Demo Abstract: Underground Root Tuber Sensing via a Wi-Fi Mesh Network

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ABSTRACT

We demonstrate a non-invasive Wi-Fi sensing system that uses channel state information (CSI) data and deep neural network (DNN) models to reconstruct the cross-section images of potato tubers underground. We design a Wi-Fi mesh network that can leverage both the space and frequency diversities of the wireless network. We apply a multi-branch convolutional neural network (CNN) model to perform data-driven image reconstruction. We have performed extensive experiments to build a Wi-Fi potato sensing dataset, and our demo and experimental evaluations show that the Wi-Fi system outperforms the state-of-the-art root tuber wireless sensing system in terms of image quality and estimation accuracy.

KEYWORDS

Wi-Fi CSI, Underground Sensing, Root Tuber Imaging, Mesh Networks, Deep Learning

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(a) Wi-Fi Mesh Network Deployment **(b) Reconstructed Cross-Section**

Figure 1: (a) Our experimental testbed with a Wi-Fi mesh network surrounding the soil container, and (b) a representative cross-sectional image reconstructed by our CNN model.

1 INTRODUCTION

Non-invasive and accurate biomass sensing is pivotal for effective crop monitoring and phenotyping in smart agriculture. Although above-ground biomass sensing has received considerable attention, below-ground biomass remains challenging to measure and has thus been comparatively understudied. Wireless sensors represent a promising approach to underground sensing due to their ability to "see through" soil, offering a cost-effective and minimally disruptive method of monitoring root systems. For instance, [4] demonstrated the feasibility of underground potato tuber imaging using ZigBee nodes. Received signal strength (RSS) measurements from a ZigBee network were used to reconstruct the cross-section images of potato tubers underground. However, relying solely on RSS and limited frequency channels often results in coarse estimates and vulnerability to environmental noise, making it difficult to achieve the spatial resolution required for detailed tuber imaging.

In contrast, Wi-Fi channel state information (CSI) provides a substantially richer characterization of the wireless channel by capturing both amplitude and phase data across multiple subcarriers. This fine-grained information is especially beneficial for underground sensing, as it enhances spatial resolution and affords greater robustness to multipath effects critical factors when signals propagate through dense, heterogeneous media like soil. Beyond mere power measurements, CSI captures the complicated interactions of signals as they propagate via multiple paths, thus facilitating more accurate feature extraction. Recent advances in Wi-Fi sensing further underscore the advantages of CSI-based approaches. For example, FruitSense exploits the wider bandwidth at 5 GHz to isolate multipath-independent components, directly correlating with physiological changes in fruit ripeness [3]. Similarly, CSI-based human activity recognition systems leverage detailed subcarrier information to significantly improve model generalization, even in varying environments or with different hardware configurations [2]. These successes collectively highlight how CSI-based fingerprinting not only offers superior spatial resolution compared to RSS, but also provides temporal stability and adaptability to complicated settings.

Motivated by these benefits, we propose a new framework for underground root tuber sensing that harnesses Wi-Fi CSI data in conjunction with deep neural network models. Our system comprises a dedicated data acquisition testbed-a Wi-Fi mesh network composed of low-cost sensor nodes and an annotation module that generates ground truth labels for buried tubers. With these annotated CSI measurements, a multi-branch convolutional neural network (CNN) is trained to reconstruct cross-sectional images of tubers, accurately capturing both their dimensions and locations.

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Experimental results validate our design, demonstrating that the proposed method achieves an average structural similarity index (SSIM) of 0.99 and an intersection over union (IoU) of 0.87. These findings highlight the efficacy of CSI-based sensing in delivering high-resolution imaging for underground agricultural applications.

2 SYSTEM AND METHOD

Our framework for underground root tuber sensing comprises two core components: a custom-developed Wi-Fi mesh network for CSI data acquisition and a deep neural network (DNN)-based model for reconstructing cross-sectional images of buried tubers. We detail each component below.

2.1 Data Acquisition System

We deploy a 2.4 GHz Wi-Fi mesh with 12 Seeed Studio ESP32-C3 nodes arranged in a 79 cm × 79 cm square around a 40 cm × 40 cm container at a 5 cm height (Figure 1a). Each node captures CSI from 52 subcarriers on three Wi-Fi channels. To synchronize data acquisition, we adapt the multi-Spin token-passing protocol [1], wherein nodes transmit beacons at 20 Hz in sequence and a sink node relays all CSI packets to a laptop.

We use a dual-container setup: a larger container has slots for smaller containers, each holding one tuber. A rotating platform beneath the larger container periodically changes tuber orientation for diversity. To mark each tuber, we bury it horizontally so that its widest cross-section is parallel to the ground, then fix four rods around it with tops protruding above the soil. A paper marker shaped like the tuber's cross-section is placed among the rods to indicate location and size; once aligned, we remove the rods to avoid interference. A camera then records the marker from multiple angles as the container rotates, and a segmentation algorithm isolates the marker region as a binary mask. Minor alignment issues are corrected via spot checks, ensuring the marker center matches the tuber's geometric center.

Each sample includes CSI across three channels. For every subcarrier, a 12×12 matrix is formed from up to 12 transmitter and 12 receiver antennas, producing 156 matrices (3×52 subcarriers). These are stacked into a $(156, 12, 12)$ tensor that feeds into our DNN.

2.2 Multi-Branch CNN Model

We employ a multi-branch CNN model, referred to as `RadioNet`, to reconstruct high-resolution cross-sectional images of the buried tubers from the aggregated CSI tensors. The model is composed of an **Encoder** and an **Imaging Module**. The Encoder features three sets of convolutional layers with progressively larger kernel sizes to capture both fine-grained local features and broader global structures. The outputs of these branches are fused element-wise, flattened, and passed to the Imaging Module.

This imaging module first uses a fully connected layer with LeakyReLU activation to project the flattened feature map into a higher-dimensional space. The resulting representation is reshaped, modulated by an attention mask, and then progressively upsampled and refined using convolutional layers until the final cross-sectional image is produced.

3 EVALUATION AND DEMO PLAN

To validate our approach, we have collected CSI data from 26 potato tubers located at four different positions in pots, and compared it against the state-of-the-art RSS-based method [4] using 16 ZigBee nodes across 16 channels, whereas our Wi-Fi system employed only 12 nodes operating on 3 channels. Datasets were split 85:15 for training and testing. Visual inspection showed that our method accurately reconstructs tuber shapes, boundaries, and spatial locations as shown in Figure 1b, whereas the RSS-based reconstructions suffered from noticeable blurring and loss of detail. Quantitatively, our custom testbed and multi-branch CNN achieved an average SSIM of 0.99 and an IoU of 0.87, outperforming the average SSIM of 0.98 and IoU of 0.86 from the RSS-based method.

Our demonstration will illustrate the entire workflow of our Wi-Fi CSI-based underground root tuber sensing system, from hardware setup to real-time image reconstruction. We will first present our custom-developed Wi-Fi mesh network, consisting of ESP32-C3 nodes encircling a soil-filled container. A small surface marker confirms tuber placement, and an overhead camera captures its position for ground truth labeling via image segmentation. We will then show how the collected CSI data is fed into our multi-branch CNN *in inference mode* (i.e., without retraining) to reconstruct cross-sectional root tuber images. A laptop running our pre-trained DNN model will display the reconstructed images alongside the marker-based ground truth, allowing attendees to assess accuracy and view high-resolution results. In summary, our framework not only demonstrates the efficacy for non-invasively imaging underground tubers, but also provides the potential for wide applications in smart-agriculture, such as growth monitoring and biomass estimation.

4 DISCUSSION

Going forward, we plan to broaden coverage by adding more nodes and channels to our Wi-Fi mesh network, paving the way for future 3D tuber reconstruction. We also intend to explore robust domain adaptation strategies to sustain sensing accuracy under diverse soil and environmental conditions.

5 CONCLUSION

We have developed a Wi-Fi networked sensing system for underground root tuber imaging. We build a Wi-Fi potato sensing dataset and train a multi-branch CNN model. Our Wi-Fi sensing system outperforms the existing ZigBee system in terms of image reconstruction accuracy, while using fewer wireless nodes.

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