Improving 3D Metric GPR Imaging Using Robotic Data Collection and DNN-based Processing

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INTRODUCTION

GPR is one of the most important NDE devices to detect subsurface objects and reconstruct the underground scene. There are two challenges for GPR-based inspection, which are GPR data collection and subsurface object imaging. To address these challenges, we propose a robotic solution that automates the GPR data collection process with a free motion pattern. It facilitates the 3D metric GPR imaging by tagging the pose information with GPR measurement in real-time. We also introduce a DNN based GPR data analysis method which includes a noise removal segmentation module to clear the noise in GPR raw data and a DielectricNet to estimate the dielectric value of subsurface media in each GPR B-scan data.

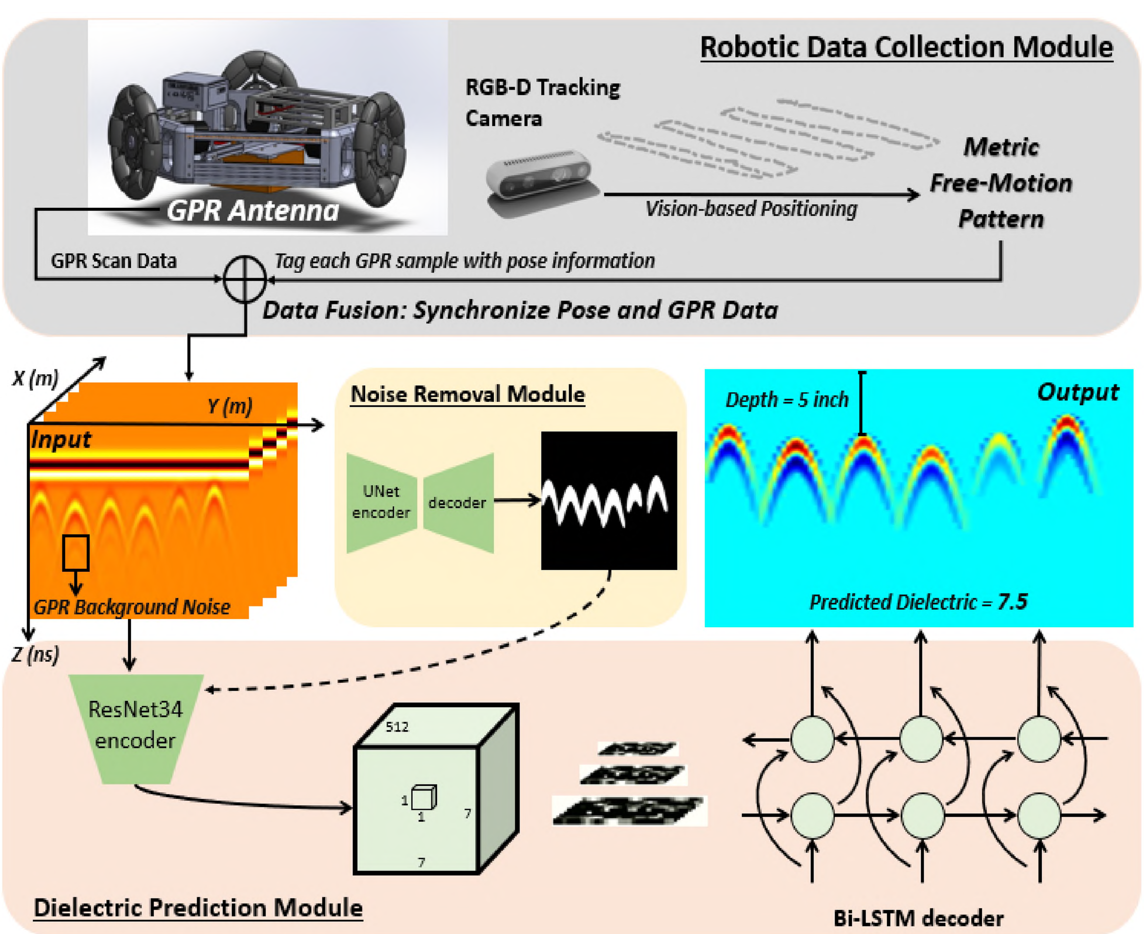

Fig. 1. The system architecture consists of a robotic GPR data collection module and a DNN-based GPR data analysis module.

METHODS

The system consists of the robotic data collection module and the GPR data analysis module.

1. The Omni-directional robot carries a GPR antenna at the bottom of the chassis to detect and map underground objects and an RGB-D tracking camera to obtain the accurate 6-DOF pose in real time.
2. By tagging the GPR measurements with accurate pose information in a synchronized way, it enables the robot to scan the ground surface in arbitrary and irregular trajectories and facilitates high-resolution 3D GPR imaging. The robot can perform a non-linear free motion that will revolutionize how GPR data is collected, interpreted, and visualized.
3. The GPR data analysis software includes the DNN-based GPR noise removal module and the dielectric prediction module. For each input B-scan image, the noise removal module directly decodes the input image into hyperbolic features. The dielectric prediction module takes the segmentation masks from the noise removal module and pools the dielectric information from a Convolutional Recurrent Neural Network (CRNN).

RESULTS

- To demonstrate the effectiveness of the proposed 3D metric GPR imaging method, we conducted both simulation and field study.

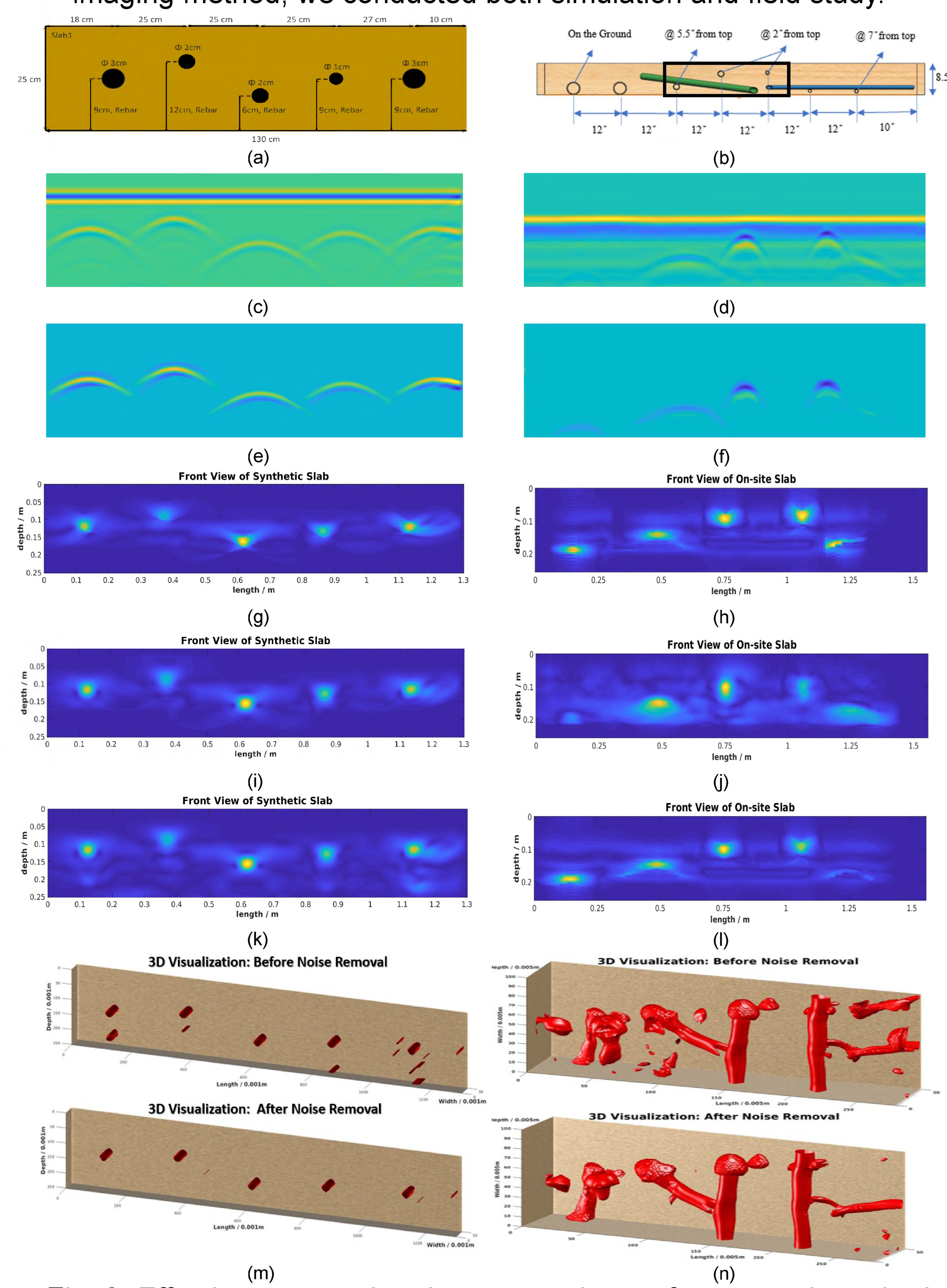

Fig. 2. Effectiveness and noise comparison of proposed method on both synthetic and field GPR data

- (a) The ground truth of the synthetic slab generated by gprMax.
- (b) The ground truth of the field CCNY Robotics Lab concrete slab.
- (c) The raw B-scan of the synthetic slab
- (d) The raw B-scan of the field slab.
- (e) Filtered B-scan of the synthetic slab.
- (f) Filtered B-scan of the field slab.
- (g) The migration result with the synthetic GPR data by proposed 3Dmetric method.
- (h) The migration result with the field GPR data by proposed 3D metric method.
- (i) The migration result with the synthetic GPR data by the conventional method [1]
- (g) The migration result with the field GPR data by the conventional method [1].
- (k) The migration result with the synthetic GPR data by the method proposed in [2]
- (l) The migration result with the field GPR data by the method proposed in [2].
- (m) The 3D GPR data reconstruction comparison result with the synthetic GPR data from the *front view*.
- (n) The 3D GPR data reconstruction comparison result with the field GPR data from the *top view*.
- we update the positioning information [X,Y] according to the orientation information theta, while [X,Y] represents the previous position state. Fig.3 illustrates how GPR B-scan data is collected and tagged with pose information along a zig-zag pattern, and it doesn't require the intervention of the human inspector.

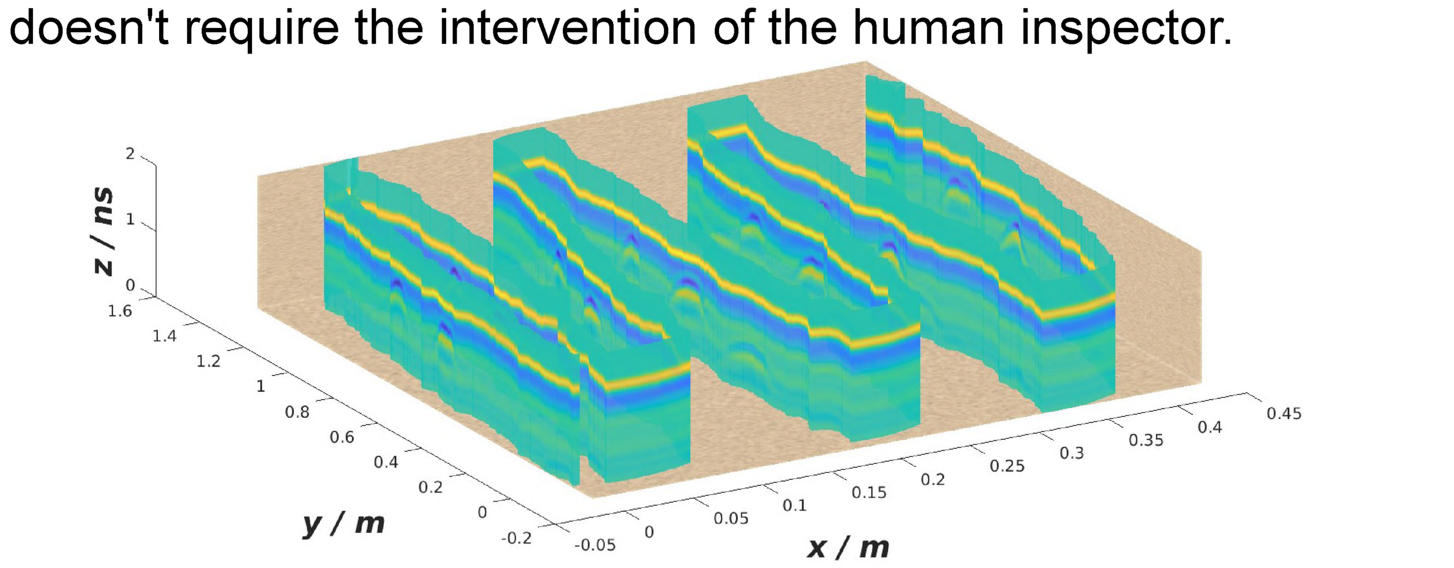

Fig. 3. The B-scan profile tagged with metric positioning information.

CONCLUSIONS

This poster introduces a robotic GPR data collection method and a DNN-based 3D metric GPR imaging method, which can improve the GPR imaging performance by taking the following steps.

1. Introducing the robotic GPR data collection that provides free motion pattern for GPR scanning and tags the position information with GPR measurements.
2. Using a DNN-based segmentation model to remove the background noise from raw GPR B-scan images.
3. Using DielectricNet to estimate the dielectric value of the underground environment.

MAIN REFERENCES

1. X. Xie, J. Zhai, and B. Zhou, “Back-fill grouting quality evaluation of the shield tunnel using ground penetrating radar with bi-frequency back projection method, "Automation in Construction, vol. 121, p. 03435.
2. J. Feng, L. Yang, H. Wang, Y. Song, and J. Xiao, “GPR-based subsurface object detection and reconstruction using random motion and depthnet,"in 2020 IEEE International Conference on Robotics and Automation(ICRA). IEEE, 2020, pp. 7035–7041