

Virtual-Camera-Based Staircase Detection and Geometric Parameter Estimation from Sparse LiDAR Point Cloud Maps for Mobile Robots in Nuclear Facilities

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1. Introduction

Nuclear facilities are predominantly multi-story structures in which staircases are the primary vertical pathways connecting the floors of reactor and auxiliary buildings. For mobile robots performing routine radiation surveys, in-service inspection, and emergency response in these facilities, the ability to autonomously detect staircases and accurately estimate their geometric parameters — riser height, tread depth, width, and the center position of each step — is a prerequisite for safe stair negotiation and for deciding traversability before committing to an ascent or descent. The lesson of the Fukushima Daiichi accident, where remotely operated robots had to negotiate stairwells under degraded conditions, underscores that stair perception is a safety-critical capability for nuclear robotics.

Existing approaches fall into two groups. Geometric methods segment tread and riser planes directly from point clouds using RANSAC variants or region growing with graph-based validation [1–4]. They achieve high metric accuracy but degrade sharply at low point density, where per-point normal and edge estimation collapses. Learning-based image methods such as the StairNet series detect stairs robustly in RGB or RGB-D images [5], but they depend on a physical camera: performance is tied to illumination, and an additional sensor and LiDAR–camera calibration are required. More critically, a further caveat is that the viewpoint is constrained to the robot’s physical trajectory. Neither group exploits a resource that a LiDAR-SLAM-equipped robot already possesses: the accumulated point cloud map itself.

This work proposes a hybrid pipeline that renders the colorless LiDAR SLAM map through virtual cameras [7] and applies 2D recognition to the rendered images, while performing all metric measurements on the 3D points recovered through an index buffer. The key observation, formalized in Section 2, is that a sparse point cloud that defeats plane segmentation can still be rendered into a recognizable image if the rendering resolution is matched to the point density: this is the computational analogue of a human stepping back to view a sparse point cloud “from a distance.” Because virtual viewpoints are physically unconstrained, the method can additionally observe descending staircases from below-floor vantage points that no onboard camera could ever occupy.

2. Methods and Results

2.1 Method

Fig. 1 shows the workflow. A local submap around the robot is preprocessed (voxel down-sampling, statistical outlier removal, normal estimation), and computationally efficient height-histogram gating proposes candidate regions exhibiting quasi-periodic elevation changes consistent with the expected riser-height range of architectural staircases (e.g. a typical range is 10–20cm).

Density-normalized virtual rendering. Each candidate is rendered from multiple azimuths by an orthographic virtual camera. The ground sampling distance (GSD, the metric extent covered by one pixel) is tied to the mean point spacing δ of the submap as $GSD = \alpha\delta$ with $\alpha \in [1.5, 3.0]$, so that the pixel gap between adjacent points, $\Delta u = \delta/GSD$, remains below one pixel and the sparse cloud appears as a continuous surface. This replaces the intuitive “distant perspective camera” with a mathematically equivalent but spatially uniform operation, since a perspective $GSD(z) = z/f$ varies with scene depth. Hidden-point removal [6] and z-buffer splatting suppress the bleed-through of background structures through inter-point gaps. Because the LiDAR map carries no color, the rendered image encodes purely geometric channels (inverse depth, surface-normal component, gravity-referenced height), making the pipeline independent of illumination. A per-pixel index buffer records which 3D point won the z-buffer at every pixel.

2D recognition with renderer-shared synthetic training. A lightweight segmentation network labels tread and riser pixels in each view. The network is trained exclusively on synthetic data: parametric staircases with randomized (h, d, w, n) are virtually scanned with the sensor’s noise and scan-pattern model, and the resulting synthetic clouds are rendered by the same rendering code used at inference time. Sharing the renderer collapses the sim-to-real gap from the uncontrollable image-appearance domain to the controllable point-cloud domain, and pixel labels are generated automatically through the index buffer, eliminating manual annotation.

3D metrology and temporal fusion. Masks from multiple views are back-projected through the index buffers and fused by per-point voting. After estimating

the stair heading, the labeled points are projected onto the heading-aligned vertical plane, where the staircase appears as a sawtooth profile fitted robustly by the staircase function $z(x') = z_0 + h[(x' - x_0)/d]$ with a Huber loss. This estimates h and d jointly over all steps without relying on riser-plane normals, which are unreliable on narrow risers [3]. Step centers are computed as the mean of per-step RANSAC plane inliers, and the width as the occlusion-robust maximum lateral extent across steps. Repeated observations of the same staircase during robot motion are associated by a Mahalanobis gate and fused by an extended Kalman filter whose measurement noise scales with local point density.

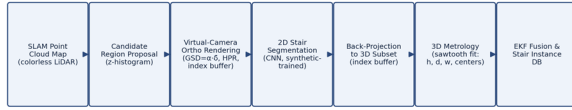
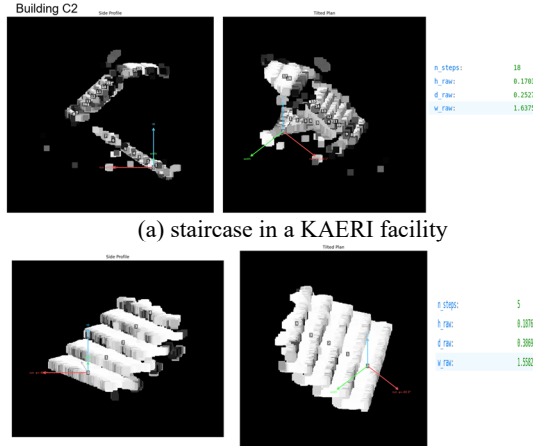


Fig. 1. Virtual-camera-based 2D detection–3D metrology workflow.

2.2 Example & Result

The pipeline is evaluated on a test dataset collected at a KAERI facility and on public datasets[1], for which ground-truth riser height, tread depth, width, and step-center positions are known from field survey and dataset annotations, respectively. Fig. 2 presents some of the results.



(a) staircase in a KAERI facility
(b) staircase from public dataset
Fig. 2. Examples

Qualitatively, the density-normalized rendering preserved the visual stair pattern at point spacings where baseline plane segmentation no longer produced coherent tread planes, and descending staircases were detected from below-floor virtual viewpoints.

3. Conclusions

A virtual-camera pipeline was proposed that detects staircases in sparse, colorless LiDAR SLAM maps by density-normalized orthographic rendering and 2D segmentation, and measures riser height, tread depth,

width, and per-step centers by index-buffer back-projection and joint sawtooth fitting. The approach decouples recognition robustness from point density, requires no camera or illumination, observes descending stairs from physically unreachable viewpoints, and trains without manual labels. Ongoing work extends the fixed multi-view scheme to information-driven active virtual viewpoint selection and to other parametric structures (ramps, curbs) relevant to nuclear facility navigation.

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