머신 러닝을 활용한 터널 콘크리트 라이닝 결함 자동 탐지 기술: GPR B-스캔 이미지 기반 접근법

Automated Defect Detection Technology for Tunnel Concrete Lining Using Machine Learning: A GPR B-Scan Image-Based Approach

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1. Introduction

This study introduces KIT-GPR, a simulation program, and a Fully Convolutional Networks (FCN) model for detecting defects in tunnel lining such as delamination, cavity, and interlayer.

By providing a user-friendly interface, users can quickly create models with various options in KIT-GPR, such as a material library, antenna libraries, and tunnel defect detection.

The simulation results confirm that the KIT-GPR program and FCN model can effectively detect anomalies in the tunnel lining demonstrating delamination, cavity, and interlayer with freshwater compared to the gprMax program.

2. Methodology

In the KIT-GPR program, two scenario cases were designed to simulate anomalies in tunnel lining. The KIT-GPR program allows users to input parameters and visualize GPR signals, while the gallery replicates the insights of tunnel lining.

Ken Perlin originally developed Perlin Noise in the 1980s and later improved in 2002 (Perlin, 2002a). It is widely used in game development, natural effect simulation, and texture creation. Although it is typically applied in 2D and 3D, it can be simplified to 1D to simulate curved surfaces or strokes.

In the KIT-GPR program, functions for creating the interlayer, cavity, and delamination are designed to facilitate the initialization of these objects for the user. Also, the interlayer between the material layers is constructed using the Perlin Noise 1D algorithm.

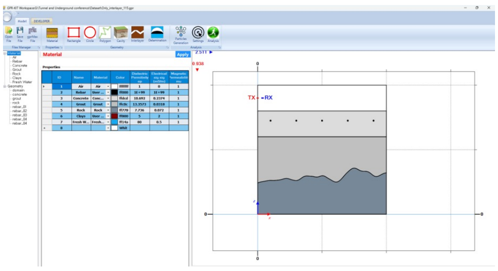


Fig 1. Graphic User Interface of KIT-GPR program

This study evaluates the KIT-GPR program's performance in the simulation of tunnel lining anomalies through two interlayer models:

(a) Interlayer Delamination with Freshwater

(b) Interlayer Delamination and Cavity with Freshwater

1D Perlin Noise is adapted to generate the interlayer, cavity, and delamination. Two models were used to validate the KIT-GPR program's ability to distinguish intact and defective layers in tunnel lining compared to gprMax software.

3. Model Simulation

Fully Convolutional Networks (FCN) have advanced in deep learning by improving the efficiency of dense prediction tasks such as semantic segmentation, boundary detection, and image restoration

This study developed an FCN model to predict tunnel damages, including cavities and delamination while considering grout layer thickness variation. Building on advancements in AI for NDT, such as Huang et al. (2024) self-supervised deep learning framework for enhancing GPR data analysis, this model improves flow detection in tunnel linings.

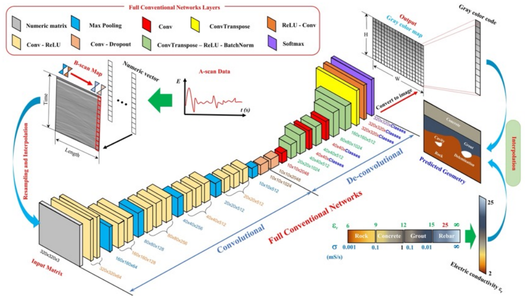
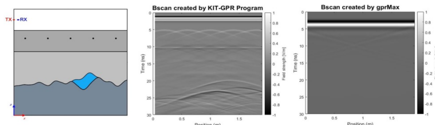
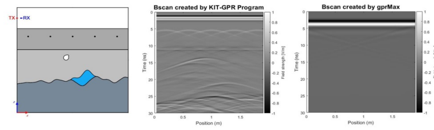


Fig 2. Schematic diagram of Fully Convolutional Networks for predicting local defects in tunnel lining



(a) Interlayer Delamination with Freshwater



(b) Interlayer Delamination and Cavity with Freshwater

Fig 3. Comparison of scenario (a) and scenario (b) and their B-scans created by the KIT-GPR program and gprMax software

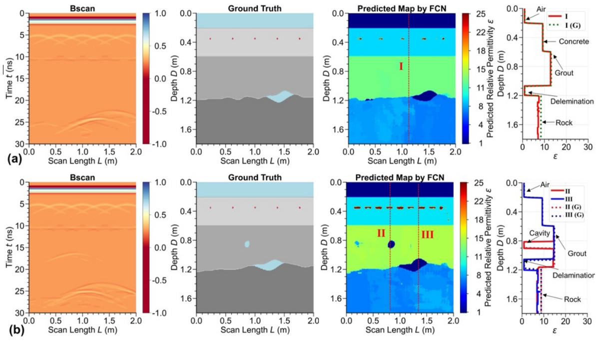


Fig 4. Predicted relative permittivity map by FCN for tunnel lining defects: (a) Interlayer Delamination with Freshwater (b) Interlayer Delamination and Cavity with Freshwater

In this study, two geometries were created for simulation in the KIT-GPR program (Fig.3). A comprehensive analysis was conducted using B-scan images obtained from the KIT-GPR program, with a 1.2 GHz antenna.

Fig. 2 illustrates the architecture of the FCN framework for predicting locations where damages have occurred in the tunnel lining. Whereas Fig.3 shows the effectiveness of the simulation of tunnel lining anomalies.

Fig 4. shows the permittivity map with interlayer, cavity, and delamination locations within the grout layer. The predicted permittivity map indicates that the interlayer and cavity position aligned well with the ground truth.

In both simulation cases, the KIT-GPR program accurately identifies the interlayer, cavity, and delamination with freshwater anomalies, further validating the KIT-GPR model's reliability in identifying tunnel lining defects.

The above simulation results highlight the KIT-GPR program's capability to generate various training databases, enabling the development of AI models for the detection of damaged objects in future research.

KIT-GPR program provides a flexible simulation platform that generates results directly without relying on third-party software like gprMax. It also enables the creation of a large database for training future machine learning models.

4. Conclusion

This study contains the development of two simulation geometries and their B-scan comparisons. The results from the KIT-GPR program were compared to gprMax software. The KIT-GPR program effectively simulates the anomalies in tunnel lining.

Therefore, the KIT-GPR program effectively simulates the anomalies under the tunnel lining.

5. Acknowledgment

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korean government(MSIT) (No. 2022R1C1C1006507)

6. Reference

1. Huang, J., Yang, X., Zhou, F., Li, X., Zhou, B., Lu, S., Slob, E., 2024. A deep learning framework based on improved self-supervised learning for ground-penetrating radar tunnel lining inspection. Computer-Aided Civil and Infrastructure Engineering, 39(6), 814-833. doi:10.1111/mice.13042.