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SWARM-BASED ROBOTIC INSPECTION AND FAULT DIAGNOSIS IN HEAVY-DUTY CONSTRUCTION MACHINERY

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Abstract: *This study presents the development of a collaborative robotic system, or robot swarm, equipped with video cameras and sensors for the periodic inspection of components in heavy-duty construction machinery. The primary aim is to detect cracks, abrasive-corrosive wear, and other defects, thereby preventing failures and/or accidents. By continuously monitoring large-scale construction equipment, the robots can transmit real-time data that can be analyzed using artificial intelligence. This enables prompt intervention in the event of anomalies and facilitates the prioritization of maintenance actions when significant wear is identified. This approach effectively reduces unplanned downtime and enhances operational safety by preventing major failures during machine operations.*

Keywords: *Robot swarm, inspection, wear, artificial intelligence, construction equipment*

1. Introduction

Construction equipment for earthmoving operations, such as excavators, bulldozers, and crawler loaders, functions under challenging conditions characterized by dust, mud, mechanical shocks, and significant load variations. Transmission and operational components, including tracks, carrier rollers, and idler wheels, are subjected to continuous abrasive and corrosive wear, and defects in these areas have a direct impact on the safety and availability of the equipment [1]. In practice, the financial implications of a major failure in the running gear can significantly surpass the costs associated with appropriate preventive maintenance.
Currently, inspections are predominantly conducted visually by specialized personnel while the equipment is not in operation. This method is time- consuming, relies heavily on the expertise of the operators, and generally precludes continuous monitoring during operation. Furthermore, certain areas are challenging to access without partial disassembly, thereby increasing maintenance costs. Modern predictive maintenance techniques, such as vibration analysis or oil analysis, serve as complements to visual inspection; however, they are not always capable of detecting all defects, such as cracks in the load-bearing structure, oil leaks, or foreign bodies [1] [2].
In recent years, advancements in computer vision and machine learning have significantly enhanced the efficiency of defect detection in mechanical components through the analysis of regions of interest (ROI) extracted from high-resolution images [2–4]. Concurrently, progress in mobile robotics, wireless communications, and artificial intelligence has facilitated the deployment of robotic swarms for the automated inspection of industrial equipment [5] [6]. Within such systems, multiple microrobots collaborate to distribute tasks related to exploration, data acquisition, and local preprocessing. This approach enables rapid coverage of extensive areas, enhances system redundancy and robustness, and provides flexibility in configuring monitoring missions.
In the context of inspecting and maintaining oversized construction machinery on-site, a significant challenge arises from the need to access multiple points within an unpredictable and hazardous environment. The deployment of multiple robots concurrently enhances the probability that at least one will successfully accomplish the task of inspecting or maintaining the construction machinery.
This paper aims to introduce an experimental platform for robotic inspection utilizing swarms of microrobots, specifically designed to diagnose defects in the running gear of heavy construction machinery. The paper details the hardware and software architecture, the method for generating

Regions of Interest (ROIs), and the testing scenarios, supported by actual images captured by the robots.

2. Implementation

The specialized literature documents numerous applications of automatic inspection of infrastructures and industrial equipment utilizing mobile robots or unmanned aerial vehicles (UAVs) [7], [8]. Predominantly, these methodologies concentrate on the inspection of power transmission lines and pipelines, the monitoring of civil structures, or the examination of rotating installations. In contrast, research concerning heavy construction machinery is comparatively limited, with a focus primarily on monitoring vibrations in bearings or conducting oil analysis for wear determination [1]. The automated visual inspection of tracks and rolling elements remains underexplored, despite these components being prone to a significant proportion of defects.
Robot swarms have been investigated for their potential applications in search and rescue operations, precision agriculture, and the exploration of uncharted environments [5], [6]. In this study, analogous principles are applied to the construction sector, characterized by intricate geometries where regions of interest (ROIs) are linked to specific mechanical components such as rollers, wheels, and track segments. An ROI, or region of interest, refers to a distinct area within an image or a three-dimensional model that the inspection system targets for analysis. Rather than processing the entire scene, algorithms prioritize these designated regions, which correspond to critical components (e.g., rollers, drive wheels, track segments), to identify cracks, wear, or other defects.
Figure 1 depicts examples of components subject to inspection, specifically detailing the running gear, including the wheels and rubber track, of an autonomous transport platform utilized in construction. Figure 2 presents the microrobots employed for inspection: the robotic platform equipped with omnidirectional wheels, based on Arduino and ESP32-CAM, and the STEM robot featuring LiDAR – MicroROS-Pi 5, positioned adjacent to the track section.

Fig. 1. Detail of the undercarriage of the construction machine: wheels and rubber track under inspection

The proposed system comprises a swarm of mobile microrobots designed to operate in proximity to a construction machine. The application discussed in the article is developed for students utilizing microrobots from the UTCB practice base, established under the CNFIS-FDI-2025-F-0289 project—RECIPA: Robotics and Ecology in Construction: Innovation and Applied Practice. Each robot is tasked with exploring a predefined or dynamic area, acquiring images and/or LiDAR data, conducting preliminary identification of Regions of Interest (ROIs), and transmitting the data to a central processing station. The central station integrates data from the entire swarm and employs machine learning algorithms for defect detection.

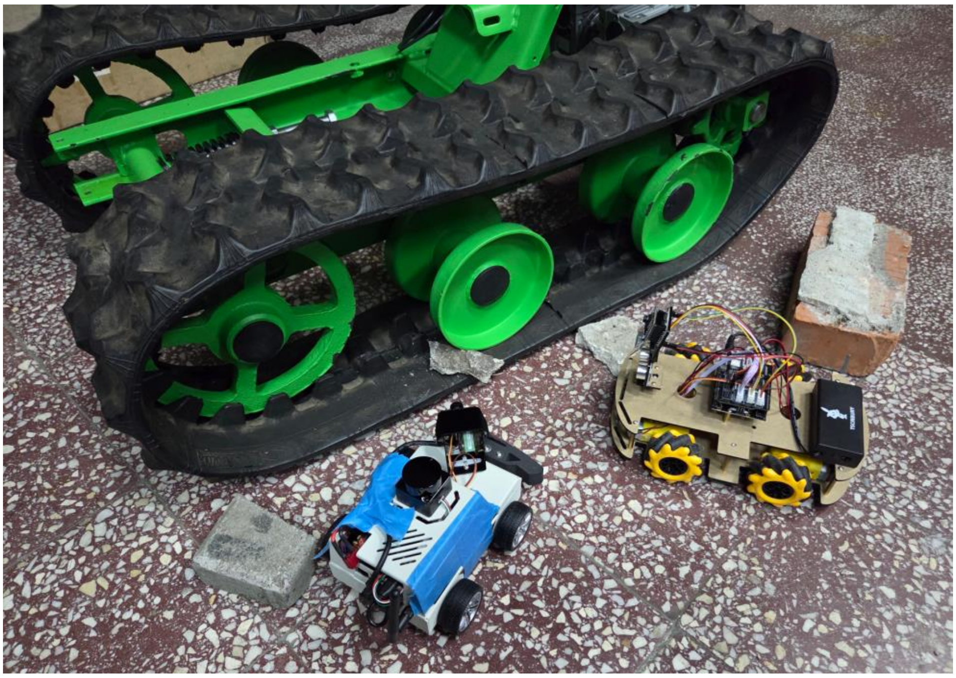

Fig. 2. Microrobots used in experiments: the omnidirectional wheeled platform with Arduino and ESP32-CAM (right) and the STEM robot with LiDAR – MicroROS-Pi 5 (left), positioned next to the track

The initial type of microrobot is equipped with a platform featuring four omnidirectional (Mecanum) wheels, facilitating movement in forward and backward directions, lateral shifts, and rotation around the vertical axis. The low-level control of movement and obstacle avoidance is managed through an Arduino microcontroller, while image acquisition is performed using an ESP32-CAM module mounted at the front. This robot is capable of approaching track elements and accurately repositioning itself in front of a region of interest (ROI) to capture high-resolution images. Its positioning, in conjunction with the STEM robot, adjacent to the train's running gear, is depicted in Figure 2.
The second category of robot serves as a STEM platform, featuring a four-wheel configuration and is equipped with a Raspberry Pi 5 computing unit. It incorporates MicroROS firmware to facilitate integration within the ROS2 ecosystem, a LiDAR sensor for both 2D and 3D mapping, additional proximity sensors, and a high-definition camera mounted on a gimbal with two degrees of freedom for viewing and video streaming. The primary function of this robot is to conduct volumetric mapping of the surrounding area and to detect obstacles or foreign objects.
Figure 3 illustrates a simulated critical scenario in which a concrete fragment becomes lodged between the roller and the track. Such scenarios are employed to assess the proposed system's capability to detect potentially hazardous anomalies.
The system components communicate through Wi-Fi, utilizing ROS2 protocols for message exchange. MicroROS nodes operate on the microrobots, tasked with raw data acquisition, filtering, and publishing. At the central station, ROS2 nodes are employed for data collection, synchronization, and processing, as well as for generating regions of interest (ROIs) and conducting preliminary defect detection, akin to industrial methodologies reported in [9].

Fig. 3. Detail capture: interaction between the roller and a piece of concrete caught in the track

The application development process employed a methodology based on Return on Investment (ROI) inspection, which adhered to the following procedural steps:
Step 1 - Identification of Regions of Interest
The regions of interest pertain to essential components of the undercarriage, including the support rollers, drive wheel, idler wheel, and segments of the track that are in contact with the ground or wheels. Based on the geometric model of the machine, these regions of interest can be delineated as projection areas within images (for video data) or as volumes in three-dimensional space (for LiDAR data).
Step 2 - Classification of Targeted Defects
The system is designed to detect the following categories of defects: longitudinal or transverse cracks on rollers and wheels, imperfections on the track surface, substantial abrasive wear on the roller flanks, the presence of foreign objects between the running elements, and indications of corrosion or material flaking.
Step 3 - Data Processing Flow
The data processing flow encompasses several stages: data acquisition; preprocessing, which includes noise reduction, illumination correction, and geometric calibration; segmentation of the region of interest (ROI); feature extraction; defect detection utilizing classifiers such as neural networks; and the reporting and formulation of maintenance recommendations.
Experimental Setup and Test Scenarios: To validate the concept, an experiment was conducted involving a track section equipped with a rubber track and green-painted metal rollers, simulating a component of a construction machine designed for heavy-duty operations. The details of this assembly are depicted in Figure 1.
In addition to the track, fragments of brick and concrete were strategically placed to simulate the presence of foreign objects on the running surface. Initially, the microrobots are positioned at a distance and subsequently move either autonomously or through teleoperation. The platform, equipped with omnidirectional wheels, approaches the edge of the track to conduct visual scans of the lower area. Concurrently, the STEM robot, which is equipped with LiDAR, traverses alongside the machine to map and identify priority Regions of Interest (ROIs) (Figure 2).
Figure 3 presents a detailed depiction captured by one of the robots, illustrating the interaction between a guide roller and a fragment of concrete lodged between the wheel and the track. This scenario poses a risk of damage if not promptly addressed.

3. Preliminary results and discussions

Preliminary evaluations have demonstrated that the microrobots are capable of accessing regions that are challenging for operators to observe directly. The omnidirectional wheeled platform

facilitates precise repositioning necessary for focusing on the region of interest (ROI), and the integration of images with LiDAR technology offers a more comprehensive depiction of the environment.
The images acquired provide detailed insights into the surfaces of the roller and track, revealing significant scratches and irregularities attributable to wear. In instances involving foreign objects, the system identifies abnormal interactions between the wheels and concrete fragments, which, if not promptly addressed, may result in damage. Additionally, limitations were noted concerning lighting conditions, potential Wi-Fi signal interference, and the necessity for precise calibration of LiDAR data integration with the images.

4. Conclusions

The paper delineates a system architecture for the robotic inspection of heavy construction machinery, utilizing a swarm of microrobots equipped with video cameras and LiDAR technology. By employing Regions of Interest (ROIs) defined on critical components of the undercarriage, the system facilitates detailed monitoring of areas susceptible to wear, early detection of defects, and identification of foreign objects in the operational area, thereby generating valuable data for predictive maintenance. Future research directions include the full integration of a real-time processing chain, the development and validation of deep learning models for automatic defect classification, the expansion of the swarm with additional robots (e.g., mini-drones), and the creation of standardized inspection and reporting protocols.

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