MITSUBISHI-A project

Title:

Estimating sensor viewpoints using a three-dimensional map

Industrial Partner:

Mitsubishi Electric Corp. Advanced Technology R&D Center.

Mitsubishi Electric (Mitsubishi Electric Global Website), founded in 1921, is an electrical and electronic equipment manufacturer developing products and solutions in widely diverse fields including home appliances, industrial equipment, and space technologies. To support Mitsubishi Electric Group businesses through the development of a broad scope of projects covering both fundamental and new advanced technologies, the Advanced Technology R&D Center was established. Its main research themes include power electronics, mechatronics, satellite communications, next-generation key devices, system solutions for electric power, transportation, factory automation, and automobiles.

The 2025 G-RIPS project will involve matching a partial point cloud detected by sensors with a whole point cloud.

Techniques:

Machine Learning, Global Feature Extraction from Point Cloud, Clifford Algebra, Differential Geometry, Low Dimensional Geometry, Topological Data Analysis, Discrete Geometry

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Background:

Any person who becomes lost in a shopping mall can estimate their current location by integrating positional information, such as locations of nearby stores or escalators, with floor map data. This method supports effective navigation to reach their destination. Similarly, autonomous robots should be able to estimate their current location by integrating 3D shape data obtained from sensors with a comprehensively prepared 3D map. In other words, by identifying the positions of the 3D shape data within the complete 3D map, various tasks become feasible. These tasks include navigation, obstacle avoidance, and efficient route planning.

This project specifically emphasizes the matching of partial 3D shape data obtained from sensors with whole 3D shape data. The 3D shape data obtained from sensors are represented as a collection of points, known as a point cloud. A point cloud is a set of points representing specific locations in space, forming a collection within a three-dimensional Euclidean space. These points are detected by measuring the reflections of lasers emitted by the sensors. By the very nature of laser-based point cloud observation, a phenomenon called occlusion occurs, whereby objects are partially hidden or completely hidden by other objects. Because of occlusion, often only parts of objects are shown in the point cloud. The 3D shapes measured by sensors include such occlusions. Therefore, the estimation process of sensor viewpoints must be robust against them. Occlusions can pose daunting challenges hindering the accurate identification and matching of shapes. Furthermore, the processing must be completed rapidly for autonomous mobile robots to estimate their position in real time. Ensuring the robustness and speed of these processes is crucially important for the practical deployment of autonomous robots in various applications such as delivery services, search and rescue, and industrial automation.

Project and Expectations:

This project specifically emphasizes the development of robust and fast mathematical methods for matching a partial point cloud to a whole point cloud.

The expected research directions are the following.

1. Developing new methods for feature extraction from discretized 3D shapes
2. Developing statistical processing methods for the extracted features
3. Developing methods for comparing the similarity of the extracted features

In pursuit of these approaches, two important methods are data embedding into vectors and deep learning.

Data embedding into mathematical vectors involves representing data as numerical sequences to facilitate efficient data processing. Research in this area includes methods such as Topological Node2vec [1], which is used for learning low-dimensional topological representations of nodes in a graph, and also geometric algebra [2], a variant of Clifford algebra [3] that provides a framework for representing geometric transformations.

Deep Learning refers to algorithms that use multi-layer neural networks to learn the nonlinear structures and relations in large-scale data. Deep Learning is related to optimization theory, probability theory, and dynamical systems theory.

The specific relations between deep learning and these theories are presented below.

1. Optimization theory: Deep Learning broadly involves the building of optimization models and the learning of parameters of the objective function from given data [4].
2. Probability theory: This is also used in modeling deep learning. Bayesian neural networks represent the weights of neural networks as distributions [5].
3. Dynamical systems theory: This is used for theoretical understanding of why deep learning can learn effectively. Among the various approaches used for dynamical systems theory, computational methods from statistical mechanics are particularly useful [6].

Required:

- Knowledge of the Theory of Curves and Surfaces [7, 8].
- Knowledge of Python at the level of Python Tutorial Chapters 3, 4, and 5 [9].

  (You can study the Chapters for 20 hours using Google Colab [10].)
- Knowledge of the definition of a manifold [7].

Optional:

Knowledge of

- Differential Geometry,
- Low-Dimensional Topology,
- Topological Data Analysis,
- Clifford Algebra,
- Discrete Geometry,
- Point Cloud, and
- Deep Learning libraries such as Torch [11] and TorchVision [12].

References:

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[10] Google, Google Colaboratory, [Online]. Available: https://colab.research.google.com/. [Accessed: Dec. 9, 2024].

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