Design of intelligent rain-polluted pipeline inspection robot based on embedded vision

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ABSTRACT

The structure and size of urban underground sewage pipes are varied and the environment inside them is complex and changeable. The local damage and blockage will threaten people's lives and property safety and cause disastrous consequences. Traditional artificial pipeline inspection is time-consuming, laborious, and prone to misdetection and missing detection. Therefore, it is of great significance to design an intelligent pipeline robot based on deep learning to carry out inspection of pipeline visual defects and effectively prevent pipeline lesions. In this paper, the hardware structure of the wheeled robot with amphibious crawling ability is designed first, and the robot's motion control under complex conditions in the tube is realized. Then, the detection algorithm based on deep learning is carried out to complete the detection and type identification of the pipeline. Deploy the trained deep learning model to the Jetson Nano embedded device while accelerating the model's reasoning process using TensorRT. The test results show that the inspection robot can effectively identify the pipeline defects and the recognition rate of the type of pipeline defects reaches 88.2%, which confirms the feasibility and effectiveness of the proposed technology.

CCS CONCEPTS

• **Computer systems organization** → Embedded and cyber-physical systems; Robotics; Robotic autonomy.

KEYWORDS

Rain-polluted, Patrol robot, Embedded vision, deep learning

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1 INTRODUCTION

A large number of rain-polluted pipes in urban underground pipe networks have to pass through various complex terrain conditions. With the increase in service life, problems such as blockage, rupture, leakage, and misopening are likely to occur due to corrosion, heavy pressure, and other factors, which seriously threaten people's life and property safety and affect transmission efficiency [1]. At present, the more mature pipeline inspection technology is mainly divided into two categories: manual and machine and its application process has experienced a technological change from equipment to man-assisted equipment. As shown in Figure 1, pipeline inspection has problems such as high labor intensity, low efficiency, and inability to adapt to more and more application scenarios. In comparison, the pipeline inspection robot shown in Figure 2 carries a camera and can move in the pipeline. Technicians can obtain the situation in the pipeline photographed by the robot through wired or wireless means, control the movement of the robot, and detect the pipeline. Therefore, it is of great significance to use mobile robots for pipeline defect detection to find an effective way to prevent pipeline lesions, extend service life, and improve pipeline integrity management.

At present, the widely used closed-circuit television (CCTV) system conducts regular inspections of sewage pipes, and the detection process relies on manual data collection analysis and evaluation, which is prone to human error [2]. Moreover, the special pipeline robots studied by various countries can only be limited to waterless pipeline environment detection due to their weak crawling ability. With the development and application of machine vision and artificial intelligence (AI), this paper proposes to integrate intelligent mobile robot technology with embedded machine vision to develop an efficient and accurate automatic pipeline defect detection robot. Based on the Keras+Tensoflow deep learning framework, the robot is equipped with NVIDIA's Jetson Nano small intelligent computer and uses a convolutional neural network (CNN) to automatically detect defect types and mark defect locations. Meanwhile, the wheeled robot can crawl to adapt to different working conditions. It can be gradually applied to the operation and maintenance of natural rain-polluted pipelines.

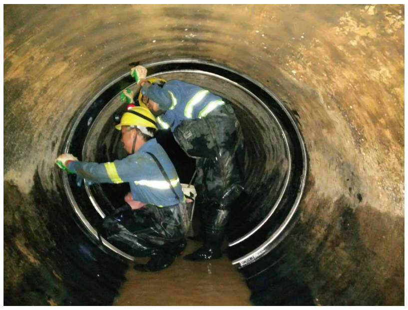

Figure 1: Manual pipeline inspection.

Figure 2: Machine pipeline inspection.

2 SYSTEM HARDWARE DESIGN

In this section, the hardware structure of the pipeline inspection robot is described, as shown in Figure 3. By controlling the walking robot to identify the defect image in the pipeline, and using the water level sensor to collect the corresponding environmental data in the pipeline, urban waterlogging management is realized. The hardware structure mainly consists of three parts: walking mechanism, sensing mechanism, and control mechanism.

2.1 Running gear

The walking structure, as shown in Figure 4, includes the robot body, wheel assembly, and two synchronous transmission belts inside. The body of the pipeline robot adopts a slender split design, which can be disassembled into three parts: the bow weight cabin, the middle closed body, and the rear weight cabin. Among them, the head is a ship-type counterweight cabin [3], and the front counterweight cabin is a bow arc design, which reduces the crawling resistance of the car body in water and silt, and has better adaptability when crossing obstacles. The wheel is a crawling mode of the machine car through the combination of six small wheels on the inside and four wheels on the outside. There are three solid rubber wheels with a diameter of 100mm on the inside and two inflatable high-pattern rubber tires with a diameter of 250mm on the outside [4]. When turning in the pipeline operation, the six wheels increase the ground gripping ability and reduce the possibility of wheel suspension. They're also better able to navigate obstacles. In addition, replacing different diameter wheels can be well adapted to different pipe diameters.

2.2 Sensing mechanism

Sensing modules include a platform, high-precision liquid level sensor, water quality sensor, and LED lighting. Through the high-precision liquid level sensor installed in the body, the change in water level in the pipe can be sensed. When the water level inside the pipe is high or there are more obstacles, the lifting function of the head can fix the camera at the appropriate height [5], which improves the adaptability of the pipeline robot to the complex tube environment. At the same time, high-precision liquid level and water quality sensors are integrated into the perception information to complete environmental monitoring and water level monitoring in the pipeline and lay a foundation for effective prevention such as urban waterlogging management and water quality pollution traceability in the city. The platform is equipped with a camera, lifting frame, platform chassis, and LED lights. The camera is installed above the platform through a 360° steering gear to realize 360° rotation of the camera, and the image signal is transmitted to the control module of the upper computer through Ethernet in real-time. LED lights are placed on the outside of the fuselage to detect the environment inside the pipe and provide a wider view.

2.3 Control structure

The mechanism comprises a main control module, a data transmission module connected with the main control module, a host computer control module used to send user operation instructions and a motor drive control module connected with the main control module.

1) The main control module is an embedded control motherboard based on STM32F103C8T6, which analyzes the control instructions of the upper computer control module through serial communication and drives the robot modules to work together.

2) The upper computer control module is the NVIDIA Jetson Nano computer as the advanced controller of the whole robot. It is a highly integrated and cost-effective deep learning embedded core processor based on ARM Cortex architecture, which is suitable for deployment on special occasions to detect robots. The upper computer control module can provide a visual robot operation interface to the user and can control the behavior of the robot by sending instructions to the robot. At the same time, the image data, sensor data, robot status, and other information collected by the camera are displayed through a visual interface.

3) Motor drive part of the motor selection is M3508 DC brushless gear motor, power P=240W, torque T=3Nm. By controlling the pulse width modulation (PWM) of the motor driver, the speed of the motor is precisely adjusted to realize the flexible movement of the robot.

4) The data transmission module includes the intelligent routing chip model MT7620A, which can simultaneously provide wireless (Wi-Fi) and wired (Ethernet) data transmission methods to communicate with the control module of the upper computer. (Since the underground pipeline is seriously shielded from wireless signals, this paper adopts a wired method for data transmission. But at the same time, it also retains the wireless transmission interface), which is used to transmit the communication data between the main control module and the upper computer control module [6].

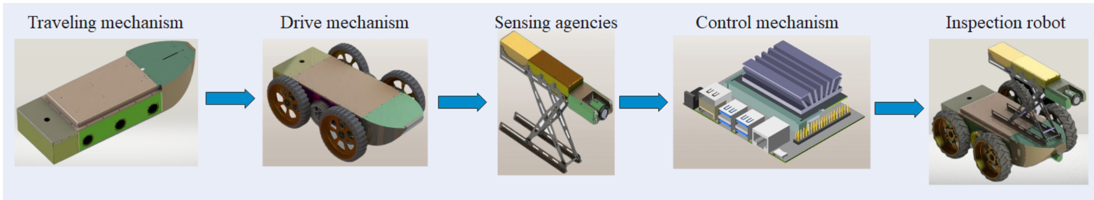

Figure 3: Hardware structure diagram.

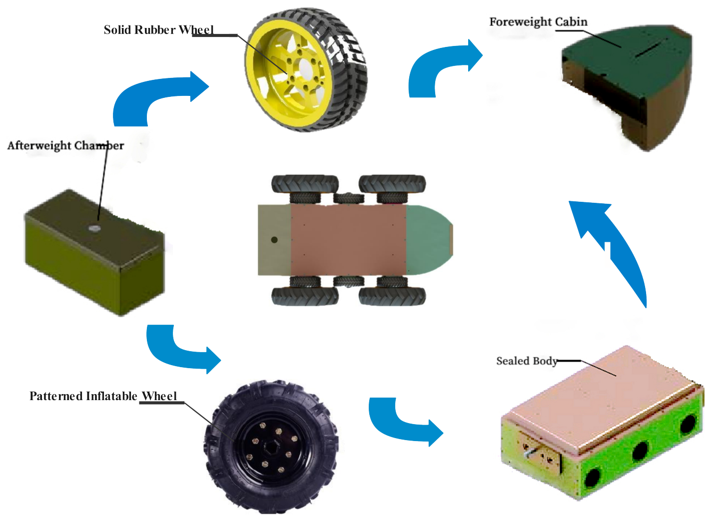

Figure 4: Traveling mechanism diagram.

3 SYSTEM SOFTWARE DESIGN

The software realization of a pipeline inspection robot with embedded machine vision mainly consists of two modules: image recognition of the upper computer control module and drive control of the lower computer main control module. Among them, the upper computer realizes the pipeline detection and defect marking based on a convolutional neural network, the lower computer realizes the driver cooperation of the underlying modules through STM32, and the two realize data transmission through USB to serial port communication.

3.1 System software

The main function of the pipeline inspection robot is to control the corresponding walking module through the motor drive control module, so that the robot can collect the internal information of the pipeline through the camera, automatically detect the defect type, and mark the defect location. First of all, the robot is started to determine whether the communication is normal, and then the rotation of the motor is driven by controlling the PWM duty cycle to ensure the movement of the pipeline robot. Then, the image collection of defects inside the pipeline is carried out. When an insufficient light source inside the pipeline is detected, the LED lighting on the platform is automatically turned on to ensure the quality of the captured images and the LED light is turned off after the collection is completed. To achieve the purpose of saving energy. Finally, upon receiving the exit command, the control system is shut down and returned to the specified position. The robot software flow is shown in Figure 5.

3.2 Deep learning algorithm

The convolutional neural network model is widely used in image recognition by replacing the full connection between network layers with the operation of convolutional image feature acquisition. The pipeline inspection robot takes the completion of pipeline detection and type recognition as its application scenario and constructs a convolutional neural network model of a small-scale image data set based on the modular Keras+Tensorflow framework [7]. The cross-entropy loss function and Adam optimization algorithm were used to implement the convolutional neural network model for the visual classification of pipeline defects on the embedded NVIDIA Jetson Nano platform.

Convolutional neural network training, image accurate recognition, and embedded system deployment. The production module of the custom dataset preprocesses and labels 5032 pictures collected online, and labels 7 types of labels from the images: cracks, joint, deformation, holes, infiltration, deposit, and root. After the tagged images are obtained, the 7 types of tagged images are expanded in the process of the data enhancement module, including random rotation, cropping, and brightness enhancement, to improve the accuracy of the test. After the data set is expanded, the training set

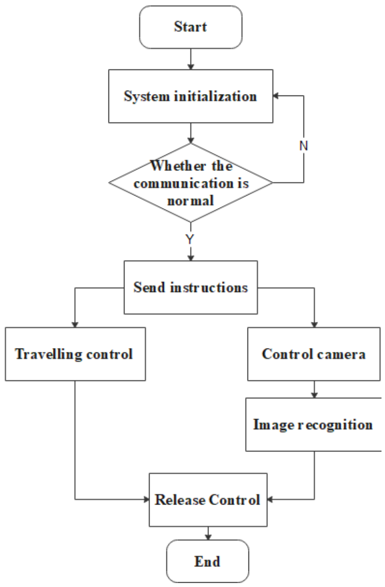

Figure 5: Robot software flow chart.

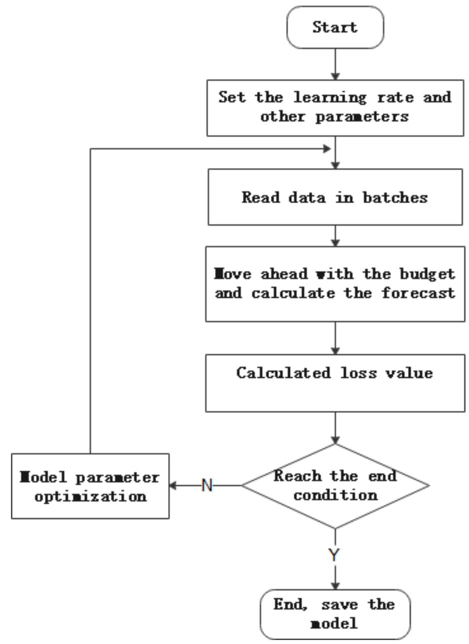

Figure 6: Deep learning training flowchart.

and test set are divided proportionally for the subsequent training of the CNN network. After the network is constructed, it first learns and adjusts the weight parameters continuously according to the training data set, then converges the model's loss function curve by relying on the cross-entropy loss function, and finally adjusts the weight value of the network by using Adam in the adaptive learning rate optimization method for error backpropagation. The training process is shown in Figure 6. The embedded deployment module introduces the trained convolutional neural network model file on the computer and uses NVIDIA's neural network inference engine TensorRT to optimize and accelerate the deployment of the deep learning model on the NVIDIA Jetson Nano platform. The specific identification process of the upper computer is shown in Figure 7.

4 EXPERIMENT

In order to test whether the function of the pipeline inspection robot is finally realized, and the reliability of the whole system is tested. In this paper, a test platform was built, as shown in Figure 8, and the normal output environment experiment test of pipeline robot was carried out. The hardware configuration for the computer deployment training model is an Intel7 processor, 8GB of memory, and NVIDIA GTX 1060.

4.1 Model test

By using Keras interface, Tensorflow as the back-end, Python as the programming language, Adam in the adaptive learning rate optimization method was used as the model optimizer for training. After training, the model loss function and the accuracy curve have converged, and the recognition accuracy rate has reached 95.62%. Higher recognition effect was achieved under the influence of model data enhancement, and the curves of model-related validation recognition accuracy and loss function were shown in the line figure 9.

4.2 Exercise testing

In a complex pipeline environment, the robot is started to crawl on a pipeline with an inner diameter of D=500mm and a length of L=5m. By studying the crawling ability of the robot when it enters the pipeline from flat ground and testing the speed stability performance when it walks in a straight line, the experimental results are shown in Table 1. It can be seen from the experimental data that the average measured speed error of 15 straight experiments is below 4%, so the robot can control reliably after issuing control instructions.

4.3 Defect identification test

After model deployment was completed in Jetson Nano, the above verification data set was used to identify and verify the pipeline defect type of the robot, ensuring the accuracy of defect image detection after deployment. The correct number of different defect images identified after the test is shown in Table 2. It can be seen from the table that the experimentally trained model algorithm can detect pipeline defects and effectively distinguish the types of pipeline defects. Although the characteristics of root defects are obvious in the types of pipeline defects, resulting in a high recognition accuracy rate, the overall recognition accuracy rate has been achieved, and a good detection effect has been achieved.

5 CONCLUSION

This paper is an embedded vision intelligent pipeline inspection robot designed for the application scenario of preventing pipeline

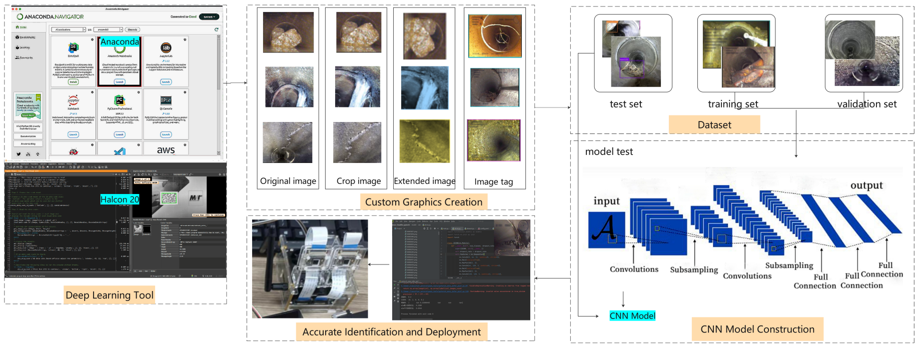

Figure 7: Upper computer identification method flow design drawing.

Table 1: Robot motion test sheet

Wheel linear speed	Time	Straight distance (Average)	Straight time (Average)	Actual speed (Average)	Error (Average)
8.85 m/min	5 times	5m	33.02s	9.083 m/min	2.63%
13.27 m/min	5 times	5m	22.43s	13.369 m/min	0.75%
17.69 m/min	5 times	5m	16.52s	18.161 m/min	1.39%

Table 2: Identification defect result

Defect Type	Test condition	Test sample	Test result	Precision
Cracks	Normal light	789 times	687 times	87.07%
Joint	Different light	584 times	466 times	79.79%
Deformation	Normal light	675 times	594 times	88.00%
Holes	Different light	509 times	468times	91.94%
Root	Normal light	478 times	461 times	96.44%
Infiltration	Different light	547 times	487 times	89.03%
Deposit	Normal light	467 times	398 times	85.22%

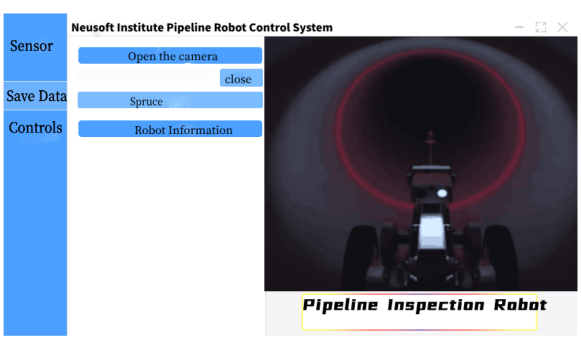

Figure 8: test platform.

lesions. The pipeline inspection machine uses Keras+Tensoflow to build a convolutional neural network model, combines a convolutional network with machine vision technology, and is deployed to the Jetson Nano embedded device to recognize and classify the target object. The lower machine uses the STM32 controller as the core to integrate into the walking structure of the inspection robot for inspection tasks. The experimental tests show that: 1. The slender split structure design of the pipeline robot can ensure the stability of the robot's crawling ability in the complex pipeline environment. 2. The convolutional neural network deployed on the embedded device can detect the internal defect information of the pipeline well, which greatly overcomes the problem that the embedded device is difficult to operate on specific occasions in the pipeline, reduces the cost, and makes up for the shortage of manual inspection, and has good practical value. 3. The detection part of the system adopts a CNN network, which has limited performance in detection. In the later stage, new lightweight deep learning algorithms can be further developed to improve the real-time stability of automatic defect detection in the tube.

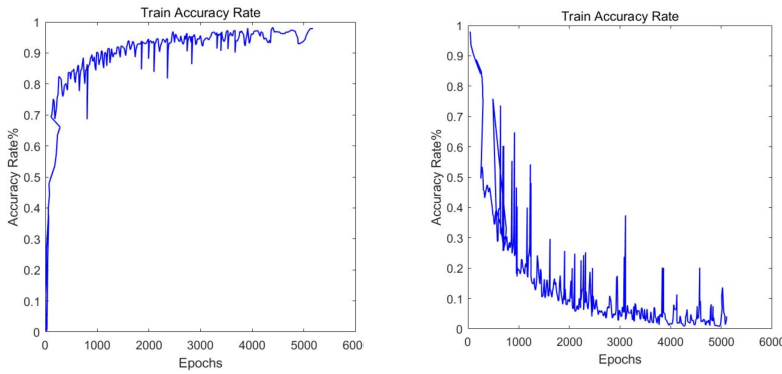

Figure 9: Linear graph of accuracy and loss function.

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