HyperPRI: A Dataset of Hyperspectral Images for Underground Plant Root Study

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1. Introduction

Researchers have studied the links between root traits and root function for the purposes of phenotyping and guiding plant choices in agriculture [8, 13]. A high-priority task is identifying genotypes and characteristics of high-yield, stress-tolerant crops that can sustain the projected needs of 10 billion people by 2050 [21]. Studies have ranged across multiple plants such as cassava [9], maize [24], chicory[19], soybean [20], and many other plants [22]. Phenotypic traits such as root length, volume, surface area, and count are utilized as features to understand the functions of roots. A couple works have also related certain physical root characteristics to genotypes that have better drought resilience [9, 12]. However, the above red-green-blue (RGB) studies provide an incomplete view of a plant's root physiology and root function.

Current methods of acquiring root traits are either destructive or non-destructive. Destructive methods include digging up plants from their original placement to image in 2D or 3D settings [10, 12]. A common non-destructive method is the use of minirhizotrons (MRs) [8, 13, 22]. An alternative to MRs is the rhizotron or rhizobox method that involves growing plants within boxes made of clear material so that root traits may be monitored over multiple time steps [2, 14, 18]. Other methods include tomography scans, X-rays, and MRIs to see beneath the soil surface [23].

Besides the last three listed non-destructive imaging techniques, each of the above uses RGB imaging to infer root function. However, the physical characteristics of root length, volume, surface area, and count lack a complete view of a plant's status and connection with the rhizosphere.

Studying spectral, phenotypic properties invisible to the naked eye can provide more information on a plant's interactions aboveground, such as plant leaf spectra studies [17]. Belowground, studies have examined near-infrared (NIR) images and hyperspectral imaging (HSI) [1, 15] to improve root component classification and root phenotyping. Nonetheless, we were unable to find publicly available visible-NIR or HSI plant root datasets that would allow further investigation into the relationship between root spectra and its surrounding rhizosphere.

2. Dataset

Here we present the Hyperspectral Plant Root Imagery dataset (HyperPRI), the first available dataset of RGB and HSI data for in situ, non-destructive plant root analysis. HyperPRI covers peanut (*Arachis hypogaea*) and sweet corn (*Zea mays*) plants and contains fully-annotated masks for root and soil pixels, as well as occasional peanut nodules and pegs. During data acquisition, we imaged 64 boxes between the wavelengths of 400 and 1000 nm for up to 15 timesteps across two months to enable insights into dynamic root growth. Within this monitoring period, most of the plants go through a natural dehydration and rewatering process (ie. some were in a control group) to provide samples for studying drought resilience of the two species. Thus, HyperPRI contains hyperspectral (HS) images over time that can reveal a deeper understanding of the relationship between plant roots and fluctuations in the surrounding rhizosphere. A sample of the timeline and HS bands for peanut images are shown in Figure 1.

HyperPRI is a unique and valuable resource for studying plant root systems. The added hyperspectral bands enhance data quality by effectively removing artifacts, ensuring reliable data for analysis. With 64 rhizoboxes representing repetitions of peanut and sweet corn plants, HyperPRI ensures reproducible and robust research. The dataset also presents machine learning (ML) experts with multiple challenges in root segmentation. Thin root features, with widths as narrow as 1-3 pixels, require robust algorithms for accurate identification and segmentation. Additionally, the dataset's highly textured soil background prompts exploration of tex-

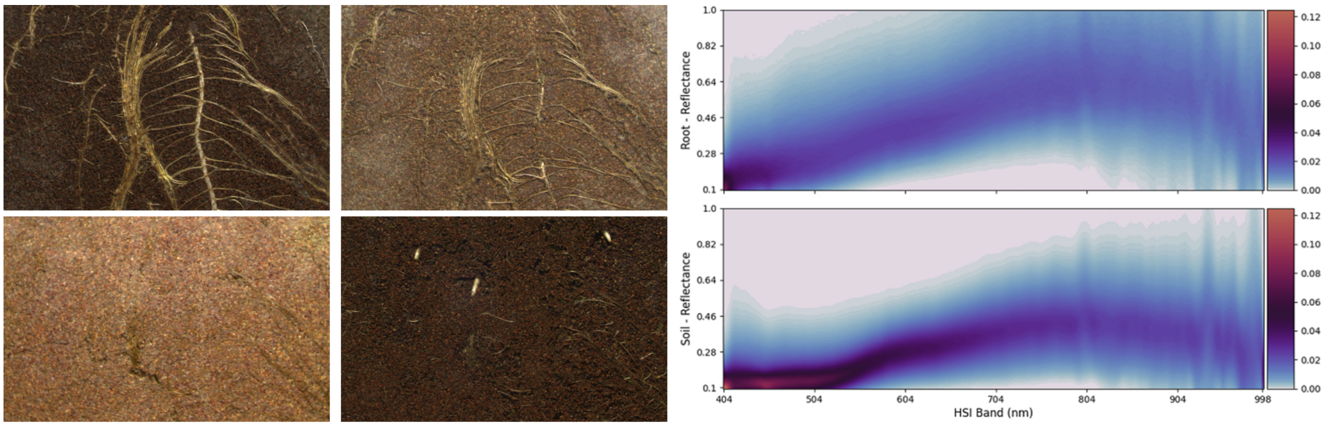

Figure 1. RGB images and hyperspectral reflectance distributions for root and soil pixels from our dataset. The images shown (left) are from a single peanut plant rhizobox across the monitoring time period. Hyperspectral reflectance data (right) is compiled from approximately 60 images of peanut rhizoboxes.

ture analysis techniques. Dealing with highly correlated hyperspectral channels, wherein reflectance differences are reduced due to high-resolution spectral data, demands innovative approaches to handle the correlated information effectively. By addressing these specific challenges, ML experts can not only advance root segmentation but also contribute to solving segmentation problems with similar characteristics in various domains, ranging from medical imaging [11] to remote sensing applications [22]. This dataset's combination of temporal aspects, hyperspectral information, and challenging features makes it an ideal dataset for advancing root science and developing accurate root segmentation algorithms.

3. Strengths and Limitations

In addition to the aforementioned applications, HyperPRI may be applied to multiple plant science research tasks. One would be to utilize HS signatures to supplement existing root phenotypic traits with more in-depth physiological evaluation ([4], Root Phenotyping). A couple studies have shown improved phenotyping prediction through added HS information [1, 16]. Researchers may also use the data to analyze roots from seedling to maturity by monitoring root growth, architecture, and turnover of root systems [6, 7]. Some images contain other potential objects of interest such as fungus, mold, and algae and could be studied at their various timesteps to determine possible interactive dynamics between root and rhizosphere. By example, previous work has studied root-fungal relationships in peatland [5]. The additional HSI data can provide researchers with a more informative look at a plant's health and physiology and may be applied to drought resiliency and nutrient concentration studies. By taking advantage of the dehydration and rehydration process in our dataset, researchers could predict plant water status in response to drought for two annual crop species [9, 24]. Creating additional links between HSI data and a plant's health could enhance studies addressing micronutrient deficiencies in populations worldwide [3].

Despite its many strengths, there are certain limitations to consider when using HyperPRI. The dataset primarily captures root images from rhizoboxes and do not fully represent root systems' complexities in natural soil environments. Neither do the HS images allow researchers to make conclusions about aboveground plant-air interactions. Consequently, generalizing findings to field conditions would require additional evaluation and caution. Moreover, HyperPRI includes only two annual crop species and is limited in its applicability to other plant species with different root characteristics. Finally, while the dataset provides HS information, it does not cover the entire electromagnetic spectrum, which could affect some spectral analysis applications.

4. Conclusion

The HyperPRI dataset holds immense potential for advancing research in plant root-rhizosphere interactions, root function, and ML-based root segmentation. Its temporal and hyperspectral aspects along with the availability of annotated masks offer numerous opportunities for exploration and innovation in various fields. Researchers interested in using the dataset should be mindful of the dataset's limitations and carefully interpret results, especially when extrapolating findings to natural soil environments or other plant species. With proper analysis, the HyperPRI dataset can significantly contribute to enhancing our understanding of root systems and their interactions, furthering advancements in both root research and machine learning techniques.

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