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種別(和文)	論文要旨
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論 文 要 旨

THESIS SUMMARY

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学生氏名： Student's Name	修 浩毅		指導教員（主）： Academic Supervisor(main)	松岡昌志
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要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

Collapsed buildings should be detected immediately after the occurrence of natural hazards for humanitarian assistance and post-disaster recovery. Airborne 3D point clouds are especially useful for this purpose as they precisely record the height of buildings. Recently, deep learning has been extremely successful in 3D point cloud processing. Despite its potential, the use of deep learning in collapsed building detection (CBD) using 3D point clouds is largely unexplored. Therefore, this research aims to explore the use of deep learning for CBD using 3D point clouds.

Chapter 1 formulates the objectives of this research. Extensive literature review and analysis show that there are two major problems that need to be solved. The first problem is the lack of an appropriate dataset. The lack of a dataset is a fundamental problem because deep learning requires a large-scale and well-prepared dataset. Furthermore, this problem also makes it impossible to investigate the potential of deep learning on CBD. The second problem is that the deep learning models are yet to be adapted to CBD. CBD is a specific application where clear assumptions can be made and implemented to improve the model design. The absence of such a design may significantly limit the performance. Accordingly, the objectives of this research are set: 1) the development of an appropriate dataset and 2) the development of a dedicated model for CBD.

Chapter 2 develops the dataset and performs benchmarking of some mainstream algorithms. The field survey and airborne LiDAR point clouds obtained after the 2016 Kumamoto earthquake are used as data sources to develop the dataset. The dataset is termed the Mashiki dataset. We design a detailed workflow consisting of five consecutive steps: 1) information extraction from the field survey; 2) building GPS coordinates adjustment; 3) building annotation; 4) visual interpretation of damage; and 5) filtering buildings. Next, we benchmark several mainstream algorithms on the Mashiki dataset. The performance of PointNet++, the standard model for point cloud analysis, is carefully investigated. The result reveals that PointNet++ fails to detect buildings that show very few damage cues.

Chapter 3 elaborates on the development of Laplacian-enhanced neural network (LE-Net), a dedicated method for CBD. The chapter begins with an analysis concerning damage characteristics and the numerical representation of building damage. Based on the above analysis, the discrete Laplacian is chosen as the tool to encode building damage because it successfully represents various types of collapse patterns. However, it responds to all discontinuities including less useful ones equally, lacking in selectivity. To resolve this problem, we propose Laplacian Unit (LU), a module designed to enhance the useful discontinuities in preference to less useful ones. Specifically, such functionality is realized by the newly introduced selectivity function that transforms the discrete Laplacian in a trainable manner. As a result, we expect that the optimized Laplacian can extract enhanced spatial patterns of building damage so that challenging collapsed buildings can be detected. Using LU as a core, we construct a dedicated network called LE-Net to tackle CBD. LE-Net enhances PointNet++ by integrating LUs at different stages of PointNet++.

Chapter 4 performs comprehensive evaluations of LE-Net. In the first part, we perform diverse experiments on the Mashiki dataset. Quantitatively, LE-Net achieves the best overall performance and outperforms PointNet++ in terms of all performance metrics. Qualitatively, LE-Net successfully detects collapsed buildings that are completely missed by PointNet++, demonstrating its enhanced sensitivity to challenging buildings. Next, we validate the usefulness of each component of LU. In particular, it is verified that the selectivity function enhances collapse-related representations while smoothing out other unrelated discontinuities, meeting our expectations. Visual explanation analysis is subsequently performed to reveal the decision-making of LE-Net. The result indicates that LE-Net successfully locates various damage to buildings. Further, the computational efficiency and robustness of the density variation are analyzed. The applicability of LE-Net to a real-world scenario and ground deformation-related damage is verified. In the second part, we validate the adaptability and transferability of LE-Net on a substantially different dataset. For this purpose, the Haiti dataset is developed using data obtained after the 2010 Haiti earthquake. As a result, LE-Net shows better adaptability compared with PointNet++. Furthermore, LE-Net shows superior transferability by outperforming PointNet++ in various situations.

The dissertation concludes with a discussion of limitations and future work.