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Study and Design of a Pipe Surface Inspection Robot

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ABSTRACT: *Monitoring and maintaining industrial pipeline systems remain complex tasks that require intelligent inspection approaches to improve operational efficiency and reduce human exposure to hazardous environments. Recent advances in artificial intelligence, embedded systems, and mobile robotics have accelerated the development of automated solutions capable of detecting early signs of deterioration with improved reliability. In this study, learning-assisted visual inspection and Internet-of-Things (IoT) connectivity are integrated to realize real-time monitoring and surface-condition recognition for pipeline infrastructure. The proposed system is built around an ESP32-CAM microcontroller and combines an HC-SR04 ultrasonic sensor for obstacle avoidance with a DHT22 sensor for temperature and humidity acquisition. In addition, an RC522 RFID module is incorporated to support robot localization at predefined inspection points inside the pipe. Experimental results indicate that the robot operates stably on both flat and curved surfaces under a payload of 1-3 kg, while achieving a temperature error of approximately ±1.7°C and a distance-measurement error of about ±2 cm. These findings confirm the feasibility and operational stability of the prototype, suggesting that the proposed model can support industrial infrastructure monitoring and automated pipeline-safety inspection.*

Keywords: *Pipeline monitoring; autonomous robot; ESP32-CAM; IoT; smart sensors.*

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I. INTRODUCTION

Ensuring safety and maintaining the integrity of technical infrastructure are fundamental requirements for sustainable development. Along with rapid industrialization and modernization, many countries are facing increasingly serious challenges in maintaining oil, gas, and water pipeline networks, which serve as critical lifelines for economic stability and social welfare. Among these challenges, pipeline degradation caused by corrosion, cracking, and environmental effects has become an urgent global issue. Practical evidence shows that conventional pipeline inspection is expensive and may expose personnel to considerable safety risks [1]. These trends highlight the need for scientifically grounded, efficient, and sustainable monitoring and inspection solutions that can reduce industrial losses and support the long-term stability of urban infrastructure.

In Vietnam, recent economic growth has been accompanied by the expansion of oil-transmission and water-supply networks in large urban areas and industrial zones. Surface inspection of pipelines is widely regarded as a necessary condition for improving maintenance efficiency and mitigating adverse environmental impacts. Although several initiatives have been introduced, including periodic inspection programs and stricter technical regulations, overall effectiveness remains limited. The gap between policy objectives and practical outcomes can largely be attributed to fragmented implementation, continued reliance on direct human labor, and persistent limitations in monitoring equipment. In particular, the absence of compact automated systems capable of accessing deeply buried or confined pipelines has increased the operational burden on industrial infrastructure-management systems [2], [4].

Against this background, pipeline monitoring and inspection technologies have expanded significantly in both scope and complexity. Autonomous robots integrated with computer vision are increasingly recognized as a promising approach for improving inspection efficiency. By exploiting image-processing techniques and wireless communication, robotic platforms can identify and analyze damage indicators from visual features on pipe surfaces. The integration of visual inspection reduces dependence on manual observation in hazardous locations and improves the accuracy and automation level of crack, leakage, and corrosion detection. Such approaches are particularly suitable for deployment in oil refineries, urban drainage systems, and irrigation facilities [3], [5]. Therefore, robot-based pipeline monitoring can be considered a key enabling component for future intelligent infrastructure-management systems.

In recent years, although technological awareness in Vietnam has increased, the adoption of autonomous robotic methods for pipeline inspection has remained relatively limited and still faces many practical challenges. By contrast, both domestic and international studies have extensively investigated tank-climbing robots and exploration robots for non-destructive inspection [2], [6]. For example, previous works have developed the VIAM-ROV600 robot model for hydraulic-structure surveys [3], as well as specialized robots for urban drainage systems [5], [7]. Nevertheless, the integration of environmental sensors, such as temperature and humidity sensors, with magnetic-card or RFID-based localization in confined spaces remains a research direction that requires further optimization to enhance monitoring effectiveness.

Overall, practical deployments and academic studies both emphasize the considerable potential of combining robotic technology with the Internet of Things (IoT) for automated infrastructure monitoring. This research direction not only addresses the remaining gap in pipeline-inspection automation in Vietnam but also demonstrates strong practical applicability for industrial zones, educational institutions, and smart urban environments. This study focuses on the design of a pipe-surface inspection robot based on the ESP32-CAM platform and smart sensors, with the aim of providing a stable and cost-effective solution for current industrial maintenance problems.

II. MATERIAL AND METHODOLOGY

2.1 Overview of the inspection robot system

Figure 1 presents the overall structure of the proposed pipe-surface inspection robot, which is designed to provide real-time visual monitoring and environmental-parameter measurement on a resource-constrained embedded platform. The architecture is organized into three main modules: the central processing unit, the environmental sensing and recognition unit, and the locomotion actuator unit. This modular configuration supports efficient information flow and enables accurate data acquisition on different pipeline surfaces.

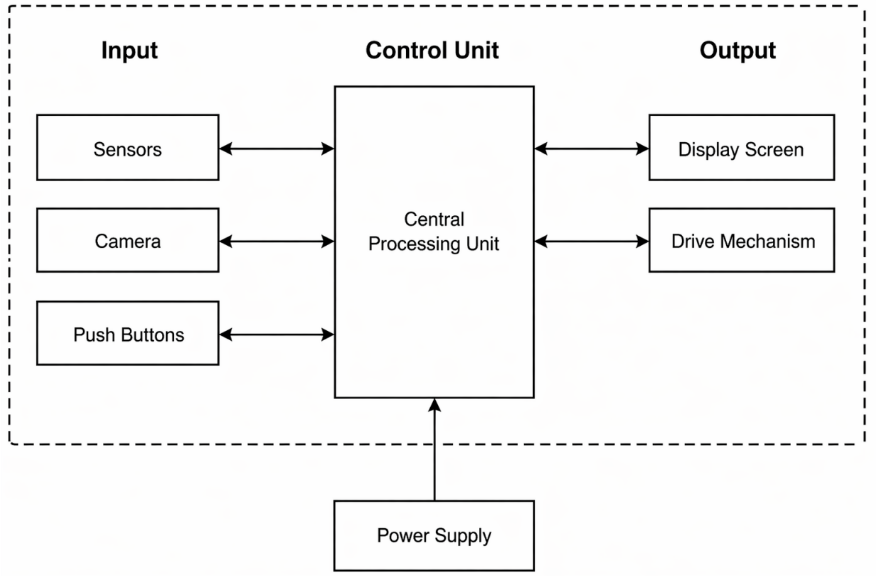

Figure 1: Block diagram of an inspection robot control system

The central processing unit uses ESP32 and ESP32-CAM microcontrollers, which are responsible for acquiring live images from the pipe surface and establishing a web server for wireless data transmission. Owing to the integrated Wi-Fi capability, the processing unit allows operators to remotely observe potential damage, such as cracks or leakage, without direct access to hazardous locations.

The sensing module functions as the environmental perception layer of the robot. It collects multidimensional data through the coordinated operation of several specialized sensors. The HC-SR04 ultrasonic sensor is integrated to estimate the distance to obstacles, allowing the robot to optimize its trajectory and adjust its direction flexibly in the confined space of the pipeline. During motion, the DHT22 sensor continuously updates temperature and humidity values inside the pipe, thereby providing important data for assessing corrosion risk and monitoring actual operating conditions.

Actuation and control unit: This module employs an L298N H-bridge driver to control the geared DC motors. The configuration provides adequate responsiveness and maneuverability, enabling the robot to carry a payload of 1-3 kg while operating on both flat and curved pipeline surfaces.

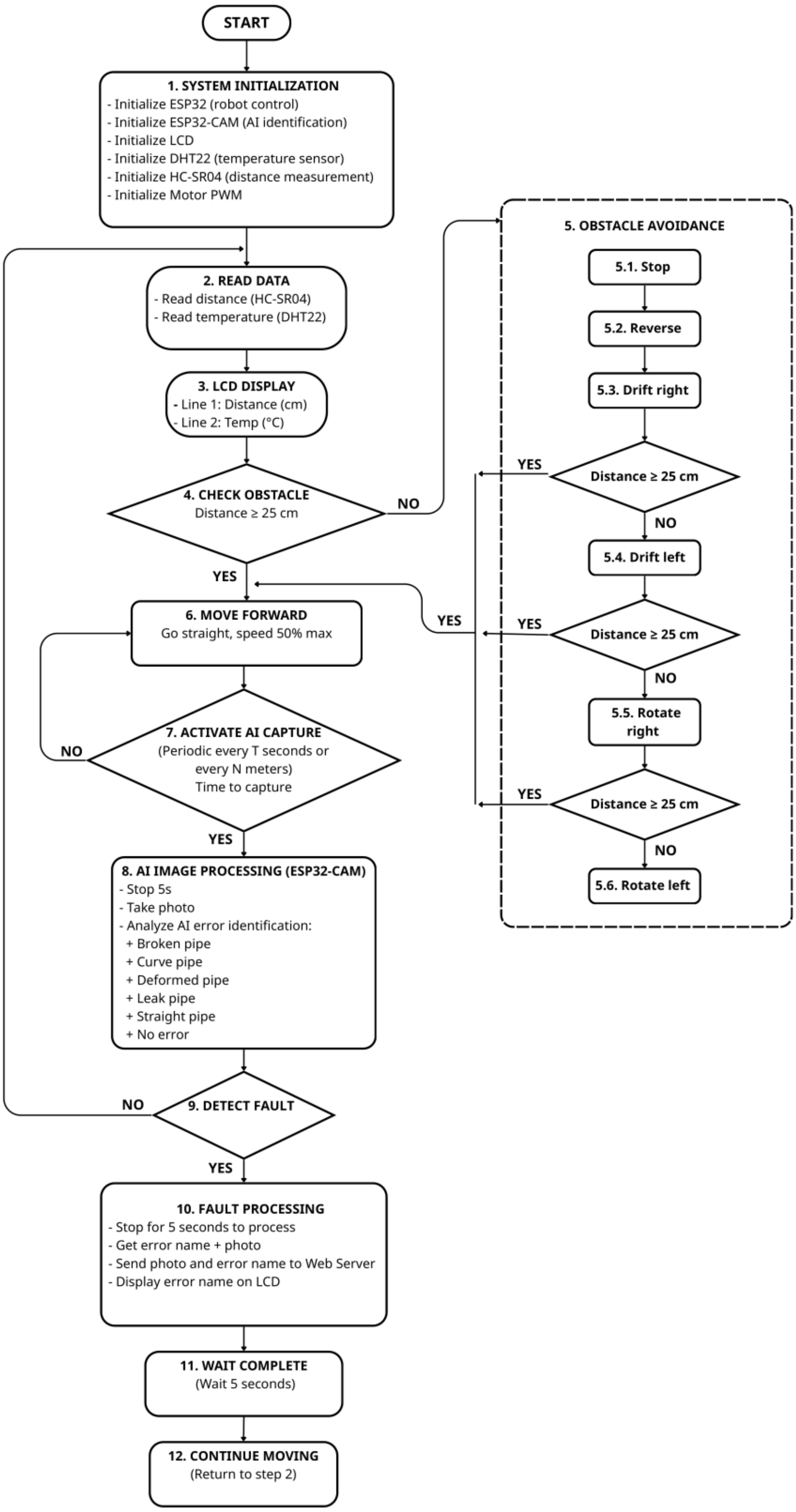

Figure 2: Algorithm flowchart of the pipeline inspection robot

Based on the system overview, the control and monitoring algorithm for the AI-integrated pipeline inspection robot is summarized in Figure 2. At startup, the system initializes the hardware components, including the ESP32 motion controller, the ESP32-CAM for image acquisition and recognition, the HC-SR04 ultrasonic distance sensor, the DHT22 temperature-humidity sensor, the I2C LCD, and the PWM motor controller. After initialization, the robot continuously reads distance and temperature data while displaying operational parameters on the LCD, allowing users to track the system status in real time.

During movement, the robot performs obstacle avoidance using data from the HC-SR04 sensor. When the measured distance is lower than the predefined threshold of 25 cm, the robot stops, reverses, and executes turning actions to find a safe path before resuming operation. In parallel, the ESP32-CAM periodically captures images for AI-assisted pipe-defect recognition, including cracks, deformation, and leakage. If a defect is detected, the system temporarily stops the robot, stores the defect image, uploads the relevant information to the web server for remote monitoring, and displays the fault status on the LCD. After the processing interval, the robot returns to the monitoring loop to maintain continuous and autonomous pipeline inspection.

2.2 Data collection, preprocessing, and dataset construction

Data collection is a key step in developing a robust pipeline inspection robot. In this study, a multilayer acquisition procedure is established by combining physical environmental parameters with a real-time visual data stream to ensure accuracy and reliability. The experimental data are classified into three main categories, as detailed in Table 1.

Table 1: Data categories for monitoring-system operation

Data Category	Acquisition Device	Monitoring Purpose
Temperature and humidity parameters	DHT22 sensor	Monitoring environmental temperature and humidity conditions
Obstacle distance	HC-SR04 ultrasonic sensor	Distance measurement for motion control and collision avoidance
Visual inspection data	ESP32-CAM module	Real-time image capture for detecting cracks, leakage, and surface defects

Throughout the experimental stage, each monitored object in the system exhibits distinct technical characteristics in terms of morphology and physical structure. These characteristics are summarized in Table 2 to support accurate observation and fault analysis under practical operating conditions.

Table 2: Recognition characteristics of monitored objects

Object	Shape Characteristics	Image Features	Surface Structure
Pipe crack / rupture	Cracks, fractures, or elongated holes along the pipe	High contrast relative to the surrounding surface; usually darker at the damaged region	Mechanical failure may be accompanied by deformation or material peeling
Leakage point	Diffuse regions or spots	Reflectivity and color variation caused by moisture	Liquid accumulation on the surface
Deformation	Geometric misalignment or distortion	Loss of symmetry and changes in the pipe cross-section	Surface may be dented, warped, or bent
Straight pipe	Straight and continuous geometry along a defined direction	Uniform appearance without visible distortion	Stable surface with no bending, cracking, or deformation

Object	Shape Characteristics	Image Features	Surface Structure
Curved pipe	Smooth curvature with continuous directional change along the bending radius	Gradual curvature with consistent perspective change along the pipe length	Curved structure while maintaining material integrity

This integrated approach is intended to improve the accuracy of monitoring and fault detection under diverse pipeline environments, while strengthening the system robustness in recognizing physical-damage indicators. Representative samples from the collected image dataset, which describe the surface condition of pipes during the experiments, are shown in Figure 3.

Figure 3: Representative dataset samples for AI training in the inspection robot

Data preprocessing is essential for preparing the system to operate reliably under complex practical conditions. In this study, an integrated data-processing procedure is applied to normalize both the image stream and the physical sensor signals before they are transmitted to the coordination center. For the sensor data, digital signal normalization is carried out through continuous sampling and edge-level noise filtering.

For the HC-SR04 distance sensor, the curved surface inside the pipe may cause non-uniform reflection of ultrasonic waves. Therefore, the measured signal is processed through a threshold filter to remove abnormal outliers. This procedure helps estimate obstacle locations more accurately and maintain a safe operating trajectory for the robot. In parallel, for the DHT22 temperature-humidity sensor, a calibration algorithm based on the experimental temperature error of ±1.7°C is incorporated to improve the accuracy of environmental data used in evaluating corrosion-related factors.

At the same time, the image stream from the ESP32-CAM module is optimized using adaptive JPEG compression and automatic brightness adjustment. These transformations help ensure that images transmitted to the web-server interface reflect practical operating scenarios, while preserving bandwidth stability and reducing latency during real-time monitoring. The configuration parameters used for preprocessing are presented in Table 3.

Table 3: Configuration parameters for data preprocessing and normalization

Component	Processing Method	Configuration Parameters
Distance (HC-SR04)	Threshold filtering and signal normalization	Sampling period: 100 ms
Temperature (DHT22)	Digital-signal calibration	Threshold: ±1.7°C
Image (OV2640)	JPEG compression and brightness adjustment	Resolution: VGA (640×480)

Table 3 summarizes the preprocessing and normalization procedure applied to the robot system. A set of transformations, ranging from distance-signal noise filtering to image-data optimization, is used to adapt the system to practical variations and improve the robustness and reliability of the monitoring process.

2.3. Operating procedure and coordination algorithm

After signal preprocessing, the system enters the experimental operating phase based on a flexible multitasking coordination architecture. This study implements a control algorithm that exploits the dual-core processing capability of the ESP32-CAM microcontroller, enabling simultaneous management of the visual data stream from the OV2640 sensor and the motor-control tasks without causing a data bottleneck. The algorithmic structure is divided into two independent processes running in parallel:

Vision task: This task is preferentially executed on Core 0 and captures live image data from the OV2640 sensor. An adaptive JPEG-compression algorithm is applied to optimize packet size, maintain a stable frame rate, and preserve continuity of the monitoring stream even when the Wi-Fi bandwidth fluctuates.

Control task: This task runs on Core 1 and executes threshold-based logic for robot navigation. It continuously analyzes data from peripheral sensors, such as the HC-SR04 ultrasonic sensor, to generate DC-motor coordination commands, while ensuring system safety through an interrupt mechanism when an obstacle is detected below the allowable threshold.

The coordination of these two tasks forms a closed feedback loop, allowing the robot to observe the internal pipe surface in detail while responding rapidly to environmental changes. The processing capability of the ESP32-CAM helps address the trade-off between image resolution and control latency, which is a major challenge in resource-constrained embedded systems.

III. RESULTS AND DISCUSSION

Experiments were conducted to evaluate the operating performance of the pipe-surface inspection robot under practical conditions. Quantitative indicators related to sensor accuracy and defect-detection performance are summarized as follows.

Table 4: Experimental results of temperature and humidity measurement

Reference Temperature (°C)	Measured Temperature (°C)	Error (°C)	Reference Humidity (%RH)	Measured Humidity (%RH)	Error (%RH)
25	23.8	1.2	60	63.5	3.5
28	29.6	1.6	65	69.2	4.2
30	31.7	1.7	70	74.8	4.8

The data in Table 4 show that the environmental-data acquisition system provides stable reliability, with an average temperature error of approximately ±1.7°C and a humidity error of about ±5%RH.

Table 5: Experimental results of obstacle-distance measurement

Reference Distance (cm)	Measured Distance (cm)	Error (cm)
10	11.3	1.3
20	18.4	1.6
30	32.1	2.1

The results in Table 5 indicate that the average distance-measurement error remains at approximately ±2 cm. This error tends to increase when the obstacle surface is highly curved or inclined because the reflected ultrasonic wave does not return uniformly to the sensor.

Table 6: Experimental results of pipe-surface defect detection

Defect Type	Number of Trials	Success Rate (%)	Technical Notes
Surface cracks	20	about 80%	Affected by vibration and camera resolution
Leakage	20	about 70%	Performs well when liquid stains are visible

Defect Type	Number of Trials	Success Rate (%)	Technical Notes
Pipe deformation	20	about 70%	Requires fusion of image data and ultrasonic sensing

The data in Table 6 demonstrate that the prototype achieves promising performance in recognizing physical defects. The surface-crack class obtains the highest success rate, approximately 80%, because its geometric features remain relatively clear when the robot operates at a low speed. However, the success rate decreases for slight leakage or deformation because of the limited resolution of the OV2640 camera and vibration noise generated by the locomotion mechanism.

IV. CONCLUSIONS AND FUTURE WORK

This study has presented a mobile robotic system specifically designed for pipe-surface monitoring, integrating embedded control and sensor-data acquisition. The system uses the ESP32-CAM as the central processing platform for real-time observation and monitoring, in combination with the DHT22 and HC-SR04 sensors for environmental-data collection and obstacle avoidance. The prototype was experimentally tested on both flat and curved surfaces under a payload of 1-3 kg. The results show stable operation, with a temperature-measurement error of about ±1.7°C and a distance-measurement error of about ±2 cm. Defect-recognition performance reaches an average level of 70-80%, depending on the type of surface defect.

The results also indicate that recognition performance is significantly affected by the robot travel speed. The system achieves optimal performance in the range of 70-90 RPM, with a recognition rate of approximately 75-82%. At excessively low speeds, the inspection process becomes less efficient because of the limited scanning rate. Conversely, at excessively high speeds, motion blur and vibration degrade image quality and consequently reduce recognition accuracy. These findings show that selecting an appropriate operating-speed range is essential for balancing inspection efficiency and system stability.

Future work will focus on upgrading the system toward a higher level of autonomy and intelligence. In particular, deep-learning models such as YOLO can be integrated to improve real-time detection and classification of surface defects, including cracks, leakage, and deformation. The mechanical design should also be improved to increase adaptability to more complex pipeline geometries. In addition, integrating an IoT-based system for remote monitoring and data storage is a promising direction that can enhance operational efficiency and reduce maintenance costs in practical industrial applications.

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