Data-driven RF Tomography via Cross-modal Sensing and Continual Learning

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August 12th, 2025

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- Introduction to underground RF tomography
  - Underground RF sensing of root tubers
  - Data-driven RF tomography
- Methods
  - Cross modal sensing for automatic data annotation
  - One-shot fine tuning for sensing in dynamic environments
- Experiments and results
- Conclusion and future work

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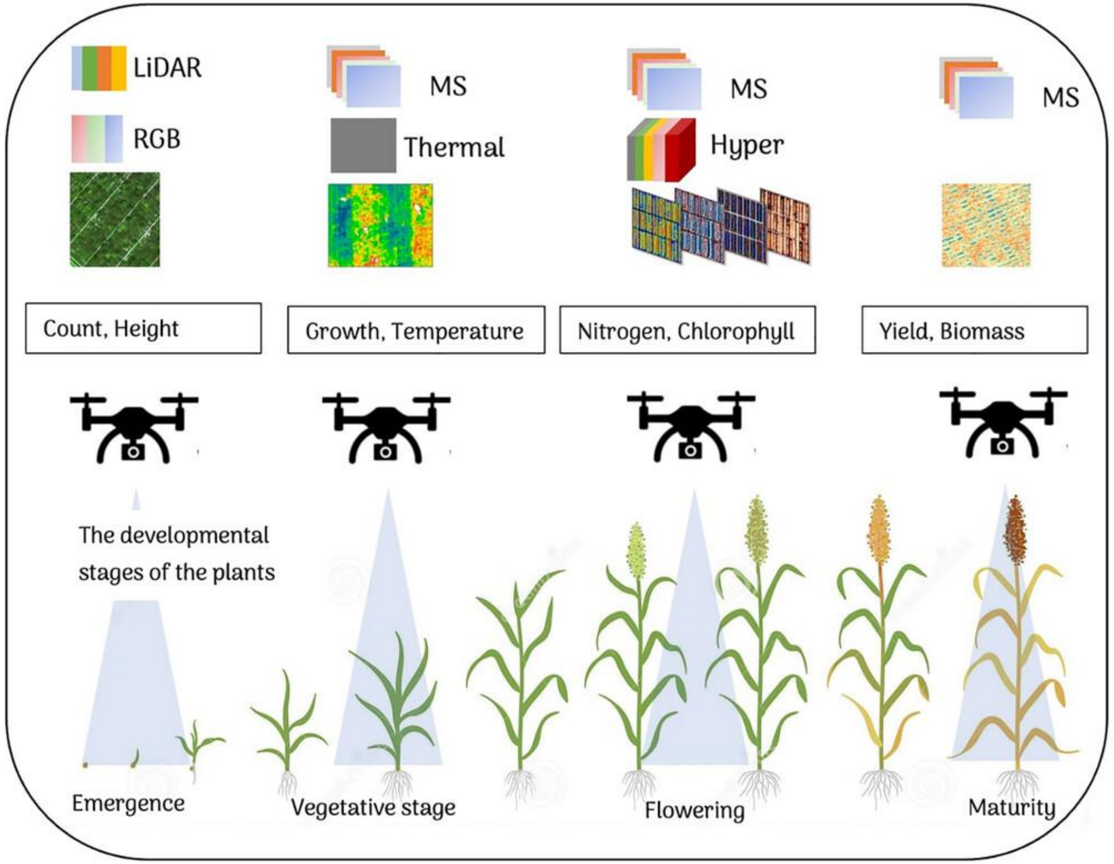
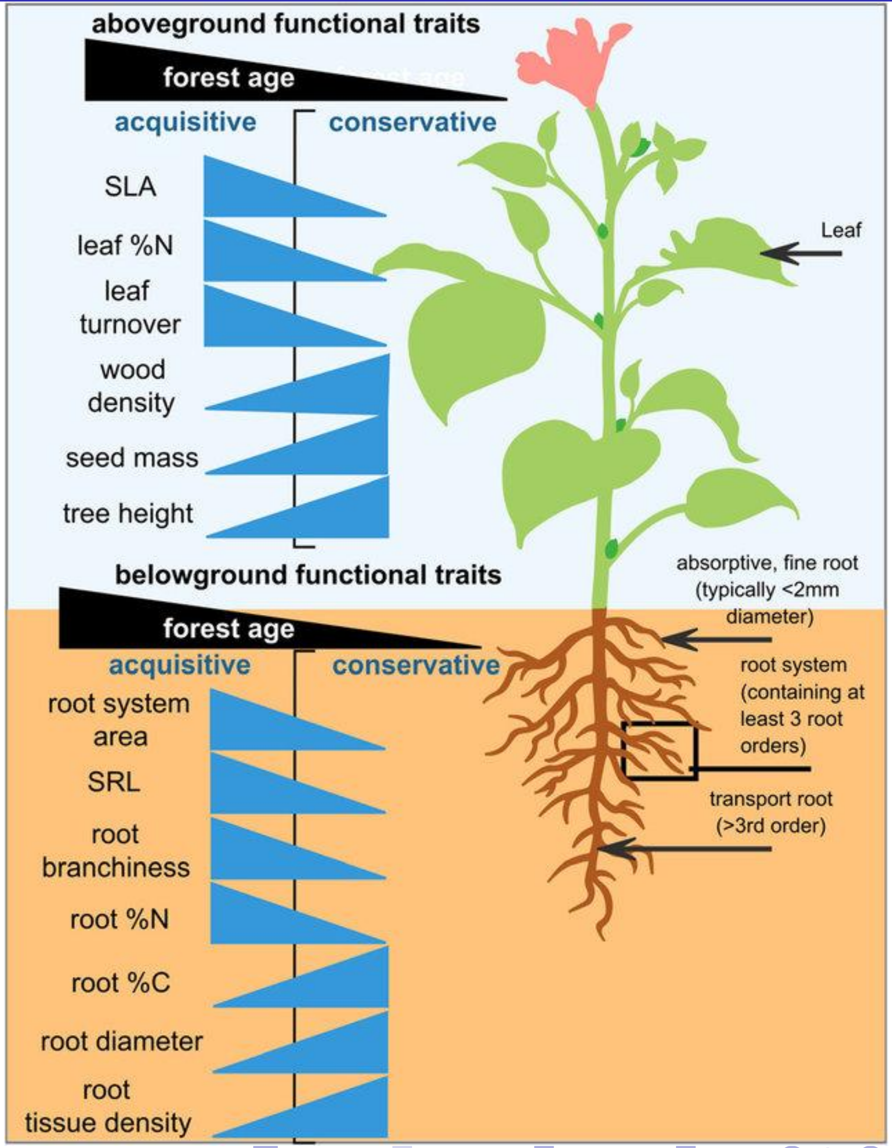
Motivation: Underground Plant Phenotyping

- Plant phenotyping：measuring
- UAV-based sensors for aboveground sensing [1]
- How about underground sensing?

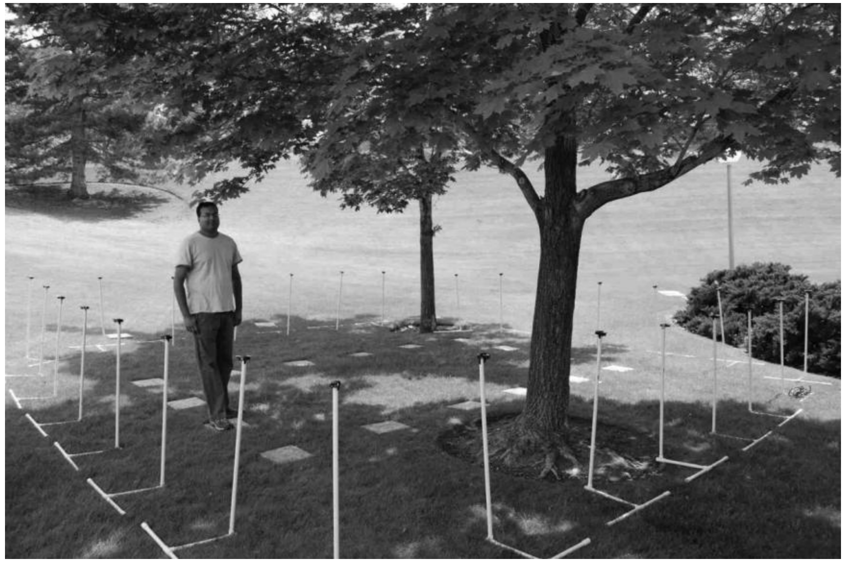


[1] Gano B, Bhadra S, Vilbig J M, et al. Drone-based imaging sensors, techniques, and applications in plant phenotyping for crop breeding: A comprehensive review[J]. The Plant Phenome Journal, 2024, 7(1).

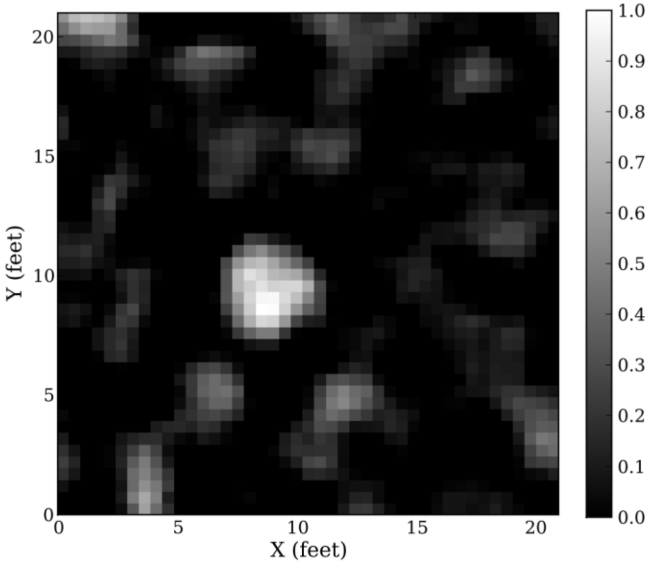


RF Tomography Technique

- Radio-frequency (RF) sensing
  - Used in localization & tracking of people [1,2]
  - Physical model-based imaging
- Underground RF sensing
  - Root tuber phenotypic trait, e.g., cross-sectional area of tuber
  - Deep neural network (DNN)-based imaging [3]



RF tomography for locating a person



RF tomography result

[1] Wilson J, Patwari N. Radio tomographic imaging with wireless networks[J]. IEEE Transactions on Mobile Computing, 2010.
[2] Wilson J, Patwari N. See-through walls: Motion tracking using variance-based radio tomography networks[J]. IEEE Trans on Mobile Computing, 2010.
[3] Wang T, Zhao Y, Liu J, et al. Demo Abstract: Underground Potato Root Tuber Sensing via a Wireless Network[C]//2024 23rd ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN).

RF Tomography for Underground Root Tuber Sensing (RTS)

- Forward model H:

$$\mathbf{g} = \mathcal{H}(\mathbf{r}) + \mathbf{n},$$

image vector **r** represents a measure of current presence of targets, i.e., root tubers; vector **g** represents RF signals, i.e., received signal strength (RSS) measurements.

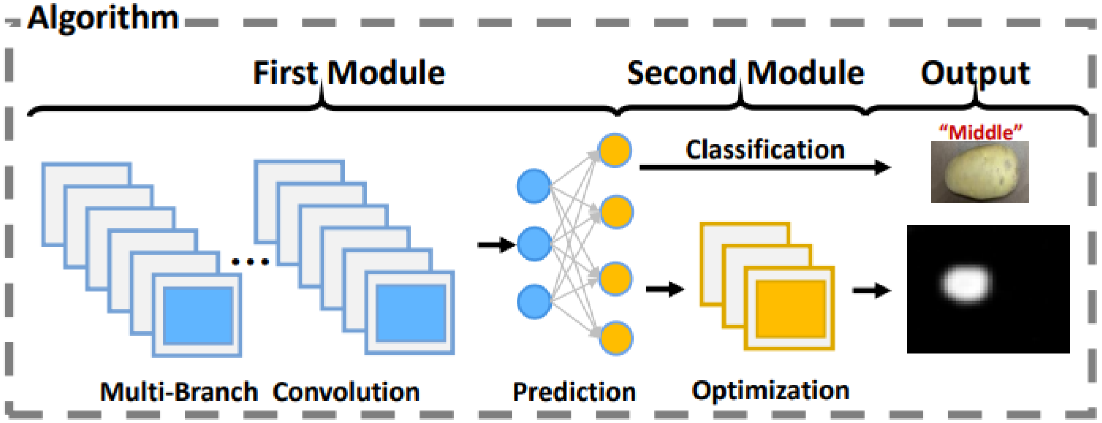
- Deep neural network (DNN)-based imaging:

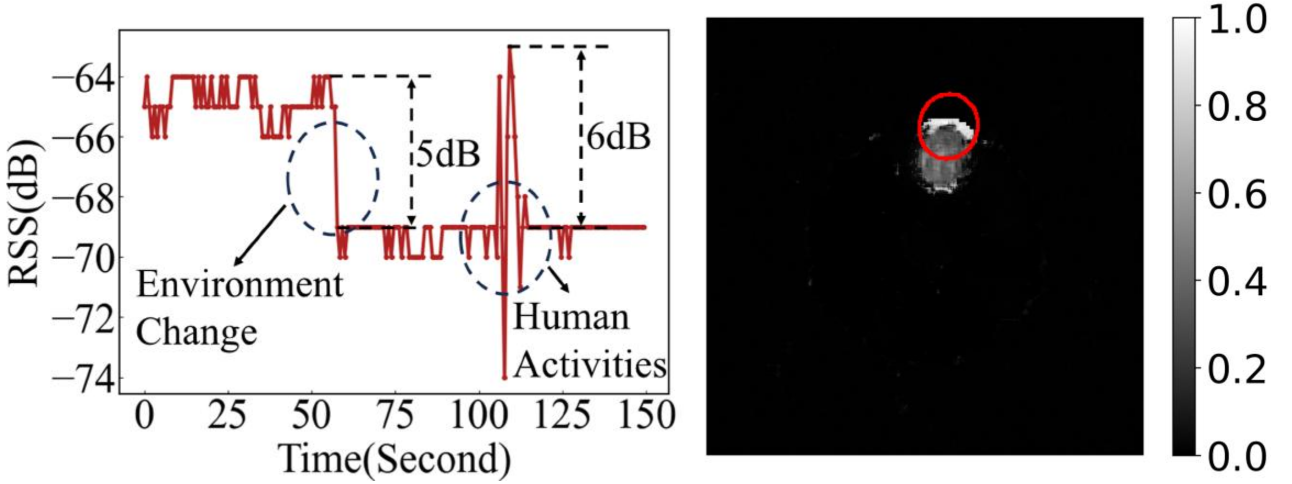
$$\hat{\mathbf{r}} = \mathcal{F}(\mathbf{g}; \Theta),$$

DNN model F can be trained to estimate **r** from RSS measurements, Θ represents the set of DNN model parameters.

Challenges in Data-driven RTS

- Annotation for training dataset
  - Different tuber size and shape
    (9 tubers → 3 size categories)
  - Different locations
- Sensitive to environment change
  - Multi-path effect
  - Demo experience [1]

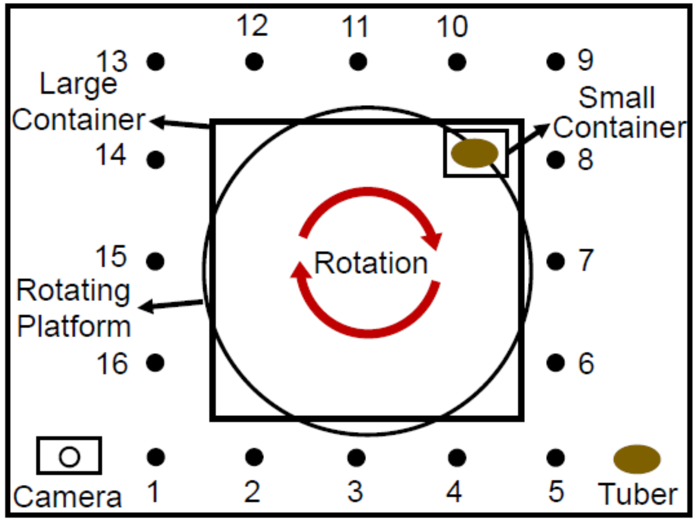




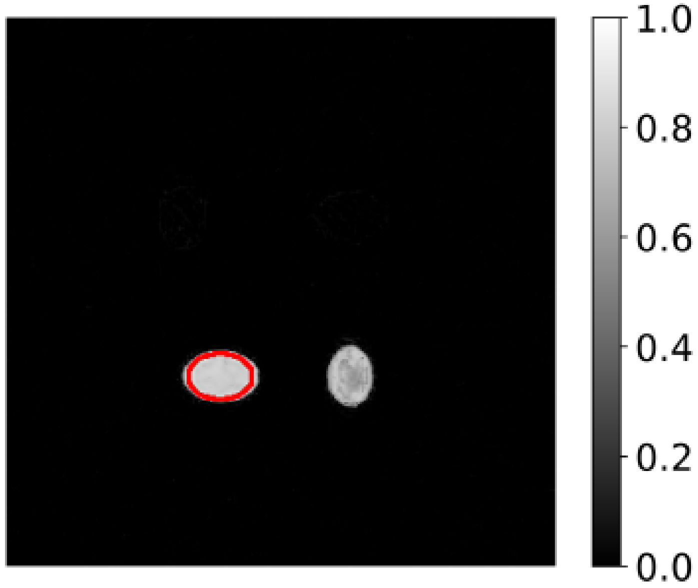
[1] Wang T, Zhao Y, Liu J, et al. Demo Abstract: Underground Potato Root Tuber Sensing via a Wireless Network[C]//2024 23rd ACM/IEEE IPSN.

Data-driven Radio Frequency Tomography (DRIFT)

- Large dataset
  - Visual-RF sensing testbed VR-Spin
  - Cross-modal sensing for automatic data annotation



- Dynamic environment
  - Statistical change detection
  - One-shot fine tuning for RF imaging in a dynamic environment



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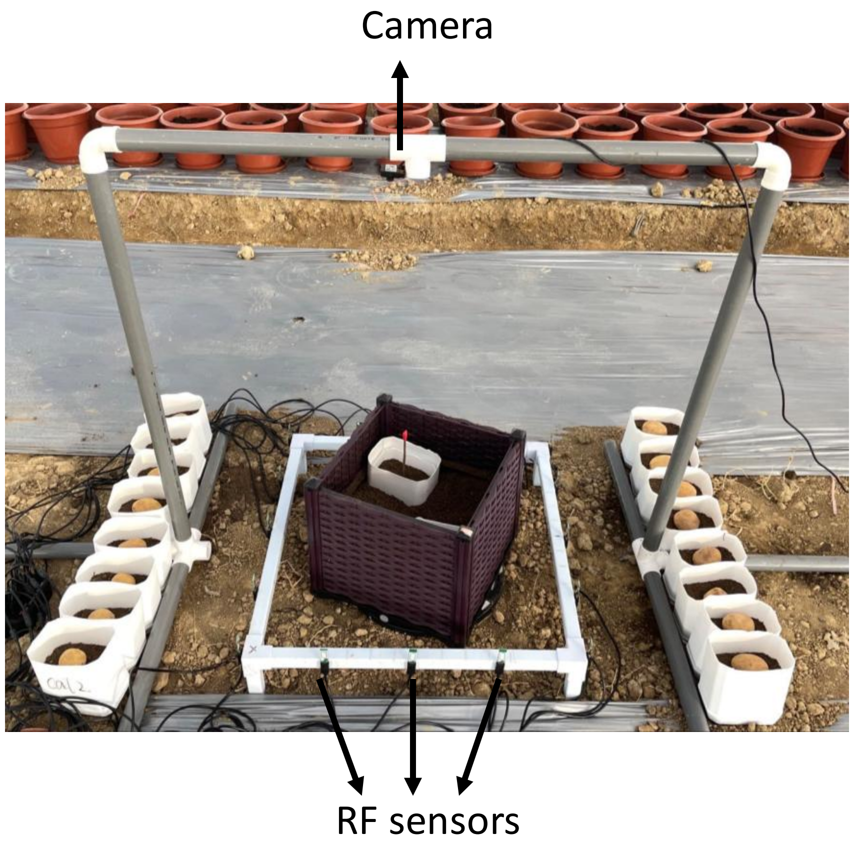
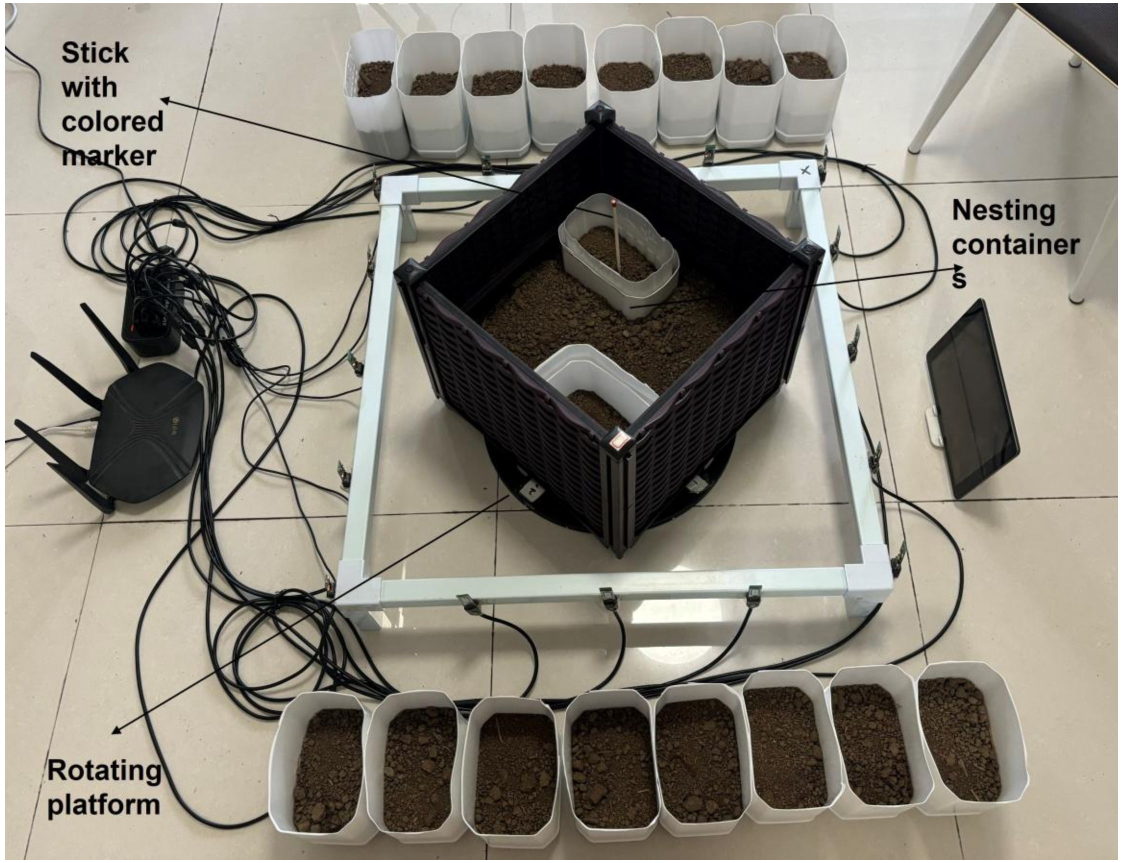
Use-case Scenario: Potted Plants in Greenhouses

- Use-case: phenotyping for crop breeding in greenhouses
- Challenges: collect and annotate data
- Solutions:
  - Visual-RF sensing testbed VR-Spin
  - Cross modal learning



Data-acquisition Testbed VR-Spin and RTS Dataset

- Rotating platform w/ nesting container
  - Tuber location diversity
  - Tuber size & shape diversity
- RTS Dataset
  - 26 potato tubers (L: 2~10.5cm, W: 1~7cm)
  - 4 locations in a sensing area of 72x72cm (frame size)
  - 16 RF sensor nodes providing 16x15 link measurements



https://ieee-dataport.org/documents/underground-root-tuber-sensing-wireless-networks

Cross Modal Learning for Tuber Cross-section Imaging

- Computer vision algorithms
  - Automatic data annotation
  - Tubers w/ irregular shape
- DNN model for cross-section imaging
  - RF signals **r** from RF sensor network
  - Root tuber masks indicating cross-section **g**

$$\hat{\mathbf{r}} = \mathcal{F}(\mathbf{g}; \Theta)$$

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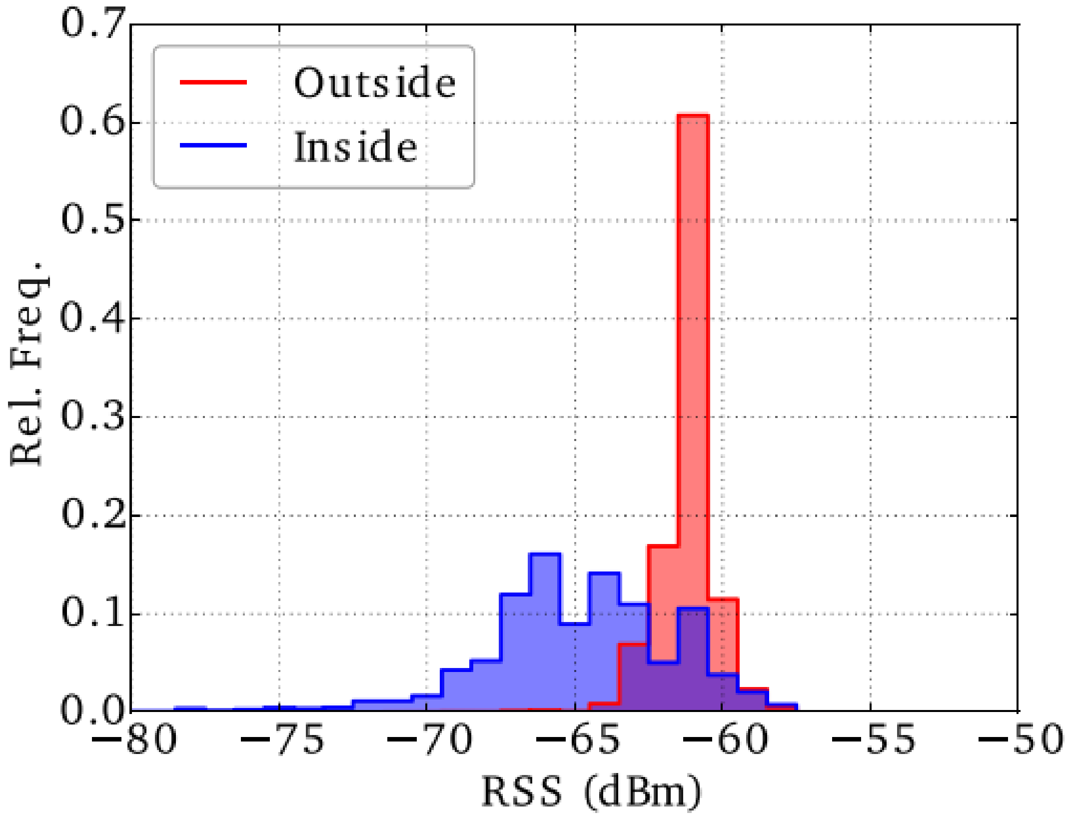
Statistical Model-based Environment Change Detector

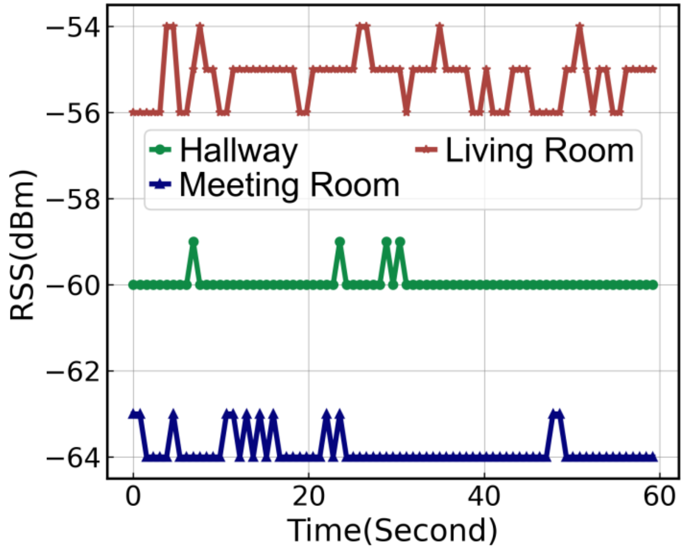
- Environment change detection
- RSS histograms for dynamic and static environments (one link) [1]
- Select top-k links from all links of the RF sensor network
- Use the average standard deviation from the static environment as the threshold

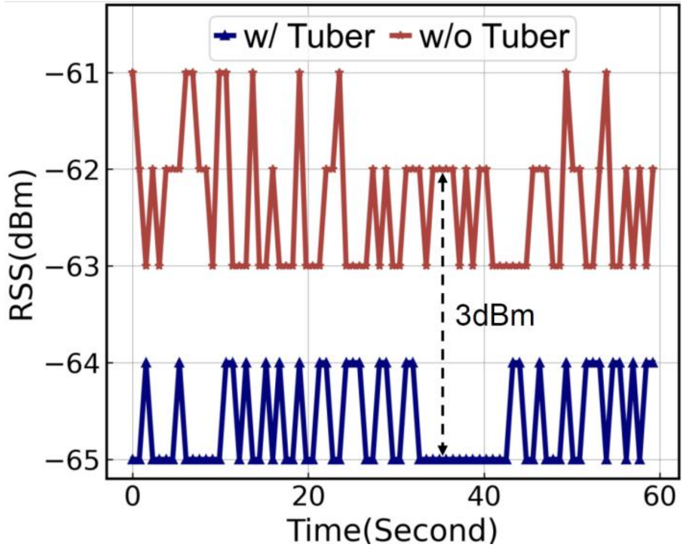


[1] Hillyard P, Patwari N. Never use labels: Signal strength-based Bayesian device-free localization in changing environments[J]. IEEE Transactions on Mobile Computing, 2019, 19(4): 894-906.

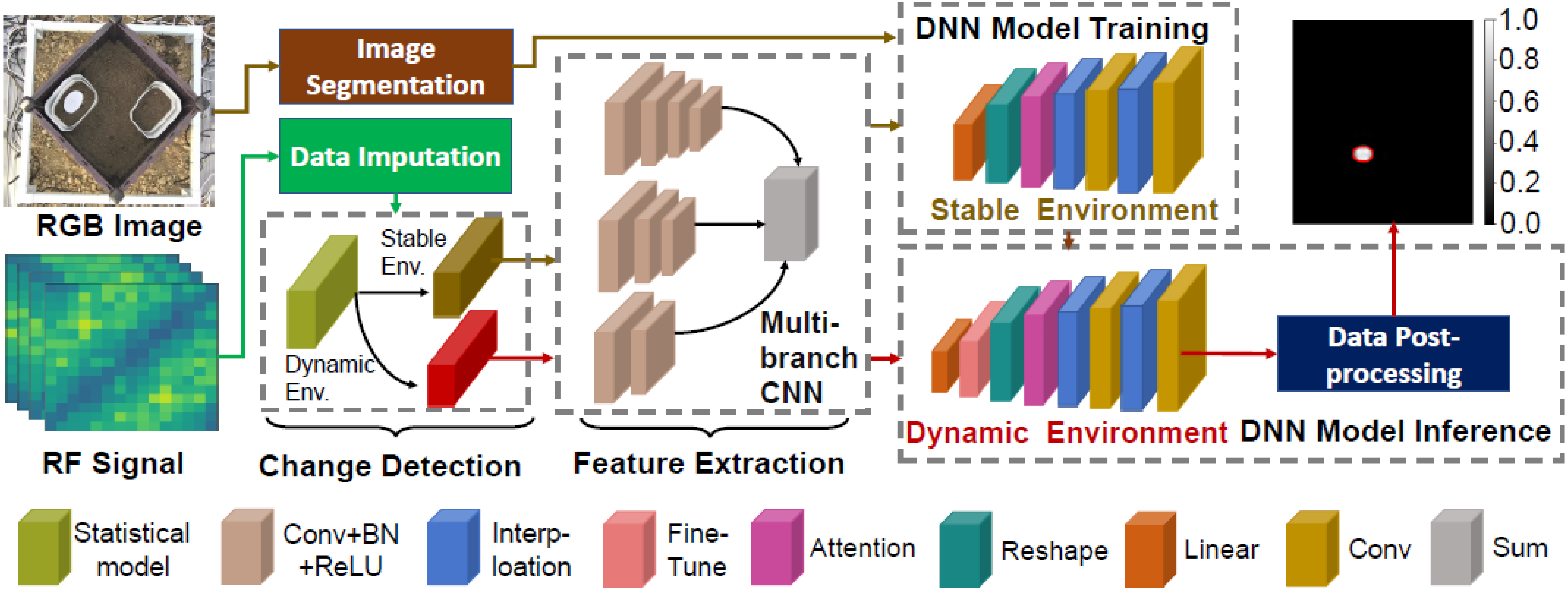
One-shot Fine-tuning

- Key observation:
  - RSS changes due to tuber growth/change are much lower than due to environment change
  - 3dBm due to tuber vs. 4-5dBm due to environment change
- One-shot fine-tuning
  - Use RSS data from new environment & image reconstruction from old environment as GT to update the DNN model





DRIFT Framework with Change Detection and Fine Tuning



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Experiments for RTS in Dynamic Environments

- Experimental setup:
  - 26 tubers are used to build an DNN model at an initial environment E_1
  - 1 of 26 tubers is used to fine tune the initial model
  - 4 of the rest 25 tubers are used in testing the DRIFT model (to simulate 4 growth stages of potato tubers) at three different environments E_2, E_3, E_4

Experiments and Evaluation

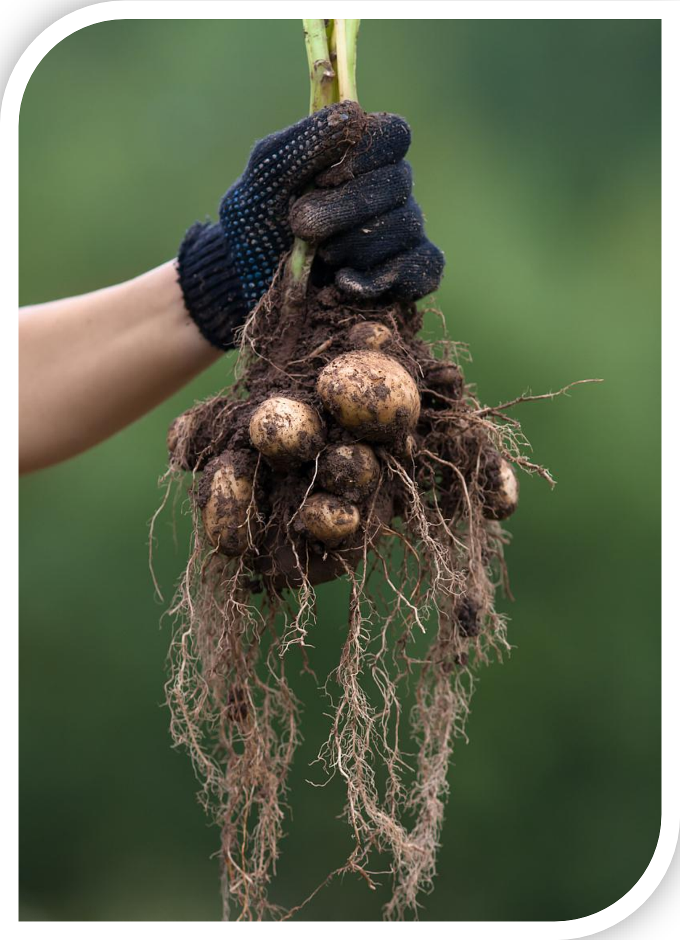
- Evaluation metrics:
  - Relative pixel difference (RPD)
  - Intersection over union (IoU)
  - Equivalent diameter error (EDE)
- Results (on average)
  - 0.07 RPD vs. 0.17 from [16]
  - 0.90 IoU vs. 0.83 from [16]
  - 1.85cm EDE vs. 2.95cm [16]

Test	Method	Leave-1-Out			Leave-2-Out		
		RPD	IoU	EDE	RPD	IoU	EDE
$E_1 \to E_1$	MC-LIM-UNet [13]	0.15	0.85	2.96	0.14	0.89	2.57
	CNN-LSTM [16]	0.17	0.81	3.15	0.21	0.82	3.18
	Ours	**0.14**	**0.84**	**2.87**	**0.10**	**0.90**	**2.22**
$E_1 \to E_2$	MC-LIM-UNet [13]	0.11	0.90	2.53	0.40	0.73	4.17
	CNN-LSTM [16]	0.10	0.88	2.46	0.24	0.81	3.29
	Ours	**0.15**	**0.83**	**2.94**	**0.08**	**0.91**	**1.98**
$E_2 \to E_3$	MC-LIM-UNet [13]	0.16	0.84	3.06	0.28	0.76	3.41
	CNN-LSTM [16]	0.13	0.86	2.73	0.18	0.85	3.07
	Ours	**0.16**	**0.83**	**3.04**	**0.05**	**0.90**	**1.55**
$E_3 \to E_4$	MC-LIM-UNet [13]	0.15	0.84	2.99	0.28	0.74	3.43
	CNN-LSTM [16]	0.12	0.87	2.70	0.16	0.85	2.87
	Ours	**0.15**	**0.83**	**2.99**	**0.06**	**0.90**	**1.66**

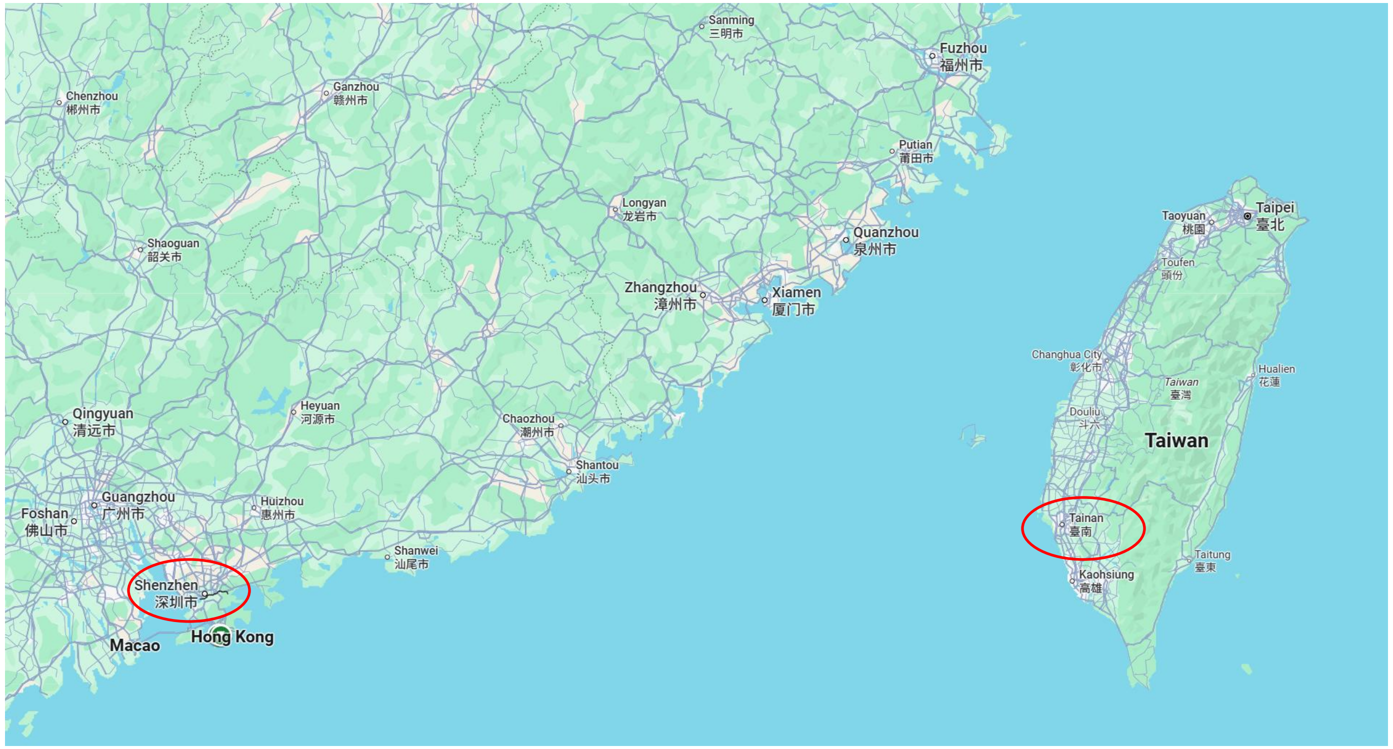
[16] Wu H, Ma X, Yang C H H, et al. Attention based bidirectional convolutional LSTM for high-resolution radio tomographic imaging[J]. IEEE Transactions on Circuits and Systems II: Express Briefs, 2020, 68(4): 1482-1486.

Conclusion and Future Work

- A cross-modal sensing testbed is built for underground root tuber sensing (RTS)
- A data-driven RF tomography (DRIFT) framework is proposed for RTS in dynamic environments
- Our RTS dataset and DRIFT code are made publicly available
- Future work includes multi-tuber detection, other DNN models and domain adaptation methods



Thank You!



IEEE DataPort: underground-root-tuber-sensing-wireless-networks

https://github.com/Data-driven-RTI/DRIFT

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