Ascending Stairway Modeling from Dense Depth Imagery for Traversability Analysis

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***Abstract*— Localization and modeling of stairways by mobile robots can enable multi-floor exploration for those platforms capable of stair traversal. Existing approaches focus on either stairway detection or traversal, but do not address these problems in the context of path planning for the autonomous exploration of multi-floor buildings. We propose a system for detecting and modeling ascending stairways while performing simultaneous localization and mapping, such that the traversability of each stairway can be assessed by estimating its physical properties. The long-term objective of our approach is to enable exploration of multiple floors of a building by allowing stairways to be considered during path planning as traversable portals to new frontiers. We design a generative model of a stairway as a single object. We localize these models with respect to the map, and estimate the dimensions of the stairway as a whole, as well as its steps. With these estimates, a robot can determine if the stairway is traversable based on its climbing capabilities. Our system consists of two parts: a computationally efficient detector that leverages geometric cues from dense depth imagery to detect sets of ascending stairs, and a stairway modeler that uses multiple detections to infer the location and parameters of a stairway that is discovered during exploration. We demonstrate the performance of this system when deployed on several mobile platforms using a Microsoft Kinect sensor.**

I. Introduction

Autonomous ground robots have traditionally been restricted to single floors of a building or outdoor areas free of abrupt elevation changes such as stairs. Although autonomous traversal of stairways is an active research area for some humanoid and ground robots, the focus within the vision and sensor community has been on providing sensor feedback for control of the mechanical aspects of stair traversal, and on stair detection as a trigger for the initiation of autonomous climbing, rather than on stair traversability.

The restriction to a single floor presents a significant limitation to real-world applications such as mapping of multi-floor buildings and rescue scenarios. Our work seeks a solution to this problem and is motivated by the rich potential of an autonomous ground robot that can climb stairs while exploring a multi-floor building.

A comprehensive indoor exploration system could be capable of autonomously exploring an environment that contains stairways, locating them and assessing their traversability, and then engaging a platform-specific climbing routine in order to traverse any climbable stairways to explore other floors. The physical properties of a stairway may limit the

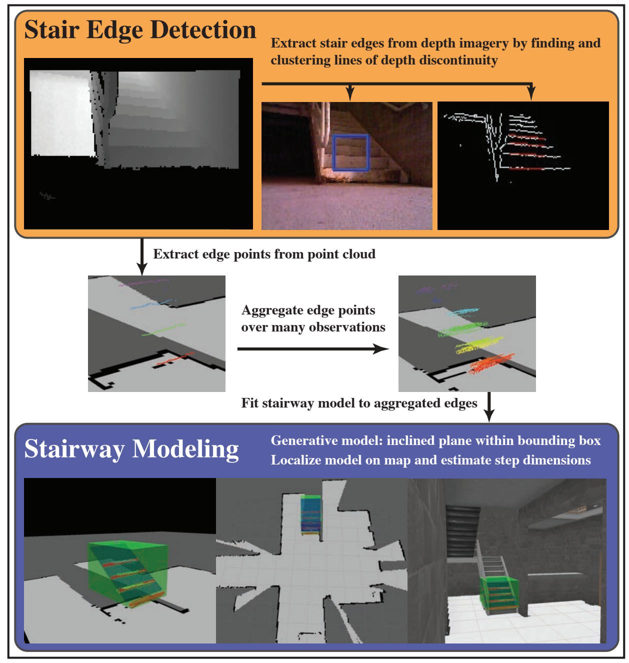

Fig. 1. High level workflow of the proposed system, consisting of two modules: stair edge detection and stairway modeling. Stair edges are extracted from depth imagery and collected over many observations into an aggregated point cloud. Periodically, a generative model of a stairway is fit to the aggregate cloud and its parameters re-estimated. The result is a model localized with respect to the robot's map of its environment. Figure is best viewed in color. (Data: Building 1 Front trial of the MOUT dataset)

platforms that are capable of climbing it. For example, a humanoid robot may not be able to climb some stairways due to step height, and a ground robot may be restricted to stairways with a low pitch due to its weight distribution. Our proposed approach is an effort to integrate the existing work in autonomous stair climbing with autonomous exploration: a system to detect and localize stairways in the environment during the process of exploration, and model any identified stairways in order to determine if they are traversable by the robot.

With a map of the environment and estimated locations and parameters of the stairways, the robot could plan a path that traverses the stairs in order to explore the frontier at other elevations that were previously inaccessible. For example, a robot could finish mapping the ground floor of a building, return to a stairway that it had previously discovered, and ascend to the second floor to continue exploring if that stairway is of dimensions (i.e. step height, width, pitch) that are traversable by that particular platform.

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ICRA 2013

Our proposed system directly addresses the needs of an exploratory platform for solving the problem defined above. We seek to answer the question "Is this traversable?" when a stairway is discovered during exploration. The questions "When should I traverse that?" and "How do I traverse that?" are left for the path planner and stair climbing routines, respectively. The system is composed of a stairway detection module for extracting stair edge points in 3D from depth imagery and a stairway modeling module that aggregates many such detections into a single point cloud from which the stairway's dimensions and location are estimated (see Fig. 1).

Our detection algorithm leverages the property of range discontinuity that step edges exhibit in the depth field. Modeling the stairway over many detections allows the system to form a complete model from many partial observations. We model the stairway as a single object: an inclined plane constrained by a bounding box, with stair edges lying in the plane. As new observations are added to the aggregated point cloud, the model is re-estimated, outliers are removed, and well-supported stair edges are used to infer the dimensions of each step. These physical properties can then be used by a path planner to determine the traversability of stairs in relation to the specific robotic platform. Section II contains a more in-depth description of our approach. Autonomous multi-floor exploration is a new behavior for ground robots, and we present this work as a first step toward the realization of that capability.

A. *Related Work*

Other systems have been proposed for related tasks, including the actual platform-specific autonomous climbing procedure, but no existing work approaches the problem in the context of the aforementioned scenario. The problem we are considering is the evaluation of stairways as traversable terrain for path planning, and as such, we aim to localize and then estimate the physical properties of a stairway to determine if it is traversable. A path planning algorithm such as [1] could incorporate these stairway properties and the robot's climbing capabilities into its decisions about obstacle traversal. Previous measures of stair traversability [2] considered stairways as generic obstacles and only evaluated the height of the first step to determine whether to attempt traversal. Unlike that system, which does not differentiate individual obstacles and groups of stairs, we attach the semantic concept of *stairway* to the obstacle because it likely leads to unexplored areas. Traversal of an *obstacle* does not have such an association, and therefore it is important, from a path planning perspective, to know both the class of the object and its traversability.

Several existing methods [3]–[5] perform stairway detection but immediately initialize a traversal procedure with their respective platforms, which is not necessarily desirable in an exploration scenario. These works assume that the robot is located near the stairway, but not aligned with it. As such, these methods do autonomous exploration until they detect the stairway, and only serve to trigger the autonomous traversal phase of their systems. Rather than model the stairway or assess the traversability, they provide only a bearing, and in some cases a distance, to the stairway relative to the robot's pose, in order to facilitate alignment and subsequent climbing. Although these capabilities are related to our problem scenario, immediate climbing is not necessarily compatible with exploration. Path planning for multi-floor exploration should take the stairway into account as a portal to more unexplored regions, but traversing stairs immediately upon a single detection makes exploring the low-cost frontiers of the original floor more difficult and may fail if the detection was erroneous.

The works by Hernandez and Jo [6] and Hernandez et al. [7] represent the most similar approaches to ours in terms of the goal of detecting and localizing sets of stairs, but are independent of modeling or mapping. In [6], they segment outdoor staircases from single monocular images using line detection and vanishing point analysis, and in [7] they use some of the same line techniques (Gabor filtering) along with motion stereo to detect and localize indoor stairways. However, the scope of the works are similarly limited to detection and a computation of bearing relative to the robot's pose.

Our proposed system overcomes these limitations by modeling the stairway and anchoring the model to a simultaneously constructed map. Since immediate climbing is not necessary, the stairway can be considered as traversable terrain for path planning, and these same climbing procedures can be initiated at a later time when the robot's path requires traversal of the stairway.

A number of existing approaches perform modeling of individual steps or sets of stairs. However, these methods produce fine-grained models for humanoid robot stair climbing [8], [9], or for obstacle negotiation for the visually impaired [10]. Another method proposes a minimal inclined plane model, but uses it to produce a 3D reconstruction for robot obstacle detection [11], and does not localize the model with respect to a map nor estimate its physical parameters. However, these detailed models and 3D reconstructions are not mutually exclusive of our proposed approach. Since precise step locations are often needed for stair climbing (for humanoid robots, for example), these models could always be produced once a path planner has decided to climb a traversable stairway.

In [9], Oßwald et al. assemble 3D point clouds by tilting a 2D ladar mounted on the robot's head, and then extract planes for the steps and risers, and estimate the average step dimensions. However, this modeling is done while the robot is already close to and manually aligned with the stairway and is repeated periodically during its ascent. Our approach, on the other hand, observes the stairs passively during exploration. For those platforms that require a more detailed plane-based model, the approach in [9] could always be performed while the robot climbs the stairway. This is the only other approach that performs parameter estimation for step dimensions, and in Sec. III we demonstrate comparable accuracy with our minimal stairway model. However, we produce our results passively, at a distance, and without explicit alignment to the stairway.

The aforementioned climbing methods use edge detection from camera imagery [5], and range discontinuity detection from horizontal ladar [3] or vertical ladar [4] data, to detect stairs. Other stair edge detection systems have been proposed in the context of controller feedback for stair traversal [12], [13] and object detection from monocular [14] or stereo imagery [11]. Our range discontinuity-based detector incorporates line extraction ideas from many of these systems, but we apply these techniques to dense depth data provided by an RGB-D camera. The registered point cloud that is output from these cameras alongside the depth image allows for extraction of 3D data corresponding to step edges, and enables our modeling approach.

Some recent work in multi-floor mapping may provide some of the tools for implementing our desired comprehensive system. Shen et al. [15] have demonstrated that multi-floor exploration is possible in open indoor environments with an unmanned aerial vehicle. Although their platform by nature avoids the need for stair detection and traversal, their approach for mapping may one day be applicable for ground vehicles. The barometric method presented by Ozkil et al. in [16] for measuring elevation, and therefore distinguishing floors of a building, will likely also be useful in implementing our desired multi-floor exploratory system.

The most comprehensive system yet presented is also one that aims to perform the complementary task to our detection and localization of ascending stairs: detection and traversal of descending staircases. Hesch et al. [17] use a combination of texture, optical flow, and geometry from a monocular camera to detect candidate descending stairwells, navigate to them, and then align with and traverse them. Although they do not perform any explicit mapping of stairwell location or present quantitative accuracy results, their implementation runs in real time and the detector module from their implementation could be extracted and paired with our ascending stair detector in a comprehensive multi-floor mapping system. No system has yet been proposed for both ascending and descending stairway detection and traversal.

B. Contributions

We have deployed our stairway detection and modeling system on an iRobot PackBot as well as a Turtlebot, both fitted with Microsoft Kinect depth sensors. In principle, this modeling system could be deployed on any platform with an RGB-D sensor, such as our Turtlebot, for stairway detection and traversability analysis. For stair climbing robots, such as the PackBot or Aldebaran Nao, this system can potentially be paired with more fine-grained and platform specific modeling approaches for facilitating the act of stair climbing. Our system runs in real time and demonstrates robust and accurate performance in both localization and parameter estimation for a wide variety of stairways (see Sec. III).

This paper presents the following contributions:

- Initial step toward new ground robot behavior: autonomous multi-floor exploration. Locate stairways during mapping of environment, assess their traversability, and later ascend them to explore new frontiers.
- A minimalist generative stairway model: an inclined plane constrained within a bounding box. This provides enough detail to determine if the stairway is traversable by the robot, and if necessary, more detailed modeling can be performed in the context of subsequent stair traversal.
- Aggregation of many partial views into a coherent object model. Re-estimation and outlier removal permits estimation of a robust aggregate model in the presence of imprecise alignment for each observation.

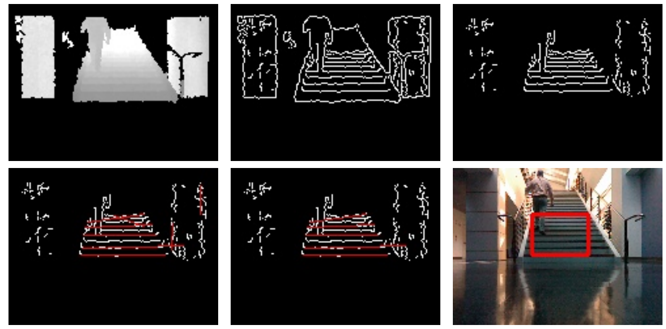

Fig. 2. An example frame from an indoor testing video. Top row (L to R): source depth image, edge image, edge image with boundary lines removed. Bottom row (L to R): candidate lines (in red) before filtering for orientation and clustering, candidate lines after filtering, marked up camera image with bounding box.

II. Methods

A. Stair Edge Detection

Inspired by some of the techniques used in other methods [4]–[6], [8], [11]–[13], we have developed an ascending stairway detector that exploits the geometric properties that steps display in depth images. On a deployed system, it runs in real time with high accuracy and robustness. In particular, we find lines in a depth image that represent discontinuities where the depth from the camera changes abruptly. In the depth field, a set of stairs will have a discontinuity at the edge of each step that is above the height of the sensor. The tops of lower steps will be visible in the sensor's field of view, and may not exhibit a strong enough depth discontinuity to be detected as edges. Regardless of the horizontal rotation of the camera relative to the stairs, these discontinuities will form a set of nearly parallel lines (with some perspective foreshortening effects) for all but tight spiral staircases. We leverage this distinct depth signature by detecting all such lines of discontinuity in the image, filtering and clustering them to find a near-parallel set, and ultimately fitting a plane to the extracted stair edge points to confirm or reject the stairwell candidate hypothesis if they lie on an inclined plane of traversable pitch. By detecting these lines of discontinuity in the depth field rather than a camera image, our detector is robust to appearance.

Given an input depth image, our algorithm proceeds following the steps in Alg. 1, further details of which can be

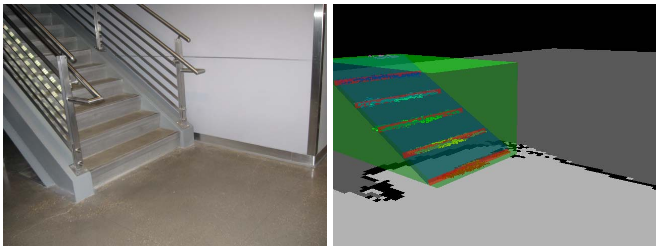

Fig. 3. Stairway with corresponding model consisting of bounding box (green), planar model (blue), and step edges (red), as well as edge point cloud support for step edge lines (rainbow). Figure is best viewed in color. (Data: Davis Hall Front trial from UB dataset)

found in [18]. Please refer to Fig. 2 for visual reference. We enforce several physical constraints to restrict the lines of range discontinuity to stair edges, and extract the 3D points that correspond to the edges that satisfy all of them. We additionally fit a planar model to each set of extracted points, and only confirm a positive detection if the plane is at a traversable angle. Observations that pass these tests are then provided to the stairway modeler.

Our depth image and point cloud based approach was motivated by our ultimate goal of 3D modeling. However, many of the existing line-based stair detection methods could be modified to produce point cloud observations of extracted step edges if they operated on data from an RGB-D camera, and could in principle provide the observations for our modeler in place of this detector. Since this paper is focused on modeling and parameter estimation, and not on stair detection, we do not fully evaluate our detector against these other approaches here.

Algorithm 1 Stair Edge Detection

Input: depth image D and co-registered point cloud P provided by depth sensor
Do Canny Edge Detection on D to produce edge image E
Remove boundary edges from E (bordering 0 valued depth)
Generate a set of candidate lines L using the Probabilistic Hough Transform on E
Merge collinear lines and compute slope histogram for L
Extract lines in the bin with largest frequency into L'
Compute bounding box B for maximal set of vertically overlapping lines in L'
Remove all lines from L' that do not fall within B
Reject if $\mid L' \mid < 3$ (enforce multiple steps)
Extract from P the points on the lines in L' into P'
Fit a least squares plane p to the points from P'
Reject if dihedral angle ($\phi = \arccos(n_p \cdot n_{horiz})$) from the horizontal is $>$ the robot's maximum climbable stair pitch
Return P'

B. Stairway Model

We propose a generative model to represent a stairway as a single object. For localization and path planning purposes, piecewise planar models provide more detail than necessary for traversability analysis, when the questions "Are these steps too tall?" or "Are these stairs too steep?" can be answered with a simpler model. Although more detail does not detract from the model, the need for close proximity and alignment with the stairway, as in [9], limits the effectiveness of other approaches for this purpose, even if the computational cost is not restrictive. We instead aim to enable passive sensing of the stairway from a distance, such that modeling can be performed concurrently with exploration. Localization on a map should enable the robot to return to ascend the stairs at a later time if they are determined to be traversable.

Our model consists of an inclined plane constrained by a bounding box, with stair edges wherever there are well-supported clusters in the plane (see Fig. 3). This model is parameterized by the bounding box centroid (B_x,B_y,B_z) and dimensions (H,W,D), pitch relative to the ground plane (P), and step dimensions (h,d). We assume that stair steps are approximately parallel to the ground plane, so the bounding box top and bottom are parallel to the XY plane. For an inclined plane model of:

$$ax + by + cz + d = 0 \tag{1}$$

the planes constituting the bounding box are given by:

$$z = B_z \pm \frac{H}{2} \tag{2}$$

$$a(x - B_x) + b(y - B_y) \pm \frac{D}{2}\left(\sqrt{a^2 + b^2}\right) = 0 \tag{3}$$

$$-cb(x - B_x) + ca(y - B_y) \pm \frac{W}{2}\left(c\sqrt{a^2 + b^2}\right) = 0 \tag{4}$$

for the top/bottom, front/back, and sides, respectively. Here, the pitch P is computed as the dihedral angle of the planar model and the ground plane: $P = \arccos\left([a, b, c]\,[0, 0, 1]^T\right)$. We infer the parameters of the model from the extracted points corresponding to step edges.

C. Localization and Modeling

In order to build up a complete model of a stairway, we piece together many incomplete views, potentially from many different perspectives, and estimate the parameters of the model from the aggregate pool of data. Our modeling system is capable of modeling multiple stairways in the same environment. Input observations are assigned to stairway models based on proximity; if an observation's centroid is within $2m$ of the centroid of an existing model, it is added to that model, otherwise a new model is spawned. In practice, this distance threshold is adequate for differentiating most real world stairways. However, a more sophisticated approach to the assignment of observations, and a thorough evaluation of the modeling of multiple stairways is left for future work on autonomous stairway discovery. Algorithm 2 details the steps in parameter estimation for each model in the environment.

Starting with an empty point cloud representing the stair edges for a new model, we add to it the extracted edge points from each subsequent observation. We do not explicitly align the detected edges, but instead rely on the robot's estimated pose to approximately align the independent observations, and implement a number of statistical techniques to ensure that the resulting model is robust to outliers and imprecise point cloud alignment. Ultimately, the quality of the model will depend on the quality of the robot's estimated pose, but individual false positive detections or misaligned observations are removed as statistical outliers, as detailed below. However, since we consider the task of stairway modeling in the context of exploration, the robot's performance at both map building and stair detection will be dependent on the quality of its odometry.

Since each observation only adds a partial view of the stairway, we periodically re-estimate the parameters of the model (in our experiments, after k = 5 or 10 observations). When deployed on the PackBot and during post-processing of recorded data on a Mac Mini, our detector operates at over $20Hz$ on average, including the time to fit the model (compared to the Kinect's $30Hz$ frame rate). Although more frequent modeling is possible, we expect the model's parameters to converge over many observations, so we do not anticipate a need for more frequent updates if the information is to be used for traversability analysis. We perform the following steps in order to estimate the model's parameters.

To prevent our aggregate edge point cloud E from growing without bound, we first downsample E to a 1cm voxel grid. We perform statistical outlier removal using the algorithm in [19] in order to reduce sensor noise in the extracted points in E. To the remaining points we fit a planar model p with RANSAC [20] and remove any outliers from the model from E.

We then infer the parameters of the stairway model from the remaining points in E. We determine the bounding box centroid and dimensions by fitting a rectangular prism to the data that is aligned with the ground plane but rotated in the XY plane to match the alignment of p. We next compute the cross-sectional orthogonal plane that passes through (B_x,B_y,B_z) and project the points of E to it. When accounting for alignment errors and unequal observation of each step, we would expect there to be a cluster of projected points around each step edge. We therefore find Euclidean Clusters on the projected plane using the Point Cloud Library's Segmentation Module [21] and treat each well-supported cluster center ($n > 250$ points) as a stair edge. We compute the differences in height and depth between each pair of adjacent cluster centers, and then average these differences to determine the step dimensions (h and d).

Algorithm 2 Stairway Modeling

Initialize point cloud E to be empty for model M_i
Define the modeling period k: number of observations between model fittings
for Each detection P' (see Alg. 1) that is assigned to M_i **do**
  Add points from P' to E
  if # of detections is divisible by k **then**
    Downsample E to fine voxel grid
    Perform statistical outlier removal (as in [19])
    Fit a plane m to E using RANSAC and compute pitch relative to ground plane
    Remove outliers of m from E
    Fit bounding box B to E and compute stairway dimensions (H,W,D)
    Project E onto cross-sectional plane x, orthogonal to m and passing through bounding box centroid
    Find Euclidean Clusters C from projected cloud E_p and compute their centroids
    Sort C by ascending height, and compute differences in height and depth between adjacent centroids with $> n$ points of support
    Average height and depth differences to compute step dimensions (h, d)
  end if
end for

III. Experiments

Our system has been tested on data collected at a Military Operations in Urban Terrain (MOUT) site, on all of the available stairway types and on numerous negative examples. It has also been tested at a building at the SUNY at Buffalo (UB) campus. These datasets consist of 5 recorded trials (3 and 2, respectively) with ground truth stairway dimensions. The set of trials included stairways of a variety of step sizes and building materials (metal, concrete, etc.), ranged from a few steps to a full flight, and included one outdoor stairway. In each case, the robot was teleoperated around an environment, observing both the stairway and its surroundings from a variety of perspectives. We are currently developing techniques for integrating our modeling approach into autonomous exploration, but for this study we wished to evaluate only modeling performance. We plan to publicly release these datasets upon publication.

Our experiments use an iRobot PackBot mounted with a Microsoft Kinect depth sensor for the MOUT trials, and a Turtlebot (also with a Kinect sensor) for the UB data. Our system is implemented in C++ in the Robot Operating System (ROS) environment, with image processing performed using OpenCV, and point cloud processing with the Point Cloud Library (PCL) [21]. Although the Kinect restricts the usable range of the detector and limits outdoor use to shaded areas, the dense depth image it produces provides high quality input data for our system. The outdoor data captured at the MOUT site indicated good performance with even somewhat compromised depth data. In principle, our approach could be applied to dense stereo depth data, with appropriate adjustments to the parameters of the algorithm, but this is as yet untested.

Visual results of modeling for all trials in the two datasets can be found throughout this paper in Figs. 1, 3, and 4. Where possible, rendered 3D models of the corresponding buildings were superimposed and aligned with the map such that the stairway model is overlaid. In each image of a model, the bounding box is represented in green, the planar model in blue, and any step edges in red.

A. Modeling Accuracy

We measured ground truth step dimensions and pitch for our trials, and we present those results in Table I. Each of these results was achieved with < 100 observations. The model estimates for step dimensions are accurate to within $2cm$ and the pitch to within $3°$, on average. However, one frequent source of inaccuracy is underestimation of the step

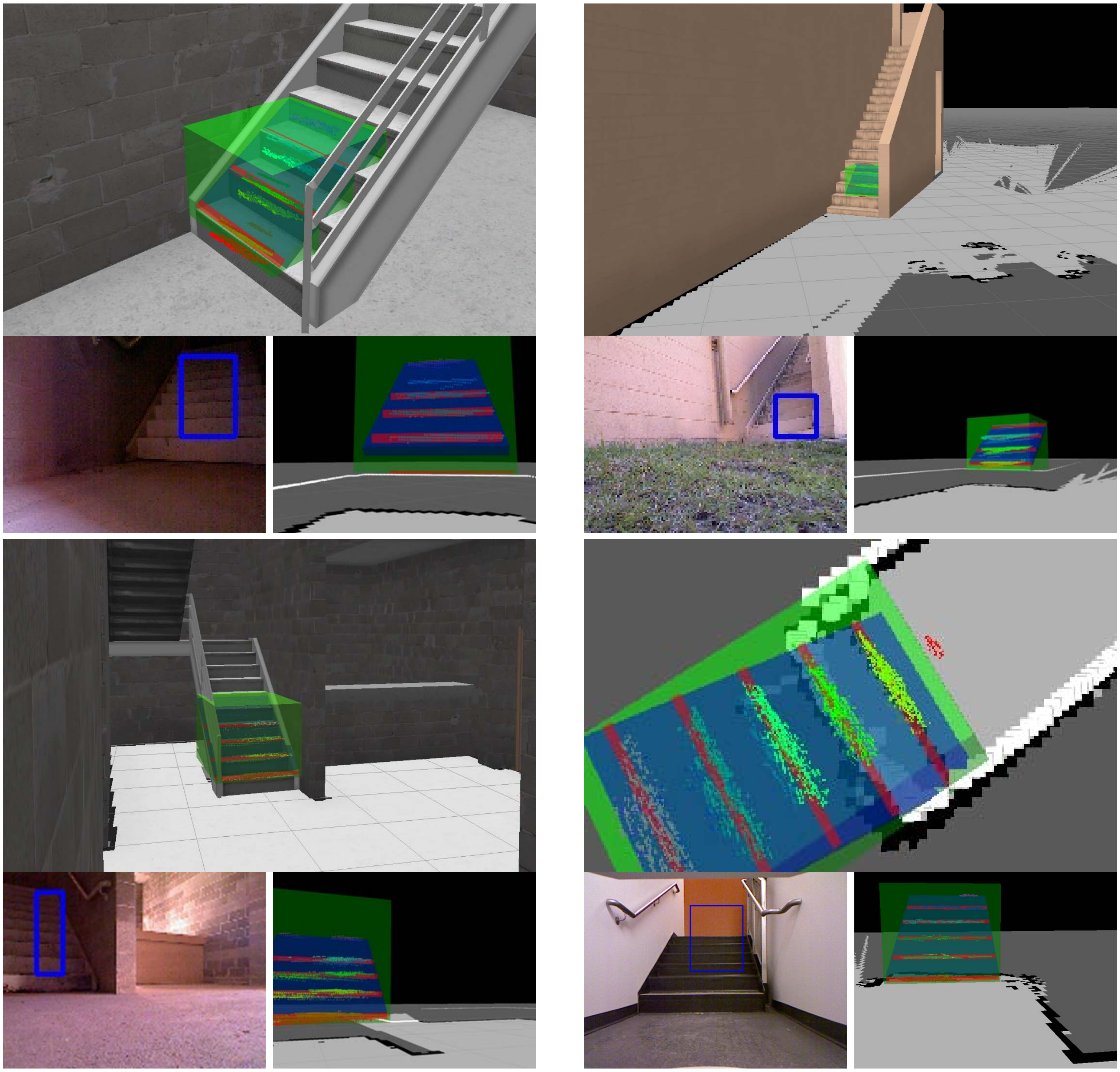

Fig. 4. Results of several runs from our datasets: Building 1 Rear (top left), Building 3 (top right), Building 1 Front (bottom left), and Davis Hall Rear (bottom right). Model components shown are the bounding box (green), planar model (blue), and step edges (red), as well as edge point cloud support for step edge lines (rainbow). Figure is best viewed in color.

width, with a mean error of $17cm$. This is expected, though, based on the stair detection procedure, which only extracts edge points in a horizontal window of the depth image where all of the edge lines overlap, leading to observations that are always narrower than the lines producing them, especially for the lower steps (see Fig. 2). Each trial's results indicate sufficient accuracy for a robotic platform to assess whether that stairway's physical dimensions would be traversable.

We also present some results showing the convergence of the models for several trials. Fig. 5 shows the evolution of the model parameters over time for the two UB trials. Here, all of the parameters are normalized by their ground truth values, so each quantity should tend toward 1 over time. Both trials indicate that after a small number of detections, the models approach their final state.

B. Comparison

The only other stairway modeling approach to present quantitative results on parameter estimation is [9]. In this work, two plane fitting algorithms are implemented (Scan-Line Grouping and Two-Point Random Sampling) for modeling stairways from point clouds for humanoid robot climbing. For their trials, the robot is aligned at a distance of $70cm$ from the base of the stairs when it captures a point cloud and fits a stairway model using one of the two algorithms, in the end estimating its step dimensions. The procedure is then repeated with the robot on odd-numbered steps as it

TABLE I

TABLE OF MODEL STEP ESTIMATES AND **GROUND TRUTH VALUES (GT)** (IN cm)

Trial	Height	Depth	Width	Pitch (°)
B.1 Front	17.4	25.7	97.7	34.0
GT	**19.6**	**25.4**	**96.5**	**37.6**
B.1 Rear	16.6	25.2	71.5	33.0
GT	**19.6**	**25.4**	**96.5**	**37.6**
B.3	16.9	24.5	68.9	35.4
GT	**19.2**	**26.3**	**101.5**	**36.2**
Davis Front	17.5	32.3	107.6	28.3
GT	**18.1**	**30.5**	**122.6**	**30.7**
Davis Rear	16.9	31.1	104.8	29.4
GT	**16.5**	**29.2**	**117.5**	**29.5**
Mean Error	1.7	1.2	17.3	2.3
Std. Dev.	1.4	1.6	12.8	1.88

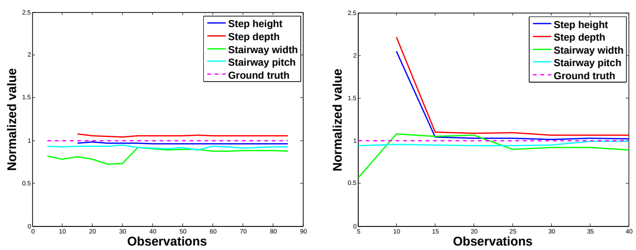

Fig. 5. Convergence of normalized model parameters for Davis Front (top) and Davis Rear (bottom) trials from the UB dataset.

climbs. Each point cloud was acquired by nodding a head-mounted 2D laser scanner to produce a 3D point cloud with approximately 130,000 points.

We compare the mean modeling errors for our trials with the results in [9], using the respective datasets. Neither the data nor the source code for their system is publicly available, so a more direct comparison using a common dataset is not possible. Additionally, the input data for the two approaches are of different modalities. A tabulated error comparison of their two methods with ours can be found in Table II. Since the stairway being modeled in [9] is specially designed so a small humanoid robot can climb it, its steps are of significantly smaller size than a regular stairway that adheres to building codes. Our trials were conducted on five distinct full-size stairways, so we give percent error for comparison for the step height, depth, and width dimensions, and for our data it is averaged over our five trials. However, since these datasets are different, some visual characteristic idiosyncracies may render the numbers not in perfect correspondence.

In step height and depth, our results are comparable, if not marginally better. The error for step width, however is $3-4$ times higher for our method. This is due to the nature of our detector's rectangular bounding boxes. In practice, unless the robotic platform is wider than a human being, the width of the step is less restrictive to its traversability than the step height or pitch, and for robotic traversal it safer to underestimate this parameter.

In their plane-based methods, Oßwald et al. [9] measure angular errors by deviations for planes that are supposed to

TABLE II

TABLE OF STEP MODELING ERRORS FOR THIS METHOD AND THE SCAN-LINE GROUPING (SLG) AND TWO-POINT RANDOM SAMPLING (TPRS) METHODS IN [9] (AVG ± STD)

Quantity	This Method	SLG	TPRS
Height Error (cm)	1.7 ± 1.4	0.42 ± 0.31	0.68 ± 0.54
Percent	8.9	6.0	9.7
Depth Error (cm)	1.2 ± 1.6	1.17 ± 0.67	0.90 ± 0.61
Percent	4.2	6.5	5.0
Width Error (cm)	17.3 ± 12.8	3.40 ± 1.95	2.25 ± 1.97
Percent	16.5	5.7	3.8
Pitch Error	2.3 ± 1.9		
Plane Error (parallel)		2.22 ± 2.17	1.14 ± 1.13
Plane Error (90°)		4.97 ± 2.13	3.12 ± 1.47

be parallel and those that are supposed to be perpendicular. However, our planar model measure pitch relative to the ground plane. Both types of angular errors have been presented in Table II. Although they are measures of different model properties, the angular errors for all three methods are comparable as well. The Scan-Line Grouping algorithm runs at approximately $40Hz$ and the Two-Point Random Sampling method at $0.32Hz$, compared to our method at $20Hz$ (concurrent with mapping).

IV. CONCLUSIONS AND FUTURE WORK

We present a novel, minimal, generative model for a set of stairs, as well as a system for fitting that model to data extracted and aggregated from many observations of a stairways with an RGB-D sensor. Our model is sufficiently detailed to permit the robot to determine the traversability of a set of stairs, while simple enough to be computed in real time and robust to errors. Providing the observations for the modeling module is a stair detector that uses image processing techniques to find lines of depth discontinuity and enforce geometric constraints on them in order to extract the points on just the lines corresponding to stair edges. We have tested our system on a variety of stairways in both indoor and outdoor environments, and we are able to achieve high accuracy in estimation of a stairway's physical parameters. Our results from passive sensing during exploration are comparable to more detailed models that require initial alignment with the stairway. Thus, our approach can serve to assess stairways that are discovered while a robot is exploring a new environment before such detailed models are used to facilitate stair climbing by the robot.

Ultimately, we want this work to enable a new robot behavior: fully autonomous multi-floor exploration by ground robots. With the localization and modeling system presented here, we aim to make some advancement toward that goal. Other problems that would still need to be solved include incorporation of elevation measurements into both mapping and exploration algorithms, execution of an autonomous stair climbing routine after a stairway is found, and modification of path planning algorithms to set stair traversal as a path with high, but finite, cost. This work represents an initial step toward autonomous multi-floor exploration by unmanned ground robots.

Acknowledgements

This material is based upon work partially supported by the Federal Highway Administration under Cooperative Agreement No. DTFH61-07-H-00023, the Army Research Office (W911NF-11-1-0090) and the National Science Foundation CAREER grant (IIS-0845282). Any opinions, findings, conclusions or recommendations are those of the authors and do not necessarily reflect the views of the FHWA, ARO, or NSF.

References

[1] M. Brunner, B. Bruggemann, and D. Schulz, "Towards autonomously traversing complex obstacles with mobile robots with adjustable chassis," in *International Carpathian Control Conference (ICCC)*. IEEE, 2012, pp. 63–68. 2

[2] K. Choi, H. Jeong, K. Hyun, H. Do Choi, and Y. Kwak, "Obstacle negotiation for the rescue robot with variable single-tracked mechanism," in *IEEE/ASME International Conference on Advanced Intelligent Mechatronics*. IEEE, 2007, pp. 1–6. 2

[3] A. M. Johnson, M. T. Hale, G. C. Haynes, and D. E. Koditschek, "Autonomous legged hill and stairwell ascent," in *IEEE International Workshop on Safety, Security, & Rescue Robotics (SSRR)*, November 2011, pp. 134–142. 2, 3

[4] E. Mihankhah, A. Kalantari, E. Aboosaeedan, H. Taghirad, S. Ali, and A. Moosavian, "Autonomous staircase detection and stair climbing for a tracked mobile robot using fuzzy controller," in *IEEE International Conference on Robotics and Biomimetics*. IEEE, 2008, pp. 1980–1985. 2, 3

[5] R. Ray, B. Bepari, and S. Bhaumik, "On design and development of an intelligent mobile robotic vehicle for stair-case navigation," in *Intelligent Autonomous Systems*. Springer, 2010, pp. 87–122. 2, 3

[6] D. Hernandez and K. Jo, "Outdoor stairway segmentation using vertical vanishing point and directional filter," in *International Forum on Strategic Technology (IFOST)*. IEEE, 2010, pp. 82–86. 2, 3

[7] D. Hernández, T. Kim, and K. Jo, "Stairway detection based on single camera by motion stereo," *Modern Approaches in Applied Intelligence*, pp. 338–347, 2011. 2

[8] S. Oßwald, A. Gorog, A. Hornung, and M. Bennewitz, "Autonomous climbing of spiral staircases with humanoids," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2011, pp. 4844–4849. 2, 3

[9] S. Oßwald, J.-S. Gutmann, A. Hornung, and M. Bennewitz, "From 3D point clouds to climbing stairs: A comparison of plane segmentation approaches for humanoids," in *IEEE-RAS International Conference on Humanoid Robots (Humanoids)*, 2011, pp. 93–98. 2, 4, 6, 7

[10] V. Pradeep, G. Medioni, and J. Weiland, "Piecewise planar modeling for step detection using stereo vision," in *Workshop on Computer Vision Applications for the Visually Impaired*, 2008. 2

[11] X. Lu and R. Manduchi, "Detection and localization of curbs and stairways using stereo vision," in *IEEE International Conference on Robotics and Automation*. IEEE, 2005, pp. 4648–4654. 2, 3

[12] Y. Cong, X. Li, J. Liu, and Y. Tang, "A stairway detection algorithm based on vision for ugv stair climbing," in *IEEE International Conference on Networking, Sensing and Control*. IEEE, 2008, pp. 1806–1811. 3

[13] A. Mourikis, N. Trawny, S. Roumeliotis, D. Helmick, and L. Matthies, "Autonomous stair climbing for tracked vehicles," *The International Journal of Robotics Research*, vol. 26, no. 7, p. 737, 2007. 3

[14] S. Wang and H. Wang, "2d staircase detection using real adaboost," in *International Conference on Information, Communications and Signal Processing*. IEEE, 2009, pp. 1–5. 3

[15] S. Shen, N. Michael, and V. Kumar, "Autonomous multi-floor indoor navigation with a computationally constrained mav," in *IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2011, pp. 20–25. 3

[16] A. Ozkil, Z. Fan, J. Xiao, S. Dawids, J. Kristensen, and K. Christensen, "Mapping of multi-floor buildings: A barometric approach," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2011, pp. 847–852. 3

[17] J. Hesch, G. Mariottini, and S. Roumeliotis, "Descending-stair detection, approach, and traversal with an autonomous tracked vehicle," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2010, pp. 5525–5531. 3

[18] J. Delmerico, J. Corso, D. Baran, P. David, and J. Ryde, "Toward autonomous multi-floor exploration: Ascending stairway localization and modeling," U.S. Army Research Laboratory, Tech. Rep. ARL-TR, 2012. 4

[19] R. Rusu, Z. Marton, N. Blodow, M. Dolha, and M. Beetz, "Towards 3d point cloud based object maps for household environments," *Robotics and Autonomous Systems*, vol. 56, no. 11, pp. 927–941, 2008. 5

[20] M. A. Fischler and R. C. Bolles, "Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography," *Communications of the ACM*, vol. 24, no. 6, pp. 381–395, 1981. 5

[21] R. B. Rusu and S. Cousins, "3D is here: Point Cloud Library (PCL)," in *IEEE International Conference on Robotics and Automation (ICRA)*, Shanghai, China, May 9-13 2011. 5