Data-driven Soil Moisture Sensing with mmWave Radar

Yujie Zhuang
Harbin Institute of Technology
Shenzhen, Guangdong, China
zhuangyujiecs@gmail.com

Yang Zhao
Harbin Institute of Technology
Shenzhen, Guangdong, China
yang.zhao@hit.edu.cn

Jie Liu
Harbin Institute of Technology
Shenzhen, Guangdong, China
jieliu@hit.edu.cn

ABSTRACT

Existing soil moisture sensing methods require either plugging probes into soil or burying sensor nodes or aluminum plate in soil. These methods either have mobility and maintenance limitations or have risks of battery leakage. To address these issues, we propose to build a soil moisture sensing dataset using millimeter-wave radar for non-invasive and non-contact moisture sensing of shallow soil. Our millimeter-wave radar soil moisture dataset includes 20 different moisture levels, filling the gap in mmWave radar-based soil moisture sensing datasets. Furthermore, we propose a mm-SoilNet model, which uses the data-driven approach to extract soil moisture features from radar data to estimate the volumetric water content of soil. Our initial experimental results show that the system achieves a mean absolute error of 5.506%.

CCS CONCEPTS

• **Computer systems organization → Sensors and actuators**.

KEYWORDS

mmWave radar, soil moisture sensing

ACM Reference Format:
Yujie Zhuang, Yang Zhao, and Jie Liu. 2024. Data-driven Soil Moisture Sensing with mmWave Radar. In *The 11th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BUILDSYS '24), November 7–8, 2024, Hangzhou, China.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3671127.3698787

BUILDSYS '24, November 7–8, 2024, Hangzhou, China

ACM ISBN 979-8-4007-0706-3/24/11
https://doi.org/10.1145/3671127.3698787

1 INTRODUCTION

Despite unfavorable climate conditions, greenhouses provide an optimal growth environment for plants, playing a crucial role in regions affected by climate change. Real-time, accurate, and large-scale soil moisture remote sensing plays a key role in intelligent irrigation for agriculture. Precise real-time soil moisture sensing enables intelligent irrigation systems to dynamically optimize irrigation schedules to meet the specific needs of the crops being cultivated, ultimately contributing to improved crop yields[12]. Accurate soil moisture information can also provide valuable insights for greenhouse management, plant breeding and other applications.

Current soil moisture sensors can be categorized into contact sensors and non-contact sensors. Contact sensor-based methods typically require placing sensor probes in soil to measure moisture, such as electricity resistance sensors[13], tensiometers, and radioactive sensors[5]. This kind of methods have several limitations. First, they rely on various peripheral devices, such as data loggers and communication modules, to store and transmit the collected sensor data. Installing and integrating these devices into the entire moisture sensing system often requires specialized knowledge and significant effort. Second, a typical greenhouse may cultivate from ten thousand to one million plants in pots, frequently necessitating soil moisture measurement in each pot. Ideally, each pot would require a soil moisture sensor to monitor its moisture level. However, most existing sensors are expensive, making the overall cost prohibitive. In addition, it is also labor-intensive for maintaining such a large-scale sensor network, including tasks like battery replacement and faulty device replacement. On the other hand, non-contact sensor-based techniques estimate soil moisture using radio frequency (RF) signals, eliminating the need to install the aforementioned specialized sensors in the soil. However, existing RF-based techniques also have their own limitations. Some approaches require battery-powered devices to be buried in the soil, such as WiFi nodes[3, 6], LoRa nodes[10], and radar backscatter tags[9]. These methods carry the risk of soil contamination due to battery leakage and incur significant maintenance costs for battery and device replacement. Additionally, due to the size constraints of flowerpots, it is difficult to embed antenna arrays within the pots for soil moisture sensing.The methods proposed by Chen W. et al.[2] and Ding R. et al.[4], require placing a metal plate beneath the soil surface. Although this method avoids the risk of battery leakage, it necessitates maintaining a constant distance between the metal plate and the soil surface, meaning the plate must be recalibrated with each planting cycle, significantly increasing the labor involved in deployment and maintenance. The method proposed by Jiao W. et al. [8]embeds WiFi tags in the soil to predict soil moisture based on the frequency response of the tag resonators. Wang J. et al. [14]attach RFID tags to flowerpots and predict soil moisture by reading their Differential Minimum Response Threshold (DMRT). Although these tags do not require batteries, a tag must be placed on each pot. In a greenhouse environment, deploying and maintaining tags for tens of thousands of pots would demand substantial manual labor.In contrast, remote sensing techniques offer a non-invasive method to sense soil moisture in large-scale areas. This technology detects soil moisture by capturing images from the optical, thermal, and microwave regions of the electromagnetic spectrum via satellites or aircraft. However, this method suffers from low measurement accuracy, low spatial resolution, and is challenging to apply to indoor greenhouse environments[11].

For soil moisture sensing in an indoor environment, such as greenhouse, we propose to build a soil moisture sensing dataset using Frequency Modulated Continuous Wave (FMCW) mmWave radar to enable data-driven non-contact and non-invasive soil moisture sensing. Our study is motivated by the following two considerations. First, mmWave radar is already used in many smart facility applications, such as occupancy detection, human activity recognition, with commercial-off-the-shelf products installed at various indoor environments [1]. Thus, we can just use existing hardware to perform soil sensing without adding more sensors. Second, a data-driven approach can extract soil moisture information from the reflected signals of mmWave radar, without the need to embed sensor nodes or metal plates in the soil. Thus, it can facilitate greenhouse management and significantly lower the deployment and maintenance costs of the system. To this end, we have collected mmWave radar data for 20 different soil moisture levels at two different indoor environments. We develop a neural network model to show feasibility of the data-driven approach to soil moisture sensing using our dataset. Note that different environments have different multipath effects and thus would result in different performance. Thus, we plan to investigate domain adaptation methods to extract domain-invariant features for soil moisture sensing in the future. This paper makes the following contributions:

- We build a soil moisture dataset based on millimeter-wave radar, which includes soil measurements with 20 different moisture levels, addressing the lack of publicly available datasets in this domain.
- We design and implement a data-driven soil moisture sensing system called mm-SoilNet, which utilizes FMCW radar signals to predict soil moisture without the need to place sensor nodes or metal plates in the soil.

2 EXPERIMENTS AND DATASET

2.1 Data acquisition system

We use the IWR1843 and DCA1000EVM evaluation modules to collect millimeter-wave radar data. The IWR1843 is a single-chip radar sensor evaluation module operating in the 76GHz to 81GHz range, produced by Texas Instruments, and features three transmit antennas and four receive antennas. The DCA1000EVM board captures raw ADC data from the IWR1843[7]. We use the YGC-SM soil moisture sensor to collect moisture data from five locations within the soil, averaging these values to serve as the Ground Truth for soil moisture.

2.2 Dataset

Our dataset contains the soil moisture level measurements from the mmWave radar device mentioned above. Soil moisture level refers to the Volumetric Water Content (VWC), denoted as θ, which is defined as the ratio of the volume of water to the volume of wet soil:

$$\theta = \frac{V_{water}}{V_{wetsoil}} \tag{1}$$

The dataset comprises soil samples with 20 different moisture levels, ranging from 6.20% to 43.82%, with intervals of approximately 2%, labeled as Soil 1 to Soil 20. We collected mmWave radar datasets in two different environments, specifically two distinct conference rooms, with variations in chair arrangements and data collection locations. All experimental results presented in the following sections were conducted using the dataset from the first environment. First, we describe the data collection process in the first environment. As shown in Figure 1, during data collection, the radar development board was mounted on a stand fixed to a small lift platform. By adjusting the height of platform and the rotation angle of the stand, we could control the distance between the radar board and the soil surface, as well as the tilt angle of the radar board, thereby enriching the dataset. The transmit and receive signals of the radar board were controlled using the mmWave Studio software.For each type of soil, 128 radar frames are collected, with each frame containing 32 chirps and 384 ADC sampling points. The data is stored in a bin file. In the bin file names, the first number after "data" represents the soil moisture level, labeled as 1 to 20. In the bin file names, the second number after "data" represents the height of the radar development board above the soil surface, measured in centimeters, specifically 16 cm, 20 cm, and 24 cm. The data collection in the second environment was similar to the first. Additionally, we performed data collection in a dynamic environment (with human movement near the soil) to study the impact of dynamic multipath effects on radar signals for future research. The dataset has been uploaded to Zenodo, and more details can be found here https://doi.org/10.5281/zenodo.13889266.

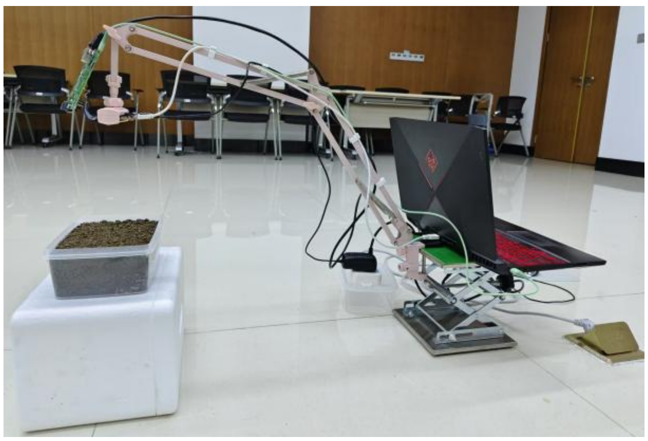

Figure 1: Schematic diagram of the experimental setup.

3 DATA ANALYSIS AND DISCUSSION

3.1 Data Analysis and Results

A single sample (chirp) has dimensions of 4×384, where 4 represents the antenna dimension and 384 is the number of ADC sampling points. As shown in Figure 2, the figure presents the results of the radar signals from soils with two different moisture levels after performing Range FFT. Given that the radar's detection range is approximately 15 meters, we applied a filtering process to the signal. Specifically, after performing FFT along the sampling point dimension, we extracted only the frequency bands near the soil surface. We believe this helps the model focus on soil moisture-related information and reduces the impact of multipath effects and environmental noise. After the extraction, the sample dimensions are reduced to 4×24, shrinking by a factor of 16, which significantly reduces computational complexity.

In the experimental design of this study, two soil samples with different moisture levels (excluding the 1st and 20th levels) are randomly selected as the test set, while the remaining 18 soil samples are used as the training set. Ten-fold cross-validation is performed, and the Mean Absolute Error (MAE), i.e., the absolute difference between the predicted and true values, is computed for each estimation. The final result is obtained by averaging these MAE values. To achieve fine-grained soil moisture detection, we designed a

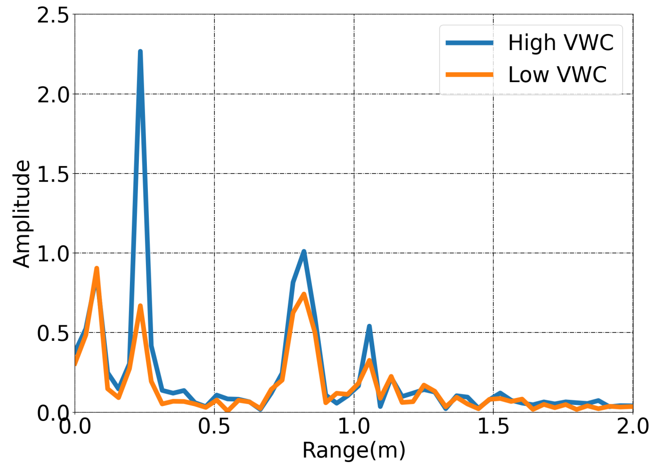

Figure 2: A single sample undergoes Range FFT. VWC refers to volumetric water content, which is the ratio of the volume of water to the volume of wet soil. The detection range of the radar is approximately 15 meters; for simplicity, only the Range FFT results within 2 meters are presented here.

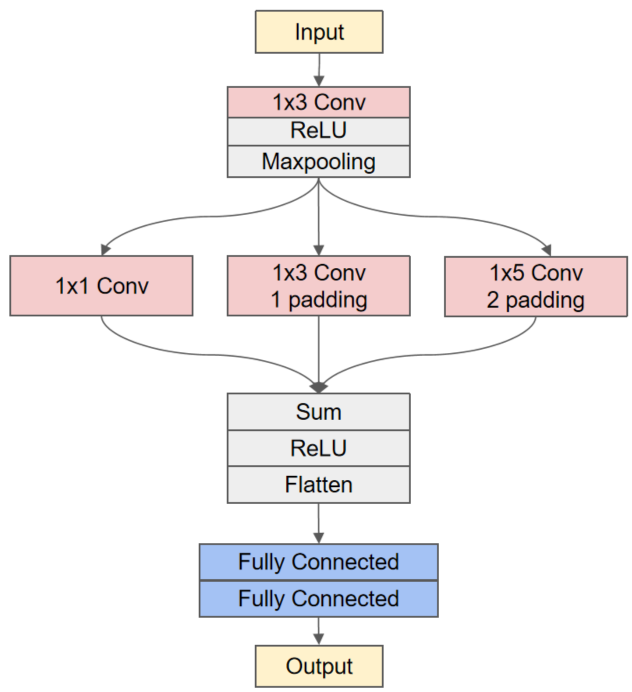

Figure 3: The architecture of the mm-SoilNet

novel neural network called mm-SoilNet. As shown in Figure 3, mm-SoilNet first applies a 1x3 convolutional kernel for large-scale feature extraction from the input data, with a max pooling layer used to extract salient features. Then, mm-SoilNet employs three different sizes of convolutional kernels to capture signal features of soil samples at varying scales. This multi-scale feature extraction prevents the loss of critical information and simplifies the model. The features extracted at different scales are then aggregated and fused, followed by flattening and feeding into two fully connected layers to predict soil moisture content. We use mean squared error as the loss function to train the model.

Table 1 compares the performance of our model, mm-SoilNet, with other machine learning algorithms. The left side of the table lists different soil moisture detection algorithms, the middle column shows the input sample dimensions, and the right column provides the average MAE. As can be seen from the table, our model exhibits the best predictive performance, with an average MAE of 5.506%, which represents an improvement of approximately 2% over other methods. Additionally, we compare the effect of filtering the input data on model performance. Without filtering, the input data includes all frequency bands, with dimensions of 4×384. The table shows that the average MAE difference between the two processing methods is minimal, indicating that the extracted frequency bands contain most of the relevant information about soil moisture and play a crucial role in the prediction accuracy of the model.

Table 1: Comparison of Different Algorithms

Algorithm	Dimension	MAE
SVM	4x384	7.906%
SVM + filtering	4x24	7.312%
MLP	4x384	7.280%
MLP + filtering	4x24	7.620%
mm-SoilNet	4x384	5.556%
mm-SoilNet + filtering	4x24	5.506%

3.2 Discussion and Future work

Our method achieves a mean absolute error of approximately 5.5%, which, while comparable to the accuracy level of typical commercial soil moisture sensors, still leaves significant room for improvement. Additionally, millimeter-wave radar has limited penetration capability, only allowing for the detection of shallow soil moisture. Therefore, our method is more suitable for applications in smart home or greenhouse scenarios for monitoring soil moisture within potted plants. Moreover, extracting fine-grained features related to soil moisture from radar signals in the presence of complicated environmental noise and multipath effects remains a major challenge. Currently, our experiments have been conducted in a single, static environment. In the future, we plan to carry out more experiments in complicated and dynamic environments to investigate the robustness of our method to environmental variations.

4 CONCLUSION

In this paper, we build a millimeter-wave radar-based soil moisture dataset, comprising 20 different soil moisture levels, addressing the lack of millimeter-wave radar datasets in this field. Additionally, we propose a data-driven soil moisture prediction model that extracts features related to soil moisture from a large amount of millimeter-wave radar data to estimate the volumetric water content of the soil. The system achieves a mean absolute error of 5.506%.

REFERENCES

[1] Aqara. 2024. Aqara Occupancy Detector. https://www.aqara.com/Aqara-Presence-Detector-FP1_overview. [Online; accessed October 2024].

[2] Wenyao Chen, Yimeng Feng, Mark Cardamis, Cheng Jiang, Wei Song, Oula Ghannoum, and Wen Hu. 2022. Soil moisture sensing with mmWave radar. In *Proceedings of the 6th ACM Workshop on Millimeter-Wave and Terahertz Networks and Sensing Systems*. 19–24.

[3] Jian Ding and Ranveer Chandra. 2019. Towards low cost soil sensing using Wi-Fi. In *The 25th Annual International Conference on Mobile Computing and Networking*. 1–16.

[4] Rong Ding, Haiming Jin, Dong Xiang, Xiaocheng Wang, Yongkui Zhang, Dingman Shen, Lu Su, Wentian Hao, Mingyuan Tao, Xinbing Wang, et al. 2023. Soil Moisture Sensing with UAV-Mounted IR-UWB Radar and Deep Learning. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 7, 1 (2023), 1–25.

[5] Wilford Gardner and Don Kirkham. 1952. Determination of soil moisture by neutron scattering. *Soil Science* 73, 5 (1952), 391–402.

[6] Steven M Hernandez, Deniz Erdag, and Eyuphan Bulut. 2021. Towards dense and scalable soil sensing through low-cost WiFi sensing networks. In *2021 IEEE 46th Conference on Local Computer Networks (LCN)*. IEEE, 549–556.

[7] Texas Instruments. 2020. DCA1000EVM: Real-time data-capture adapter for radar sensing evaluation module.

[8] Wenli Jiao, Ju Wang, Yelu He, Xiangdong Xi, and Xiaojiang Chen. 2022. Detecting soil moisture levels using battery-free Wi-Fi tag. *arXiv preprint arXiv:2202.03275* (2022).

[9] Colleen Josephson, Manikanta Kotaru, Keith Winstein, Sachin Katti, and Ranveer Chandra. 2021. Low-cost in-ground soil moisture sensing with radar backscatter tags. In *Proceedings of the 4th ACM SIGCAS Conference on Computing and Sustainable Societies*. 299–311.

[10] Daniel Kiv, Garvita Allabadi, Berkay Kaplan, and Robin Kravets. 2022. Smol: Sensing soil moisture using LoRa. In *Proceedings of the 1st ACM Workshop on No Power and Low Power Internet-of-Things*. 21–27.

[11] Abhilash Singh, Kumar Gaurav, Gaurav Kailash Sonkar, and Cheng-Chi Lee. 2023. Strategies to measure soil moisture using traditional methods, automated sensors, remote sensing, and machine learning techniques: review, bibliometric analysis, applications, research findings, and future directions. *IEEE Access* 11 (2023), 13605–13635.

[12] Alon Tal. 2016. Rethinking the sustainability of Israel's irrigation practices in the Drylands. *Water research* 90 (2016), 387–394.

[13] He Tian, Yi Shu, Xue-Feng Wang, Mohammad Ali Mohammad, Zhi Bie, Qian-Yi Xie, Cheng Li, Wen-Tian Mi, Yi Yang, and Tian-Ling Ren. 2015. A graphene-based resistive pressure sensor with record-high sensitivity in a wide pressure range. *Scientific reports* 5, 1 (2015), 8603.

[14] Ju Wang, Liqiong Chang, Shourya Aggarwal, Omid Abari, and Srinivasan Keshav. 2020. Soil moisture sensing with commodity RFID systems. In *Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services*. 273–285.