Towards Root Phenotyping in situ Using THz Imaging

N. Smith[1], L. A. Rivera[1], N. Burford[2], T. Bowman[2], M. O. El-Shenawee[2], and G. N. DeSouza[1],
[1]ViGIR - Vision-Guided and Intelligent Robotics Lab, University of Missouri, Columbia, MO, 65211
[2]Terahertz Imaging and Spectroscopy Lab, University of Arkansas, Fayetteville, AR, 72701

***Abstract*—Root growth and development are critical for plant survival and productivity. While systems have been developed to automate the process of extracting root traits using 2D and 3D imaging under controlled conditions, to date, no systems exist that can non-destructively and repeatedly provide high-quality information on roots of field-grown plants. At the same time, Terahertz (THz) imaging is becoming a valuable tool in many areas, including medicine, pharmacology, security, etc. and has the potential for non-destructive, repeated imaging of root systems growing in pot and eventually field conditions. In this paper, we present a framework for investigating root growth and function of plants by analyzing and classifying THz data. The proposed system can successfully identify organic materials from potting soil or sand using both THz transmitted and reflected signals.**

I. Introduction

ROOT System Architecture (RSA) is the spatial representation of a plant root system. It plays a vital role in determining the life and growth of plants. Many researchers have long correlated root traits present in the various RSAs to physiological functions of the plant, such as as drought tolerance, carbon allocation, nutrient-acquisition capacity, etc. The key difficulty in measuring and classifying RSAs is the ability to measure root traits without destroying the plants. In order to facilitate this, some researchers opt to growing plants in hydroponic, aeroponic or translucent gel-based media. This approach allows for the inspection of plant roots while still inside a cylinder or solution [1], but they do not recapitulate the nature of RSA in soil while they restrict analyses to young plants. Others are using X-ray CT or MRI based approaches to non-destructively image roots in solid non-translucent media. However, the primary disadvantages of these approaches are the cost, the scanning times, and their limitation to plants grown in pots, where translation of these systems to field conditions does not seem likely. Terahertz (THz) imaging is an emerging and significant nondestructive evaluation technique used for analyzing non-conducting materials [2]. THz signals can be captured at the emitter side (reflection) or on the opposite side of the object, at the detector side (transmission) [3], [4]. In both cases, THz signals interact with the different materials in the object under investigation (e.g. soil, roots, rocks, etc) resulting in multiple reflections or transmissions that are captured by the sensor – this is usually referred to as signal crosstalk. We have developed classification frameworks – Hierarchical Guided Under-determined Source Signal Separation (HiGUSSS) – for dealing with problems involving crosstalk [5]. In this paper, we present the results from applying this framework to Pulsed Terahertz imaging of plant samples buried in sand and potting soil.

II. Methods

A similar problem with crosstalk has been approached in different contexts: for pattern recognition of Surface Electromyography (sEMG) signals for the operation of power wheelchairs [6], [7]; diagnosis of voice dysfunctions [8]; and even identification of multiple chemical compounds using THz signals [9]. In all these cases, a classification framework called Guided Under-determined Source Signal Separation (GUSSS) and more recently the HiGUSSS [5] were developed and applied with high indexes of success, with accuracies as high as 97% for four to ten signatures (also called gestures, in the framework). The idea behind GUSSS is to inject a sought-out signature – e.g. a previously learned signal which is typically reflected off or transmitted through a specific object (root, soil, etc.) – into the classifier and observe the response obtained in terms of the statistical independence of the original signal and the one created by the injected signature. If these two signals are statistically independent, this indicates that the sought out signature was not present (crosstalk) in the original signal. Otherwise, the signature was present and we can classify the signal as containing the sought-out object.

III. Experiments and Results

Samples including carrots, sweet potatoes, turnip, rocks and wood pieces were buried in sand and in potting soil and imaged using both transmission and reflection signals. This allowed us to compare the two imaging methods in order to determine their effectiveness at acquiring the shape and size of different buried organic materials.

A. *Results from THz Transmission*

For this experiment, a carrot of approximately 18*cm* in length was placed in a plastic container filled first with sand and then potting soil. The total depth of the material in both cases was approximately 5*cm*. Figure 1(a) and (b) present photos of the samples investigated in this experiment with THz transmission imaging. Figure 1(c) and (d) show the measured THz signal with the emitter (or detector) located over (or under) dry sand only and the carrot buried in dry sand, respectively. Figure 1(e) shows a THz transmission time domain image for carrot buried in sand, and (f) shows the HiGUSSS classification results. Table I shows the classification results for the sand and the soil cases.

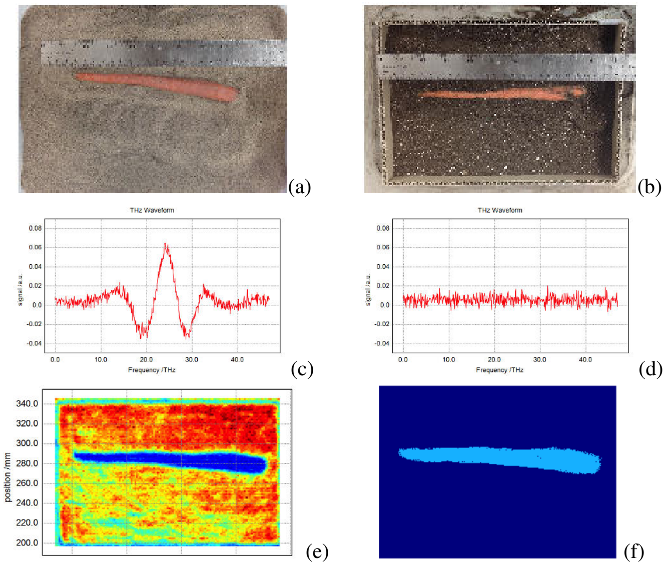

Figure 1. Carrot samples in (a) sand and (b) soil; Time domain THz signals transmitted (c) through sand and (d) through the carrot buried in sand; (e) THz transmission time domain images for carrot buried in sand; (f) Results of the HiGUSSS classification (sand).

Table I
CLASSIFICATION ACCURACY FOR THE THZ TRANSMISSION EXPERIMENTS.

Classification Accuracy %	
Sand + Carrot	96.04
Soil + Carrot	96.06

B. Results from THz Reflection

To investigate the reflection mode, the THz emitter and detector were both positioned above the sample at a 30-degree angle of incidence relative to the surface. The samples investigated in these experiments included a sweet potato, a turnip, a piece of dry tree branch and four rocks of different sizes, all covered by $3-4mm$ of sand as shown in Figure 2(a). The time-domain window of the system was set such that both the sand surface reflection and the reflection from the buried objects could be measured. This is illustrated in Figure 2(b), which shows the measured reflected THz signal from both the sand and potato surfaces when emitter/detector are positioned above the potato. Similar to the transmission mode, an image can be formed from the reflected time-domain signals. This is shown in Figure 2(c), which illustrates the amplitude of the subsurface reflection. Figure 2(d) shows the results of the HiGUSSS framework applied to the THz reflection signals to identify the multiple classes of objects buried in the sand.

Comparison between Figure 2(a) and 2(d) demonstrate that the results are promising. The HiGUSSS achieved an average accuracy of 91.58% for all five types of objects (potato, turnip, rocks, tree branch and sand). Table II presents the classification percentages of each of the four types of objects (potato, turnip, rocks, and tree branch) against the sand.

IV. CONCLUSION

The results presented in this paper demonstrate the potential of THz imaging to detect and identify the different objects buried in sand and potting soil. This system is the first step towards revolutionizing root phenotyping in situ, and thus genetic improvement on the basis of root characteristics.

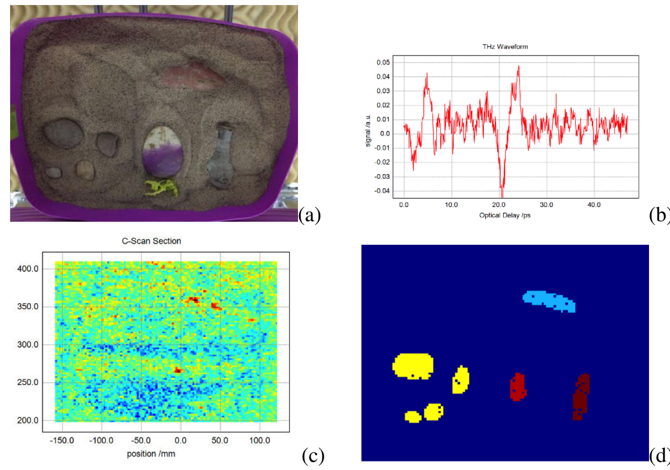

Figure 2. (a) Photo of the samples used for the THz reflection test including a sweet potato, a turnip, four rocks and a piece of tree branch (uncovered to show the objects); (b) The time domain reflected signal at a particular point in (c); (c) Time domain THz reflection image of the objects after being completely buried by dry sand; (d) Final classification using the HiGUSSS Framework.

Table II
CLASSIFICATION ACCURACY FOR THE THZ REFLECTION EXPERIMENTS.

Classification Accuracy %	
Sand + Potato	92.50
Sand + Rock	94.68
Sand + Turnip	91.43
Sand + Wood	87.73

REFERENCES

[1] T. Nakini and G. DeSouza, "Distortion correction in 3d-modeling of roots for plant phenotyping," in *European Conference on Computer Vision (ECCV) Workshop on Computer Vision for Plant Phenotyping*, Sept. 2014, Zurich, Switzerland.

[2] T. Bowman, M. El-Shenawee, and S. G. Sharma, "Terahertz spectroscopy for the characterization of excised human breast tissue," in *2014 IEEE MTT-S International Microwave Symposium*, Jun 2014, tampa Bay, FL.

[3] D. Woolard, E. Brown, M. Pepper, and M. Kemp, "Terahertz frequency sensing and imaging - a time of reckoning future applications?" *Proceedings of the IEEE*, vol. 93, no. 10, pp. 1722–1743, Oct 2005.

[4] T. C. Bowman, M. El-Shenawee, and L. K. Campbell, "Terahertz imaging of excised breast tumor tissue on paraffin sections," *IEEE Trans. on Antennas and Propagation*, vol. 63, no. 5, 2015.

[5] L. A. Rivera, N. R. Smith, and G. N. DeSouza, "High-accuracy recognition of muscle activation patterns using a hierarchical classifier," in *5th IEEE RAS & EMBS International Conference on Biomedical Robotics*, Aug. 2014, BioRob2014, Sao Paulo, Brazil.

[6] L. A. Rivera and G. N. DeSouza, "Recognizing hand movements from a single sEMG sensor using guided under-determined source signal separation," in *12th IEEE International Conference on Rehabilitation Robotics*, Jun. 2011, pp. 450–455, ETH Zurich, Switzerland.

[7] ——, "A power wheelchair controlled using hand gestures, a single sEMG sensor, and guided under-determined source signal separation," in *4th IEEE RAS & EMBS International Conference on Biomedical Robotics*, Jun. 2012, pp. 1535–1540, BioRob2012, Rome, Italy.

[8] N. Smith, T. Klongtruagrok, G. DeSouza, C. Shyu, M. Dietrich, and M. Page, "Non-invasive ambulatory monitoring of complex sEMG patterns and its potential application in the detection of vocal dysfunctions," in *e-Health Networking, Applications and Services (Healthcom), 2014 IEEE 16th International Conference on*, Oct. 2014, pp. 447–452.

[9] L. A. Rivera and G. N. DeSouza, "Detecting terahertz signatures using guided under-determined source signal separation," in *40th International Conference on Infrared, Millimeter, and Terahertz Waves*, Aug. 2015, IRMMW-THz, Hong Kong, China.