

Non-destructive underground fiber Bragg grating sensing system with ResNet prediction for root phenotyping

Steven Binder^a, Kabir Hossain^b, Alexander Bucksch^b, Mable Fok^{*a}

^aPhotonics and Soft Robotics Laboratory, College of Engineering,
University of Georgia, Athens, GA, 30602

^bSchool of Plant Sciences, University of Arizona, Tucson, AZ, 85721

ABSTRACT

The quantitative evaluation of plant organs in a non-destructive and continuous fashion is the technological bottleneck to meet the food, fuel, and fiber needs for the 10 billion people on earth by 2050 [1]. Quantifying crop root architecture paves promising ways to improve resource uptake in the face of the resource limitations in the degraded soils of future climates [2]. Current root measurement methods either have low resolution or involve uprooting the plant. In all cases, the measurement methods do not provide any prediction on how well the plant is growing. We propose the usage of three fiber Bragg gratings (FBG) embedded within soil to measure underground strain change due to pseudo-root growth and a Residual Neural Network (ResNet) to predict its characteristics in a non-destructive fashion. To generate large amounts of sensor data similar to that of a growing root, we developed an automated robot that inserts pseudo-roots of 1mm and 5mm in diameter to 15cm below the soil's surface over the span of 11 minutes. We used 2,582 and 240 samples in training of the diameter and depth models, while testing was performed using 646 and 60 samples. The models were able to achieve accuracy of 92% and 93% for diameter and depth prediction, respectively. Through transfer learning, our base models will be expanded so that real time prediction on actual plant roots diameter and depth can be achieved.

Keywords: Fiber optic sensing, fiber Bragg grating, ResNet, plant phenotyping

1. INTRODUCTION

With climate change causing a degradation in soil quality, nutrient availability for crops will be limited. An exponentially growing population set to outpace agricultural output by 2050 will place an additional strain as land becomes overused and nutrient availability is restricted further [1]. To improve nutrient uptake of crops, selective breeding techniques can be employed to tailor the next generation of plants to a changing environment. Measuring plant root architecture in a non-destructive and continuous fashion provides breeders with insightful phenotypical information for improving nutrient uptake [3]. By rapidly developing more efficient crops, output of agricultural fields most affected by soil degradation can be increased. Additionally, growers will be able to conserve critical resources such as water and fertilizer as their plants will be more efficient at extracting nutrients from their surroundings, ensuring less damage is done to local environments. However, development of accurate root sensing systems faces many challenges such as varying soil composition and susceptibility to environmental variations [4].

The shovelomics protocol [5, 6], X-ray tomography, magnetic resonance imaging (MRI) [7], and ground penetrating radar (GPR) [8] are popular root phenotyping methods currently employed. However, their widespread deployment is severely limited due to inherent disadvantages. Shovelomics is the process of physically removing a root system from the soil for measurement by hand [9]. While providing highly accurate root structure measurements, destructive excavation prevents analysis of a plant's interaction with its surrounding environment. Electromagnetic wave-based methods, such as GPR, X-ray, and MRI can provide non-destructive measurements of a plant's root system. However, varying soil composition leads to a reduced throughput, low resolution, and at times inaccurate measurements [9]. While providing rapid measurements, X-ray tomography can only be performed on plants grown within portable containers. Making it a viable option only for measuring young plants whose root phenotype has not been affected by the growth container's size [10]. MRI systems have recently shown promising results for in-field and non-destructive measurements of root structure. Overall deployment of MRI systems is limited however due to complex calibration requirements and their susceptibility to distorted measurements when magnetic materials are present [11]. In addition to the disadvantages stated above, each system also requires technicians to operate equipment in the field when measurements

*Corresponding author: mfok@uga.edu

are taken. Additionally, as the output data has a continuous time series format, obtaining measurements becomes time consuming and labor intensive. By developing an autonomous sensing system that obtains measurements in a non-destructive and continuous format, a plant's root structure can be analyzed throughout its entire lifecycle. The sensing system provides greater insight into its phenotype and interactions with the growing environment.

When compared to traditional electronics-based systems, fiber optics-based sensors have several advantages making them ideal for root structure sensing. Primarily, their silica-based construction ensures that the presence of magnetic materials within soil will not affect measurement quality and accuracy. Their low attenuation also allows long distance sensor arrays to be deployed without severe signal decay [12]. Recently, distributed fiber optic sensors (DFOS) [13] and fiber Bragg grating (FBG) based sensors [14] have shown promising results in providing non-destructive measurements of root structures. While providing accurate measurements, current DFOS root sensing systems based on Rayleigh backscatter are restricted to growing vessels containing Greens Grade and complex fiber configurations [13]. Widespread deployment is further limited by the requirement of complex components and characteristically low signal-to-noise ratio (SNR) due to weak Rayleigh backscatter [15]. While not sensing actual root growth, we have shown promising results in measuring an object undergoing shape deformation below soil with FBGs [14]. Using a reflected power measurement from FBGs provides a cost-effective and scalable solution for non-destructive and continuous measurement of root growth. With this method, an affordable system that may be widely deployable to crop fields of varying sizes can be constructed. Additionally, optical fiber's hair thin diameter and inert construction ensures they will not interfere or interact with crops or their growing environment [16].

To further enhance the aforementioned system, we propose a root phenotype prediction system based on a Residual neural network (ResNet) trained on the reflected power output of an FBG sensor array. By utilizing a reflected power measurement instead of a spectral analysis, our system's cost and output data size is reduced. By using two ResNet models, sensor data is converted into a more meaningful measurement that is correlated to physical pseudo-root parameters, such as depth and diameter. While many neural network configurations exist, ResNet was selected as it ensures gradient flow of measurement data is preserved during backpropagation [17, 18]. By preserving gradient flow, our resultant models are more proficient in understanding complex relationships. The proposed system is able to accurately detect root diameters of 1mm and 5mm and predict root depths ranging from 0cm to 15cm with a 1.5cm resolution. By deploying ResNet models, the complex optical signal is converted into a more meaningful form with known significance for plant breeding programs [19].

2. EXPERIMENTAL SETUP

Three FBG sensors with Bragg wavelengths of 1550.0nm, 1552.5nm, and 1553.3nm are used in constructing the root parameter sensing system. Additionally, each FBG is supplied with a tunable laser diode and optical power meter to allow for precise calibration and independent measurement collection. For accurate strain measurements, each laser diode is tuned to a wavelength longer than the Bragg wavelength such that the calibrated reflected power is 3dB lower than the maximum possible value. This is done due to the increase in Bragg wavelength a FBG experiences as strain is applied. Calibration to this point ensures the FBG's Bragg wavelength does not shift too far from the laser's wavelength and that each sensor is operating in its most linear region. Using a custom-built NI LabVIEW program, each sensor's output is saved to a text file. Providing concise measurement data for training and prediction by the ResNet models. Figure 1 provides a schematic of the entire root parameter sensing system.

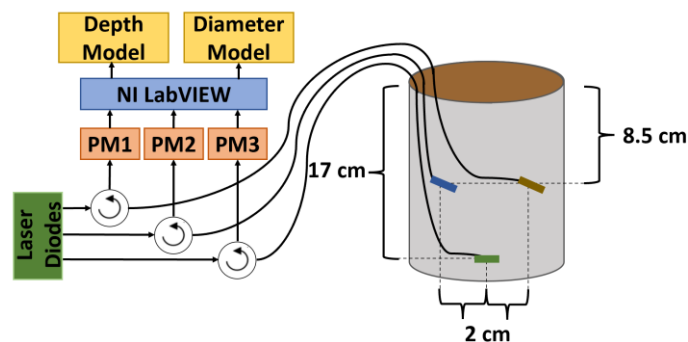


Figure 1. Root parameter sensing system with the 1550.0nm, 1552.5nm, and 1553.3nm FBGs denoted by the blue, brown, and green lines, respectively.

Sensor locations within the testing vessel were selected to measure strain generated at different locations. The two side FBGs (Bragg wavelengths 1550.0nm and 1552.5nm) are located 8.5cm below the soil surface and 2cm offset from center. While the bottom FBG (Bragg wavelength 1553.3nm) is located 17cm below the soil surface directly centered within the vessel, as seen in Figure 1. Due to deep learning models requiring large datasets for effective training and the long periods of time required to grow plants to maturity, a robotic root system was constructed for generation of pseudo-root data. Comprised of two stepper motors controlled by an Arduino, the robot lowers an aluminum pseudo-root rod into potting soil within the testing vessel to a maximum depth of 15cm in 11 minutes. Figure 2(a) provides a visualization of the physical robotic root system. By controlling the insertion duration, a better correlation between sensor output and root depth is achieved during model training, results in increasing their overall performance. To generate datasets for training and testing both models, a 1mm and 5mm pseudo-root is used. 10 trials using each root diameter were performed to ensure sufficient data generation for model training and subsequent testing. An example of the sensor output from one trial is seen in Figure 2(b).

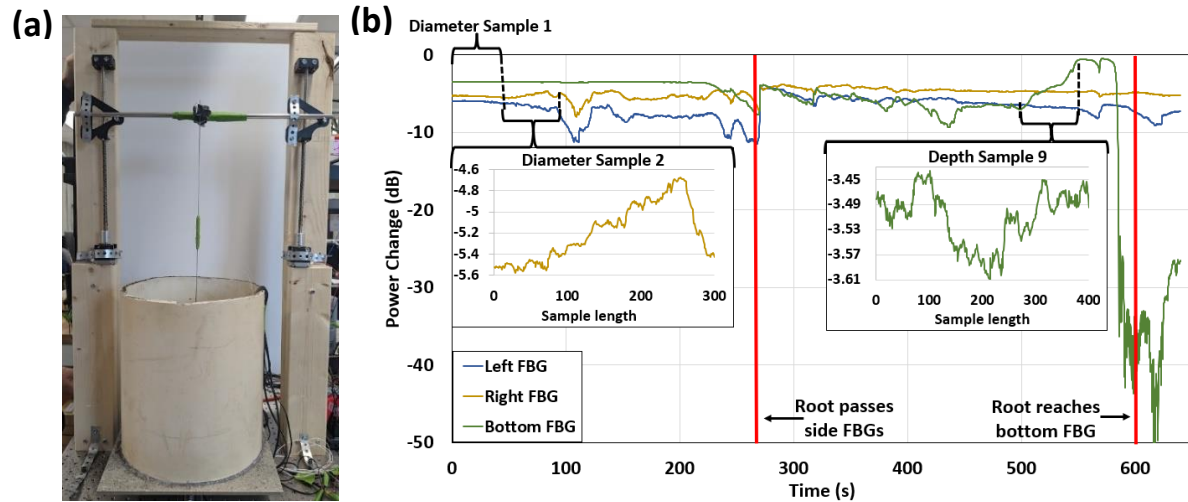


Figure 2(a). The robotic root system capable of controlled insertion of pseudo-roots with varying diameters used for generation of the diameter and depth datasets. Figure 2(b). The sensor output when the 1mm pseudo-root is inserted into the phenotyping system. Insets: segmentation of trial data into samples with uniform data point lengths.

Also seen in Figure 2(b) is the preprocessing all trial data underwent before usage in the ResNet models. To train each model most effectively, all samples must have the same length, or number of data points. Only the bottom FBGs output was used in generating the depth dataset with each trial segmented into 11 samples. Each sample contained 400 datapoints corresponding to one minute of data. All samples were then labeled with a depth range from 0cm to 15cm in 1.5cm increments. For example, depth sample 9 seen in the inset of Figure 2(b) is set to a depth range of 10.5cm to 12cm. With all trials processed, the resultant depth dataset contained 300 samples for training and testing. When generating the diameter dataset, the FBG output from both side FBGs are used and samples are comprised of 300 data points. Corresponding to approximately 45 second intervals of trial data. After processing, the diameter dataset contained a total of 3,228 samples with each containing a single diameter pseudo-root. Finally, to enrich both datasets with extra samples, a sliding window approach was employed where samples were overlaid on top of each other with overlap amounts ranging from 0% to 83.3%.

Our proposed ResNet models begin with a 2x2 convolutional layer with its output undergoing a batch normalization. Afterwards, the data enters a Rectified Linear Unit (ReLU) activation function followed by a max-pooling layer. The output is then connected to 25 residual blocks, each containing two 5x5 convolutional layers comprised of 16 feature maps. Experimentation focused on tradeoffs between computation time and model complexity resulted in the selection of 25 residual blocks. After each 5x5 convolutional layer, the output passes through two additional batch normalizations and another ReLU activation function. Finally, all output is input to an average pooling layer then into three in series dense layers with values of 50, 40, and 20, respectively. The major difference between our two models is the output values each provide. The diameter model provides an output of either one of two classes (1mm or 5mm diameter root) while the depth model outputs one of 10 different depth ranges (0cm to 15cm in 1.5cm increments). Seen below in Figure 3 is the architecture used in constructing both ResNet models.

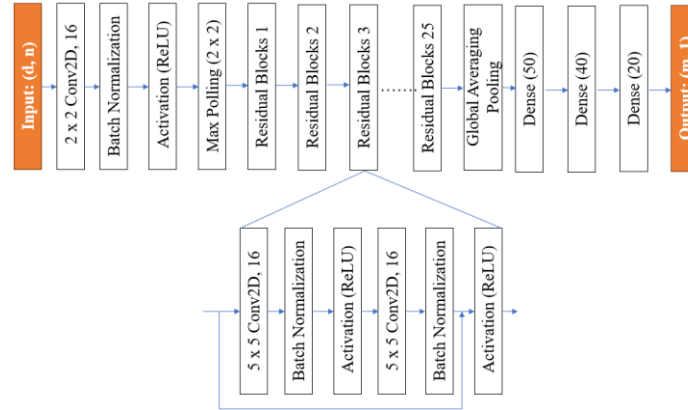


Figure 3. The proposed ResNet architecture.

3. RESULTS AND DISCUSSION

During model creation, 80% of each dataset was used in training while 20% was used for performance testing. To evaluate both model's performance, metrics such as precision, accuracy, true positive rate (TPR), and false positive rate (FPR) were recorded as seen in Table 1. Focusing on the depth model's performance, its high precision indicates a correct prediction was made 94% of the time as it processed test data. The model also proved highly reliable, indicated by TPR and FPR values of 93% and 0.74% respectively. Suggesting that predictions were generally correct. While not as high performing, the diameter model still achieved remarkable results during testing. A FPR of 9.2% highlights there was an issue in minimizing false positives by the model. However, its precision of 90% illustrates that the model was still able to correctly predict root diameter almost every time.

Table 1. Performance metrics of each model during the testing phase.

Model	Accuracy	Precision	TPR	FPR
Diameter	92%	90%	93%	9.2%
Depth	93%	94%	93%	0.74%

Figure 4 contains the (a) depth model's confusion matrix, (b) labels for each depth level, and (c) the diameter model's AUC. The diagonal confusion matrix values illustrate instances of correct classification by the model. While any value outside suggests that an incorrect classification has occurred. Allowing an easy determination of depth regions the model struggled to predict, such as between 3cm – 6cm and 10.5cm – 13.5cm. The issue with prediction in these regions may be due to soil's inhomogeneous nature. There could be large soil clumps or pieces of debris in both regions that the pseudo-root encounters, leading to abnormal signals being generated. The diameter model's AUC curve, seen in Figure 4(c), provides a quantitative measurement of overall performance. As the AUC value increases, a better differentiation between true and false positive predictions is achieved. Our models AUC of 92% suggests that when a diameter output is provided, our model is very confident in its classification.

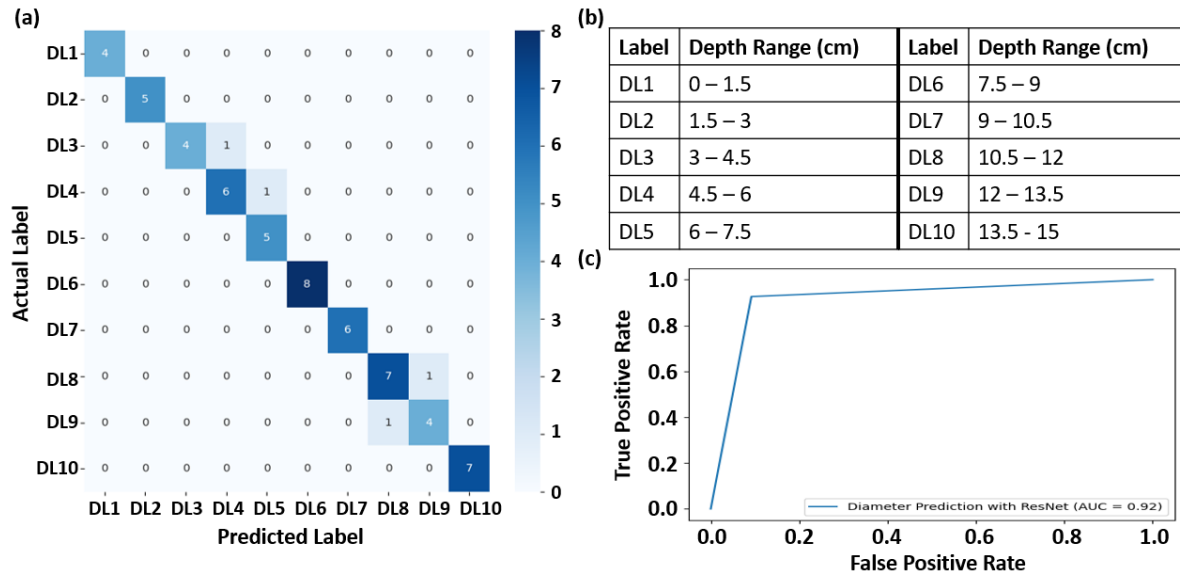


Figure 4. (a) The confusion matrix provided by the depth model. (b) Depth range that corresponds with each labeled class. (c) Area-Under-Curve plot provided by the diameter model.

4. CONCLUSION

A continuous root parameter sensing system that obtains measurements in a non-destructive fashion has been proposed. Comprised of three FBG sensors embedded around a region where a root will grow, our system provides continuous growth data. With sensor data being input to two ResNet models, one focused on depth prediction and the other on width, the hard-to-interpret optical power reading is converted into an easy-to-understand spatial measurement. Performance metrics of both proposed ResNet models suggest that both the predicted depth and diameter values are accurate. Providing breeders with critical information for developing new climate resilient plants. By employing a reflected laser power-based measurement method over a spectral analysis, our system becomes more cost-effective and allows for the easy addition of more sensors. With adding more sensors, measurement resolution can be increased or multiple plants can be monitored at one time. While a current limitation, the small dataset sizes used for model creation is a first step towards widespread deployment of the current root parameter sensing system. They allowed for development of proficient base models that, through transfer learning, will be trained on growth data generated by actual crops grown under lab conditions. During this phase our system will become more generalized to root parameters. Allowing it to be widely deployed in a variety of environments for measuring how crop roots grow in an everchanging environment.

5. ACKNOWLEDGEMENTS

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