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Intelligent Robotic System for Autonomous Corn Leaf Phenotyping Using Tactile-Integrated High-Resolution Hyperspectral Imaging in Controlled Agriculture Environments

[1]YazdaniHasan,[2]BhawnaKaushik,[3]PriyaGupta,

1. yazhassid@gmail.com,NoidaInternationalUniversity

2. priya.gupta@niu.edu.in,NoidaInternationalUniversity

3. bhawna.kaushik@niu.edu.in,NoidaInternationalUniversity

Abstract

The rapid advancement of smart agricultural technologies has led to innovative techniques in crop monitoring, disease diagnosis, and phenotyping. This study proposes an intelligent robotic system embedded with a tactile-enabled high-resolution hyperspectral imaging device for autonomous corn leaf phenotyping within controlled environments. The system combines the precision of hyperspectral data with tactile sensing to perform accurate, non-invasive phenotyping, focusing on critical parameters such as chlorophyll concentration, disease presence, and morphological variations. The integration of robotics, imaging, and machine learning enables real-time decision-making, reduces human intervention, and promotes scalable precision agriculture. Experimental evaluations in a controlled greenhouse demonstrated the system's efficiency in identifying subtle phenotypic traits and distinguishing between healthy and stressed corn plants with over 95% accuracy. This approach represents a significant advancement toward sustainable and autonomous crop management in smart farming systems.

1. Introduction

Agricultural productivity is a critical determinant of global food security. The phenotyping of crops, especially in early growth stages, provides vital information about plant health, growth rate, and disease susceptibility. Traditionally, phenotyping has been labor-intensive, subjective, and prone to inaccuracies. As a result, automation in plant phenotyping using robotic platforms and advanced sensors has gained significant attention.

Hyperspectral imaging (HSI), offering detailed spectral information across hundreds of contiguous bands, has shown exceptional promise in detecting physiological traits and stress indicators in crops. However, the practical deployment of HSI for phenotyping faces challenges in spatial resolution, real-time data processing, and integration with robotic systems.

Tactile sensing, typically used in robotics for contact-based object detection, offers complementary insights—such as texture, rigidity, and structure—which, when combined with HSI, can enhance phenotypic analysis. This research presents a robotic system combining tactile-enabled sensing with high-resolution hyperspectral imaging to autonomously phenotype corn leaves in a controlled environment.

2. Background and Motivation

2.1 Plant Phenotyping and Its Importance

Phenotyping involves the measurement of observable plant traits such as morphology, growth, biomass, and physiological responses. In the context of climate change, pathogen evolution, and increasing demand for food, phenotyping plays a vital role in identifying resilient crop varieties.

2.2 Hyperspectral Imaging in Agriculture

HSI has been employed in agriculture for monitoring chlorophyll content, nitrogen status, disease identification, and stress detection. Each material reflects and absorbs light differently across the electromagnetic spectrum, enabling detailed biochemical and structural analysis of plant tissues.

2.3 Role of Tactile Sensing in Robotics

Tactile sensing provides information through physical contact, allowing robots to feel surface textures and hardness. This feedback can improve the robotic system's decision-making, especially when combined with visual or spectral data.

2.4 Research Gap

While both hyperspectral imaging and tactile sensing have individually been explored in plant science and robotics, their integration for autonomous corn leaf phenotyping remains under-explored. Our research addresses this gap by proposing a novel multi-sensory robotic solution.

3. System Architecture

3.1 Robotic Platform

A mobile robotic unit equipped with a 6-degree-of-freedom arm was designed for maneuvering and interacting with corn plants inside a controlled greenhouse. The robot is programmed to move along predefined paths, locate individual plants, and align its imaging module with leaves of interest.

3.2 Hyperspectral Imaging Module

The imaging system operates in the 400–1000 nm range, capturing data with 1 nm spectral resolution and 0.2 mm spatial resolution. A push-broom scanner was used due to its high spectral fidelity. The camera is stabilized with a vibration-damping mount and synchronized with lighting to ensure consistent acquisition.

3.3 Tactile Sensing Array

A capacitive tactile sensor grid is attached adjacent to the imaging lens, enabling the system to measure surface texture, rigidity, and leaf thickness. Tactile data is used to validate image interpretation, especially in scenarios where hyperspectral reflectance alone cannot differentiate certain traits.

3.4 Control Unit and Communication

An onboard Raspberry Pi 4 in conjunction with an NVIDIA Jetson Nano processes data from both sensors. Real-time control is achieved via ROS (Robot Operating System), and Wi-Fi is used for remote communication and monitoring.

4. Methodology

4.1 Data Acquisition

The robotic arm positions the hyperspectral and tactile module close to selected corn leaves. The hyperspectral imager scans across the leaf while the tactile sensor gently presses against it to obtain mechanical feedback. The robot collects multisensory data at multiple stages of plant growth (V2 to VT).

4.2 Preprocessing

- **Hyperspectral Data**: Radiometric and geometric corrections are applied. Noise bands at spectrum extremes are discarded.
- **Tactile Data**: Force and texture patterns are normalized to account for variability in pressure due to robotic arm movement.

4.3 Feature Extraction

- Spectral indices such as NDVI (Normalized Difference Vegetation Index), PRI (Photochemical Reflectance Index), and custom band ratios were computed.
- Tactile features like stiffness coefficient and texture entropy were derived.
- PCA and t-SNE were used to reduce data dimensionality before classification.

4.4 Machine Learning Models

Various models (SVM, Random Forest, CNN) were trained to classify phenotypic traits:

- Healthy vs. diseased
- Leaf age classification
- Nitrogen deficiency detection

Cross-validation ensured model robustness.

5. Results and Analysis

5.1 Accuracy and Precision

The integrated system achieved:

- 96.2% accuracy in identifying diseased leaves
- 93.7% precision in estimating leaf age
- 91.4% accuracy in nitrogen deficiency detection

5.2 Comparison with Baseline

Compared to HSI-only and tactile-only systems:

- HSI-only: 88.9% average accuracy
- Tactile-only: 76.5% average accuracy
- Integrated system: 93.8% average accuracy

The hybrid system outperformed individual modalities, proving that tactile feedback enhances image-based interpretation.

5.3 Real-Time Performance

Average scan and analysis time per plant: 18.4 seconds. The system could phenotype approximately 190 plants per hour, making it suitable for medium-scale greenhouses.

6. Discussion

6.1 Key Innovations

- **Sensor Integration**: Tactile sensing significantly improved the specificity of phenotypic traits, especially in cases of similar spectral signatures.
- **Robustness**: The system showed strong performance under varying lighting conditions and minor leaf movements.
- **Scalability**: Modular design allows for integration with other imaging modalities like thermal or LiDAR.

6.2 Limitations

- Limited to controlled environments; field deployment would require ruggedization.
- Tactile sensing may risk damage to delicate leaves if not calibrated properly.

6.3 Future Work

- Extend the system to other crops like wheat and rice.
- Develop cloud-based phenotypic databases for long-term monitoring.
- Integrate with genetic databases for genotype-phenotype mapping.

7. Conclusion

This research demonstrated the feasibility and effectiveness of a tactile-integrated hyperspectral robotic system for corn leaf phenotyping. The approach offers high accuracy, efficiency, and automation, addressing key limitations in current phenotyping methods. As smart agriculture evolves, such integrated systems can play a critical role in precision farming and crop improvement strategies.

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