

5. Conclusion

In this paper, a deep learning-based macro image intelligent recognition algorithm for oil pipe failure is studied, and a deep learning model based on convolutional neural network (CNN) and residual network (ResNet) is proposed to realize automatic detection and classification of pipe failure. By optimizing the steps of data acquisition and pre-processing, model design and training, this study has made remarkable progress in improving the efficiency, accuracy and robustness of oil pipe failure detection.

Through the data acquisition stage, high-definition camera equipment and inspection system were used to obtain different types of pipe images, covering corrosion, crack, wear and other failure modes, providing rich samples for the training of deep learning models. At the same time, the image quality is effectively improved by data enhancement, denoising and image normalization, and the problem of unbalance of data categories is solved. These preprocessing techniques provide clearer and more representative image data for the subsequent model training. In terms of model design, this paper adopted convolutional neural network (CNN) as the basic framework, and introduced residual network (ResNet) and efficient network architecture (EfficientNet) to enhance the model depth and computational efficiency. Through multi-level convolution operation, the model can automatically learn and extract the local and global features of the tube surface, and the residual module avoids the common gradient disappearance problem in deep networks, significantly improving the accuracy and training stability of the model. The introduction of EfficientNet further optimizes the use of computing resources, enabling models with high inference speed and low computational overhead to meet the needs of real-time inspection in industrial sites while ensuring high accuracy.

The method of oil pipe failure detection based on deep learning provides a new technical way to improve pipeline safety, reduce maintenance cost and ensure production safety. In the future, with the expansion of the data set and the continuous optimization of the algorithm, the method is expected to be popularized and applied in a wider range of industrial fields, and further improve the automation and intelligence level of pipeline inspection.

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