Robust Detection and Recognition of Buildings in Urban Environments from LADAR Data*

R. Madhavan and T. Hong
Intelligent Systems Division
National Institute of Standards and Technology
Gaithersburg, MD 20899-8230.
Email: raj.madhavan@ieee.org, tsai.hong@nist.gov

Abstract

Successful Unmanned Ground Vehicle (UGV) navigation in urban areas requires the competence of the vehicle to cope with Global Positioning System (GPS) outages and/or unreliable position estimates due to multipathing. At the National Institute of Standards and Technology (NIST) we are developing registration algorithms using LADAR (LAser Detection And Ranging) data to cope with such scenarios. In this paper, we present a Building Detection and Recognition (BDR) algorithm using LADAR range images acquired from UGVs towards reliable and efficient registration.

We verify the proposed algorithms using field data obtained from a Riegl LADAR range sensor mounted on a UGV operating in a variety of unknown urban environments. The presented results show the robustness and efficacy of the BDR algorithm.

1. Introduction

The National Institute of Standards and Technology (NIST) is developing architectures and algorithms for autonomous vehicle navigation in both urban and off-road domains using the the 4D/RCS (Real-Time Control System) reference model architecture [1]. The 4D/RCS architecture developed for Demo III [9] specifies the simultaneous representation of information about entities and events in a hierarchical distributed knowledge database wherein information is presented in a form that is ideally suited for path planning and task decomposition. Maps are populated both with knowledge from *a priori* sources such as digital terrain databases, and with knowledge from sensors. The range and resolution of maps at different levels are specified to correspond to the range and resolution of planning algorithms.

In this paper, we present a Building Detection and Recognition (BDR) algorithm in urban environments from LADAR (LAser Detection And Ranging) data. Our motivation behind the development of this algorithm is many fold:

Positioning via registration: We are interested in a secondary positioning scheme for UGV navigation during Global Positioning System (GPS) outages. Towards this, we have developed an iterative temporal range registration algorithm that provides position estimates continually whenever GPS is unavailable or unreliable. The details of this algorithm for an air to ground registration scenario are briefly outlined in Section 2.

World modeling: In 4D/RCS, the World Model (WM) acts as a bridge between sensory processing and behavior generation by providing a central repository for storing sensory data in a unified representation [4]. Using the Knowledge Database (KD), it directly dictates behavior generation and in turn the level of intelligent planning that is achievable. Accordingly, it is necessary to have an underlying rich WM with a current and consistent KD which enables the UGV to analyze the past and plan for the future.

Registration across different sensing modalities: A continually updated and maintained WM will allow the sensors aboard the UGV to focus their attention on regions of future images where maximal useful information will be available. Complementary fusion and registration of information from different sensors offer distinct advantages over any one sensing modality.

Several building detection algorithms are readily available for the detection and recognition of buildings from

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aerial LADAR/LIDAR (LIght Detection And Ranging) images [3], [6], [7]. Our approach is to classify the data points according to whether they belong to the terrain, buildings or other object classes. We are not aware of algorithms that detect and recognize buildings for UGV navigation from ground-based LADAR data and we believe that the work presented in this paper is the first of its kind.

The paper is organized as follows: Section 2 presents a brief overview of the temporal iterative algorithm for air to ground registration. Section 3 describes the BDR algorithm. Section 3.1 discusses the results of the BDR algorithm using LADAR range images obtained from a UGV traversing urban environments. Section 4 concludes the paper by summarizing the contributions and suggesting further research efforts.

2. Air to Ground Feature-based Registration

Towards registering LADAR images from the UGV with those from an Unmanned Aerial Vehicle (UAV) that flies over the terrain being traversed, we have developed a hybrid registration approach. At the core of the registration process is a modified version of the well-known Iterative Closest Point (ICP) algorithm. These modifications provide robustness to outliers, occlusions and false matches/spurious points. In this approach to air to ground registration to estimate and update the position of the UGV, we register range data from two LADARs (one on the UGV and the other on the UAV) by combining a feature-based method with the modified ICP algorithm [5]. Registration of range data guarantees an estimate of the vehicle's position even when only one of the vehicles has GPS information. Temporal range registration enables position information to be continually maintained even when both vehicles can no longer maintain GPS contact.

The ICP algorithm [2] can be summarized as follows: Given an initial motion transformation between the two point sets, a pair of correspondences are developed between data points in one set and the next. For each point in the first data set, find the point in the second that is closest to it under the current transformation. It should be noted that correspondence between the two point sets is initially unknown and that point correspondences provided by sets of closest points are a reasonable approximation to the true point correspondence. From the pair of correspondences, an incremental motion can be computed facilitating further alignment of the data points in one set to the other. This find correspondence/compute motion process is iterated until a predetermined threshold termination condition. To deal with spurious points/false matches and to account for occlusions and outliers, the least-squares objective function that is to

be minimized was weighted such that [10]:

$$min_{(\mathbf{R},\mathbf{T})} \sum_i w_i \left\| \mathbf{M}_i - (\mathbf{R}\mathbf{D}_i + \mathbf{T}) \right\|^2 \qquad (1)$$

where $\mathbf{R}$ is a 3×3 rotation matrix, $\mathbf{T}$ is a 3×1 translation vector and the subscript i refers to the corresponding points of the sets $\mathbf{M}$ and $\mathbf{D}$.

If the Euclidean distance between a point x_i in one set and its closest point y_i in the other, denoted by $d_i \triangleq d(x_i, y_i)$, is bigger than the maximum tolerable distance threshold $\mathcal{D}_{max}$, then w_i is set to zero in Equation (1). The value of $\mathcal{D}_{max}$ is set adaptively in a robust manner by analyzing distance statistics. The results of the modified adaptive thresholding registration algorithm in rugged terrain and urban environments using real field data acquired from a LADAR on the UGV is shown in Figure 1.

3. Building Detection and Recognition

The BDR algorithm consists of the following four main stages:

A1. First, we perform ground detection by using several small fixed areas of patches in front of the UGV to fit a plane for estimating and initializing the ground surface. Then, we subtract these 3D ground points such that the points corresponding to objects above a certain height from the ground are available.

A2. Second, we compute the projection distance to the ground plane. Each range data point is projected to the ground surface which has a grid map representation of 10 cm resolution. The distance to the ground surface is stored in the grid data structure and is used to filter potential building segments.

A3. Third, an eight-connected component analysis on the projected grid map is used to group potential building segments.

A4. Finally, geometric properties are computed on each connected component and are used for building recognition.

3.1. Experimental Setup and Results

The military High Mobility Multipurpose Wheeled Vehicle (HMMWV) shown in Figure 2(a) is a one and one quarter ton, diesel-powered four-wheel-drive truck actuated with electric motors for steering, braking, throttle, transmission, transfer case, and park rake and sensors to monitor speed, engine RPM and temperature. It utilizes the NIST developed RCS architecture using Neutral Message Language (NML) communications for autonomous navigation in unstructured and off-road domains.

(a)   (b)   (c)

(d)   (e)   (f)
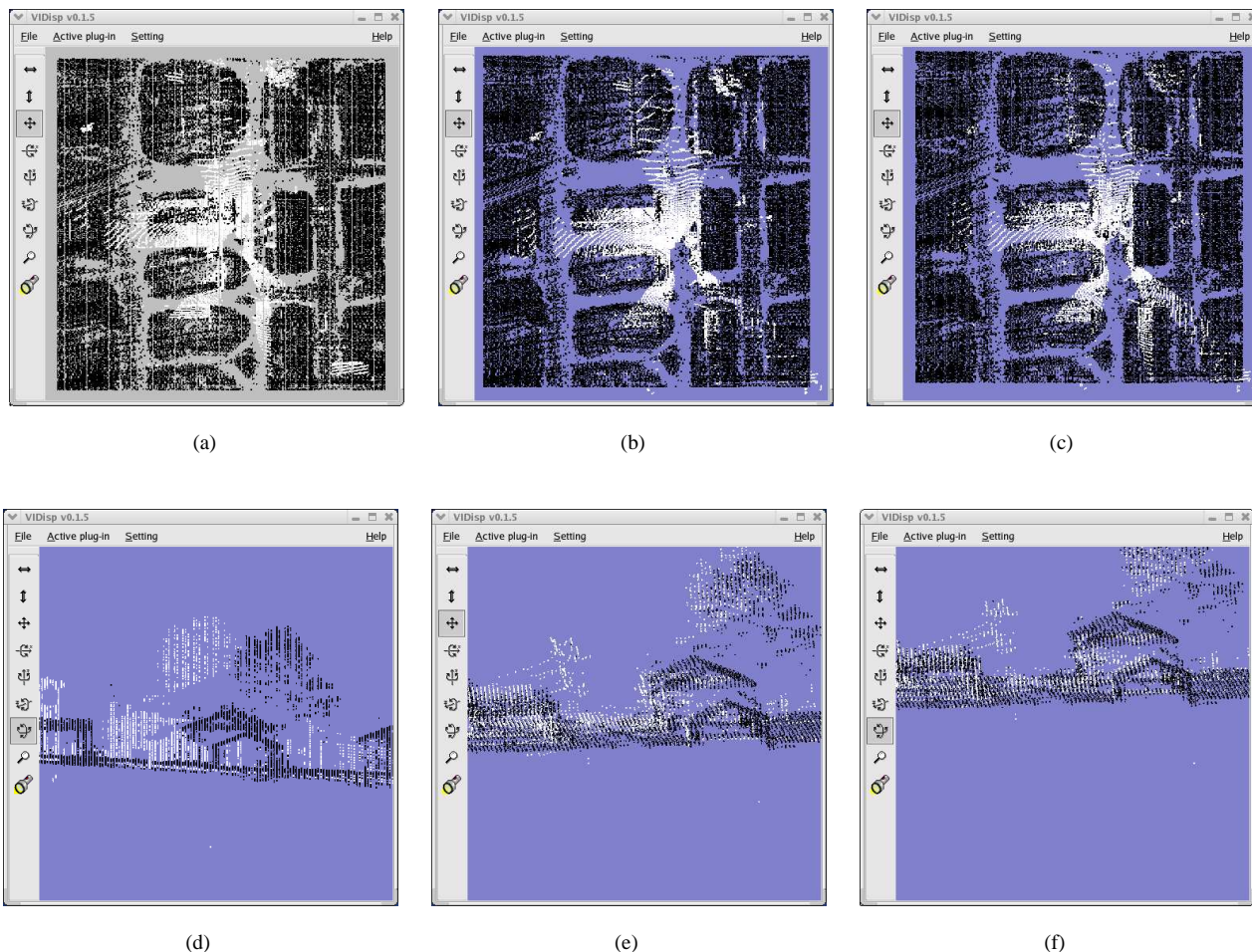
Figure 1. A top view of unregistered range images of UAV (black) and UGV (white) LADARs, the feature-based translation obtained using the extracted corners, and the registered UAV and UGV LADAR range images obtained by utilizing the feature-based translation results are shown in (a), (b) and (c), respectively. (d), (e) and (f), respectively, show magnified side views of their counterparts in the top column.

The data was obtained from the Riegl LADAR mounted on the HMMWV as shown in Figure 2(a) as the vehicle traversed urban environments. The effective field of view of the LADAR is $80° \times 330°$ thus providing an almost panoramic view of the environment with an angular resolution of $0.036°$. The scan rate of UGVL2 is $1°/s - 15°/s$ providing 10000 pts/s with range up to 800 meters [8].

Figures 2(b) and (c) show a top-down view of the raw sensor data points before and after ground subtraction[1]. Fig-

ure 2(d) (middle) shows the potential building segments. The intensity (top) and the panoramic color camera (bottom) images are also included in Figure 2(d) for comparison. Figure 2(e) depicts the 8 components resulting from the connected-component analysis. The final output of the algorithm after filtering small components is shown in Figure 2(f). The top figure shows a top-down view of the connected components projected onto the ground plane and the bottom figure shows that to the 3D point cloud.

In Figure 3, the left column shows the potential building segments, intensity, and color camera images, respectively,

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1   The figures corresponding to the results of the BDR algorithm in this paper are better viewed in color and are available from http://www.isd.mel.nist.gov/downloads/AIPR2004. The range images are shown in false color for better clarity (dark blue means no LADAR

return).

Data Set	No. of Buildings	No. of Other Objects	False Recognitions
#1	8	0	0
#2	6	1	0
#3	4	5	1
#4	5	6	1

Table 1. False-Positive rates of the building detection and recognition algorithm. Data sets #1 through #4 correspond to Figures 2(b)-(e), Figures 3(a)-(b), Figures 3(c)-(d), and Figures 3(e)-(f), respectively.

for three different sets of LADAR data. In the right column, the top and bottom figures show the top-down view of the connected components and their projection to the 3D point cloud, respectively, for the same sets of LADAR data. It is evident from Figures 2 and 3 that the buildings are reliably detected and recognized in the LADAR data.

Table 1 summarizes the false-positive rates of the BDR algorithm for four different LADAR data sets. Data sets #1 through #4 correspond to Figures 2(b)-(e), Figures 3(a)-(b), Figures 3(c)-(d), and Figures 3(e)-(f), respectively. These data sets are representative of typical scenarios encountered in urban environments from which the buildings need to be detected. Whenever the BDR algorithm is unable to detect and recognize structures from the LADAR data as building or non-building, then that occurrence is deemed as a false-positive. For data sets #3 and #4, one of the buildings was not detected due to increased clutter in the environment.

4. Conclusions and Further Research

An algorithm for building detection and recognition from LADAR data was presented in this paper. Our primary motivation behind the development of this algorithm was its use in reliable and efficient 3D LADAR registration-based position estimation of UGVs whenever GPS is either unavailable or unreliable. The results of a hybrid iterative algorithm for registering 3D LADAR range images obtained from unmanned aerial and ground vehicles were briefly presented. The proposed BDR algorithm was tested on field data obtained from a UGV traversing urban environments and the resultant false-positive rates were found to be sufficiently reliable and efficient for use in temporal registration.

In the work described in this paper, we have assumed that the ground is relatively flat for ground detection. In scenarios where this assumption does not hold, the BDR algorithm may result in false-positives. However, in urban environments, the ground immediately in front of the UGV is almost always relatively flat. In cluttered environments, buildings can be wrongly grouped together with other objects thus increasing the false-positive rate of the algorithm. To counter this problem, we are investigating the use of texture analysis using LADAR range values. The presence of varying texture within a given range image is indicative of different classes of objects which can used for improving building detection and recognition. In addition, we are also considering using color as an additional cue for feature detection.

References

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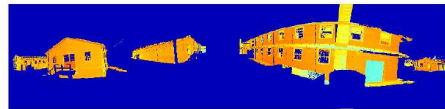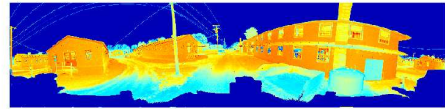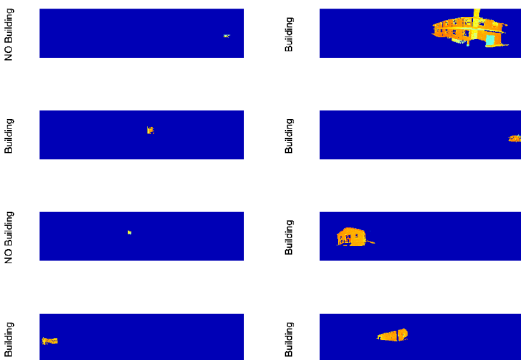
(a) HMMWV sensor suite
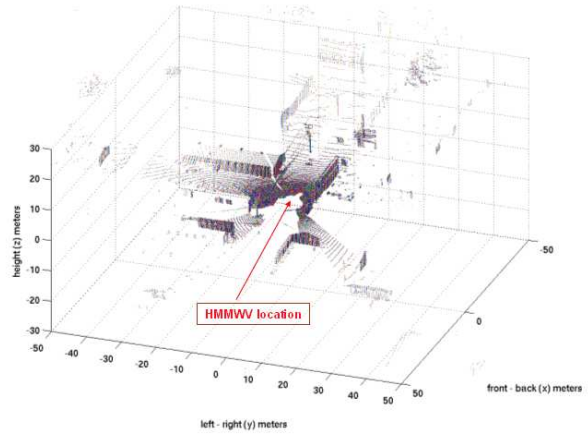
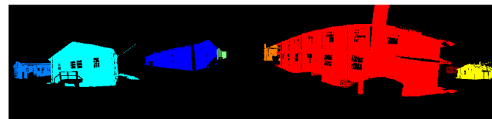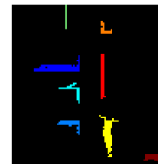(b) 3D point cloud before ground subtraction
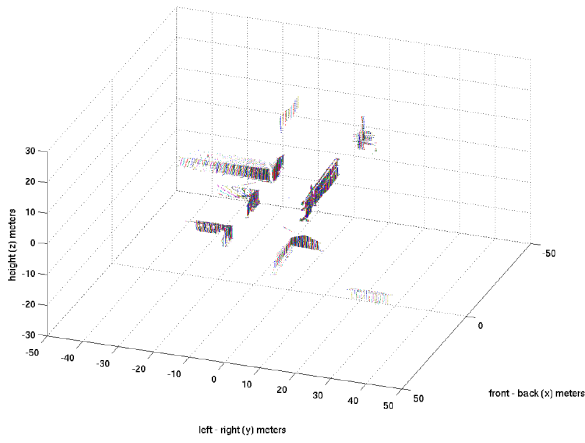
(c) 3D point cloud after ground subtraction

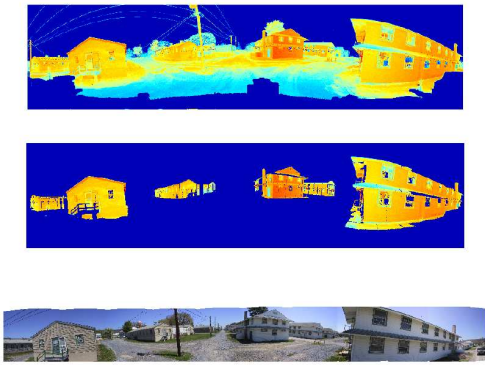(d) Potential buildings, intensity, and color camera images
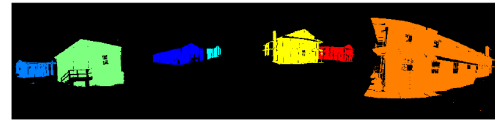

(e) 8 components

(f) Final output of the BDR algorithm

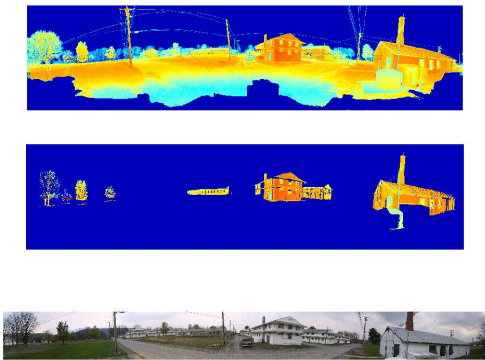**Figure 2. Experimental setup and the results of the building detection and recognition algorithm.**
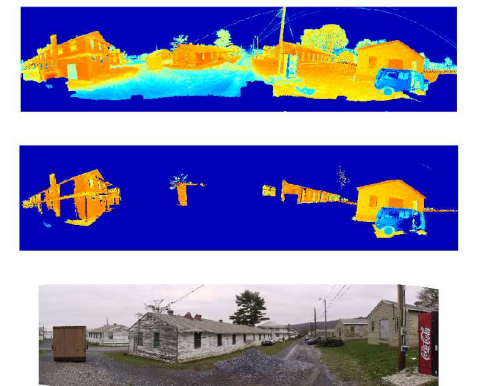
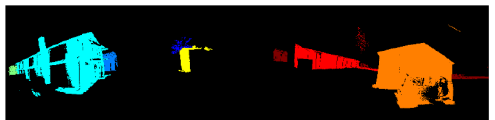(a) Data set #2

(b) Data set #2

(c) Data set #3

(d) Data set #3

(e) Data set #4

(f) Data set #4

Figure 3. Building detection and recognition for three different sets of LADAR data.