Ground Segmentation based on Loopy Belief Propagation for Sparse 3D Point Clouds

Mingfang Zhang  
School of Automobile  
Chang’an University  
Xi’an, China 710064  
mimgfangzhang@163.com

Daniel D. Morris  
Dept. of Electrical and Computer Engineering  
Michigan State University  
East Lansing, MI 48824  
dmorris@msu.edu

Rui Fu  
School of Automobile  
Chang’an University  
Xi’an, China 710064  
furui@chd.edu.cn

Abstract—Ground segmentation is an important pre-processing task for local environment perception using 3D LIDAR, and it is particularly challenging in unstructured environments with rough or sloped terrain. To solve the ground segmentation problem we propose a novel cost-based ground measurement model that is incorporated into a Markov Random Field and solved using loopy belief propagation. Our cost-based measurements operate on columns of a cylindrically-binned map of the LIDAR points and provide robust, non-parametric estimates for ground height. These estimates can model ambiguous situations as well as occlusions from nearer objects. A multi-label Markov Random Field in polar coordinates incorporates local smoothness and slope assumptions to filter out obstacles, while at the same time allowing sharp discontinuities in ground height when warranted by the measurements. An efficient loopy belief propagation method is used to solve for the maximum belief ground height at each cell. Experimental results show good performance in rough terrain, particularly in comparison to other local ground segmentation methods.

I. INTRODUCTION

Local environment perception for outdoors is an important task in autonomous driving and intelligent vehicles, and the topic of much ongoing research [1], [2], [3]. Laser range scanners, or LIDARs, provide complementary data to video-based sensors including accurate 3D measurements and invariance to illumination. They can be used with video systems for much richer environment modeling [4], [5]. Given the set of 3D irregular point clouds obtained from a LIDAR sensor, the perception tasks include ground segmentation, 3D object detection, classification and tracking. Ground segmentation is an important pre-processing step that enables other tasks to be performed more efficiently. The objective of segmentation is to separate 3D point clouds into disjoint subsets representing ground and non-ground. The main challenge is reducing over- and under-segmentation which affect subsequent steps of object detection and classification based on 3D non-ground point clouds.

Existing ground segmentation methods for 3D point clouds can be classified into four categories, namely, elevation map methods [6], [7], [8], [9], ground modeling methods [10], [11], methods based on relationship between the adjacent points [12], [13], [14], and MRF-based methods [15], [16], [17]. The ground segmentation method in this paper is inspired by the existing graph-based approaches in [15], [17]. However, these papers focus on detecting drivable road detection regions, not the more general segmentation of ground from non-ground points. In contrast to simple terrain in urban areas, this paper focuses ground segmentation of rough terrain in unstructured environments; a significantly more challenging task.

This paper proposes a cost-based measurement model that operates on columns of a 3D cylindrical grid map built from a LIDAR measurements. These costs generate nonparametric probabilistic ground height measurements that can account for the information loss due to partial occlusions from closer objects. These cost functions are much more informative that the single average feature value generated from neighboring cells in [15], [17]. Measurements are combined with terrain assumptions using a multi-label Markov Random Field (MRF), and a Loopy Belief Propagation (LBP) method updates ground-height probabilities over the local environment producing ground heights and a segmentation of the 3D points. Experimental results demonstrate the proposed approach can segment the ground from non-ground points accurately, even in rough terrain and steeply sloped regions.

II. RELATED WORK

Algorithms for ground and non-ground segmentation with 3D LIDAR vary according to the local environment characteristics, the point cloud density and application. Methods can be categorized as follows:

1) Elevation map methods: In most situations, the 3D point cloud is projected onto a horizontal plane with an elevation map to reduce dimensionality, which is commonly classified as 2.5D grid model. A standard approach to compute an elevation map is to average the height values of the laser points in each cell [6]. Another elevation map Min-Max calculates the difference between the maximum and minimum height of the returns falling in each cell [7], [8], [9]. The cell is defined as a part of non-ground if its feature value exceeds a pre-defined threshold. The third dimension of these elevation maps is only partially modeled since each grid cell in the terrain contains only one feature value. Although the segmentation algorithms based on elevation maps are efficient, one obvious drawback of the approaches is under-segmentation. When an obstacle is in a cell the whole cell is classified as non-ground even though it may contain ground pixels. In addition, it is hard to select the appropriate threshold for sloped ground with vegetation, hills, or curbs in outdoor environments.

2) Ground modeling methods: Himmelsbach et. al proposed a line-based ground model for every sector in polar
grid map [10]. This algorithm estimates local ground plane by applying 2D line extraction algorithms to the unorganized 3D points. Every single point is compared with the obtained ground plane lines in order to separate ground from non-ground points. Chen et al. [11] split a large-scale 2D ground segmentation problem into many one-dimensional GP regression problems to distinguish the ground points or obstacles in each segment of a circular polar grid. This method enjoys a lower complexity than the method in [18] where a GP incremental sample consensus with stationary covariance function is utilized to model the global ground in 3D grid map.

3) Methods based on the relationship between adjacent points: Those approaches benefit from neighborhood relations between points to address the ground segmentation problem in full 3D view [12], [13], [14]. The neighborhood is used to extract local point features from the normal vectors of estimated points. Under the smoothness constraints derived from these features, Euclidean clustering algorithms and region growing algorithms are employed for 3D points to segment the objects, which are fast and easy to implement [19], [20]. However, these algorithms are not considered as robust since different seed points usually generate different segments. A local convexity criterion calculated from local geometric features is introduced in [13] to segment both the ground and 3D objects and keeps the full 3D information acquired by 3D sensors unlike many other approaches.

4) MRF-based methods: Wellington et. al [21] proposed a generative probabilistic terrain model, combining two MRF models with a Hidden semi-Markov model for each column. They measure 3D structure using laser remission, infrared temperature and color measurements and represent probabilities with Gaussian Mixture Models. Unlike our method which is designed to capture height discontinuities using a truncated step function, their ground height is modeled using a Gaussian MRF which propagates to vegetation cells where height is not directly observed. Tse et. al [22] fused the information from the sensor and terrain, and estimated the unified mixture-model based terrain with MRF, without the independence assumption among cells in the 2.5D map.

It is notable that there exist several MRF-based road detection methods in [15], [17] which have the potential for ground segmentation. These methods use the gradient cues of the road geometry to partition the surrounding environment into the different regions. The feature of each cell is actually an individual average value calculating from the neighboring nodes without considering the state of current cell. Hence, the results of these approaches are relatively coarse, rather than the precise segmentation of ground and non-ground points aimed for in this work.

Motivated by the analysis of the above methods, we propose a novel MRF-based ground segmentation approach in this paper, which is an evolution of the works in [15], [17]. This novel method differs from other MRF-based methods in two aspects. First, our proposed unary data costs in MRF formulation are discrete probabilistic models of terrain given LIDAR points, which are based on the heuristic categorization of each vertical column and the columns closer to the LIDAR along the radial direction. When applied to the LIDAR points, these data cost models cover produce probabilistic height measurements for each node of the graph. Second, a LBP inference algorithm is applied to the labeling process of ground segmentation and makes it feasible to obtain the maximum belief ground segmentation after multiple message passing iterations.

The rest of the paper is organized as follows. Section III presents the details of ground segmentation algorithm, including the data acquisition and preprocessing, MRF-based multiple labeling, and cost function calculation. Section IV shows the experimental results in real environments including comparisons to other methods.

III. GROUND SEGMENTATION

Our ground segmentation approach seeks the maximum-belief ground height over a polar grid of cells around the sensor, and segments LIDAR points based on these heights. Initial ground-height measurements are performed using cost functions that operate on columns of a binned cylindrical grid of the LIDAR point cloud. The multi-valued outputs of these cost functions are incorporated into a 4-connected multi-label MRF with one node per cell and one label per possible ground height. Inference is performed on the MRF using LBP, resulting in a maximum belief height per node and thus ground segmentation. Details of each component are explained in this section.

A. Data acquisition and preprocessing

The point cloud generated by our Velodyne HDL-32E LIDAR is binned into a 3D cylinder of height \( h = h_{\text{max}} - h_{\text{min}} \) and radius \( R \), as shown in Figure 1(a). Grid elements have angular intervals \( \Delta \theta \), radial intervals \( \Delta r \), and height intervals \( \Delta h \). Each vertical column of grid elements belongs to a cell in a polar map and provides measurement data for the corresponding node of the MRF. Before processing the data we eliminate overhanging structures such as tree branches, (which we assume cannot be ground), on a per column basis. These overhanging points are detected by being above a vertical gap of at least 3 contiguous bins and their bin values are zeroed.

B. MRF-based Multiple Labeling

The undirected graphical model MRF can describe the spatial interactions of nodes in the scene, and assign the labels for the nodes. Here, we formulate the ground segmentation problem as a multiple labeling process in the MRF under the standard 4-connected neighborhood system. Define \( G = (V, E) \) as an undirected graph with nodes \( v_i \in V \), the grids in the grid map, and edges \( (v_i, v_j) \in E \) describing the dependency of adjacent nodes \( v_i \) and \( v_j \).

In order to find a proper label value to segment LIDAR points at each node into ground and non-ground subsets, we define the label of each node by the point distribution and height values of the points at each node. The range of labels is \( L = \{1, ..., B\} \) for \( B \) bins. We assume that the labels should vary slowly and smoothly almost everywhere but may change abruptly between nodes along terrain boundaries. A labeling function \( f \) assigns a label \( f(v_i) \in L \) to the observed node \( v_i \in V \), depending on 4 neighboring nodes and the observed node’s
state under Markov assumptions. The quality of a labeling is evaluated by an energy function $E$:

$$E(f) = D(f(v_i)) + W(f(v_i), f(v_j)),$$

where $E$ corresponding to pairs of adjacent nodes $(v_i, v_j)$ in the 4-connected neighboring grid map. The data cost $D(f(v_i))$ is the cost of assigning label $f(v_i)$ to node $v_i$. The smoothness cost $W(f(v_i), f(v_j))$ measures the cost of assigning labels $f(v_i)$ and $f(v_j)$ to two neighboring nodes. In this category, the label assignment will be determined by the sequenced indices of bins $b = \{1, \ldots, B\}$.

C. Data Cost Modeling

Our cost function, $D(f(v_i))$, incorporates a statistical model for how LIDAR points are distributed given a ground height specified by the label $f(v_i)$. Costs can be considered as negative log probability and so labels with low cost should have high probability of being the true height. This cost depends on the distribution of the points within the cell and may also depend on the height change between the sensor and the node as well as the existence of occluding objects between the sensor and the node. The cost is designed to constrain the ground height over bin heights where there is evidence, and not to constrain it where evidence is lacking. Four categories of cells are considered, and for each a data cost $D(f(v_i))$ is defined.

Category 1: Although the Velodyne sensor can take 3D scans of the environment and provide millions of points per second, there are still many grids in the map that have no returned values. If there is no point at the node (see Figure 2(a)), the data cost at the empty node should be a constant value $C$, as shown in Figure 3(a), namely:

$$D(f(v_i)) = C,$$

(a) Category 1

(b) Category 2

(c) Category 3

(d) Category 4

Fig. 2. Different categories of cell-point distributions. (a) There are no points in cell $m$, then the data cost of this cell is a uniform distribution, shown in Figure 3(a); (b) Cell $m$ is on the flat or rough ground surface, and small slope or rough terrain exists between cell $m$ and LIDAR. Then the data cost model should be a truncated step function, shown in Figure 3(b); (c) Cell $m$ is on the surface of obstacle, there is a steep obstacle between cell $m$ and LIDAR. Then the data cost model in this category is a half truncated step function, shown in Figure 3(c); (d) Cell $m$ is a steep slope or an obstacle, and there is no object occlusion between this cell and LIDAR. We choose the index of the bottom bin with the lowest point as the feature of this cell. Then the data cost model of cell $m$ is a half truncated step function, shown in Figure 3(c).

Fig. 3. Different data cost models based on point distribution and height values.

Category 2: Points exist in cell $m$, and after the overhanging points are removed, the difference between the highest and the lowest points (called maximum height difference $\delta z$)
in grid cell $m$ is less than the height $\Delta b$ of one bin. Also the maximum height differences (denoted as $\delta_f$) of the grid cells with smaller radius than cell $m$ in the same radial direction is smaller than the threshold $t_b = 3 \times \Delta b$ (see Figure 2(b)), and so there is no occlusion between LIDAR and this cell. Thus the points in cell $m$ have a high probability of being ground points and we will select the index $b_s$ of the bin with lowest points as the feature of this cell when calculating the probability model of point distribution for the cell $m$. In this way, we not only set the constraints for this cell, also consider the other cells with smaller radius in the same radial direction. The parameter $\Delta b$ allows the existence of slopes and eliminates the incorrect identification of a vehicle roof as ground, which may happen if local plane fitting is applied for ground surface construction as in [14]. In this situation, the data cost for each node is calculated with a truncated step function:

$$D(f(v_i)) = \min(||g(v_i) - f(v_i)||, t),$$

where $t$ is a truncation value, $g(v_i)$ is the feature of cell $v_i$. The truncation procedure makes the data cost model robust to large difference of labels from adjacent nodes calculating from the distribution of points, as shown in Figure 3(b).

**Category 3:** Points exist in cell $m$, and after the overhanging points are removed, the maximum absolute difference of vertical coordinates of all points falling into this grid cell has a low residual $t_a = \Delta b$, but there exist several maximum absolute height differences (denoted as $\delta_f$) of the grid cells with the smaller radius in the same slice larger than the threshold $t_b$ (see Figure 2(c)). Hence there are some occluded regions between LIDAR and this cell, or in some cases this cell is located on an elevated object or a vehicle roof. Thus, we need to build another cost model for this cell. We select the index $b_s$ of the bin in which the lowest point is located as the feature of this cell. The data cost for the bins above this boundary is a sloped step function, while the data cost for the bins below the boundary is a constant value $C$, as shown in Figure 3(c). This asymmetric cost captures the intuition that the ground height in this cell is unlikely to be higher than $b_s$, and could have any value lower than this.

$$D(f(v_i)) = \begin{cases} \min(||g(v_i) - f(v_i)||, t), & \text{if } g(v_i) \geq b_s, \\ C, & \text{otherwise.} \end{cases}$$

**Category 4:** Points exist in cell $m$, and after the overhanging points are removed, the maximum absolute height difference $\delta_f$ for all points falling into the grid cell $m$ exceeds the height tolerance $t_a = \Delta b$ (see Figure 2(d)). The cell $m$ is considered as part of obstacle, such as wall or pedestrians, and it also can be a small slope, whether there exist points in the grid cells with the smaller radius in the same slice or not. The boundary bin must be a member of the lowest set in height of adjacent non-empty bins in the same grid cell. The measurement model for this cell is the same as Category 3.

**D. Smoothness cost function**

The change in terrain height between adjacent nodes is modeled with a smoothness function $W(f(v_i), f(v_j))$. This captures our assumption that adjacent nodes are most likely to have the same height label with a linearly increasing cost as height difference increases. Large height differences are permitted by truncating this cost in the form:

$$W(f(v_i), f(v_j)) = \min(s||f(v_i) - f(v_j)||, d),$$

where $s$ is a weight on height differences, $d$ is a constant truncation value which allows for ground discontinuities when evidence supports this.

**E. Loopy Belief Propagation-based Ground Segmentation**

Loopy belief propagation algorithms calculate the marginal distribution at each node [23], [24]. LBP consists of passing messages among the adjacent nodes on MRF, updating the message to its neighbor at each iteration for each node based on the incoming messages from its residual 3 neighbors at the previous iterations, and normalizing the message for each node. During message passing, the label $f(v_j)$ is traversed in the label set $L$ to minimize the energy function $E$. LBP based on max-product outperforms the one based on sum-product in terms of computational complexity [23] and is employed to minimum cost labeling process in our algorithm.

The max-product BP algorithm passes messages around the graph defined by the 4-connected MRF network. The calculation process is briefly introduced in the following way:

1) All messages are initialized to be zero using negative log probabilities. Each message is a vector of one dimension given by the number of the possible labels at each node.

2) LBP propagates the message along 4 directions, forward and backward in radial direction and clockwise and counter-clockwise in circular direction, as shown in Figure 4. For iteration $t = 1, 2, \ldots, T$, new message that node $v_i$ sends to a neighboring node $v_j$ at iteration $t$ for the label at node $v_j$ is updated as follows:

$$m^{t}_{v_i,v_j}(f(v_j)) = \min_{f(v_j)} \left\{ W(f(v_i), f(v_j)) + D(f(v_i)) + \sum_{s \in N(v_i) \setminus v_j} m^{-1}_{v_i}(f(v_i)) \right\}$$

Fig. 4. Here we show the message passing along the clockwise direction as a demonstration. In the 4-connected neighborhood system, the message passed from the node $v_j$ to the neighboring node $v_j$ at time $t$ consists of three parts. The first part is the smoothness cost between these two nodes. The second part is the data cost of node $v_j$. The third part is the sum of the messages at node $v_i$ received at time $t - 1$ from the neighbor nodes $v_1, v_2$ and $v_3$, excluding the message from the destination node $v_j$ to $v_i$. 
where $N(v_i) \setminus v_j$ denotes the neighbors of $v_i$ other than $v_j$. The minimum message for the bins at node $v_j$ from the bins of neighboring node are selected as the new message for the label at node $v_j$.

3) After $T$ iterations, one may calculate the belief vector at each node to find the best label by

$$b_{v_j}(f(v_j)) = D_{v_j}(f(v_j)) + \sum_{p \in N_{v_j}} m^T_{v_j,v_j} f(v_j). \quad (7)$$

4) The label $f(v_j)$ at node $v_j$ is selected to separate the point data in the ground and non-ground points by

$$f(v_j) = \arg \min_{f(v_j)} b_{v_j}(f(v_j)), \quad (8)$$

which minimizes $b_{v_j} f(v_j)$ individually at each node. LIDAR points at each node below the corresponding label are defined as ground points, while the points above this label are non-ground points. In this way, the labeling process is transformed into the segmentation of the points at each node. Boundary pixels of both the obstacle region and the ground are segmented with 4-direction message passing to reduce the probability of under-segmentation or over-segmentation.

Message passing in 4 directions compensates for sparse distributions of point clouds and the segmentation method based on this has a better robustness than the one based on surface interpolation. One issue arising from the sum of messages when calculating the belief vector is that the belief will tend towards infinite value and eventually exceed floating point limits. So the complete message vector should be normalized before sending to adjacent nodes. Finally, after a finite number of message passing iterations, messages at each node typically converge and the change of the energy function drops below a threshold.

IV. EXPERIMENTAL RESULTS

To demonstrate the proposed algorithm, experiments were carried out with various typical but challenging scenarios including rough terrain scene from the public KITTI dataset [25] and sloped terrain scene acquired by Velodyne HDL-32E sensor mounted on our Husky robot.

Due to the sparsity of point clouds at long range, we mainly test the data sets collected nearby the LIDAR. Set $R = 30m$, $\Delta \theta = 0.5^\circ$, $\Delta r = 0.1m$, then the grid map size is $720 \times 300$. Considering that the ground height location with highest potential tend to be located in the lower part of each grid cell, we set the valid vertical spatial range $h_{\text{max}} - h_{\text{min}} = 6m$ with $B = 30$ to contain the lowest scan point, so the height of each bin $\Delta h = 0.2m$. The threshold parameters of data cost model are fixed to $C = 0$, $t = 5$ throughout the experiments.

A. Simple rough terrain

In order to highlight the details of segmentation in rough terrain, a scan area within a sector of 100 degrees is plotted in Figure 5. As the LIDAR beams sweep on the rough terrain, the radius of the 3D points varies with clutter. The ground segmentation method in [8] determines the points in one cell as the ground when the height difference of the points in the cell is less than a pre-defined threshold. This method incorrectly classifies some ground points as non-ground points, as shown in Figure 5(b). In contrast, the proposed method accurately segments the ground points even beneath or around the vicinity of the vehicle, since it combines the constraints of the height difference with the point distribution in the columns closer to the LIDAR.

B. Complex sloped terrain

3D point clouds are collected in two complex sloped environments by a Velodyne HDL-32E sensor installed on the robot Husky. The first scenario is a sloped rocky area which results in irregular scan lines. The segmentation result of our proposed method is compared in Figure 6 with the one illustrated in [10], which estimates local ground plane by using 2D line extraction algorithm. Figure 6 reveals that the latter method performs acceptably only in the vicinity of the LIDAR, and has significant under-segmentation at long range due to

![Fig. 5. Ground segmentation in rough terrain via (a) our proposed method and (b) the method in [8]. Our method succeeds in segmenting the ground beneath or around the vicinity of the vehicle.](image)
Fig. 6. Ground segmentation in rocky scene: (a) ground and non-ground points are segmented correctly by our proposed method; (b) the 2D line fitting method in [10] shows under-segmentation results at long range.

Fig. 7. Ground segmentation in complex off-road scene (a) and its detail view (b). Besides the good segmentation results, the slope tendency of the terrain is accurately estimated in form that the elevation of the upper-right area is higher than the lower-left region.

poor 2D line fitting of the rough terrain. Our method operates well even in the presence of a discontinuity and occlusion.

The second scene involves a complex off-road terrain to demonstrate the potential of our method. The segmentation results are provided in Figure 7. Several interesting phenomena can be easily observed. First, the ground points below tree branches or vegetation are segmented from non-ground points; second, the contact edge between pedestrians standing on the slope and the terrain surface is also segmented correctly; finally, after multiple message passing iterations are conducted, the proposed approach successfully classifies the slope variation into the downhill or uphill direction.

These two scenarios proves that our algorithm is superior to the method in [10] in the aspect of dealing with complex sloped environments.

C. Quantitative Evaluation

Quantitative evaluation is conducted for both simple rough and complex sloped terrains. We calculate true positive rate (TPR) and false positive rate (FPR) by comparing the segmentation results from different segmentation algorithms in [8], [10] and our proposed method with manually labeled ground truth information. Since the main novelty in this paper lies in proposing 3 different data cost models based on heuristic categorization of point distribution, our segmentation result is also compared with the results of our method with the conventional cost models in Figure 3(b) when points exist in the cell and Figure 3(a) when there is no point in the cell. These quantitative results are shown in Table I.

From Table I we can see that the algorithms in [8][10] show good segmentation performance in simple rough terrain, and our method are slightly better, while in rocky area and complex off-road scene, our method outperforms the other methods. The phenomenon can be explained as follows. The first two
of large 3D clutter. Experiments show improved performance robust and accurate ground segmentation, even in the presence of points exist in the cell and Figure 3(d) when there is no point in the cell. D) Our method.

<table>
<thead>
<tr>
<th>Scene 1: Sample rough terrain (Fig. 5)</th>
<th>TPR(%)</th>
<th>FPR(%)</th>
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<tr>
<td>A) Method in [21]</td>
<td>95.74</td>
<td>0.54</td>
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<tr>
<td>B) Method in [13]</td>
<td>94.72</td>
<td>0.23</td>
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<tr>
<td>C) Our method with conventional cost</td>
<td>97.19</td>
<td>2.10</td>
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<td>D) Our method</td>
<td>99.91</td>
<td>0.06</td>
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<th>FPR(%)</th>
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<tr>
<td>A) Method in [21]</td>
<td>98.03</td>
<td>2.37</td>
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<td>B) Method in [13]</td>
<td>76.33</td>
<td>3.21</td>
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<td>C) Our method with conventional cost</td>
<td>98.09</td>
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<th>Scene 3: Complex off-road environment (Fig. 7)</th>
<th>TPR(%)</th>
<th>FPR(%)</th>
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<td>A) Method in [21]</td>
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<td>86.39</td>
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<td>D) Our method</td>
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methods behave poorly in the Scene 3 because it is hard to select an adequate parameter for line fitting method, and the segmentation based on the height difference is relatively rough for the complex environment where the slope with different height larger than the given threshold is still possibly the ground. The explanation for the result of Method C in Table I is that the truncated step function is not feasible for the cells with occlusion. Actually, when the occlusion occurs, the ground plane can be located at an arbitrary bin below the boundary bin that LIDAR hits; hence, the probability of being ground plane for the bins below the boundary bin are equal. This situation is not adequately modeled in Method C. In contrast, our method proposes a new data cost model for the occlusion cells as shown in Figure 3(c), which overcomes this drawback. Moreover, we select the proper data cost model based on the point distribution of both the current cell and the cells closer to the LIDAR.

We implemented the algorithm on an Intel Core with 3.20 GHz using unoptimized MATLAB code. The average processing time per frame in the third complex scene is more than 1 second. This is not real-time with a scanning frequency of 10 Hz, but optimizing and parallelizing the code using C++ instead of MATLAB language to improve the running speed is one of our future works.

V. CONCLUSION AND FUTURE WORK

In this paper we proposed a novel MRF-based ground segmentation method for sparse 3D point clouds. The main contributions are twofold. First, we designed a multi-model data cost measurement process that selects an appropriate measurement model for a ground cell depending on the point distribution between the cell and the sensor. This produces separate probabilistic representations for empty cells, partially occluded cells, cells containing objects as well as visible-terrain cells. Second, we combine terrain smoothness assumptions and height measurements using a multi-label MRF, solve for the maximum belief estimate using LBP, and use this to segment the LIDAR points. The resulting algorithm obtains a robust and accurate ground segmentation, even in the presence of large 3D clutter. Experiments show improved performance compared to competing segmentation methods especially in rough terrain and sloped areas.

A limitation of our method is that there must be sufficient ground measurements. In heavily cluttered environments such as dense foliage the ground may be occluded for large areas and our ground height estimate will be unreliable.

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