A SOIL SCIENCE ROVER: AN INTELLIGENT AGRICULTURAL AUTONOMOUS GROUND MOBILE ROBOT

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Abstract:

The integration of artificial intelligence (AI) and computer vision in agricultural scenarios provides a significant advancement in crop monitoring, autonomous navigation, and disease detection. The following research proposed a system to improve agricultural automation incorporated with deep learning-based object detection models such as RCNN, ResNet50, and DenseNet121. Using computer vision models, this research aims to optimize the identification of potential obstacles and crops in farming environments. Moreover, this research justified the role of autonomous ground robots for navigation, path planning, and real-time decision making. The following study evaluates existing methodologies and presents an improved framework that combines deep learning architectures with robotic perception systems to enhance agricultural automation. Furthermore, a Soil Science Rover Test Module (SSRTM) has been proposed in this study, which is responsible for in-situ soil analysis focusing on moisture percentage, pH levels, and nutrient composition. Experimental results justified the effectiveness of the proposed systems in real-life scenarios. This research contributes to the growing field of AI-driven precision agriculture, which will eventually come up with intelligent and fully autonomous farming systems.

Keywords:

Obstacle detection; Autonomous rover; Soil test

1. Introduction

Automation in the field of agriculture has been moved forward notably with the addition of intelligent autonomous systems, which primarily authorize intensified productivity and precision in farming [9]. The introduction of unmanned ground vehicles (UGV) to the agricultural industry has become a crucial proportion among modern-day innovations, which has already proven the ability to perform some pivotal agricultural operations such as soil analysis, autonomous navigation, and field monitoring [11]. Soil Science Rover (SSR) has been presented in this paper with the characteristics of rough agricultural terrain traversing along with real-time soil analysis.

The SSR consists of a rocker bogie suspension system, which ensures steady movement across rough and unbalanced cultivation land. The proposed system is facilitated with an efficient GPS module for proper navigation. Computer vision used in this system provides features like obstacle detection and environmental awareness, moreover, SSR is equipped with Faster R-CNN ResNet50 for the proper detection of obstacles such as rocks, trees, and fences to provide secure movement [11]. Furthermore, DenseNet121 with transfer learning has been incorporated into the system to classify the obstacles, which eventually allows SSR to avoid any potential obstacle by rerouting [14]. These deep-learning models enable real-time image processing to ensure efficient and adaptive navigation.

Further on than navigation, SSR is also designed for in-situ soil analysis with the help of its Soil Science Rover Test Module (SSRTM). Essential properties of soil, such as moisture percentage, pH levels, and nutrient composition, can be examined by the onboard sensors. The integration of computer vision along with GPS navigation and autonomous decision-making allows SSR to gather accurate data and provide optimized farming strategies. This paper provides a complete rundown of

SSR's architecture, navigation system, computer vision capabilities, and soil analysis functionality. The following sections cover the literature review, system design, testing, and experimental analysis.

2. Literature Review

The addition of autonomous systems in agriculture has obtained significant recognition with the aim to provide optimized efficiency, accuracy, and sustainable solutions. This section reviews recent expansions in autonomous agricultural rovers, primarily focusing on their navigation systems, computer vision applications, and soil analysis capabilities.

Navigating a rover autonomously is a crucial system for agricultural robots. It ensures flawless movement of the rover around uneven farmlands. So many GPS-based navigation systems are already being implemented, such as the R2A2 robotic rover, which consists of a GPS-based autonomous navigation system to perform different levels of tasks in agricultural environments [6]. However, relying only on GPS for navigation may limit the movement of the rover by signal obstructions caused by dense crop fields. To deal with challenges like this, a new approach has been explored, focused on vision-based navigation solutions. Research by Wang et al. (2022) calls attention to how vision sensors process real time environmental data, detecting crops, trees and obstacles to support autonomous localization and path planning [7,13]. Likewise, Agronav, a vision-based navigation framework, incorporated semantic segmentation and line detection to optimize path planning in an agricultural environment [1]. Research by Fasiolo, D. T. et al. (2023) proposes an integrated LiDAR and camera-based navigation system that allows real-time path correction in rough terrain with optimized obstacle avoidance [3].

For practicing precision in agriculture, computer vision is widely recognized, which emphasizes crop monitoring, pest detection, and autonomous navigation [12]. The research in Zhang et al. (2021) proposed an AgriRover that integrates an agricultural object recognition module, which mainly detects obstacles such as trees and fences for improving navigation accuracy [8]. Moreover, detecting the crop rows and obstacles, machine vision has provided significant improvement, which makes it an indispensable tool in agricultural robotics [4].

Deep learning models upgraded the agriculture-focused computer vision applications with different frameworks [15-16]. Faster R-CNN with ResNet50 is broadly incorporated for real-time object detection in agricultural fields, whereas DenseNet121 has been propitiously optimized for the classification of disease in crops [10]. Fasiolo, D. T. et al. (2023) present the combination of YOLOv5 and Transformer networks to create a hybrid model to achieve 89.4% accuracy in obstacle detection, which outperforms traditional CNN-based models [3].

To optimize the nutrient assessment and soil health monitoring, soil analysis performs a crucial role in agricultural environments. The research in Martinez et al. (2021) proposed Agrobot Lala for real-time nitrate analysis, which eventually enabled site-specific fertilization [5]. Moreover, a study on autonomous soil contamination detection proposes combining AI models with multi-spectral imaging to double the accuracy [2]. Fasiolo, D. T. et al. (2023) propose a multi-sensor fusion approach using hyperspectral imaging, pH sensors, and deep learning models to differentiate soil conditions properly [3]. This method hits 94% classification accuracy, which clearly demonstrates the effectiveness of AI-driven soil analysis techniques.

3 Rover Architecture

Soil Science Rover (SSR) is an unmanned ground vehicle (UGV) designed with diverse kinematic solutions to better adapt to rough agricultural terrains. It is a four-wheel drive vehicle with a rocker boggie suspension system. Onboard sensors are installed in the rover for automated soil analysis purposes. An advanced GPS mechanism is used for navigation. The rover is equipped with Neo-M8N GPS along with a compass. For camera vision, a Logitech C920 PRO HD webcam (1080 × 720 resolution) is attached to the rover.

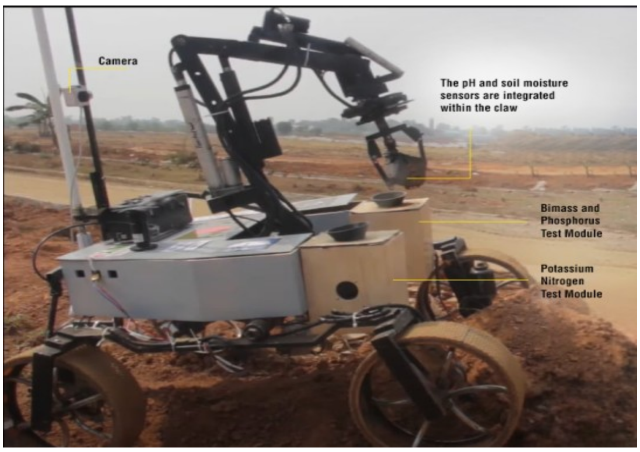

FIGURE 1. Architecture of Soil Science Rover

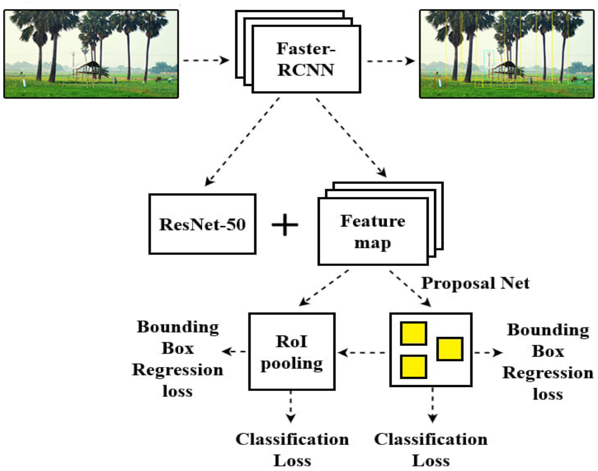

FIGURE 2. Obstacle detection mechanism

FIGURE 3. Segmenting the obstacles

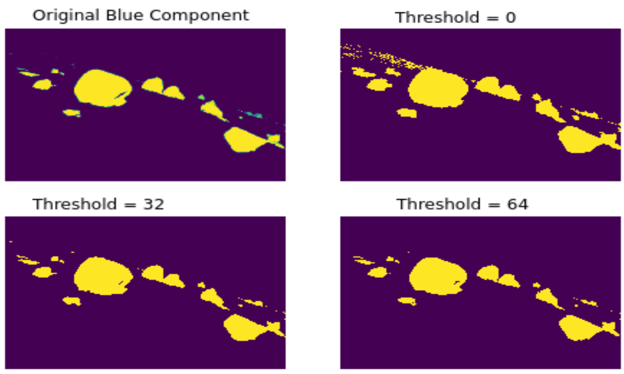

FIGURE 4. Applying intensity threshold

4. Driving and Navigation System

A properly functioning Soil Science Rover has a strong and suitable autonomous system for long-range traversal and on-board soil tests. Using GPS navigation and computer vision system, the rover can traverse automatically.

4.1 Autonomous Planning and Integrated Approach

Soil Science Rover evaluates a few key techniques for planning and execution. A set of coordinates have been provided for the rover to navigate the area and test the soil of the farmland. A GPS sensor determines its location, and the path is planned using the A* search algorithm. The rover moves autonomously to get to the target places.

4.2 Computer Vision

For obstacle detection and identification, the rover uses computer vision technique. To ensure efficient performance, the computer vision system is divided into two main sections. The first section is detecting obstacles, and the second section is to identify the obstacle to take the appropriate action.

Our rover has adopted the computer vision technique to detect any obstacle, and it has used Faster RCNN ResNet50 (Figure 2). Using this process, the rover detects any obstacle (e.g., larger rocks, trees, humans, fences, etc.), and it moves to the target points to perform an onboard soil test. For performing the second section of our driving and navigation system, which is obstacle identification, the rover identifies the obstacle using Transfer Learning with pre-trained DenseNet121.

Faster RCNN ResNet50 helps to detect obstacles using less complexity and minimal computational power with mechanical noise. As Faster RCNN has been detecting in real time, it has captured frames from the live feed and generated an initial subsegment. After that, the rover runs a greedy algorithm to recursively integrate similar regions into a large one. Finally, the generated regions have to be used for producing final dedicated regions in the figure where it detects the obstacle.

Figure 3 shows the segmentation output. In this figure, the image is the output image, where the color represents different types of obstacles. The rover moves autonomously in order to get near to the identified obstacle using the A* search algorithm as it is used to navigate.

Without any mechanical damage, the rover can reach its destination. Also, it creates a subset of the target location for testing the soil. After detecting the obstacle, it avoids the obstacle and reroutes the rover. In this way, the rover can change its current position. For this purpose, it has to fix the root node at first and plan different paths using the A* search algorithm. If it finds an obstacle, the rover would calculate the distance between the obstacle and the rover using the Euclidean Distance formula as well as utilizing the threshold parameter. Figure 4 shows the autonomous system of the rover with different intensity thresholds. The rover uses 64 intensity threshold as an upper threshold to visit. It is an autonomous system of the rover with different intensity thresholds. In addition, according to rock detection distance, our autonomous system of the rover is suitable to detect obstacle distance and perform the autonomous task.

By doing this, the first part of the autonomous system has been completed. Whenever it becomes possible to reach the targeted soil position, the rover performs an onboard soil test and analyzes the soil. The second part is identifying the obstacle to avoid it. To complete this part, the rover uses DenseNet121 with a few images of the obstacle. Using a transfer learning trained model, it tries to identify the obstacle. Transfer learning is a process that uses stored knowledge from a pre-trained model and applies it to other data to get the required specific result. For this task, we engineered the last layer of the model.

4.2.1 Dataset

We are using the CIFAR-100 dataset, which was created by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. The CIFAR-100 dataset consists of 100 classes, each containing 600 images. There are 500 training images and 100 testing images per class. The 100 classes are categorized into 20 superclasses. Each image is assigned a "fine" label, representing its specific class, and a "coarse" label, indicating its corresponding superclass.

5. The In-Situ Atmosphere and Subsurface Analyzer

Soil Science Rover Test Module (SSRTM) is an in-situ automated soil analysis tool developed by the Soil Science Rover research team. Before building our onboard subsurface analyzer tool, we studied different agricultural rovers [5].

5.1 Soil Characteristics Exploration Mission

At the beginning of each soil test operation, the rover reaches the GPS-locked targeted location. Using multiple cameras, it captures the surface image and sends it to the base station for survey and selects an ideal place to dig and acquire soil samples for in-situ analysis. After reaching there, using an excavator claw, it begins digging soil and extracting soil from the subsurface. Moreover, the rover inserts its probe in the created trench to obtain initial data of soil properties such as biomass, soil moisture, pH, and NPK. After that, the rover extracts soil from the trench and distributes it in the respective test chambers for onboard deep analysis, which is an automatic process. Finally, all the data and observations are sent to the base station for results evaluation.

5.2 Experiment Unit

Our soil test unit consists of three units called SSRTM (Soil Science Rover Test Module), where a real-time sample analysis unit detects biomass, soil moisture, pH, and NPK, and gives a subsurface view of the soil. Our fully automated onboard science unit is activated after the location verification process that is done by the rover intelligence.

5.3 Collection and Sample Distribution

This is the very first step of the experiment process, where the rover collects the soil using a robotic arm. After collecting soil samples, the excessive soil is removed and two separate soil distributors control the distribution of the required amount of soil to each of the units. This distributor is only required for NPK and biomass test.

5.3.1 Real Time Sample Analysis

This part of the SSRTM is fully water resistant and well built to handle any harsh environment so that all the sensors remain intact and provide continuous data without endangerment. It consists of two per-calibrated sensing probes: pH and soil moisture sensors enclosed by metallic tubes to protect their sensitive parts. This unit is located at the top of the science arm.

6. Result Analysis

6.1 Driving and Navigation System

The primary focus was on object detection and object identification as the main system is based on GPS navigation and computer vision techniques. As a part of model testing figure 5 shows that trees, fence, cows, and rocks have been detected and identified successfully using Faster RCNN Resnet50 and DenseNet121 model.

During the outdoor experiment of the autonomous rover, we provided 4 different geo-locations in the 3 acres farmland. Our rover successfully identified seven different objects, completed

TABLE 1. Location wise soil characteristics

Location	pH	Nitrogen (N)	Phosphorus (P)	Potassium (K)	Organic matter	Soil moisture
Rajshahi	6.35–8.28	0.11%	3.2 ppm	0.03%	1.88%	20–25%
Sylhet	4.0–5.5	0.12%	2.1 ppm	0.05%	0.95%	30–35%
Jamalpur	6.35–7.46	0.13%	3.2 ppm	0.03%	1.95%	22–28%
Khulna	5.8–7.2	0.10%	2.8 ppm	0.04%	1.65%	25–30%
Chittagong	4.5–6.0	0.11%	2.0 ppm	0.03%	2.10%	35–40%

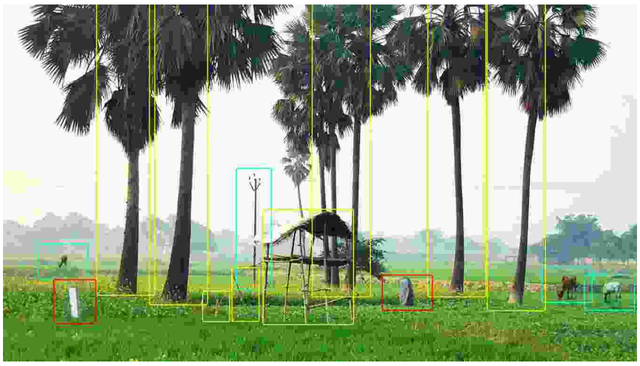

FIGURE 5. Identifying different types of obstacles

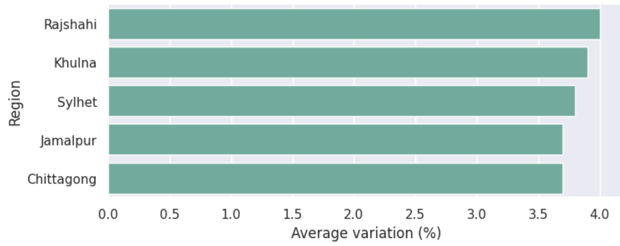

FIGURE 6. Average variation of different locations

an onboard soil test, and sent the soil test data to the rover. It took approximately 30 minutes to complete this operation.

6.2 The In-Situ Atmosphere and Subsurface Analyzer

One of the prime concerns for an autonomous agriculture rover is an onboard soil experiment unit named Soil Science Rover Test Module (SSRTM), which adds the capability of soil sample analysis. Using the robotic manipulator, the rover can collect soil samples from a depth of 10cm through the customized end effector.

For measuring the performance of the onboard analysis system, soil samples have been tested using it from a couple of locations. Using the data from the analysis of soil from five different locations in Bangladesh. A table (Table 1) is presented to compare the findings.

Figure 6 represents the average variation between the onboard soil test module data and lab test data of the five different locations. We used the percentage difference formula. According to the formula, it quantifies how much the onboard soil test module's readings deviate from the lab test values, expressed as a percentage. The formula is given below.

$$V(\%) = |\frac{O\ - L}{L}| \times 100 \qquad (1)$$

Here,
V = Variation
O = Onboard soil test data
L = Lab test data

For example, let's calculate the variation in nitrogen levels in Rajshahi.
Onboard soil test data: 0.11%
Lab test data: 0.10%
Using the variation formula, the variation for Nitrogen in Rajshahi is 10%.

In the figure 6, the variation of Rajshahi, Khulna, Sylhet, Jamalpur, and Chittagong is 4%, 3.90%, 3.80%, 3.70%, and 3.70% respectively. The average variation is less than 4% in those five locations. So, it justifies that the onboard soil test error rate is very low.

7. Conclusions

Our research examined the current supportive technologies for ground mobile robots used for autonomous soil analysis in agriculture. Detection and identification of objects through faster RCNN Resnet50 and DenseNet121 model upgraded the autonomy of the designed rover for driverless operations. Different soil cache samples from multiple locations have been collected through the rover for onboard analysis. The customdesigned Soil Science Rover Test Module (SSRTM) helped us to visually realize different aspects of soil and generate comparisons between a couple of soil samples from different locations. A YOLOv5 can be introduced for more efficient object detection, which will ultimately upgrade the driverless operation of the rover. The uses of wet materials for onboard testing can be replaced with dry materials as wet materials are toxic, which may harm the rover electronics. The work is still going on with every module to produce the best version of each subsystem eventually. Also, this work revealed that mobile robotics in agriculture is a present and active field of research driven by the need to optimize agricultural production, reduce waste, and improve sustainability, as dictated by climatic and social factors.

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