LiDAR-to-LiDAR Global Localization

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Problem Statement

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Problem Statement

Perform **global localization** by matching LiDAR point clouds to a pre-built HD LiDAR map using 3D-BBS (3D Bag of Binary Words) for **feature extraction** and a Branch-and-Bound (BnB) algorithm for efficient **scan matching**.

Use **monocular depth estimation** models to generate depth maps from camera images. Convert the depth maps into a 3D point cloud, that mimics LiDAR data, for localization.

Accomplishment

- Generation of HD LiDAR Maps, using KISS-ICP [1].
- Feature extraction and scan matching, using 3D-BBS [2].
- Depth estimation and reprojection to point clouds, using Depth Anything v2 [3].

Previous Works

- Histogram based methods to establish correspondences, coupled with outlier removal [4].
- Frame based methods that aggregate geometrical features [5].
- Bag-of-words feature representations [6].
- Branch and bound based frameworks for efficient search [7].

Dataset

- We employ Velodyne LiDAR scans and RGB images from KITTI Odometry dataset [8].
- Specifically, our demonstration will be based on hundred scans from the first sequence of the dataset.
- The dataset focuses on outdoor urban environments involving roads, vehicles, trees, buildings, etc.

Problem Formulation

- Occupancy Map

$$\mathbf{x}^* = \arg\max_{\mathbf{x}\in\mathcal{X}} \sum_{k=1}^{K} \mathcal{M}(T_{\mathbf{x}}\mathbf{s}_k)$$

where $T_{\mathbf{x}}$ is the transformation matrix corresponding to pose $\mathbf{x}$, $\mathcal{M}(\cdot)$ denotes the occupancy function of the map $\mathcal{M}$ at a given point, and $\mathcal{S} = \{\mathbf{s}_k \in \mathbb{R}^3 \mid k = 1, \ldots, K\}$ denotes the LiDAR scan.

- Spatial Hashing Function

$$\mathcal{H}_l(\mathbf{v}) = \begin{cases} 1 & \text{if voxel } \mathbf{v} \text{ is occupied,} \\ 0 & \text{otherwise.} \end{cases}$$

Problem Formulation

- Branching

  $C_{c_l} = \{(2x + j_x, 2y + j_y, 2z + j_z, a_\alpha c_\alpha + j_\alpha, a_\beta c_\beta + j_\beta, a_\gamma c_\gamma + j_\gamma, c_{l-1}) \mid$
  $j_{x,y,z} \in \{0, 1\}, j_{\alpha,\beta,\gamma} \in \{0, \ldots, a_{\alpha,\beta,\gamma} - 1\}\}$

  where $a_{\alpha,\beta,\gamma}$ are the number of divisions for each rotational component of a node.

- Score Computation

$$\text{score}(\mathbf{x}) = \sum_{k=1}^{K} \mathcal{H}_l(T_{\mathbf{x}} \mathbf{s}_k)$$

$$\text{score}_{\text{upper}}(c) = \sum_{k=1}^{K} \max_{\mathbf{v} \in \mathcal{N}(T_{\mathbf{x}_c} \mathbf{s}_k)} \mathcal{H}_l(\mathbf{v})$$

  where $\mathcal{N}(\cdot)$ denotes the neighborhood voxels surrounding the transformed scan point.

Algorithm

Algorithm 2 Batched 3D-BBS

$best\_score \leftarrow score\_threshold$
while C is not empty **do**
  Pop c from the queue C
  if $\overline{score}(c) < best\_score$ **then**
    continue
  if c is a leaf node **then**
    $match \leftarrow c$
    $best\_score \leftarrow \overline{score}(c)$
  else
    Branch: Split c into nodes $\mathcal{C}_{c_l}$
    Add $\mathcal{C}_{c_l}$ to $\mathcal{C}_{\text{CPU}}$
  if $|\mathcal{C}_{\text{CPU}}| > b$ **then**
    $\mathcal{C}_{\text{GPU}} \leftarrow \mathcal{C}_{\text{CPU}}$
    Compute and memorize a score for each element in $\mathcal{C}_{\text{GPU}}$
    $\mathcal{C}_{\text{CPU}} \leftarrow \mathcal{C}_{\text{GPU}}$
    Push $\mathcal{C}_{\text{CPU}}$ onto the queue C, sorted by score
    Clear the all elements of $\mathcal{C}_{\text{CPU}}$.
return $best\_score$ and $match$ when set.

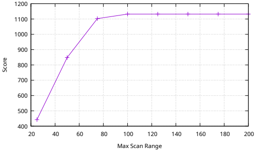
Figure: 3D-BBS Algorithm [2]

Construction of HD LiDAR Map

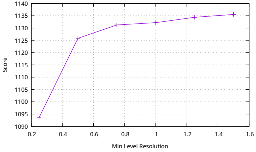
(a) Sample LiDAR Scan (b) LiDAR Map constructed using ICP

Figure: Sample LiDAR scan and the corresponding LiDAR map constructed using ICP.

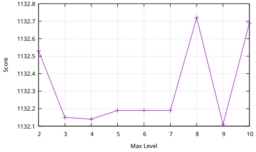
Ablation Study for Localization



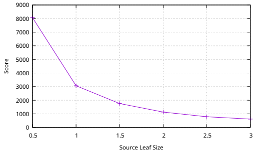
(a) Max Scan Range



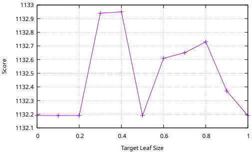
(b) Min Level Resolution



(c) Max Level



(d) Source Leaf Size



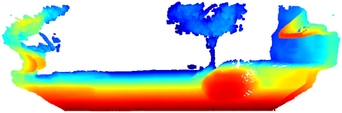
(e) Target Leaf Size

Figure: Change in localization score with variation of parameters in 3D-BBS.

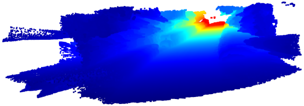
Image to 3D Projection

(a) Sample RGB Image

(b) Metric Depth Estimate



(c) Projected Point Cloud



(d) Concatenated Point Cloud

Figure: Reprojection from the image to 3D space, using depth estimatation.

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References II

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